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Process-Based Models: A Synthesis of Models and Applications to Address Environmental and Management Issues*

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8.1 Introduction

The development of process-based models, also known as mechanistic or ecosystem models, has a shorter history than empirical or gap models (Chapters 6 and 7). Numerous empirical models have been developed since the early 1960s to simulate forest growth using forest inventory data. For forest managers, empirical models became more useful tools than the traditional growth and yield tables, as their implementation on computers facilitated

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* This chapter is dedicated to our colleague Alexander Komarov, Professor at the Institute of Physicochemical and Biological Problems in Soil Science of Russian Academy of Sciences, who passed away in Pushchino, Russia, on May 31, 2015.

the management of large datasets of predicted stand growth attributes and the simulation of silvicultural treatments. The development of gap models, which simulate forest succession using semiempirical relationships, began in the early 1970s with the JABOWA model (Botkin et al. 1972) (see Chapter 7). It is only in the 1980s that the development of process-based models really began when the need to simulate the effects of environmental disturbances, such as acid rain, air pollution, or climate change, on the functioning of forest ecosystems was identified.

Process-based models represent and simulate physiological and biogeochemical processes and their interactions with the abiotic environment (water, climate, and nutrients) in forest ecosystems by using functional relationships (Johnsen et al. 2001; Landsberg and Sands 2011). These functional cause–effect relationships are structured within a complex hierarchy of processes of different levels of importance within a system. As forest ecosystems are characterized by many interactions and feedbacks between vegetation, soil, and the atmosphere, the capacity of process-based models to make realistic predictions depends on a logical integration of matter and energy fluxes (Friend et al. 1997). Key physiological processes that may be considered for tree growth modeling include photosynthesis; mineral metabolism; respiration; carbon partitioning; absorption and accumulation of water, minerals, and gases; translocation; growth regulation; and litter decomposition (Pastor and Post 1985; Dixon 1990; Landsberg 2003a). Other processes that may be found in process-based models include tree phenology, plant functional–type competition, mortality, responses to fire or pest disturbances, and effects of human and land management. However, few process-based models include representations of all these processes, as the amount of data to initialize them is considerable. Also, for the prediction of some ecosystem processes, such as growth or turnover rate of some ecosystem pools, it is not necessary to include model components for all possible ecophysiological processes. The challenge that modelers face when they develop process-based models is to determine the extent to which the complexity in the representation of processes is sufficient to meet specific objectives and make realistic predictions. As there are many processes and interactions in forest ecosystems, the relationships can have a high degree of complexity that cannot necessarily be solved using analytical mathematical techniques, which explains why the majority of process-based models have been developed by applying the basic principles of systems analysis. Process-based models are seen as powerful tools that allow scientists to better understand ecosystem functioning and give a realistic prognosis if some factors change in the future (Landsberg 2003b).

The basic framework of the majority of process-based models includes model components that interact to simulate productivity and nutrient, water, and carbon cycles. There are different levels of complexity in these models. Also, some models focus on the simulation of only some of the ecosystem components or fluxes, such as nutrient or water cycles. These are abiotic interactions, but there are also biotic interactions, such as competition. Typical models include the representation of the effects of environmental factors, including temperature, precipitation, photosynthetic active radiation (PAR), or soil properties, on the ecosystem processes: photosynthesis, respiration, organic matter decomposition, and so on. Concerning productivity, two basic levels are to be considered. For trees and understory woody and herbaceous vegetation, productivity is the allocation of the net production of carbohydrates in the different compartments: stems, branches, foliage, and roots. Productivity at the ecosystem (or stand) level is the result of biotic processes, such as competition, that affect carbon allocation among individual trees. As stand density increases, each individual tree sees its available growing space reduced by the presence of neighboring trees. As a result, crown development is inhibited because the potential

amount of PAR they can absorb for photosynthesis is reduced by neighboring crowns and the amount of nutrients they can potentially uptake is captured by neighboring root systems. Carbon, water, and nutrients are transferred among ecosystem compartments from trees to the forest floor and to the soil. The soil system is a biological reactor that is responsible for the biomass decomposition and elements' return in trees and forest vegetation. The rate of soil processes influences tree and forest productivity as well as photosynthesis. These cycles influence tree and ecosystem productivity by regulating the movement of water from the canopy to the soil, transferring and synthesizing carbon from vegetation to the soil, and recycling nutrients contained in the litters of vegetation and roots.

There are two main benefits of process-based models. First, their development, validation, and application may lessen the need for expensive experimental studies. For instance, the analysis of the dynamics of a forest ecosystem type to all possible combinations of climatic conditions, site properties, and management regimes that would require the establishment of a statistically replicated large-scale experimental design is theoretically possible, but very expensive and impractical (Korzukhin et al. 1996). The development of models based on the representation of the rules of changes in the main processes may be used as substitutes for experimentation, as long as the rules of change are adequately represented. Second, process-based models have the potential to address issues related to the basic principles of ecosystem management and to provide sound predictions of the dynamics of ecosystems when changes in environmental conditions are unprecedented (Korzukhin et al. 1996). This is the case of climate change or any external impacts such as pollution. Many short-term studies have examined the effects of increase in temperature and atmospheric CO_2 concentration either in growth chambers or in FACE experiments. However, the contributions of these types of experiments have limits, as they cannot consider all ecosystem components and interactions and capture the longevity factor (Ceulemans and Mousseau 1994; Luo and Reynolds 1999).

The objective of this chapter is to review different types of process-based models and describe how they can be used in a context of the application of the basic principles of ecological forest management. Relatively, few process-based models have been used to address forest management questions (Battaglia and Sands 1998; Johnsen et al. 2001; Shanin et al. 2011; Bond-Lamberty et al. 2014). However, as the international community increasingly demands that forests be managed sustainably, which requires that forest managers evaluate the impacts of environmental disturbances on ecosystem dynamics, it is likely that process-based models will be used more frequently in the decision-making process for forest management. The next section gives a short overview of physiological models that focus on the modeling of single processes: light-use and photosynthesis models. Section 8.3 describes the basics of different ecosystem process-based models. The term *ecosystem model* is used here to include different types of model formulations to simulate ecological processes. Thus, hybrid models may combine empirical as well as process-based formulations and may facilitate the linkage with traditional forest inventory data. Process-based models are commonly viewed as focusing on ecosystem-level predictions, but there are global-scale process-based models that were developed to simulate ecological processes over large regions. Finally, linkages between process-based models and ecological indicators are discussed in the context of biodiversity and ecosystem management. In Section 8.4, model evaluation and uncertainty analyses will be discussed to highlight their importance for model development and usefulness. Different case studies that used process-based models to predict the effects of climate change, fire, and management will be reviewed in Section 8.5.

8.2 Physiological Single-Process Models

8.2.1 Light-Use Models

Light-use models are among the simplest forms of process-based models to predict forest growth. They have the following general form (Landsberg and Sands 2011):

$$P_n = \varepsilon(\theta, N, T)\phi_{abs} - R \tag{8.1}$$

where
  P_n is the net primary production (NPP)
  ε is the light-use efficiency factor that converts the absorbed photosynthetic radiation, ϕ_{abs}, to carbohydrates
  θ is the soil water effect
  N is the nutrient effect
  T is the temperature effect
  R is the total respiration

According to Landsberg and Sands (2011), the model developed by Byrne et al. (1986) is an early application example of forest growth prediction of the monthly biomass production of *Pinus radiata* grown in three sites differing in climatic conditions. Light-use models are relatively simple models that can easily be linked to remote sensing data to predict NPP or global terrestrial balance (Medlyn 1998). However, there are examples to estimate light interception at the individual crown level (see Duursma and Mäkelä 2007).

8.2.2 Photosynthesis Models

The modeling of photosynthesis has been the subject of many papers since the 1970s and 1980s. This situation can be attributed to the increased availability of gas exchange instruments (Landsberg 2003a). Several types of models were developed to predict photosynthetic rate. There are different levels of complexity with respect to the details included in the representation of biochemical processes and scaling methods, which may vary from individual leaves to canopy levels. Only the models that have been studied and used most often will only be reviewed in this section.

One of the simplest forms of photosynthesis model was derived by McMurtrie et al. (1990) using a Blackman function:

$$A_n = \min\left(\delta\phi(1 - \rho_l - \tau_l), P_{max}\right) - R_d \tag{8.2}$$

where
  A_n is the net photosynthetic rate
  δ is the quantum yield
  ϕ is the photosynthetic photon flux density on a leaf
  ρ_l and τ_l are the leaf reflectance and transmittance to PAR, respectively
  P_{max} is the light saturated photosynthetic rate at ambient CO_2
  R_d is the dark respiration rate

Photosynthesis models based on the nonrectangular hyperbola model have been used very often to model canopy photosynthesis for different species (Johnson et al. 2010). It is defined as follows (Johnson and Thornley 1984; Thornley 1998):

$$P_{leaf} = \frac{\alpha I_{leaf} + P_{max} - \sqrt{\left[\left(\alpha I_{leaf} + P_{max}\right)^2 - 4\theta\alpha I_{leaf}P_{max}\right]}}{2\theta} \tag{8.3}$$

where
  P_{leaf} is the leaf gross photosynthetic rate
  α is the initial slope value of the photosynthetic light response (PLR) curve (also known as photochemical efficiency)
  I_{leaf} is the incident light on the upper leaf surface
  P_{max} is the photosynthetic rate that can be reached at saturated light conditions
  θ is the convexity parameter of the PLR curve

The nonrectangular hyperbola model was used in several studies in which the effect of environmental factors was integrated. For instance, Johnson et al. (2010) incorporated equations to account for the effect of temperature, nitrogen, protein, and CO_2 atmospheric concentrations on the parameters of the nonrectangular hyperbola model. Calama et al. (2013) examined the effect of leaf temperature and soil water content on P_{max} and of leaf temperature on α. Xu et al. (2014) incorporated the influence of chlorophyll and leaf nitrogen.

The photosynthesis model that has had the greatest influence in terms of conceptual development and application was developed by Farquhar et al. (1980) and Farquhar and von Caemmerer (1982) (Landsberg 2003a). This model is universally recognized and is used to simulate photosynthesis in many ecosystem process-based models. This model assumes that the net photosynthetic rate is regulated by the ribulose bisphosphate (RUBP) concentration, the activity of RUBP carboxylase/oxygenase (Rubisco) at saturating RUBP, or by triosephosphate utilization. However, most applications of the model do not consider the triosephosphate utilization. Only the basic model components will be presented here. For more details, readers are encouraged to browse the abundant literature on this model.

The model component regulated by the RUBP concentration is as follows:

$$A_n = J \frac{C_i - \Gamma}{4\left(C_i + 2\Gamma\right)} - R_d \tag{8.4}$$

where
  A_n is the net photosynthetic rate
  J is the potential electron transport rate
  C_i is the CO_2 intercellular concentration
  Γ is the CO_2 compensation point
  R_d is the dark respiration rate

The model component when A_n is regulated by the activity of RUBP carboxylase/oxygenase is

$$A_n = V_{cmax} \frac{C_i - \Gamma}{C_i + K_c \left(1 + O/K_o\right)} - R_d \qquad (8.5)$$

where
   V_{cmax} is the Rubisco potential capacity for CO_2 fixation per unit leaf area
   K_c is the Michaelis–Menten coefficient for carboxylation
   O is the intercellular O_2 concentration
   K_o is the Michaelis–Menten coefficient for oxygenation

Since this model was developed, several studies have been conducted to improve its potential applicability for different species. Wullschleger (1993) conducted an analysis of A_n/C_i curves for 109 species that resulted in a dataset of coefficients for V_{cmax} and maximum potential electron transport rate (J_{max}). Parameters were related to site conditions, including the influence of temperature or concentrations of nitrogen and proteins in the foliage (e.g., McMurtrie and Wang 1993; Leuning et al. 1995; Niinemets and Tenhunen 1997; Evans and Poorter 2001; Larocque 2002; Sharkey et al. 2007). The spatial variation within crowns through change in specific leaf area in different crown sections was modeled by Niinemets and Tenhunen (1997), Larocque (2002), and Evans and Poorter (2001).

8.3 Ecosystem Process-Based Models

8.3.1 Biogeochemical Cycles

Process-based models that simulate the functioning of forest ecosystems usually include mathematical representations of several ecophysiological processes and carbon, water, and nutrient cycles in a hierarchy of cause–effect relationships. They are characterized by a sufficient degree of flexibility to predict the impacts of external environmental influences (Landsberg and Sands 2011). The modeling of the allocation of carbohydrates synthesized in the different physiological processes and carbon partitioning in the different pools in forest ecosystems has been the focus of the great majority of ecosystem process-based models. Table 8.1 includes examples of biogeochemical models, with a summary of the main processes modeled, domains of application, and main contributions. As indicated by the examples of Table 8.1, these models simulate several processes; some of them are common to nearly all models, such as photosynthesis, but some models focus on the detailed modeling of specific processes, such as the cycling of soil organic matter (SOM) (e.g., model of Raw hummus, mOder and MUL [ROMUL], European Forest Institute Model [EFIMOD]).

   The majority of process-based models that have been developed in the last three decades are descendant of FOREST-BGC (BioGeochemical Cycles) (Running and Coughlan 1988; Running and Gower 1991). FOREST-BGC was one of the early models with detailed mechanistic model components that established a benchmark for the modeling of carbon, water, and nitrogen cycles (Landsberg and Sands 2011). The design of its framework facilitates the use of remote sensing data, surface climate and vegetation structure and

TABLE 8.1

Examples of Process-Based Models for Forest Ecosystems

| Model name	References	Cycles	Main Processes[a]	Forest Type(s)/Scale(s)/Region(s)	Main Contributions
FOREST-BGC	Running and Coughlan (1988); Running and Gower (1991)	Carbon, nitrogen, and water	PSN, IPAR, RM, RG, LF, LD, CF, CS, CR, NF, NS, NR, EVP, SR, NM, RT	*Picea glauca, Pinus elliotti, Pinus resinosa, Tsuga heterophylla, Alnus rubra, Pseudotsuga menziesii, Pinus ponderosa, Quercus pubescens, Quercus cerris, Ostrya, Acer campestre, Picea mariana /* ecosystems and regions/south to north transects in the United States, Oregon (United States), northwestern Ontario	Major advances in the modeling of biogeochemical cycles and linkages with remote sensing data Study of the impacts of climate change scenarios and comparison of predictions with CENTURY
BIOME-BGC	Running and Hunt (1993)	Carbon, nitrogen, and water	PSN, IPAR, RM, RG, LF, LD, CF, CS, CR, NF, NS, NR, EVP, SR, NM, RT	Mediterranean forest types (*Quercus ilex, Q. cerris, Pinus pinaster, Picea abies, Pinus sylvestris, Fagus sylvatica, Quercus robur, Quercus petraea, Larix decidua, Pinus cembra*) /ecosystem and regions/northwestern Italy, central Europe, United States	Major advances in the modeling of biogeochemical cycles and linkages with remote sensing data
TREE-BGC	Korol et al. (1995a,b)	Carbon, nitrogen, and water	PSN, IPAR, RM, RG, LF, LD, CF, CS, CR, NF, NS, NR, EVP, SR, NM, RT, TD, TH, COM	*Pseudotsuga menziesii /* tree and ecosystem /British Columbia (Canada)	Application of a biogeochemical process-based model at the individual tree level
Hybrid	Friend et al. (1997); Friend and White (2000)	Carbon, nitrogen, and water	PSN, RM, RG, TR, NU, PN, LF, CF, CS, CR, NF, NS, NR, TB, TD, TH, SR, SOMM, NM, COM, EVP, RT	Winter deciduous oak-hickory forest/tree and stand level/ southwestern Pennsylvania, United States and C3 and C4 grasses, broadleaf evergreen, broadleaf cold deciduous, broadleaf dry deciduous, needleleaf evergreen, needleleaf cold deciduous, needle dry deciduous/global scale/world	Prediction of the global distribution of vegetation primary productivity, carbon content in vegetation, and soil under preindustrial conditions for different plant functional types

(Continued)

TABLE 8.1 (*Continued*)

Examples of Process-Based Models for Forest Ecosystems

Model name	References	Cycles	Main Processes[a]	Forest Type(s)/Scale(s)/Region(s)	Main Contributions
TREEDYN and TREEDYN3	Bossel and Schäfer (1989); Bossel (1996)	Carbon and nitrogen	PSN, IPAR, RM, RG, LF, LD, LH, LM, CF, CS, CR, CFU, CL, NF, NS, NR, EVP, SR, NM, HD, HM, NIF, ND, NI, AND, AV, AF, NIM, RT	Tropical acacia, *Picea abies*/tree and ecosystem/south China, central Europe	Parameterized for several European species and applied on several sites across Europe to examine the long-term effects of climate change on carbon dynamics and tree growth
3-PG	Landsberg and Waring (1997)	Carbon and water	PSN, IPAR, EVP, CF, CS, CR, LF, SMOR, RT	*Eucalyptus* spp., *Pinus contorta*/ecosystem/Australia *Eucalyptus nitens*/ecosystem/Spain *Betula platyphylla*/ecosystem/Japan *Pinus sylvestris*/ecosystem/United Kingdom	Improvement of linkages with remote sensing and geographic information system data
ROMUL	Chertov et al. (2001); Nadporozhskaya et al. (2006); Yurova et al. (2010); Kalinina et al. (2013)	Carbon, nitrogen	LM, SOMM, LH, LM, SOMHI, NRE, NM, CE	*Pinus sylvestris*, *Picea abies*, *Betula pendula*/soil, stand, local, regional, and global/Russia	Simulation of primary succession and effects of climate change
EFIMOD	Komarov et al. (2003); Bhatti et al. (2009); Chertov et al. (2009); Shanin et al. (2011)	Soil carbon and nitrogen	IPAR, LF, LD, NF, NS, NR, SR, NM, NU, CA, TB, TD, TH, SOMM, COM, CW, CL, LH, LM, HD, HM, SM, RT	*Pinus sylvestris*, *Picea abies*, *Betula pendula*/ecosystem, local, and regional/Russia	Prediction of the impact of management regimes, climate changes, N deposition, and forest fires

[a] AF, ammonia fixation; AND, atmospheric nitrogen deposition; CA, carbon allocation; CE, CO_2 emission; CF, carbon allocation in foliage; CFU, carbon allocation in fruits; CL, carbon allocation in litter; COM, effect of competition; CR, carbon allocation in roots; CS, carbon allocation in stems; CW, carbon allocation in stems, branches, twigs, and coarse and small roots; EVP, evapotranspiration; HD, decomposition of humus; HM, mineralization of humus; IPAR, intercepted photosynthetic active radiation; LD, litter decomposition; LF, litterfall; LH, litter humification; LM, litter mineralization; ND, denitrification; NF, nitrogen allocation in foliage; NI, nitrification; NIF, nitrogen fixation; NIM, nitrogen immobilization; NM, nitrogen mineralization; NPP, net primary productivity; NR, nitrogen allocation in roots; NRE, nitrogen release; NS, nitrogen allocation in stems; NU, nitrogen uptake; PN, phenology; PSN, photosynthesis; RM, maintenance respiration; RG, growth respiration; SMOR, stem mortality based on the $-3/2$ power law; SOMH, soil organic matter humification; SOMM, soil organic matter mineralization; SR, soil respiration; RT, fine roots turnover; TB, tree biomass; TD, tree diameter growth; TH, tree height growth; TR, transpiration.

topographic and physical site characteristics obtained from geographic information systems to make predictions at regional scales. For processes at the canopy level, such as photosynthesis or respiration, FOREST-BGC is based on the big-leaf approach in which the canopy is viewed as a *giant leaf*, using leaf area index (LAI) values that can be obtained from remote sensing data. Thus, the predictions of FOREST-BGC are very sensitive to LAI. FOREST-BGC simulates the main processes of the carbon, nitrogen, and water cycles, including photosynthesis, maintenance and growth respiration, evapotranspiration, root turnover, litterfall, litter decomposition, and carbon allocation in the foliage, stems, and roots (Figure 8.1). There are 20 state variables and 41 parameters, and daily temperature and precipitation data must be provided as input. While photosynthesis, evaporation, maintenance respiration, evaporation, evapotranspiration, and litter mineralization are simulated daily, the allocation of carbon and nitrogen in trees, foliage, roots, and soil is simulated on an annual time cycle. Good examples of the application of FOREST-BGC for different forest ecosystem types can be found in Running (1994), Chiesi et al. (2002), Hoff et al. (2002), Luckai and Larocque (2002), Rodrigues et al. (2010), or Veganzones et al. (2010). Subsequently, FOREST-BGC evolved toward BIOME-BGC (Running and Hunt 1993), which retained the basic framework of FOREST-BGC, but with modifications in some model components, such as photosynthesis and the dynamics of soil fluxes. Also, the interface with remote sensing data was improved. Recent examples of the application of BIOME-BGC can be found in Tatarinov and Cienciala (2006), Chiesi et al. (2007), Jung et al. (2007), Pietsch et al. (2005), Petritsch et al. (2007), and Wang et al. (2009).

The *giant leaf* approach used in FOREST-BGC to model canopy CO_2 fluxes is one of the methods that have been considered in different models. The modeling of the scaling of physiological processes from leaf to canopy is very complex, as there are nonlinear relationships involved (Leuning et al. 1995; Friend 2001). In addition to the *giant leaf* approach, other methods were proposed, such as the stratification of the canopy into foliage under sunlight and foliage in shade conditions, the establishment of scale factors based on photochemical efficiency and PAR absorption, and the average illumination or foliage energy balance related
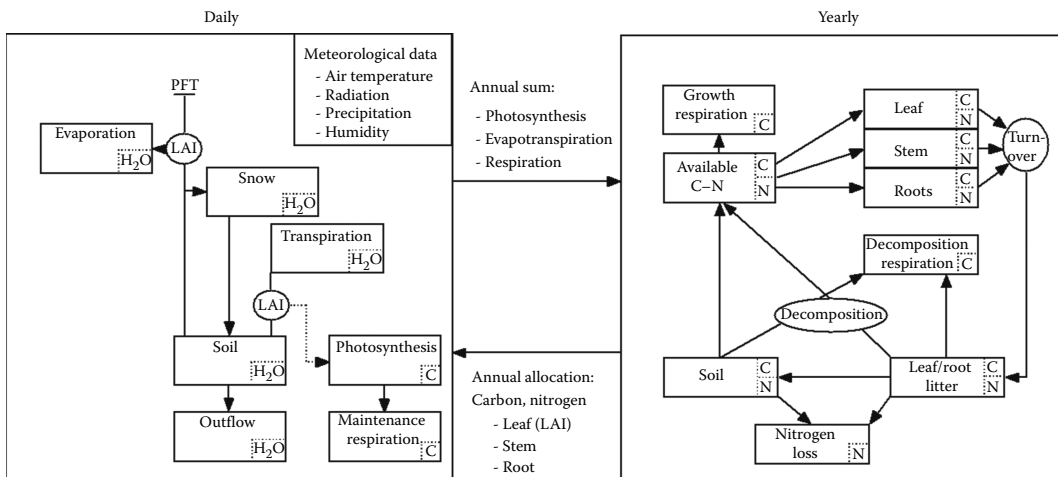
FIGURE 8.1
Basic diagram illustrating the main pools and daily and annual fluxes of FOREST-BGC. C, carbon; N, nitrogen; LAI, leaf area index. (Reprinted from *Ecol. Modell.*, A general model of forest ecosystem processes for regional applications. I. Hydrologic balance, canopy gas exchange and primary production processes, 42, Running, S.W. and Coughlan, J.C., p. 125, Copyright 1988, with permission from Elsevier.)

to environmental gradients (Norman 1993). Examples of the application of sunlit and shaded leaf portions of the canopy can be found in Chen et al. (1999) and Wang (2000). Further developments were inspired by these approaches. For instance, Larocque (2002) used the Weibull function to represent the change in foliage area and biomass with canopy depth and a linear relationship between foliage nitrogen content per unit leaf area and leaf dry mass area from the top to the bottom of crowns of sugar maple (*Acer saccharum* Marsh.).

For the last three decades, the literature on process-based models has considerably increased. A complete review of all the models is beyond the scope of this chapter, but some models will be discussed to illustrate the evolution in the concepts or modeling approaches that took place. The *hybrid model* is a biogeochemical model that is similar in concept to FOREST-BGC (Friend et al. 1997). In fact, its development was based on both FOREST-BGC and ZELIG (Urban 1990), a gap model, and the soil decomposition model component shares similarities with CENTURY (Parton et al. 1993). Hybrid is an individual tree model that simulates 14 processes in two time cycles, daily and annual time steps (Table 8.1). It also includes a grass layer that is subject to the same processes as the trees, and the values of 40 parameters and daily temperature and precipitation data must be provided as input. Hybrid was subsequently modified to allow global-scale simulations of different plant functional types (PFTs) under preindustrial conditions (Friend and White 2000). In particular, it was parameterized for two grass and six tree PFTs by accounting for differences in physiological and phenological characteristics. The model TREEDYN is also similar in concept to FOREST-BGC (Bossel and Schäfer 1989) (Table 8.1). However, compared to FOREST-BGC, the modeling of the physiological processes is simplified and there are more state variables and fluxes among the ecosystem pools. Good examples of other models with similar concepts that have been developed and applied include BIOMASS (McMurtrie et al. 1990, 1992; Bergh et al. 1998, 2003) or G'DAY (Comins and McMurtrie 1993; Marsden et al. 2013).

PnET-CN is another process-based model that simulates the carbon, nitrogen, and water dynamics with a monthly time step. Temperature, precipitation, PAR conditions, wet and dry nitrogen deposition, and atmospheric CO_2 concentration drive the model (Aber and Driscoll 1997; Aber et al. 1997; Ollinger et al. 2002). The developers of PnET-CN modeled complex interactions using measurable parameters or state variables (e.g., foliar nitrogen concentration) to simulate key carbon, nitrogen, and water dynamics. For example, the model simulates potential photosynthesis as a function of foliar nitrogen concentration and light-use efficiency with a multilayered canopy approach (Aber and Federer 1992). CO_2 fertilization is considered through constant ratios of leaf internal to ambient CO_2 concentrations (Ollinger et al. 2002). More details about the model structures and functions were previously reported (Aber et al. 1997; Ollinger et al. 2002). PnET-CN was used to simulate the effects of disturbances. Good examples can be found in Peters et al. (2013) and Wang et al. (2014). Forest management operations in PnET-CN can be treated as prescribed disturbance events that can be simulated in the model through four parameters: disturbance year, disturbance intensity, biomass removal fraction, and the loss rate of SOM. Regarding the tests performed by Peters et al. (2013), PnET-CN was used to investigate how the type, intensity and frequency of disturbances influenced forest net primary productivity across 107 stands in midwest region, United States. They suggested that soil disturbance had greater negative effects on net primary productivity than on stand mortality and biomass removal. Wang et al. (2014) used PnET-CN to simulate the effects of clearcuts on forest carbon dynamics against observations from two northern temperate forest eddy covariance chronosequences, indicating that forest management practices should aim at decreasing soil disturbance caused by clearcut operations.

Recognizing the need for simplified ecophysiological models that could be accessible by forest practitioners for operational needs and easily linked to remote sensing and geographic information system data, Landsberg and Waring (1997) developed the generalized model physiological principles in predicting growth (3-PG). This model, which drew much attention, is based on the use of the general knowledge of physiological processes. Compared to the models described earlier, soil processes are more simplified. The allocation of photosynthate production to foliage, stems, and roots is based on empirically derived ratios obtained from field data, allometric equations, or the literature. Respiration rate is only indirectly considered by computing the ratio of NPP to gross primary production. The value of this ratio, 0.45, is assumed to be constant for many forest types. The changes in stand density over time are based on the application of the −3/2 power law, and the physiological effect of age on stand growth rate decrease is represented in the model. As aforementioned, 3-PG drew much attention and has been applied for many forest types around the world. Good examples can be found in Landsberg et al. (2003), Paul et al. (2003), Nightingale et al. (2008), Xenakis et al. (2008), Rodriguez-Suárez et al. (2010), Pérez-Cruzado (2011), and Potithep and Yasuoka (2011). In particular, Xenakis et al. (2008) combined 3-PG with a SOM model. Paul et al. (2003) combined 3-PG with CAMFor, a carbon accounting model, GENDEC, a litter decomposition model, and ROTHC, a soil carbon turnover model.

The majority of biogeochemical models perform simulations at the stand, landscape, or regional levels. Relatively, few models were developed to simulate the development of individual trees using mechanistic relationships. Korol et al. (1995a,b) developed TREE-BGC using FOREST-BGC as a framework to better integrate the effect of stand density and structure on productivity. Photosynthate production is computed at the stand level, but its partitioning among individual trees is computed using a competition algorithm based on tree height, leaf area, and light saturation threshold. The amount of carbon allocated to each tree in a stand is converted into diameter and height growth using allometric relationships. Zavala and Bravo de la Parra (2005) used a similar approach for Mediterranean forests. However, compared to TREE-BGC, the allocation to individual trees was directly linked to physiological resource limitation factors, including light and water availability and transpiration. A review of different single-tree process-based models may be found in Le Roux et al. (2001).

8.3.2 Soil Processes and Tree and Stand Development

Soil is a destructive component of terrestrial ecosystems responsible for nutrients and water supply to ecosystem organisms (first of all for plants) due to (1) dead organic matter decomposition with both its full mineralization and accumulation in soil and (2) weathering of minerals in geological substrate. These processes lead to the release of nutrients for plant growth from decomposing organic matter and soil minerals; the accumulation of transformed organic matter, nutrients, and water in a soil profile; and the formation of underground pathways of biological cycle of elements in terrestrial ecosystems.

There are abiotic and biotic factors responsible for soil functioning and especially for forest ecosystem productivity. Abiotic, environmental factors are as follows:

1. Solar radiation and heat flow from the atmosphere responsible for energy input and the rate of all biochemical, chemical, and physical processes.

2. Atmospheric input (deposition) of water, elements (N, S, P, etc.), mineral and organic dust, and pollutants. These substances seriously influence soil development.

It is especially clear in relation to water and nitrogen. Nitrogen is absent in geological rocks and sediments. The nitrogen input from the atmosphere goes in a form of nitrogen oxides and ammonium that can be consumed by soil biota. In pure atmosphere, nitrogen input varies from 1 to 4 kg [N] ha^{-1} year^{-1}, but due to air pollution nitrogen deposition can reach 40–60 kg [N] ha^{-1} year^{-1}.

3. Weathering of minerals in a soil leads, first, to element release for green plants and soil biota (all elements with the exception of nitrogen) and, second, to formation of friable loose soil material, which are favorable for plants and soil biota physical properties. It is the disintegration of solid geological rocks, clay formation in sandy soils, and loss of clay in heavy loamy soils.

4. Lateral input and output of water and nutrients that can significantly modify soil development and ecosystem functioning.

5. Heterogeneity of water regime and parent material that form complex spatial mosaics of microsites in forest ecosystems. This mosaic structure can increase ecosystem stability.

Biotic factors of soil functioning can be arranged as follows:

1. Biological fixation of atmospheric nitrogen (symbiotic and nonsymbiotic) is a very powerful process in all terrestrial and forest ecosystems, especially after their disturbance by various natural and anthropogenic factors. It is a natural process to cover nitrogen deficit, and the value of fixed nitrogen can be 10–20 kg [N] ha^{-1} year^{-1} in temperate forests and up to 150 kg [N] ha^{-1} year^{-1} in humid tropics.

2. Accumulation of SOM, humus, and elements in topsoil due to input of organic litter as a product of ecosystem functioning. This is the main process of soil formation from an ecological point of view.

3. Spatial heterogeneity of SOM and elements' accumulation as determined by trees' growth. This "biogenic" mosaics of soil conditions (which can interfere with abiotic mosaics) plays an important role on ecosystem functioning.

Minimally, the soil functioning can be expressed by the following equations:

$$dH/dt = L - \left(k_1 + k_2 + \ldots + k_n\right)H$$

$$dM/dt = D - \left(k_4 + k_5 + \ldots + k_m\right)M \qquad (8.6)$$

$$k_i = f\left(C, R, P, W, B, A, t\right),$$

where
  H and M are the SOM and mineral matrix, respectively
  L is the input of organic matter to soil (litterfall)
  D is the input of mineral particles to the soil due to various deposition processes
  $k_1, \ldots k_i, \ldots k_m$ are the kinetic parameters expressing the rate of various processes of SOM
    and soil mineral transformation and destruction
  C is the climate
  R is the landform (relief)
  P is the parent rock

B is the soil biota and vegetation
t is the time
W is the soil water regime
A represents the effect of anthropogenic factors

In this conceptual model, consideration of H and M in definite temperature and moisture regimes allows for calculations of all other soil parameters (physical and chemical characteristics, cation exchange capacity, available nutrients, etc.), depending on these two basic soil components.

The aim of SOM dynamic modeling is to solve a mathematical problem: if the initial values of SOM pools are known, then it is possible to predict the amounts and pools of available nutrients for plant growth and carbon dioxide evolution using data on (1) organic litter input and its chemical composition, (2) soil temperature and moisture, (3) impact of other environmental factors (e.g., effect of frost melting, soil drainage, and erosion), and (4) land use regimes (various regimes of forest management, damages due to forest fires and insect attacks, etc.).

In recent SOM models, the rate of organic matter mineralization is mostly expressed by a negative exponential function as in early Olson (1963) model for prediction of the rate of forest floor mineralization:

$$\frac{X}{X_0} = e^{-kt} \tag{8.7}$$

where
X is the residual mass of organic layer at time "t"
X_0 is the initial mass of the layer
k is the mineralization rate

The model by Pastor and Post (1985), a component of the ecosystem model LINKAGE, was applied in numerous forest ecosystem models, resulting in a good correlation between the rate of organic debris mineralization and vegetation evapotranspiration at yearly time step. It is a one-compartment model where the rate of decomposition is determined by the following equation:

$$PWTLOS = \left(0.9804 + 0.09352 \times AET \right) \ \left(-0.4956 + 0.00193 \times AET \times R \right) \tag{8.8}$$

where
PWTLOS is the annual percent weight loss
AET is the actual evapotranspiration rate (mm year^{-1})
R is the lignin/nitrogen ratio of organic litter

The Institute of Terrestrial Ecology model of Thornley and Cannell (1992) is a two-compartment (SOM and soil bugs) model. It takes into account four types of organic debris and calculates the mineral nitrogen transformation from ammonium to nitrates.

The CENTURY model (Parton et al. 1988, 1993) for grassland ecosystems was successfully tested in different natural zones and forest ecosystem models as well. The litter is divided into two classes: metabolic (fast decomposing compounds) and structural

(slow decomposing lignin and cellulose). The SOM compartments are represented by pools of active soil C (biomass of microorganisms), slow soil C, and passive soil C. The model also calculates soil nitrogen and other elements' dynamics with the formation of mineral nutrient pools for plant growth. There are four other agricultural SOM models with forest versions as well. The ROTHC model (Coleman and Jenkinson 1995) has two inputs of litter and a cascade of repeated pairs of biomass (microorganisms) and humified material, distinguished by the rate of SOM mineralization. The additional specific feature of ROTHC is a pool of inert organic matter (IOM) that is not participating in SOM turnover. This pool is included in the DAISY model (Hansen et al. 1991; Bruun et al. 2003) and CANDY model (Franko et al. 1995) by taking into consideration litter and SOM C/N ratios and transformation of nitrogen with more detailed SOM compartmentalization. The Yasso forest soil model (Liski et al. 2005) is also related to these types of models.

The SOM modeling is a crucial issue for the development of forest ecosystems models. These models are widely implemented for the evaluation of the carbon balance dynamics in terrestrial ecosystems under the impact of changing environmental factors. The SOM criterion of ecosystem sustainability has also been proposed (Morris et al. 1997). This criterion postulates that the sustainable use of ecosystems can be reached only if SOM and soil elements' pools will not be decreased or unbalanced by ecosystem exploitation, modification, or transformation to other ecosystem types. Following is a description in details of the ROMUL model of SOM dynamics in forest soils.

ROMUL (Chertov et al. 2001) and its earlier version, SOMM (Chertov and Komarov 1997; Chertov et al. 2002), describe the biological turnover of organic matter and nitrogen. It simultaneously allows for the calculation of the rate of mineralization and humification of litter and SOM with the corresponding CO_2 emission and nitrogen release for plant growth. The initialization of the model uses pools of organic matter and nitrogen in correspondence with usually discriminable horizons of forest floor in field studies: L, F, H, and top horizon of mineral soil Ah. This definition of main variables shows that the ROMUL model best describes the specificity of forest boreal soils, even though it is possible to apply it with corresponding average of the variables for arable and more differentiated soils. The experimental basis of the ROMUL model consists of laboratory experiments (Chertov and Komarov 1997; Chertov et al. 2001) in controlled temperature and moisture conditions with validation using field experimental data.

The model also has input pools of fractions of above- and belowground litters that differ in nitrogen and ash contents (decomposition rates for belowground litter fractions are calculated with different temperature and moisture dependencies) and a cascade of SOM fractions: undecomposed litters, partly humified organic materials (forest floor, peat, and so-called labile humus [Lh] in mineral topsoil), and relatively stable humus (Sh) bonded with the mineral matrix of the topsoil. The litter input in the model can be represented by an unlimited number of fractions that have species-specific ash and nitrogen contents. There are three processes of SOM humification by three communities of microorganisms and soil fauna (without consideration of their biomass) and three processes of mineralization. The model is represented by a system of ordinary differential equations with coefficients that depend on the soil temperature and moisture, the nitrogen and ash content in litter, and the C/N ratio in the mineral topsoil. The model also considers nitrogen release and gross carbon dioxide emission from the soil.

There are several variables in ROMUL that represent different pools of organic matter (Figure 8.2). L_{above} (kg m^{-2}) is a pool of organic matter corresponding with the L horizon of the forest floor. It contains undecomposed and partly decomposed litter with big plant fragments. L_{below} (kg m^{-2}) is a pool of SOM that contains undecomposed and partly
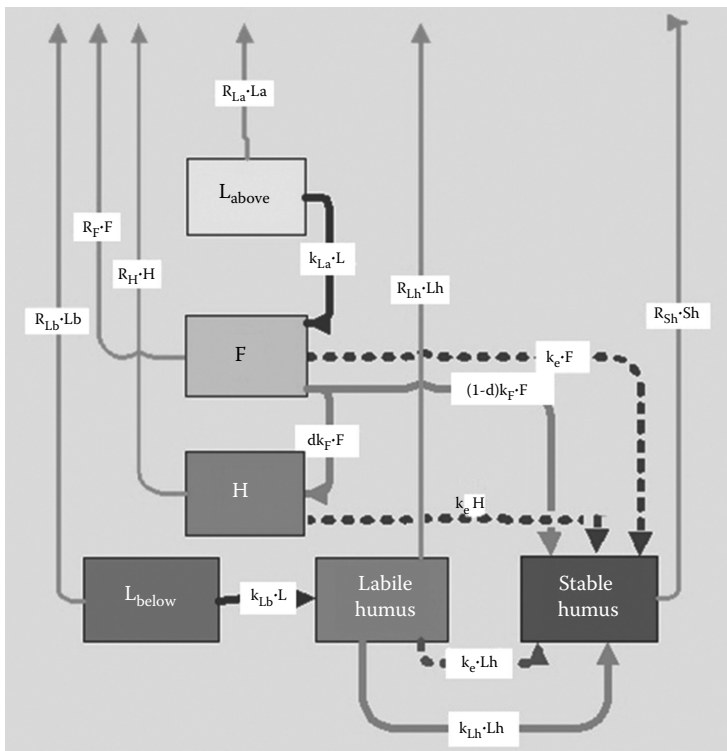
FIGURE 8.2
Flowchart of the ROMUL model. Explanations of symbols are in the text.

decomposed root litter. Part of this pool is metabolized by the decomposing organisms and the corresponding carbon is released as gaseous CO_2 (flows with rates R_i marked arrows in Figure 8.2). The majority of the organic matter ends up in a more slowly decomposing complex of partly decomposed organic matter F (kg m^{-2}), which is a pool of organic matter that contains partly decomposed litter with small plant fragments treated as humus substances and corresponds to the F horizon of the forest floor. This pool is transformed by several groups of organism destructors into different forms. The community of bacteria, fungi, and arthropod species with rate dk_F transforms part of the SOM into a H pool and part of the SOM ($1 - dK_F$) into Sh of mineral horizons pool Sh that produces raw humus with a C/N ratio 15. The parameter *d* is a ratio between both pathways that depends on the C/N and F/B (fungi to bacteria) ratios in *F*. The greater part of humified matter stays in the organic layer H as C/N is increased. Transformation (humification) of SOM by community of earthworms and soil invertebrates forms the mull humus Sh in mineral horizons with rate k_E and a C/N ratio ≤8. Lh (kg m^{-2}) is a pool of "belowground forest floor." The transformation of this pool also goes by two groups of organism destructors. k_{Lh} is the rate of transformation by bacteria and arthropod species. k_{Ef} is the rate of transformation by earthworms. The immobilized humus pool H decomposes at a rather slow rate modified by the soil temperature and moisture conditions. The decomposition flux has a range of a minimum 1%–2% annually up to 15% annually, depending on the soil texture and the clay content. The maximal rate of H decomposition may be observed for arable soils. On the other hand, as roughly half of the SOM in the boreal zone is in the compartment H, the value of the rate factor k_{Ef} has a significant effect on the total storage of organic matter in the soil.

The temperature and soil moisture modifiers of the fluxes have various patterns given as stepwise defined functions. Typically, all these show an optimal range of values, where the decomposition takes place at a full rate and tapers off outside the optimal conditions. The optimal conditions for different fluxes are, however, somewhat different (Linkosalo et al. 2013). This simple scheme of SOM transformation allows for the description of elements contained in the pools of organic matter, but using some modifiers in the main scheme of SOM decomposition, because carbon and nitrogen dynamics have different rates of transformation (Chertov et al. 2001). For instance, the transformation of nitrogen in the compartment H, that is, two different mass flows (Figure 8.2), is based on the assumption that all the matter in the compartment H is mostly produced by the metabolism of the decomposing organisms (bacteria, protozoan, arthropod, and lumbricid species), and the C/N ratio is used for these groups obtained from soil biology experiments. Therefore, nitrogen has a special role in this phase: first, the rates k_E and k_F of nitrogen moving from compartments F_i into the compartment H are calculated, and, thereafter, a corresponding amount of organic matter, typical for the type of decomposers and depending on the C/N ratio of produced humus (24.0 for bacteria and arthropod species and 12.8 for lumbricid species), is moved from the compartment F_i to the compartment H.

Soil stability is an important additive criterion of sustainable forest management in the changing environmental and economic world (Kimmins 1996; Morris et al. 1997; Boyle and Powers 2001; Akselsson et al. 2007; Komarov et al. 2007). Many forest ecosystem models do not accentuate and analyze the dynamics of SOM and elements of forest nutrition, particularly nitrogen, in relation to stand productivity, soil formation, management, disturbances, and environmental changes. There is an example of the model that describes closed turnover of carbon and nitrogen in a tree–soil system of the EFIMOD model (Komarov et al. 2003).

The EFIMOD model is an individual-based model that simulates the development of tree–soil systems (Figure 8.3). The simple approach used successfully in statistical physics was applied for the representation of the standby separate trees with simple growth models and located in space as a sessile organism with precise locations, but with detailed
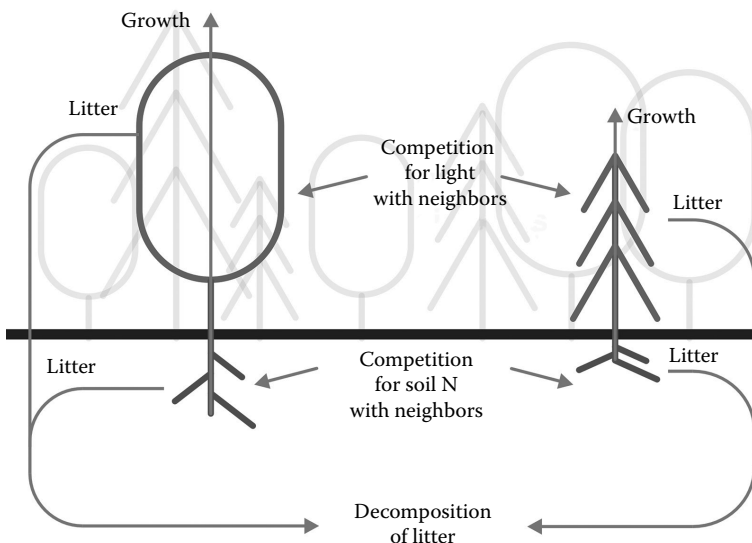
FIGURE 8.3
Flowchart of the EFIMOD system of models.

description of its interactions with its neighbor trees. Simple models of tree growth may be used in the EFIMOD system of models, depending on the problem to solve: from simple regression models of potential (usually maximal) growth to more complicated growth models accounting for available PAR with dependencies on available soil nitrogen, water regime, and other factors if necessary. Then, tree increment is reduced by two types of competition: shadowing that defines concrete light flux and belowground root competition that distributes available nitrogen for tree growth.

The simulated stand consists of separate trees that are located on a square lattice whose cell is small enough. Each tree creates a shadow zone S_i, which is a quadrate centered at a tree's cell x_i with quadrate size R_i. The tree x_i shadows the neighbor tree x_j if (1) shadow zone S_i covers the tree's cell x_j, and (2) ratio of the height H_i of a tree x_i to the height H_j of a tree x_j is greater than a fixed value β, that is, $H_i/H_j > \beta$. The symmetric shadowing occurs when two trees shadow each other. A contribution of a tree in the shadow formed by all trees shadowing the cell is assumed to be additive. Thus, we have for the shadow coefficient $0 \leq K_E \leq 1$ corresponding to the tree x_i:

$$K_E\left(x_i\right) = 1 - \sum \lambda_1 k_1 \tag{8.9}$$

where
  λ_l is a species-specific parameter describing the proportion of PAR absorbed by the crowns of shadowing trees
  k_l is a numbers of trees of certain species shadowing the x_i tree (when some trees of different species shade one cell and then the total shadowing of the cell represents a sum of their λ_l values)

The values of λ_l are calculated on the basis of experimental data on the absorbed radiation under canopies of different tree species at maximal crown density (Tselniker 1978).

After the calculation of a spatial mosaic of shadowing (available light in every cell), the light response multiplier, K_{SH}, is calculated for every tree. The value of K_{SH} as a function of shadowing has different shapes for shade-tolerant and shade-intolerant species, that is, K_{SH} is linearly dependent on K_E for the Scots pine (*Pinus sylvestris* L.) and silver birch (*Betula pendula* Roth) (shadow-intolerant trees):

$$K_{SH} = K_E \tag{8.10}$$

It is also nonlinearly dependent for shadow-tolerant Norway spruce (*Picea abies* (L.) H. Karst.) (Tselniker 1978):

$$K_{SH} = 1 + 0.44 \log K_E \tag{8.11}$$

Thus, the light response multiplier K_{SH} reflects the local stand density in relation to a set of neighbors for each tree in the form of overlapping of shadowing zones and species-specific light response of trees.

Each tree has also a nutrition zone that is a second form of competition acting together with shadowing. The average and maximal distance of lateral root spreading are calculated on the basis of stem diameter derived from empirical data using a logistic equation. As maximum and average root spreading distances decrease with increasing soil fertility and moisture, these parameters have site-specific modifiers. The model calculates potential

rooting area as the surface of a circle with a radius equal to the average root spreading distance. Then, for each cell, the probability of occupation is calculated, which is positively related to the amount of available nitrogen in the current cell and inversely related to the distance between this cell and stem base and the mass of roots of other plants. The distance from each cell to the rooting cell cannot be more than the maximal root spreading distance for the given tree. All cells in the rooting area of individual trees must be arranged in continuous connected contours. The vertical distribution of roots depends on species-specific features, soil characteristic, and strength of belowground competition. It is calculated as the decreasing exponential function of depth. The model also calculates horizontal distribution of biomass of coarse and fine roots as a function of the distance from the base. The uptake rate for water and nutrients depends on the biomass of fine roots in each cell, tree age, and species-specific modifier.

Areas of nutrition for neighboring trees can overlap, and available nitrogen is consumed proportionally to the mass of fine roots of neighboring trees in these overlapped areas. This definition of belowground competition is species specific and depends on the spreading of roots and their density per square unit, which are different for different species. Thus, two possible types of tree increment can be calculated: that due to light or that due to soil nitrogen (Komarov et al. 2003). The calculation requires species-specific estimates of foliage and fine root biomass, maximal biological productivity of foliage, and the specific consumption rate of nitrogen. The joint impact of both types of competition can be evaluated either by the minimal value of two types of increment taken as the annual increment, following Liebig's principle or using weighting of particular reducing coefficients. Due to the two different types of competition, simple procedures were inserted to simulate adaptations of trees to the lack of some resources: (1) if tree increment is restricted by light, then its biomass gain will be allocated mainly to increases in stem height and foliage biomass; (2) conversely, if the growth of a tree is limited by nitrogen uptake, then the relative increase in biomass of fine roots and stem diameters will be higher than those of foliage and stem height. A deterministic procedure of tree death is based on the idea of lethal threshold, defined by the ratio of leaf mass B_l to total biomass B_T, below which the tree dies:

$$r = g_1 - g_2 \ln B_T$$

where
  r is the lethal ratio B_l/B_T
  g_1 and g_2 are the species-specific parameters evaluated from corresponding regional growth tables

In addition, we inserted a probabilistic mortality function that depends on tree age, which reaches 1.0 at a species-specific maximal tree age.

The sensitivity analysis and simulation experiments with the model showed that the spatial structure of plant community had a stronger influence on competition than species-specific features or environmental conditions.

8.3.3 Hybrid Models

Models that contain both empirical and process-based components are termed *hybrid models* (Mäkelä et al. 2000; Landsberg 2003a,b). The hybrid approach explores methods that combine forest growth and yield equations, based on statistical relationships derived from

empirical data (see Chapter 6) and mechanistic or theoretical relationships that represent physiological and biogeochemical processes that govern the dynamics of forest ecosystems (see Mäkelä et al. 2000). These models may be driven by both environmental variables (e.g., PAR, temperature, precipitation, or soil properties) and dendrometric variables obtained from forest inventories to simulate a set of tree and stand growth characteristics (e.g., diameter at the breast height, tree height, and stand density) and the effects of forest management (e.g., harvesting and thinning) on forest productivity (e.g., gross primary productivity and net primary productivity) for a given stand. In addition, many empirical relationships (e.g., diameter distribution and biometrical equations) have been incorporated into hybrid models to simulate some largely less known ecological processes (e.g., plant carbon allocation). For example, diameter distribution—a type of growth and yield model—has been demonstrated to be able to help ecosystem process-based models to predict stand structure (e.g., Lasch et al. 2005; Wang et al. 2011), since climate change has little effect on competition mechanisms for even-aged pure stands. Therefore, these models can be effective tools for exploring the effects of forest management and climate change on forest growth and carbon sequestration (Landsberg 2003a,b).

Several hybrid models have been developed for this purpose like 3-PG (Landsberg and Waring 1997), CroBas (Mäkelä 1997), FORCYTE-11 (Kimmins 1993), FORECASE (the successor to FORCYTE-11 Kimmins et al. 1999), FVS-BGC (Milner et al. 2003), CanSPBL (Pinjuv et al. 2006), TRIPLEX (Peng et al. 2002), and SECRETS-3PG (Sampson et al. 2006). These models have been used to explore the best *practices* of forest management under climate change. For example, Wang et al. (2013) conducted a simulation experiment that combined three climate change scenarios and 36 forest management scenarios with different thinning intensities and occurrence and rotation length using the TRIPLEX model. They argue that precommercial thinning does not change mean annual net ecosystem productivity for boreal coniferous stands over their simulation period (2010–2100), while moderate warming with the rotation length of 50 years could enhance mean annual net ecosystem productivity. Simulations showed that intensive forest harvests may obstruct forest recovery for a very long time for Douglas fir stands in British Columbia, Canada (Blanco 2012). Using FORECAST, Wei and Blanco (2014) suggested that mixed plantations in subtropical regions with stand densities in the 2000–3000 stems ha^{-1} range could increase their amount of carbon by 68% compared with traditional pure plantations. As the understanding of physiological process improves, the use of such hybrid models will likely continue to investigate the effects of forest management and climate on forest growth (Twery and Weiskittel 2013).

8.3.4 Global-Scale Models

Local process-based models can be used in very detailed situations, such as being used against a forest stand with single-tree species. At large regional scales, tree species usually have to change to loosely defined tree groups such as PFTs in some Dynamic Global Vegetation Models (DGVMs) like MCI (Bachelet et al. 2001a,b) or IBIS (Foley et al. 1996). Also, there is a need to better represent biosphere–atmosphere interactions with vegetation dynamics (Olchev et al. 2008; Quillet et al. 2010). Many large-scale modeling exercises need to consider potential new processes because environmental conditions become different from that of the site scale. For example, the effect of lateral C redistribution across landscapes becomes noticeable at large-scale C accounting and has been considered to link with carbon models (e.g., the General Ensemble Biogeochemical Modeling System [GEMS], Liu et al. 2003). Also, some expected constant driving factor,

such as atmospheric CO_2 concentration, can become variable across a large region, and therefore, a regional model application may need additional treatment on using spatial varying CO_2 data instead of a fix ppm value (e.g., Zhang et al. 2014). Broader model expansions can be seen when simulation considers wider simulation scope like including fire disturbance, land use change effect, and movement of C from land to aquatic systems (e.g., USGS LandCarbon Project, Zhu et al. 2010). The NCAR community earth system model (CESM) is a recent development trend for large-scale process models.* The biogeochemical models used in the system need additional links with other models. In addition, models like CESM also need modern high-performance computing resources to perform intensive simulations. This alone requires significant computational changes of the models.

When process-based model are applied to large regions, some key sources of uncertainty will become significant, such as model incompleteness, limited input and validation data, limited computing ability over large regions, and spatial scaling issues. When the study region is large enough, differences between subregions could be quite different, such as tropical region compared to temperate region. Ecoregions, provinces, states, and counties are all examples of regions that each may have their distinct geographical features, including climate, soil, vegetation, and land use. Process-based models may need to change parameter sets, driving variables or some algorithms to deal with significant location changes. Without those significant model processes or component changes, spatial variability can sometimes be dealt with empirical spatial scalars. For example, the USGS LandCarbon project (Zhu and Reed 2012) used county-level forest growth and grain yield data to calibrate the GEMS model (Liu et al. 2003) to generate spatial scalars to deal with the unknown causes of county-level differences. Another example is the GHG modeling in the Triplex-GHG model, in which a different Q_{10} parameter value is used to control GHG emission for different regions: boreal = 2.03, temperate = 2.66, and subtropical and tropical = 3.75 (Zhu et al. 2014, 2015).

For large regions, simulation on higher spatial resolutions faces the issue of availability of high-resolution input data. Many models like IBIS (Liu et al. 2011) use internal data interpolation procedure to solve this problem. A simple nearest-neighbor procedure was built in IBIS to do spatial interpolation so that all input layers are of the same resolution. On the other hand, spatial sampling simulation is useful for quick testing and calibration runs for large region with higher-resolution input data. With a sampling interval of 5, which means selecting one land pixel every five rows and five columns on the land cover map, IBIS will first read in the original coarse-resolution inputs, perform spatial interpolation to base resolution, conduct spatial data sampling by the interval, perform actual simulation on sample data, and produce outputs at the coarser resolution defined by the sampling interval.

Pure land cover at high resolution will change to mixed land pixel when aggregated to coarse resolution. IBIS is a DGVM that allows multiple PFTs to potentially coexist in a single land pixel. Also, it allows competition among the PFTs under the changing climate and land use conditions. In recent modified IBIS, unlike most biogeochemical models, IBIS takes in fractional land cover data and allows fractional vegetation changes following fire or land use change events. Although a typical land pixel in simulation can change relative LAI of trees and grasses, the extent of change is limited by both physiological parameter and physical area fraction. For example, a land pixel with a small forest fraction may have healthy trees and high LAI per forest area, but the whole pixel may be

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* http://journals.ametsoc.org/doi/abs/10.1175/JCLI-D-12–00565.1.

dominated by grass or crop. Therefore, the land pixel could be classified as a grassland or cropland. The nonvegetation fraction is a major controlling factor in rocky areas, desert, water body, and urban development areas so that simulated vegetation will not take over a whole land pixel in the model. When logging happens, the forest area fraction will remain unchanged and only the forest biomass level will be reset. When deforestation happens, the forest cover is converted to the target land cover (cropland, grassland, or urban) and the forest fraction decreases. When reforestation happens, other land covers convert to forest; hence, forest fraction increases. Fractional land cover data products can be seen in a recent large global land cover dataset generated from the Global Change Assessment Model (GCAM*), which indicates the upcoming trend of ecosystem modeling with fractional input data. Other related data changes also exist. For example, biomass initialization for a single land pixel could include forest biomass, shrub biomass, and grass biomass separately. Fire disturbance on a land pixel could be containing percentages of low, medium, and high burn severity.

Process-based models can be calibrated at the local scale with actual field observation data (e.g., flux tower data). When changed to large regions, local calibrated parameters may not always fit in other locations or broader extents. This is partly because regional input datasets are often interpolated data and may be at very coarse resolution. For example, the spatial resolution of interpolated climate data for the United States could be 4–50 km, which is potentially much different from the field data. So simulation with interpolated data will likely give a different output than the simulation with local field observation data. This indicates that regional-level simulations need regional observations for calibration. There exist some regional-level inventories and statistics that serve as validation data. For example, the global MODIS NPP maps (1 km MODIS NPP of 2001–2005, Zhao et al. 2005), the Forest Inventory and Analysis (FIA) growth curves at county level, and the crop grain yield statistics by county are used in IBIS for coterminous U.S. simulations. In order to validate the model, an automatic calibration procedure against county-level averages of forest biomass, NPP, and grain yield is developed as a postprocessing step. NPP observations from remote sensing products are first aggregated to county level and then compared with IBIS NPP outputs averaged at county level. Then IBIS calculates the county-level differences and the related adjustment scalars. The scalars are assumed to help dealing with unknown environmental factors. For example, the scalars for each county will be used to modify the forest V_{max} parameter (maximum Rubisco-limited rate of carboxylation) in a second simulation. On the other hand, forest biomass inventory data and crop grain yield statistics data are also summarized at county level in order for IBIS to compare with. The forest growth curves published by USDA Forest Service, the Carbon OnLine Estimator (COLE†) database, are the general forest growth references to be compared with IBIS growth curves. An indicator of growth rate, for example, total biomass carbon increase from 1 to 100 years, can be calculated from the IBIS biomass pool. Comparing simulated biomass values with the COLE 100 year growth values for the same geolocations, a scalar can be generated to increase or decrease IBIS biomass pools in a renewed simulation. When iterated three to four times, a stable carbon scalar can be obtained. For forest ecosystems, the NPP and biomass scalars can be used at the same time. It may happen that one observation could be better than other observations. Or the IBIS model can be calibrated to match one type of observation well, but fail with the other. Then more in-depth manual adjustments are used.

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* http://www.globalchange.umd.edu/models/gcam/.
† http://www.fs.fed.us/ccrc/tools/cole.shtml.

8.3.5 Process-Based Models and Ecological Indicators

Ecological indicators are defined here, and in Chapter 7 (see also Chapters 11–17), as an index of measures that characterizes an ecosystem or one of its critical components. In addition, ecological indicators are typically used to assess the state of a specific environment and evaluate the trajectory of that system under current and future conditions. Ecological indicators should represent key information about the composition, structure, function, and/or vigor of an ecosystem. For example, biodiversity, including genetic diversity and functional diversity, can be an important ecosystem service (Mace et al. 2012) and an ecological indicator of forest health.

   To be able to quantify the potential changes in biodiversity, it is necessary to understand the role and impact that climate has on species' ranges at the regional and continental scale. There are many ecological, evolutionary, and physiological processes that influence species' distribution and abundance, thus biodiversity (Kearney and Porter 2009). Similarly, limits and enhancements to plant functional processes, which can be simulated with process-based models, can be used to predict changes to biodiversity patterns, species abundances, tree distributions, and potential future migration patterns. As an example, the process-based model PHENOFIT was used to identify the climatic factors and biological processes that limit the ranges of 17 North American boreal and temperate tree species, ultimately with a goal of predicting potential species distributions (Morin et al. 2007). The model PHENOFIT (Chuine and Beaubien 2001) simulates species' distributions based on a phenological submodel, a frost-injury submodel, a survival submodel, and a reproductive-success submodel. This study showed that species distributions were limited, due to climatic constraints that impact phenological processes, such as the inability to achieve full fruit ripening or flowering. Later, the same model was used to reduce uncertainty in species range shifts under future climate change scenarios (Morin and Thuiller 2009). The need for understanding the implications of climate change on biodiversity and forecasting the shifts in biodiversity under climate change is immediate (Thuiller 2007).

   Araujo and New (2007) argue that utilizing process-based models in conjunction with additional model classes and ensemble forecasting is an improved framework to diagnosing bioclimatic constraints on species distributions. An example of using multiple process-based perspectives was conducted in the study by Kleidon and Mooney (2008), which used components from the land surface model ECHAM4 (Roeckner et al. 1996), and the terrestrial biosphere models CASA (Potter et al. 1993), SDBM (Knorr and Heimann 1995), and SILVAN (Kaduk and Heimann 1996) to create a "generic" plant model. This method was applied at a global scale with multiple climatic forcing constraints, finding that a major factor leading to distribution of diversity occurs during the early stage of a plant's life when a plant is more sensitive to changes in water availability due to variability in precipitation.

   Ecological indicators linked with models can be used as a guide and/or enhance forest management (Lindenmayer et al. 2000), but can have challenges (Dale and Beyeler 2001; Failing and Gregory 2003). For example, indicators that express vulnerability to environmental disturbance and land use change can be useful to forest managers. For example, the study of Morales et al. (2005) compared and evaluated the ability of four process-based models (i.e., RHESSys, GOTILWA+, LPJ-GUESS, and ORCHIDEE) to simulate fluxes of water and carbon within terrestrial ecosystems and can be a useful tool and methodology when evaluating ecosystem flux vulnerability to disturbance and/or climate change impacts. In addition, quantifying the consequences of land use change on the terrestrial carbon budget, water

resources, and nutrient availability can be achieved with process-based models (McGuire et al. 2001). For example, four process-based terrestrial biosphere models were used to evaluate the 20th century carbon balance as a result of land use, in addition to CO_2 and climate effects (McGuire et al. 2001). Cramer et al. (2001) used six DGVMs as a tool to report the varying ranges and uncertainties in the terrestrial carbon sink as a function of rising CO_2 and climate change. It is likely that process-based models will be used more often in forest management planning and the evaluation of the impacts on ecological indicators as a result of environmental disturbance, climatic changes, and land use change. However, variations among and between models and large uncertainties in simulating response variables and ecological indicators (Cramer et al. 2001; Morales et al. 2005; Balshi et al. 2007) warrant improvements to the models and our understanding of ecosystem processes.

8.4 Model Evaluation and Uncertainty Analysis

The majority of process-based models are deterministic: their predictions are provided without estimates of the errors. Regardless of their level of complexity or degree of realism, accuracy, or precision, there is always a degree of uncertainty in the predictions because models are imperfect representations of reality. For biogeochemical as well as biological models, uncertainty originates from different sources (O'Neil and Rust 1979; Medlyn et al. 2005; Larocque et al. 2008a,b, 2011; Matott et al. 2009): (1) errors in measurements, estimates, or spatial or temporal scales, (2) lack of understanding of the mechanisms of the biological processes and interactions, (3) model structure and adequacy of the mathematical representations of processes, (4) parameter estimates, and (5) amplitude of natural variation within ecosystems under study.

Any modeling exercise should include two major steps: evaluation and uncertainty analysis. The model evaluation step contributes to the development of more reliable and accurate models to address the problems of the real world and is one of the important steps in model development and application. It can help to either build up confidence for model applications or allow model selections (Tedeschi 2006). Uncertainty analysis, which consists in computing the variability in model outputs that may be attributed to errors associated with the aforementioned sources, allows model users to evaluate the level of confidence in the predictions and draw appropriate inferences. For instance, the uncertainty analysis that Larocque et al. (2008b) performed in a soil carbon cycle model to compare different scenarios of temperature increase allowed them to conclude that the gradual increase in temperature was likely to have a marginal effect over a short time period. Significant effects were evident only on some soil carbon pools and over a long time period.

To understand the model evaluation process, it is necessary to understand the following concepts (Rykiel 1996):

- Verification is defined as a technical step on the extent to which a mathematical model is logically consistent or represents well the mechanisms being modeled. In some cases, it is not easy to verify whether a complex computer program (model) is entirely error free. For model developers, model verification process needs to be addressed prior to any other processes in testing process-based models.

- Calibration is the estimation and adjustment of model parameters to improve the accuracy and precision of model simulations against a measured dataset.
- Validation is often defined as a process to evaluate the model output against another independent dataset using the calibrated parameters. This process indicates if the model is acceptable for use within a certain domain. It is important to distinguish the terms *verification* and *validation* in the modeling circumstance. As validation of ecological models is impossible to some extent (Oreskes et al. 1994), hereafter such a process is referred to as *model evaluation*.

Model evaluation/model testing could be generally categorized into two groups: (1) qualitative evaluations that compare the model behavior with hypothesized patterns and (2) quantitative methods that compare model simulations with observatory data.

Qualitative testing aims at evaluating the model behaviors, which is included in a standard development routine (Jakeman et al. 2006). The key point of qualitative testing is to find out if model behaviors match hypothesized patterns or observational patterns by using visualization techniques. If the comparison of simulated results between the model and observation data or theoretical patterns is unfavorable, then the model users or developers have to figure out why and how the model behaviors do not match as expected. A list of graphical display techniques is listed as follows:

- Comparison of matched estimated and measured time series values and/or residuals
- Comparison of measurements and estimates (bivariate plots)
- Comparison of ranges, medians, and means (box plots)
- Cumulative/probability frequency distributions (histograms)

Many different statistical techniques can be used to test the performance of a model in the case when observatory data are available and the model behaved as expected. It could be more useful to statistically test the model directly against observation data than to compare the time series (Kirchner et al. 1996). Previous review work has summarized these techniques for accessing model accuracy and precision, which are two important aspects of model testing (Tedeschi 2006). Accuracy measures the ability of a model to predict the right values and precision measures the ability of a model to predict similar values consistently (Tedeschi 2006). Some quantitative methods are listed as follows:

- Linear regression and its analysis (Tedeschi 2006)
- Correlation coefficient (parametric and nonparametric)
- Nonparametric analysis: Kolmogorov–Smirnov test, rank test, etc.
- Distribution comparison and its analysis: χ^2 test, Kolmogorov–Smirnov D test
- Residual analysis: mean bias, mean square error, root mean square error, mean absolute error, etc.
- Model efficiency: the Willmott index (d) (Willmott 1982), Nash–Sutcliffe model efficiency coefficient (E), etc.

No single evaluation index is sufficient to adequately assess the model performance when comparing observed and predicted values. Therefore, we suggest that multiple statistics

in evaluating precision and accuracy should be used in model evaluation. In the context of modeling forest management under changing climate conditions, multiple variables (e.g., DBH, height, biomass, and gross primary productivity) and multiple statistics should be used to compressively evaluate the performance of models.

Model evaluation is important and delivers important messages in model structure and/or sensitive model parameters to model developers and users. Such a feedback can contribute to developing useful models. Identifiability analysis is one of such a process that is defined as the identification of the model structure and its corresponding parameter set that are most representative of study area by taking into account research questions (Wagener et al. 2003). In many cases, identifiability analysis was used to estimate sequential parameters or to identify the discrepancy of the model behavior from the expected ecosystem behavior (Wagener et al. 2003; Matott et al. 2009). Sensitivity analysis is performed by varying systematically the model parameters or inputs and quantifying their relative effect on model predictions. Thus, it contributes to identifying how the uncertainty in the output of an ecological model can be attributed to uncertainty in its inputs and parameters (Saltelli et al. 2008). Overall, model evaluation is not a straightforward process over the course of model development, as such analyses (e.g., sensitivity and identifiability analysis) play an important role in developing credible and useful ecological models for decision-making purpose.

Different approaches are available to conduct uncertainty analysis, but two methods have been used most often in process-based models: the Taylor series technique and the Monte Carlo technique. Both techniques are described in Chapter 6.

8.5 Case Studies: Prediction of the Effects of Climate Change, Fire, and Management

It is in the 1980s that the development of process-based models really began when there was a need to simulate the effects of climate change and physical and human disturbances, such as acid rain, air pollution, harvesting, or wildfire, on the functioning of forest ecosystems. This trend accentuated in the 1990s. An important advantage of process-based models is that they can simulate multiple *what-if* scenarios. It is especially true when novel climates are predicted.

Many aspects of projected climate change and altered disturbances will likely affect forest growth and productivity. Climate change could alter the frequency and intensity of forest disturbances, such as insect outbreaks, invasive species, wildfires, or storms. These disturbances can reduce forest productivity and change the distribution of tree species. In some cases, forests can recover from a disturbance. In other cases, existing species may shift their range or die out. In these cases, the new species of vegetation that colonize the area create a new type of forest (U.S. Climate Change Science Program 2008).

8.5.1 Climate Change

There is increasing evidence that climate change has had and will continue to have a significant effect on forest ecosystems by affecting the ecophysiological processes that govern their dynamics (Dresner et al. 2009; Fischlin et al. 2009; Lucier et al. 2009;

Medlyn et al. 2011; Seidl et al. 2014). Forest models are key tools that have the potential to contribute to better understanding the long-term changes in the complex interactions between changing environmental conditions and ecosystem processes, allowing the prediction of the likely impact of climate change on forest productivity (Medlyn et al. 2011). There are good examples in the literature of studies that examined different scenarios of climate change on forest ecosystem dynamics.

The EFIMOD model was used to predict the long-term effects of different scenarios of climate change, fire, and harvesting on the carbon cycle of black spruce (*Picea mariana* (Mill.) B.S.P.) and jack pine (*Pinus banksiana* Lamb.) forests in central Canada (Bhatti et al. 2009; Chertov et al. 2009). The scenarios of change in temperature and precipitations were estimated from three global circulation models: CGM2, HadCM3, and CSIRO. For black spruce, 150-year simulation results indicated that the disturbances resulted in a decrease in net primary productivity (NPP), stand productivity, and SOM content and an increase in CO_2 emission to the atmosphere. Similar results were obtained for jack pine, but differed among the three climate change scenarios. Bergh et al. (2003) used the model BIOMASS (McMurtrie et al. 1990) to predict the effect of both increases in temperature and atmospheric CO_2 concentration on NPP of Scots pine, Norway spruce, European beech, and black cottonwood (*Populus trichocarpa* Torr. & A. Gray) forests located in Denmark, Finland, Iceland, Norway, and Sweden. Simulation results indicated that both temperature and atmospheric CO_2 increase resulted in increasing NPP, but there was substantial variation among forest types.

Existing studies using process-based models to examine the effect of climate change have provided realistic results and have also generated many questions and uncertainties. For instance, Luckai and Larocque (2002) compared the long-term simulation results between CENTURY and FOREST-BGC by using identical scenarios of climate change in black spruce in northwestern Ontario, Canada. Predictions between both models differed in the amount of carbon content in large wood (stems, coarse roots, and branches) in the scenario of both temperature and CO_2 increases. While CENTURY predicted a decrease, FOREST-BGC predicted an increase. They attributed the discrepancies in the predictions to differences in the structures, algorithmic approaches, and assumptions between both models and lack of empirical and scientific knowledge. Medlyn et al. (2011) recently highlighted these issues by suggesting specific questions to consider in modeling studies to improve the capacity of models to predict climatic impacts on forest productivity: the type of model under study, the representation of the effects of increase in atmospheric CO_2 and temperature, the representation of water availability and nutrient cycling, the potential influence of other global change effects, and the climate change scenarios used in the simulations.

Loustau et al. (2005) used three process-based models, CASTANEA, GRAECO, and ORCHIDEE, to model the effects of climate change and two forest management scenarios on wood production and forest carbon balance in French forests. All models predicted a slight increase in potential forest yield until 2030–2050, followed by a plateau or a decline around 2070–2100, with an overall greater increase in yield in northern France than in the south.

PnET is a suite of nested process-based models (PnET-Day, PnET-II, PnET-CN) that provide a modular approach to simulate the carbon, water, and nitrogen dynamics of forest ecosystems. They have been used to predict forest productivity under climate change in various forests. Aber et al. (1995) described an improved version of a forest carbon and water balance model (PnET-11) and the application of the model to predict stand- and regional-level effects of changes in temperature, precipitation, and atmospheric CO_2 concentration.

They found that a combination of increased temperature (+6°C), decreased precipitation (–15%), and increased water use efficiency (2×, due to doubling of CO_2) generally resulted in increase in NPP and decrease in water yield over regional levels.

Process-based models are also better able to deal with the enhanced productivity possible via elevated CO_2 and increased water use efficiency. Peters et al. (2013) used PnET-CN to compare the long-term effects of changing climate and atmospheric CO_2 on productivity, evapotranspiration, runoff, and net nitrogen mineralization in current Great Lakes forest types. The results suggested that ecosystem responses varied among geographic locations and forest types. With rising CO_2 and without changes in forest type, average regional productivity could increase from 67% to 142%, changes in evapotranspiration could range from –3% to +6%, runoff could increase from 2% to 22%, and net N mineralization could increase by 10%–12%.

Process-based models are used to predict the effects of climate change on various aspects of forest ecosystems. Bachelet et al. (2001a,b) used the DVGM MC1 to predict continental-scale changes in tree life forms and carbon in a warming climate. The warmer and drier scenarios in these experiments showed some potentials for the habitats of the eastern deciduous and mixed forests to shift to a more open canopy woodland or savanna type, while the boreal forests disappeared almost entirely from the Great Lakes area by the end of the 21st century (Bachelet et al. 2001a,b). These changes would obviously markedly modify the character of these biomes and greatly reduce carbon storage in the eastern United States. Other studies using DGVMs have shown potential large impacts of climate change in high latitudes over the tropics on the African continent and globally.

Another process-based model that incorporates climate is the Regional Hydro-Ecologic Simulation System (RHESSys) (Tague and Band 2004). In a Sierra Nevada mountain system, Tague et al. (2009) found significant elevational differences in vegetation water use and sensitivity to climate, which will probably be critical for the vulnerability of similar ecosystems under climate change. In these model results, transpiration was consistent across years at the lowest elevations because of topographically controlled high moistures. The middle-elevation transpiration rates were controlled primarily by precipitation and the high-elevation transpiration rates were controlled primarily by temperature. These dynamics, along with evidence for reduced snow accumulation and earlier melt of seasonal snowpacks, are expected to influence future species composition in mountainous systems. These studies generally provide evidence, as with the SDMs, that forest composition and productivity are likely to change, often substantially, as the climate changes during this century and beyond.

8.5.2 Impact of Forest Fires on Coniferous Forest Ecosystems

The EFIMOD model was also used to simulate the dynamics of coniferous forest ecosystem dynamics in western European taiga and North American boreal forests with different forest fire scenarios (Chertov et al. 2013). The simulation scenarios comprise canopy and ground fires in combination with clearcutting (Table 8.2). The simulation results showed that forest fires led to a decrease in growing stock and SOM in both regions in comparison with a clearcutting scenario without fires. The long-term reduction of net biological productivity was also found with a negative carbon balance (net ecosystem exchange, NEE). A maximal simulated loss of carbon took place after crown and ground fires and after clearcutting. In Europe, the negative carbon balance with a loss of carbon from forest ecosystems was found only in the case of crown fires with burned wood cutting. In other cases, there was a slight amount of carbon sequestered even after fires. In North America,

TABLE 8.2

Changes in Soil Carbon Pools and Growing Stock at the End of a Second 70-Year Rotation with One Thinning and Clearcutting Management Scenario and Average Net Ecosystem Exchange (NEE) over Two Rotations

Forest Stands	Disturbance Regimes[a]	Changes of Soil C Pools, %	Changes of Growing Stock, %	Average NEE, kg[C] m^{-2} $year^{-1}$
East European taiga				
Scots pine	1	0	0	0.053
Pinus sylvestris	2	**−31.80**	**−3.1**	0.054
	3	**−11.20**	**−13.8**	**−0.008**
	4	**−40.20**	**−9.9**	0.015
Norway spruce	1	0	0	0.024
Picea abies	2	**−23.30**	**−6.1**	0.022
	3	**−7.30**	**−8.5**	**−0.018**
	4	**−17.70**	**−6.7**	0.015
North American boreal forest				
Jack pine	1	0	0	0[b]
Pinus banksiana	2	**−34.40**	**−25.9**	**−0.034**
	3	**−18.70**	**−23.4**	**−0.053**
	4	**−27.80**	**−16.9**	**−0.004**
Black spruce	1	0	0	0.003
Picea mariana	2	**−43.30**	**−19.5**	**−0.002**
	3	**−24.60**	**−21.3**	**−0.034**
	4	**−35.60**	**−14.6**	**−0.011**

Source: Chertov, O.G. et al., *Contemp. Probl. Ecol.*, 6, 747, 2013.

Negative values are in bold

[a]   1, two 70-year rotations and clearcutting without fires; 2, two canopy fires at the end of every 70-year rotations before cutting; 3, two ground fires after thinning at 30 year, 4, two ground fires after final clearcutting.

[b]   NPP=Rh, that is, the carbon of net primary productivity is equal to one of soil respiration.

all fires led to negative carbon balances with the maximal carbon losses at crown fires with cutting burned wood. This effect was determined by the soil reaction on any forest fires: a carbon loss from burned forest floor and a decrease in soil carbon in young stands due to imbalance between carbon input with litter and carbon output with soil respiration. These differences reflect the influence of a rather mild climate of European sites in comparison with extracontinental cold climate of modeled sites in central Canada.

8.5.3   Forest Management

Ecosystem models have played key roles by providing guidance on uncertain future or unexpected problems to decision makers and information for public debate in the management of terrestrial ecosystems (Harris et al. 2003). As they focus on the modeling of processes and flows of nutrients, water, and energy in ecosystems, process-based models are well adapted to predict the impacts of environmental disturbances (see Mäkelä et al. 2000). For instance, Driscoll et al. (2003) used two process-based models, PnET-BGC and WATERSN, to examine the effects of different management options on the reduction of nitrogen deposition to forests and watersheds in the northeastern United States. Process-based models can also contribute to improving the modeling of the productivity of mixed

species or heterogeneous tropical forests and planning for the analysis of the impact of management scenarios on water balance and nutrient cycling (Mäkelä et al. 2000) or ecosystem services. Ooba et al. (2010) used the biogeochemical model BGC-ES to evaluate the impacts of different management practices on ecosystem services, including water supply, carbon sequestration, timber production, and biodiversity conservation. The predictions of the different scenarios were associated with economic values. The next two sections are case studies that illustrate the application of process-based modeling to address management issues.

8.5.3.1 Modeling the Effects of Rotation Length on Forest Productivity and Soil

The aim of this simulation using EFIMOD was to demonstrate the effect of various silvicultural regimes on carbon balance and wood production on forest ecosystems. The experimental data on soil and climate for a very productive Norway spruce ecosystem on Distric Cambisols in Höglwald, Germany were used as initial parameters for stand, soil, and climate (Kreutzer and Göttlein 1991). The site had mild temperate climate with a mean annual temperature of +8.2°C and a total annual precipitation of 811 mm. The simulations were conducted between 1961 and 2050 with scenarios of increasing temperature and high atmospheric nitrogen deposition. Initial stand density was 10,000 3-year-old seedlings per hectare. The rotation lengths simulated were 15, 30, 45, and 90 years. There was regular thinning at 35, 45, 55, and 65 years in the 90-year rotation scenario and one thinning in the 45-year one. Two types of cutting were simulated: ecological (EC) with the remaining cutting residues on the harvested area for decomposition and whole tree harvesting (WTH) with the removing of all the aboveground biomass from the ecosystem.

The results demonstrated the productivity potential of the clearcutting regimes with different rotation lengths (Figure 8.4). They indicated that the shortest rotation had twice lower accumulated wood productivity over a long-term time interval. One can also see that the WTH had a little bit lower productivity in comparison with the *ecological* wood harvesting. These results can be seen in relation to soil carbon dynamics as well (Figure 8.5). There was no negative soil organic carbon effect following the ecological cutting. While the soil carbon slightly decreased at a 15-year rotation with WTH, there is no soil carbon loss at 45- and 90-year rotations. These results clearly showed that the short rotation system was not an ecologically and economically optimal forestry practice without site amendments. It can be concluded that the methodology of this simulation can be used to evaluate in more depth carbon sequestration potentials of different wood harvesting methods.

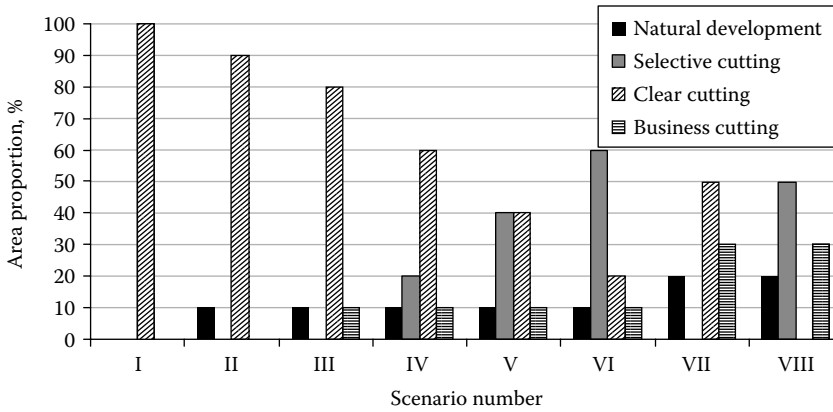### 8.5.3.2 Combination of Silvicultural Regimes

EFIMOD can be used to demonstrate the possibilities of forestry regime combination at the forest enterprise/regional level to reach a satisfactory balance between carbon budget and forest productivity from an environmental and economic point of view. The case study is an area of forest unit in central eastern Europe 100 km south from Moscow with Scots pine and mixed stands of average ages of 30–70 years that had high productivity on sandy mesic forest sites on the Oka River terraces. The modeling of four management regimes was performed for every stand in the selected forest lots to compare ecological and silvicultural consequences of different management regimes (Chertov et al. 2005; Komarov et al. 2007, Figure 8.6). It was assumed that the initial structure of forest sites, stand composition, and age structure were identical for all simulated forest regimes. The total simulated area corresponded to the area of the Dankovsky management unit (7000 ha). It was also assumed that
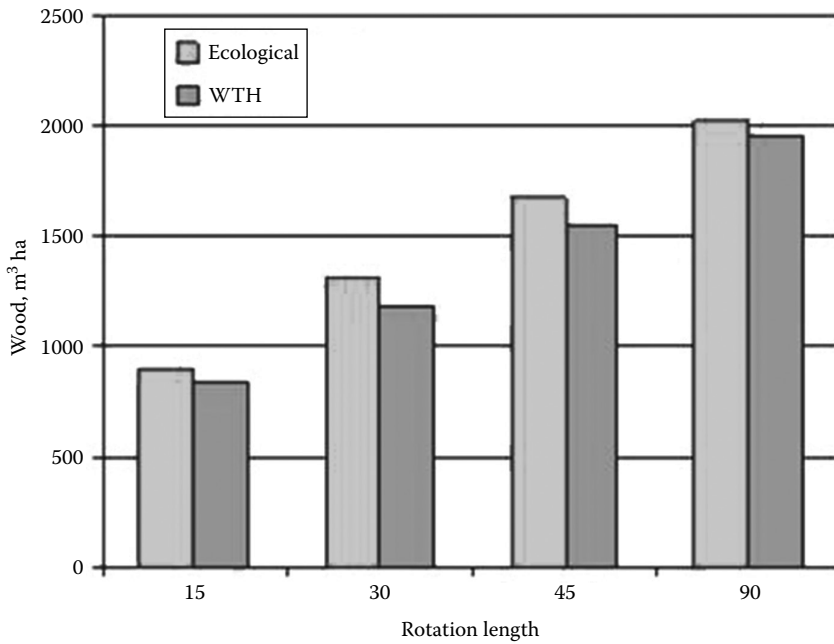
FIGURE 8.4
Accumulated harvested wood over a 90-year time span with different rotation lengths and two different clearcutting scenarios: ecological with the exposure of cutting residues for decomposition in the forest and whole tree harvesting with extraction of all aboveground tree biomass from ecosystems.
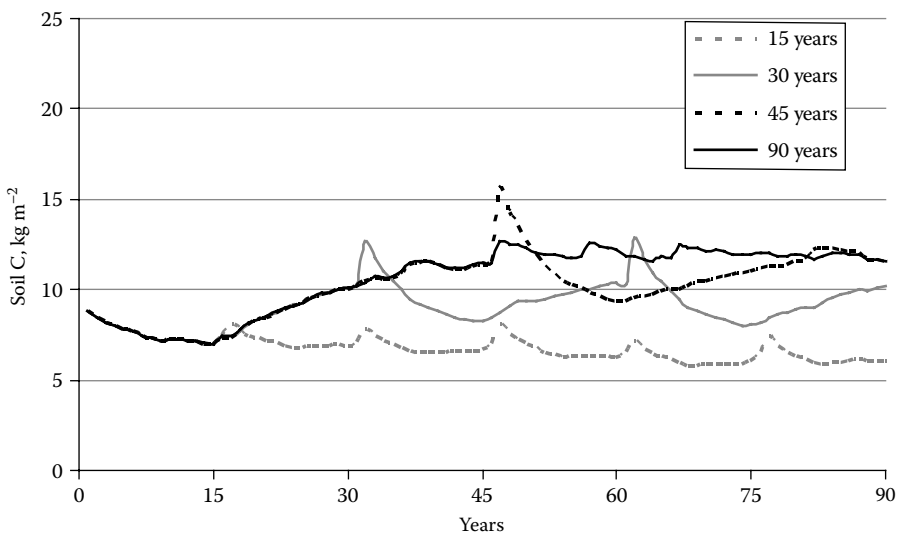
FIGURE 8.5
Predicted soil carbon dynamics for different rotation lengths and a scenario of whole tree harvesting.

FIGURE 8.6
Scenarios based on the combinations of proportions of silvicultural regimes (natural development, selective cutting, clearcutting, and business cutting) based on the percentages of total areas in forest units.

the scenario of "business cutting" corresponded to "legislation breach" with the following principle "take the best just now." Some preliminary model runs showed that this regime was very close to the short rotation forest plantations demonstrating the negative carbon balance on the territory. The scenarios represented a consecutive series from "Russian legislative clearcut system" (scenario I) to scenarios with decreased ratio of clearcutting and finally to combinations of natural development and "business cutting" with clear and selective cutting (scenarios VII and VIII). Relations between different silvicultural operations are presented in Figure 8.6. The parameters of carbon balance from the basic simulations were recalculated for every scenario as weighted averages proportionally to the percentage of every regime area:

$$P_{comb} = \frac{(P1A1 + P2A2 + P3A3 + P4A4)}{100} \tag{8.12}$$

where
P_{comb} is a calculation parameter of carbon balance or productivity at the combination of forestry regimes
P_1–P_4 are the parameters for every separate regime
A_1–A_4 are the areas of every regime in the modeled scenario

The results of this exercise (Figures 8.7 and 8.8) showed a consistent increase in net primary productivity and soil carbon dioxide emissions as soon as the proportion of clearcutting decreased on the territory (Figure 8.7). A small admixture of naturally developed forests and *business cutting* did not change this trend. The maximal values of NPP and soil carbon dioxide emission occurred for scenarios with a domination of selective cutting with 20% clearcutting and 10% natural forest and *business cutting* (scenario VI). This scenario also demonstrated a maximum carbon production of harvested wood: 1.05 ton [carbon] ha^{-1} year^{-1} in average for 200-year simulations that correspond approximately to 4.5 m^3 ha^{-1} of wood annually. It was found unexpectedly that two regimes with 30% of *business cutting* and 20% of naturally developed forest (scenarios VII and VIII) demonstrated rather
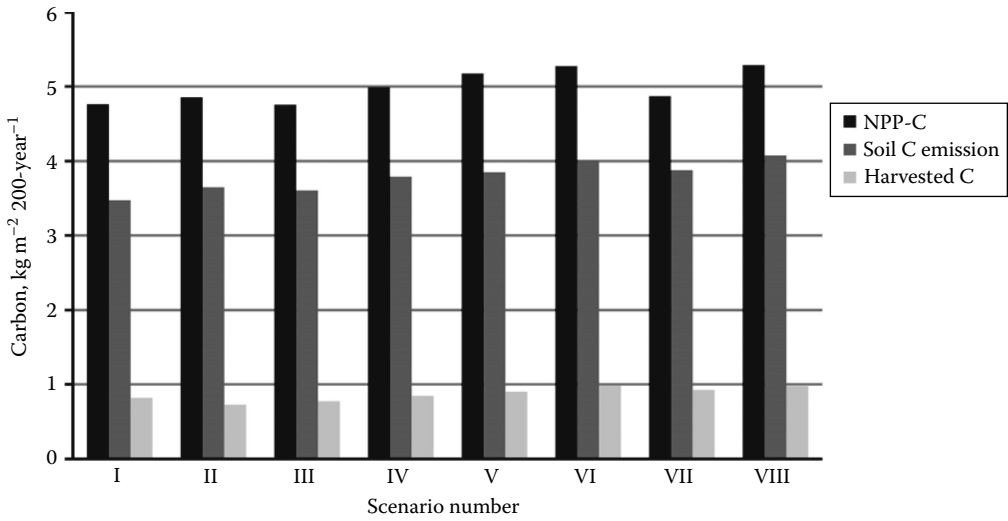
FIGURE 8.7
Components of carbon balance for different combinations of silvicultural scenarios (see Figure 8.6) averaged for the entire territory over 200-year simulations. Carbon emission from soil also includes carbon loss with burning cutting residues.
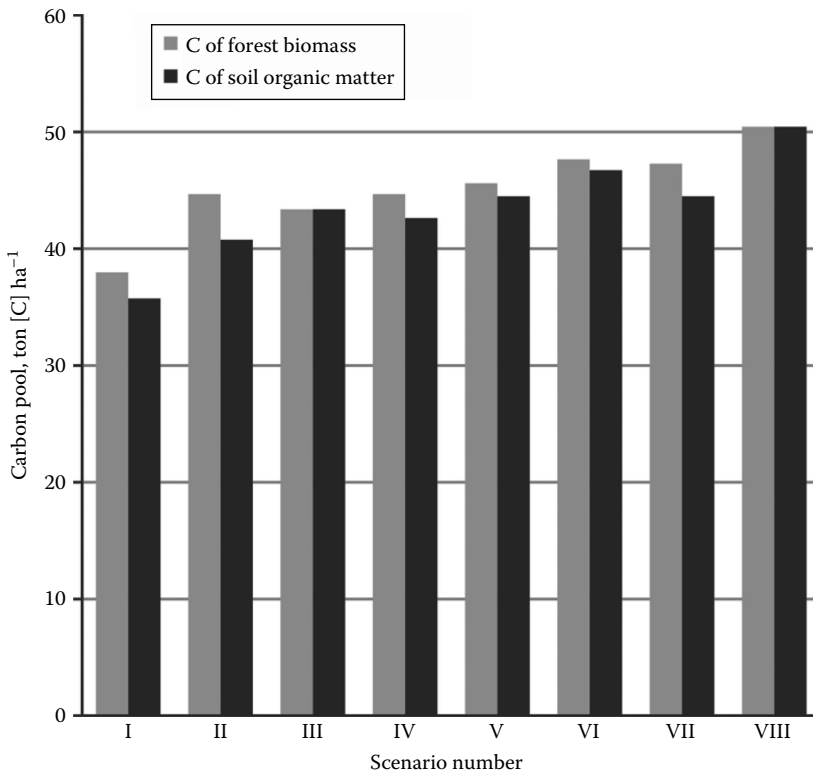
FIGURE 8.8
Amounts of carbon in forest biomass and soil organic matter averaged for the entire territory over 200-year simulations.

good parameters of carbon balance and forest productivity. Moreover, scenario VIII with combination of selective and *business cutting* had just the same capacity of harvested wood carbon as scenario VI with domination of selective cuttings.

These results were confirmed by the patterns of NEE for different combinations of silvicultural regimes (Table 8.3). This table shows that all combinations with some ratios of naturally developing forests had a positive carbon budget. Again, the maximum carbon sequestration in the territory for this 200-year simulation was observed for the combination of natural development with selective and *business cutting* (scenario VIII).

Figure 8.8 shows carbon pools in forest biomass and SOM at the end of the simulations and exhibits similar dynamic trends as previous ones: the accumulated carbon in stands and soils increased as soon as clearcutting reduction took place. However, the largest pools were found for scenario VIII and the lowest pools for clearcutting scenario I. In addition, similar work was conducted for suburban forests in dense populated areas and recreational management (Table 8.4). Recreational scenario means a modest selective cutting to increase a scenic beauty of landscapes in combination with the creation of recreational infrastructure. In this case, the results give also a possibility for the selection of optimal combination of regimes taking into account both recreational and productive functions of suburban forests. The fourth and fifth scenarios seem to be optimal from a carbon balance point of view, allowing also to get some wood from forest plantations, though it is disputable that plantations represent a good option for this area.

We can conclude that this is an idealized picture because the productivity and stand characteristics can be in reality different combinations of forestry practices. For example, the best productive sites can be used for *business cutting* and forests of lower productivity for other regimes.

These case studies demonstrate an exploratory potential of the forest ecosystem simulation for the investigation of carbon budget, wood productivity, and even biodiversity of different silvicultural regimes. These simulations demonstrate an effectiveness of the idea of "offset areas" (Knaus et al. 2006): making of some areas with a positive effect of

TABLE 8.3

Components of Carbon Budget (ton [C]) Averaged over 200-Year Simulations for an Entire Forest Unit in Central Eastern Europe Composed of Scots Pine and Mixed Stands with Combination of Different of Silvicultural Regimes and Proportions of Management Regimes

Proportion of the Area of Natural Development/ Selective Cutting/Clearcutting/ Plantation Forests, %	NPP[a]	Soil C Respiration (Emission)	C Removed with Cuttings	NEE[b]	Tree Biomass C[c]	Soil C[c]
		ton [C] ha^{-1} year^{-1}			ton [C] ha^{-1}	
0/0/100/0	4.75	3.48	0.81	0.000	38	36
10/0/90/0	4.91	3.67	0.73	0.099	45	41
10/0/80/10	4.85	3.61	0.76	0.074	44	44
10/20/60/10	5.01	3.75	0.84	0.112	45	43
10/40/40/10	5.17	3.89	0.91	0.150	46	45
10/60/20/10	5.33	4.03	0.99	0.188	48	47

[a] NPP, C of a net primary productivity, increment of total biomass (leaves, branches, bole, roots).

[b] NEE, net ecosystem exchange, a measure of carbon balance: NEE_C = NPP_C – (Soil_respiration_C + Cutting_C + Deadwood_decomposition_C + Disturbance_loss_C); deadwood decomposition and disturbance losses did not reflect in the table.

[c] Average values of stand, soil (with deadwood) C for the entire forest area at the end of a 200-year simulation.

TABLE 8.4

Components of Carbon Budget (ton [C] year⁻¹ ha⁻¹) Averaged over 200-Year Simulations for an Entire Forest Unit in Central Eastern Europe Composed of Scots Pine and Mixed Stands with Combination of Different Silvicultural Regimes in a Dense Populated and Industrial Region

Proportion of the Area of Natural Development/ Recreational/Plantation Forests, %	NPP[a]	Soil C Respiration (Emission)	C Removed with Cuttings	NEE[b]	Tree Biomass C[c]	Soil C[c]
		ton [C] ha⁻¹ year⁻¹			ton [C] ha⁻¹	
0/100/0	5.54	4.17	1.18	0.190	45	47
0/90/10	5.40	4.04	1.20	0.146	43	46
10/80/10	5.48	4.16	1.06	0.226	49	49
30/60/10	5.65	4.41	0.84	0.386	62	57
50/40/10	5.82	4.65	0.61	0.546	75	64
100/0/0	6.37	5.38	0.00	0.990	110	83

[a] NPP, C of a net primary productivity, increment of total biomass (leaves, branches, bole, roots).

[b] NEE, net ecosystem exchange, a measure of carbon balance: NEE_C = NPP_C – (Soil_respiration_C + Cutting_C + Deadwood_decomposition_C + Disturbance_loss_C); deadwood decomposition and disturbance losses did not reflect in the table.

[c] Average values of stand, soil (with deadwood) C for the entire forest area at the end of 200-year simulation.

any management action to compensate negative effects of the other ones. In our case, it is the regimes of "natural development" versus *business cutting* in relation to carbon balance of forest territory at a long-term prospect. The other conclusion can be as follows: the larger the diversity of management regimes, the more optimal are the parameters of carbon balance and forest productivity, but it needs additional verification. Nevertheless, it is clear that forest model could be an effective science-based forest planning instrument for an optimization of forest area splitting by management regimes to harmonize conflicting environmental and economic criteria of sustainable forest management.

There are other examples in the literature on the application of process-based models to predict the effects of human disturbances, such as harvesting forest ecosystems. Thompson et al. (2006) used the Landscape Management Policy Simulator (LAMPS) to project the effects of several forest policies, including disturbance-based policies. Simulated disturbance-based policies produced age-class distributions closer to the estimated historical range than those created by the current policy. Within 100 years, the proportions of younger forests were within the historical range, while older forests moved closer to, but remained below, historical conditions. In the near term, disturbance-based policies produced annual harvest volumes 20%–60% lower than those produced by the current policy. However, relative costs of disturbance-based policies diminished over time. The results suggest that if expediting a return to historical age-class distributions at a provincial scale was a goal, then public lands would be needed to provide large patches of old forests. In addition, this experiment illustrated that distributing costs and benefits of conservation policies equitably across multiple private landowners is a significant challenge.

8.5.4 Limitations and Challenges for Practical Implementation

Process-based models have limitations in that they require (1) detailed parameterization of life histories and physiologies, (2) capacity to capture the complexity of many interacting disturbance factors, and (3) high-resolution modeling over very large areas. A limitation

that affects the precision and realism of many process-based models is that they do not cover the full range of forest dynamic processes. Some of the important aspects that models often lack include the effects of climatic conditions, disturbance, and site quality. In addition to model complexity, difficulties associated with their implementation, accessibility to user guidance, and degree of relevancy to answer questions important for decision makers are other factors that explain their marginal application to forest management planning (Sands et al. 2000). Besides these logistical limitations, there are intrinsic problems with controlling cumulative errors associated with the sheer number and diverse spatiotemporal scales of parameters, most of which ultimately being derived from a limited number of empirical studies.

Continued research is needed to move the science forward on detecting and modeling and potential assisting of actual and potential forest change in a changing climate and disturbance. Understanding the effect of individual assumptions allows the identification of major uncertainties in the models and working toward improving them. Process-based models are also better able to deal with the enhanced productivity possible via elevated CO_2 and increased water use efficiency. An assumption-centered approach to modeling could improve our understanding of the effects of rising CO_2, temperature, and water availability on forest function.

Much of this uncertainty can be incorporated in reporting projections. Medlyn et al. (2011) reviewed several process-based models that simulate forest productivity under climate change and provided a checklist for evaluating modeling studies and argued that models and experimental research should be closely integrated. Long-term, intensively studied experiments are needed to generate sufficient data to test alternative model hypotheses. Many additional advances will be possible by making continued improvements in the integration among the avenues here. The merging of process-based models, demography models, and species distribution models allows for some of the best attributes of each.

In summary, process-based models of forest ecosystems are widely used to predict the likely future impacts of environmental change and disturbance. These models are valuable tools in predicting the effect of climate change and disturbances on forest ecosystems and have the potential to address issues related to the basic principles of ecosystem management and provide sound predictions of the dynamics of ecosystems when changes in environmental conditions are unprecedented. This is the case of climate change or any external impacts such as large disturbance events.

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