

Chapter 7

Modelling Future Growth of Mountain Forests Under Changing Environments



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Abstract Models to predict the effects of different silvicultural treatments on future forest development are the best available tools to demonstrate and test possible climate-smart pathways of mountain forestry. This chapter reviews the state of the art in modelling approaches to predict the future growth of European mountain forests under changing environmental and management conditions. Growth models, both mechanistic and empirical, which are currently available to predict forest

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growth are reviewed. The chapter also discusses the potential of integrating the effects of genetic origin, species mixture and new silvicultural prescriptions on biomass production into the growth models. The potential of growth simulations to quantify indicators of climate-smart forestry (CSF) is evaluated as well. We conclude that available forest growth models largely differ from each other in many ways, and so they provide a large range of future growth estimates. However, the fast development of computing capacity allows and will allow a wide range of growth simulations and multi-model averaging to produce robust estimates. Still, great attention is required to evaluate the performance of the models. Remote sensing measurements will allow the use of growth models across ecological gradients.

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Acronyms

CSF	Climate-smart forestry
C	Carbon
CO ₂	Carbon dioxide
GHG	Greenhouse gas
GCM	Global climate model
RCM	Regional climate models
IPCC	Intergovernmental Panel on Climate Change
SRES	Special Report on Emissions Scenarios
RCP	Representative Concentration Pathway
AR5	Fifth Assessment Report
YM	Yield model
EM	Empirical model
PM	Mechanistic models
ES	Growth simulator
SES	Hybrid (semi-empirical) model
SFM	Sustainable forest management
TRW	Tree-ring width
VS	Vaganov-Shashkin
LDM	Landscape dynamics or forest landscape model
NFI	National forest inventory
EFDM	European Forest Dynamics Model
EFISCEN	European Forest Information Scenario model
ICP Forests	International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests
EC	Eddy covariance
NEP	Net ecosystem productivity
MODIS	Moderate Resolution Imaging Spectroradiometer
GPP	Gross primary productivity
NPP	Net primary productivity
LUE	Light-use efficiency
APAR	Absorbed photosynthetically active radiation
NDVI	Normalised difference vegetation index
PAR	Photosynthetically active radiation
ER	Ecosystem respiration
LiDAR	Light detection and ranging
SAR	Synthetic aperture radar
EVI	Enhanced vegetation index
NDWI	Normalized difference water index
WDRVI	Wide dynamic range vegetation index
PI	Phenology index
LAI	Leaf area index
DA	Data assimilation

ALS	Airborne laser scanning
TRW	Tree ring width
ITRDB	International Tree-Ring Data Bank
NCEI	National Centers for Environmental Information

7.1 Introduction

Globally, the forest sector plays a crucial role in climate change mitigation because forests store a significant amount of carbon (C) and absorb around 30% of the annual anthropogenic global carbon dioxide (CO₂) emission. For example, Pan et al. (2011) estimated a total forest sink of 2.4 ± 0.4 petagrams of C per year (Pg C year⁻¹) globally from 1990 until 2007. However, in the same study, the authors estimated a C source of 1.3 ± 0.7 Pg C year⁻¹ due to land-use change in the tropical forests.

Climate change imposes direct effects on forest ecosystems through increasing the concentration of atmospheric CO₂ or change in temperature and precipitation (Keenan et al. 2013). Individual organisms living in forest ecosystems respond to climate change in different ways. If their adaptation to new environmental conditions is successful, forest ecosystems continue to provide ecosystem services specific to the type of forest ecosystem, and, by storing C, they can significantly aid in mitigating the impacts of climate change too (Fig. 7.1). However, signs of C saturation in European (Nabuurs et al. 2013) and tropical (Hubau et al. 2020) forests indicate that forests cannot infinitely absorb CO₂. Moreover, trees can adapt to new conditions by reducing their biomass production, which may, in turn, lessen the mitigation effect (Sperry et al. 2019).

Forestry actions that lead to a reduction in greenhouse gas (GHG) emissions and maximise carbon sequestration are considered climate-smart (Nabuurs et al. 2018; Yousefpour et al. 2018). The recently developed comprehensive definition of climate-smart forestry suggests that it should enable forest practitioners to

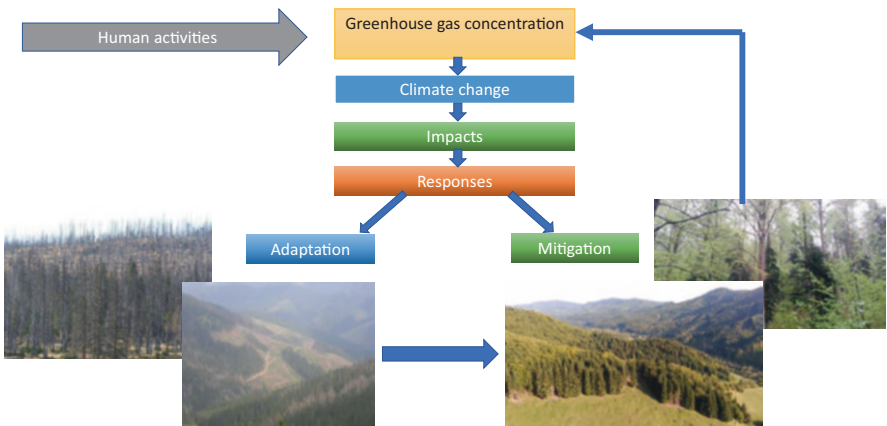


Fig. 7.1 Scheme describing the links between climate change and forests and the role of forests in mitigation of climate change impacts

transform management targets, allowing forests to adapt to and mitigate climate-induced changes while delivering other services to the society (Bowditch et al. 2020).

Mountain forests (for a definition see, e.g., Kapos et al. 2000), are particularly affected by environmental changes, because they are energy and temperature limited, and potentially exposed to warming-induced drought stress (Albrich et al. 2020). In addition, mountain forests are further exposed to and affected by large-scale wind disturbances, frequently followed by outbreaks of pests and fungal diseases (Seidl et al. 2014). Therefore, forest policy decision-makers and forest managers need to be advised by science about the potential and vulnerability of different tree species under predicted climate change.

Predictions by growth models are the best available source of information to optimise forest management and to assess the potential adaptation of the forests to climate change and the mitigation of climate change by the forests. Forest growth models have the potential to test many different variants of forest management, including various species compositions and silvicultural systems, from stand to regional or landscape levels (Fontes et al. 2010; Kramer et al. 2010; Merganič et al. 2020). Example applications of growth models include prediction of future yields, exploration of silvicultural options, preparing resource forecasts, providing insights into stand dynamics, etc. Growth models are generally classified into (i) empirical and (ii) process-based (also known as mechanistic) models. Empirical models are based on empirical equations (regression functions) describing particular relationships without knowing the causal mechanism of the complex system (Fontes et al. 2010; Mäkelä et al. 2012). In contrast, process-based models are based on a theoretical understanding of relevant ecological processes.

Currently, not all available models can test different management variants relevant for ecosystem management and ecopolitical decisions. In the following sections, we review the potential of various models to test the effects of climate change on the growth (the difference in standing volume between the beginning and end of a specified period of time) and productivity (the potential amount of wood produced by the forest within a specified time period, usually rotation period) of mountain forests and their potential to continue to be or become climate-smart.

7.2 Prediction of Future Climate Conditions

To obtain consistent predictions of future tree and forest growth, reliable past climate data as well as predictions of future climate in specific spatial and temporal resolutions must be provided as input into growth models and simulators. To obtain past climate data, spatially interpolated databases at varying spatial and temporal resolutions have been developed (Harris et al. 2014; Moreno and Hasenauer 2016; Cornes et al. 2018). The continental and global databases of past climate data are often the products of spatial interpolation of instrumental time series from climate stations. Therefore, the precision of the interpolated data depends on the density of climate station data provided by individual countries. In the following section, we briefly review the existing approaches to model and predict climate conditions.

7.2.1 *Climate Models*

Climate models are numerical representations of the Earth's climate system based on global patterns of physical processes, including chemical and biological components of the climate system, simulating the transfer of energy and materials through the system. Currently, there are a variety of models available from simple, simulating only a certain process in the atmosphere, to complex, simulating many processes of the climate system.

Global climate models (GCMs) are general circulation models, which were developed on general principles of fluid dynamics and thermodynamics (Stute et al. 2001). A crucial limitation of global models for their use in ecological modelling is the coarse spatial resolution. Therefore, regional climate models (RCMs) were developed by downscaling GCMs to the region of interest. The more recently developed RCMs have provided a tool to characterise past and future climates at various spatial scales (Rummukainen 2010).

7.2.2 *Climate Change Scenarios*

The intensifying greenhouse effect leads to global warming and to change in other climate characteristics on the Earth. The most serious consequences are changes in general atmospheric circulation, shifting in frontal and climate zones and the high speed of climate change, exceeding all previous climate changes at least tenfold. This is what scientists have learned from the mathematical modelling of the Earth climate system, where critical physical and chemical processes in the atmosphere and the oceans and physical processes associated with the cryosphere, biosphere and lithosphere were considered (IPCC 2014).

In 2000, the Intergovernmental Panel on Climate Change (IPCC) issued its Special Report on Emissions Scenarios (SRES) and introduced four scenario families to describe a range of possible future climate conditions. Each scenario (A1, A2, B1 and B2) was based on a complex relationship between the socioeconomic forces driving greenhouse gases and aerosol emissions (Nakicenovic et al. 2000). The SRES scenarios have been in use for more than a decade.

In 2009, a new set of scenarios was developed based on the concentration of greenhouse gases in the atmosphere in 2100 (Moss et al. 2010). These scenarios are known as Representative Concentration Pathways (RCPs). Each RCP indicates the amount of radiative forcing, expressed in watts per square metre, that would result from greenhouse gases in the atmosphere in 2100. These four RCPs were used for climate modelling in the IPCC Fifth Assessment Report (AR5) (IPCC 2014): RCP2.6 with radiative forcing peaking at approximately 3 W m^{-2} , RCP4.5 at 4.5 W m^{-2} , RCP6.0 at 6 W m^{-2} and RCP8.5 peaking at 8.5 W m^{-2} , being the most pessimistic scenario at the time.

As in the case of SRES, the GCM/RCM is used to derive data under different RCP scenarios (Jacob et al. 2014). The simulations from the climate models are then used as input to growth models, in some cases with a preceding statistical downscaling to account for topographic effects at a scale below 10 km and to match the grain size of forest models (Temperli et al. 2012; Seidl et al. 2019).

7.3 Simulating Future Forest Growth in the Context of CSF

Forest growth models are used to predict the development of trees, stands and forest ecosystems in the near or distant future, under various scenarios. Forest modelling science has developed from simple empirical yield models (YM), based on either single-time inventories or repeated empirical measurements and regression equations, to more complex empirical models (EM) and dendroclimatic models (DM) and to mechanistic models (PM), which describe physiological mechanisms and processes to predict forest growth. More complex empirical growth simulators (ES) and hybrid (semi-empirical) models (SES), which combine empirical regression equations with physiological processes, are better placed to be used to simulate future forest development than the simple YM and EM, because they often directly include growth sensitivity to climate. A range of growth models available include whole landscape or biome models, stand models, diameter distribution and size class models and individual-tree models (Burkhart and Tomé 2012a). The classification of forest growth models was presented in many studies (Porté and Bartelink 2002; Mäkelä et al. 2012; Fabrika and Pretzsch 2013; Fabrika et al. 2019). Growth models can be classified according to their ability to account for inter- and intraspecific competition and according to the sensitivity of simulated tree/stand growth to climate variation (Fig. 7.2). Tree-level (individual tree or gap/patch) ecophysiological models (the rightmost dark green box in Fig. 7.2) are believed to be most suited for simulations of forest development, because they combine causal effects of climate change and inter- and intraspecific competition (Rötzer et al. 2010; Seidl et al. 2012).

Simulations of forest development with forest growth models require input data, according to the spatial scale for which the prediction of future forest development is required (Fig. 7.3). Input data sources are reviewed in Sect. 7.4 in more detail.

Until recently, forest growth models (mainly ES) were used to predict biomass production and to test the effects of different management approaches and climate change scenarios. However, increasing requirements for a variety of ecosystem services as well as for sustainable forest management have raised the demands on models to expand the spectrum of outputs (Mäkelä et al. 2012; Temperli et al. 2020).

To allow assessment of CSF with modelling approaches, forest growth models must be able to simulate forest stand development under varying forest management alternatives (e.g. different silvicultural treatments) and policy strategies (e.g.

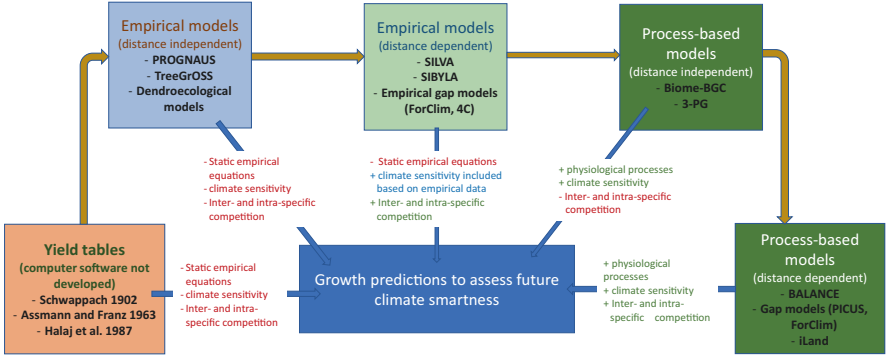


Fig. 7.2 Classification of forest growth models in the context of climate-smart forestry with some examples of existing models or groups of models for each class (in bold black letters). The brown arrow denotes increasing details on ecosystem processes implemented in models

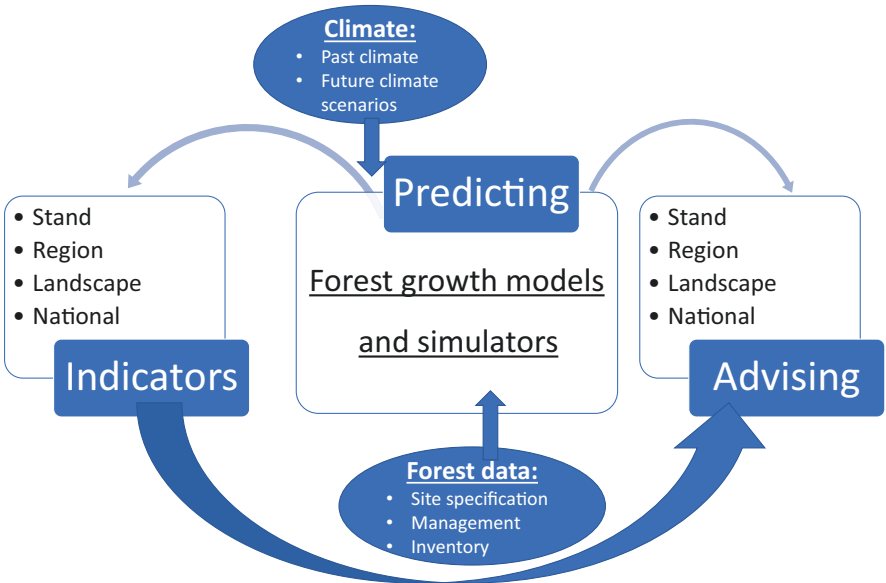


Fig. 7.3 Scheme of the process of predicting future growth and development of forest ecosystems and advising at different spatial scales

emission scenarios). Models should be able to simulate direct and indirect effects of different silvicultural treatments not only on tree growth rates (representing their potential to store carbon) but also on wood quality (the potential of timber to be used for substitution of carbon-intensive materials or fossil fuels) (e.g. Mäkelä et al. 2010).

Bowditch et al. (2020) selected a set of CSF indicators, by combining the pan-European indicators for sustainable forest management (SFM) (FOREST EUROPE

2015) with the ecosystem services defined by the European Environment Agency in the Common International Classification of Ecosystem Services (Haines-Young and Potschin 2018), to assess if the applied CSF practices are on track to meet the goals of forest adaptation and mitigation to climate change. Annex 7.1 resumes the ability of example growth models to address the indicators of CSF based on Bowditch et al. (2020). The models listed in the table represent individual groups following the classification provided above (Fig. 7.3).

7.3.1 Empirical Growth Models

Empirical models use correlation relationships translated into a set of regression equations to simulate tree and/or stand growth. Empirical models include YM, DM and ES.

7.3.1.1 Yield Models

YMs, experiencing more than 250 years of history, are the oldest models in forestry science and practice. They “predict” forest development over the rotation period or longer and are usually based on long-term monitoring or permanent research plots. They are based on regression functions derived from the empirical data and are often presented in the form of handy yield tables (which summarises expected yield tabulated by measurable stand characteristics, such as age, site index and stand density) to enable their use in forestry practice. Pretzsch (2009) and Fabrika and Pretzsch (2013) provided a comprehensive review of yield tables developed since the eighteenth century.

These models mainly rely on the classical assumption of the stationarity of site conditions (Vanclay and Skovsgaard 1997; Skovsgaard and Vanclay 2008) and thus are not capable of predicting forest growth under changing environmental conditions. They predict stand characteristics, such as stand height and diameter, standing volume (merchantable), stand density, etc., and do not consider inter-tree and inter-specific competition when used to simulate the growth under different forest management. They use a species site index (top or mean stand height at a standard age, e.g. 100 years) based on height-age curves to consider site potentials to produce wood. In mixed forests, they are used to predict the growth of individual species and their predictions are subsequently combined to a stand level. An exception is the YM developed for mixed forests (Christmann 1949).

These models are, in many cases, well suited to estimate the current amount of wood in forests based on a few measurements but not to predict the future growth of tree species under scenarios of various environmental changes.

7.3.1.2 Empirical Growth Simulators

ES have the second longest tradition in forest modelling after YM. Therefore, in the recent decades, these models began to be intensively used to forecast the development of the forest and to study the impact of changed conditions (environmental, economic, socio-economic) on the growth and structure of the forests (Sodtke et al. 2004). Compared to YMs, the range of conditions for ES application has been largely expanded. Their applications are no longer limited to monospecific and even-aged forests. ESs can model forest stands of various species, age spatial structures. Their ability to account for these forest characteristics depends on the spatial detail of modelling (population, class/cohort or individual) and how the model accounts for the spatial changes in environmental conditions due to inter-tree competition for resources (Fabrika and Pretzsch 2013). Based on the competition for resources, we recognise distance-independent models (Sterba 1995; Nagel 1996) and distance-dependent models (Hasenauer 1994; Pretzsch et al. 2002) (Fig. 7.3). Distance-independent models are biogroup-, ecosystem- or landscape-scale models, whereas distance-dependent models simulate individual trees and thus require spatial coordinates of trees in the stand. The emergence and development of ES made it possible to address the impact of different forest management on forest growth and structure (e.g. thinning) and thus eliminated the limitations of YM, i.e. their applicability only for a few methods of forest management. The range of applicable forest management variants is increasing from population through class/cohort to individual-tree models and from distance-independent to distance-dependent models (Fabrika et al. 2019). This advance in the modelling has opened the space for the use of models, if they are, at the same time, sensitive to climate, to assess the impact of climate change on forest growth and structure (Hlásny et al. 2011). However, an additional limitation related to the response of the increment in tree size to environmental conditions needed to be further addressed in EMs. First EMs used the phytocentric method to quantify site quality that affects the growth of trees and stands (Nagel 1999). However, the static nature of the site index (discussed in Sect. 7.3.1.1) is at odds with the principle of the forest's response to climate change. Therefore, models with a geocentric method (Kahn 1994) have been developed. The geocentric approach considers a direct response of the tree/stand growth to climatic and soil characteristics, for example, expressed by a direct regression model (Monserud and Sterba 1996) or by means of a dose-effect function (Kahn 1994). The link between environmental conditions and diameter/height/volume increment is ensured through empirical (statistically derived) relationships. Such a modification of the models allows their use to assess the impact of climate change on forest growth and structure. Although the introduction of the geocentric approach has expanded the range of ES applications for environmental studies, the very nature of empirical models still limits their use. They cannot be used outside the range of environmental conditions for which they were developed. Therefore, to assess the climate smartness of forest management, statistical relationships should be replaced with causal relationships, which represents the shift from empirical to process-based (mechanistic) models.

7.3.1.3 Dendroecological Models

Dendroecology refers to the use of annual tree rings and dendrochronological techniques to address questions in ecology (Fritts and Swetnam 1989). Tree rings are the products of multiple processes related to the energy, water, carbon and nutrient budget (Babst et al. 2014a). They represent a part of the above-ground carbon accumulation. Dendroecological models establish relationships between tree-ring measurements and environmental factors (Fritts 2001). Originally, dendrochronologists used the relationships between tree-ring formation and climate variance as a proxy to estimate climate variability in a distant past for which weather measurements did not exist. Recently, tree rings have been increasingly used by forest scientists to investigate and model the effects of climate on tree growth and to build empirical models to predict the future growth of forest tree species (Girardin et al. 2008; Chen et al. 2010).

Although tree rings represent only radial stem growth at a particular stem height, tree-ring data-based estimation of above-ground carbon sequestration has been found to be coherent with the net ecosystem productivity measured using eddy covariance techniques (Babst et al. 2014b). However, the contrasting results found in other studies dealing with tree-ring data (Rocha et al. 2006) suggest that there is often a problem with scaling from a tree stem to a forest ecosystem because of sampling bias and stand dynamics (Cherubini et al. 1998; Nehrbass-Ahles et al. 2014).

The developed models were often based on linear relationships between mean tree-ring width (TRW) chronologies and climate variables (Cook and Kairiukstis 1990; Fritts 2001; Dorado-Liñán et al. 2019). They did not consider changes in the relationships over time due to changes in the environment other than climate variation (Guiot et al. 2014). Such empirically-based models should not be used to predict the growth outside the period and the range of site characteristics for which they were developed. Therefore, process-based dendroecological models have been developed to reproduce the daily cellular development (Wilson and Howard 1968; Rauscher et al. 1990; Fritts et al. 1991; Tolwinski-Ward et al. 2011). The first dendroecological process-based model was the TRACH model (Fritts et al. 1991). More recently, the Vaganov-Shashkin (VS) model of tree-ring formation was developed (Vaganov et al. 2006). The VS model and its simplified version called the VS-light model (Tolwinski-Ward et al. 2011), which uses daily climatic input variables and more than 30 parameters for simulating secondary growth of xylem and anatomical features of annual rings, are now frequently used in dendroecological studies (e.g. Sánchez-Salguero et al. 2017).

Although some studies indicated the potential of empirical models developed from tree-ring data for predicting the future growth of forest trees (Dorado-Liñán et al. 2019), process-based models are currently preferred over EMs. However, the crucial role of tree-ring data is to inform vegetation models about long-term forest growth variability and disturbance regime from local to global scales (Babst et al. 2014a). Moreover, process-based models, in general, should be compared against regional and stand-level tree-ring data in shorter periods to avoid potentially biased estimations of net primary productivity by mechanistic models.

7.3.2 *Process-Based Growth Models*

Unlike empirical model and dendroecological process-based models that focus only on tree-ring formation, PMs simulate physiological processes in the whole plant (photosynthesis, respiration, allocation, mortality, transpiration, translocation and nutrient uptake) and their interactions with processes in the atmosphere and soil. The models relate plant carbon budgets to environmental drivers, climatic variables and/or biogeochemical processes (Battaglia and Sands 1998). This enables PMs to simulate forest responses to changing environmental conditions (e.g. future climate change).

However, our understanding of individual processes differs, some being understood better than others. For example, carbon allocation, which has a critical role in forest adaptation to environmental changes, is often simplified due to insufficient knowledge on driving mechanisms (Merganičová et al. 2019). The other crucial uncertainties in PMs include mortality and regeneration (Mäkelä et al. 2000; Bugmann et al. 2019).

In contrast to EMs, PMs usually work at a finer temporal resolution, starting from less than a minute (Fontes et al. 2010; Pretzsch et al. 2015). Only a few process models, such as 3-PG, FORMIND or TRAGIC, use a coarser scale than 1 day (Hauhs et al. 1995; Köhler and Huth 1998; Forrester and Tang 2016). Many process-based models use different temporal resolutions for simulating different processes, e.g. carbon allocation is frequently simulated at a coarser scale than photosynthesis (Merganičová et al. 2019).

To incorporate physiological processes as realistically as possible, PMs use many physiological parameters as well as input stand and environmental variables. Environmental variables often include solar radiation, temperature, precipitation, wind speed and direction, vapour pressure deficit, nitrogen deposition, CO₂ content in the atmosphere and available soil water content measured at fine temporal resolutions. Long-term, cost-effective and highly instrumented monitoring plots may provide such data, enabling key forest indicators to be modelled. Discussion on highly instrumented experimental plots is presented in Chaps. 10 and 16 of this book (respectively, Tognetti et al. 2021; Pappas et al. 2021). Several models are more simplistic and use only some of these variables and at a coarser temporal resolution (e.g. 3-PG, Landsberg and Waring 1997), whereas others are more complex requiring most of the variables at a finer scale (e.g. ANAFORE, Deckmyn et al. 2008, or FORCLIM, Bugmann 1996). The models range from biome-scale (e.g. Biome-BGC, Thornton et al. 2005) to individual-tree models (e.g. BALANCE, Rötzer et al. 2010).

Landscape dynamics or forest landscape models (LDM) are another group of PMs. The LDMs are based on the interaction of spatial patterns and ecological processes at various spatio-temporal scales. They usually simulate forest dynamics at a site scale (up to 300 ha) and landscape processes at a larger scale (He 2008; Shifley et al. 2017). For example, the process-based model of forest landscape dynamics iLand (Seidl et al. 2012) simulates forest landscape dynamics via

modelling spatially explicit resource availability at the landscape scale and integrating local resource competition and physiological resource use. Moreover, it simulates spatial and temporal interactions of vegetation and disturbance agents, which place this model among the most complex models from the point of simulated landscape dynamics. Another widely used LDM in Europe is LandClim (Schumacher et al. 2004). It basically uses a gap-model approach to simulate forest dynamics in individual grid cells of 25×25 m of a landscape wide up to 50 km^2 and accounts for spatial processes, such as wind, fire disturbance, bark beetle, seed dispersal and forest management. Recent applications include estimates of adaptive management effects on forest ecosystem service provision (Temperli et al. 2012), reconstruction of species range shifts in the Holocene (Henne et al. 2013), analyses of disturbance interaction with climate change (Temperli et al. 2015) and biodiversity (Schuler et al. 2019). The FLM TreeMig is also raster based but can be applied from the watershed to the continental scale (Lischke et al. 2006). While it primarily focuses on tree migration under climate drivers (Meier et al. 2012; Scherrer et al. 2020), it has also been applied to assess avalanche-forest interactions (Zurbriggen et al. 2014). Remote sensing technologies may contribute with spatially explicit time series of vegetation traits to estimate temporal changes in CSF indicators at the landscape scale as well as to serve as input for models. Benefits and challenges of remote sensing for monitoring forest ecosystems are presented in Chaps. 11 and 16 of this book (respectively, Torresan et al. 2021; Pappas et al. 2021).

Reliability of growth predictions using PMs depends on various factors, including the spatio-temporal scale of the predictions, level of details available to calibrate and validate the models, etc. The scale and detail of various types of forest monitoring data strongly influence the reliability of simulations. In this regard, new approaches include, for example, model-data fusion with Bayesian inference, which have the potential to strongly reduce the prediction biases and increase their reliability (Trotsiuk et al. 2020).

PMs are thus well placed to address the CSF and support decisions in adaptation and mitigation strategies, because they consider species sensitivity to environmental conditions via physiological processes. PMs can be used to test different scenarios of future environmental conditions. However, there are some components that still need to be developed or improved in PMs to predict future forest growth and landscape dynamics more realistically. These include, for example, intra- and interspecific competition/facilitation, tree mortality, deadwood, natural regeneration and carbon allocation to different tree components. In particular, below-ground carbon allocation needs to be further validated in most of the PMs and analysed with greater accuracy, since it can strongly affect the ecosystem response to climate change. Management is often not simulated by PMs in detail – particularly in the group of models that do not account for the inter-tree competitive interactions in the stand. In such cases, simplified rules need to be applied to test the impact of different management scenarios, e.g. the proportion of biomass extracted (Merganičová et al. 2005).

7.3.3 *Considering Environmental Conditions in Growth Models*

In the case of YMs, environmental conditions are indirectly considered by the site index. Site index usually refers to the mean (Halaj and Petráš 1998) or dominant (Burkhart and Tomé 2012b) stand height at a standard age (e.g. 100 years). However, YMs consider that site index is a temporarily static parameter that represents site conditions at the time of data collection. Once used for predictions outside the conditions and region of empirical data, small to large systematic errors can be expected, and reliability of predictions is strongly limited. Recently, advanced methods were proposed to develop dynamic site index models (Socha and Tyimińska-Czabańska 2019), which consider the changes of site index due to changing environmental conditions.

In ESs and SESs, site conditions affect tree or forest growth potential defined by a growth function (Burkhart and Tomé 2012c) using a modifier based on, for example, ecological site classification (Pretzsch et al. 2002). Among the ESs that apply this growth reduction approach are SILVA (Pretzsch et al. 2002) and SIBYLA (Fabrika 2005). Other ESs use explicit empirical relationships between climate predictors (temperature, precipitation, drought indices) and growth, regeneration and mortality processes to simulate forest development (Stadelmann et al. 2019; Zell et al. 2019).

Unlike YMs and ESs, PMs simulate physiological mechanisms that are directly affected by environmental conditions. PMs are thus more reliable and better suited to simulate future growth of forests under alternative climate change scenarios under the assumption that processes are correctly described, whereas ESs are confined to the climatic space that is represented by the data they have been parameterised with.

7.3.4 *Integrating the Effects of Species Mixture into Growth Models*

Recently, a strong research activity with the aim to explore how species interactions influence wood and biomass production (Pretzsch and Schütze 2009, 2015; Rötzer et al. 2009; Pretzsch et al. 2010; Jucker et al. 2014; Toïgo et al. 2015) and how to improve forest multifunctionality (van der Plas et al. 2016) has been ongoing. According to Pretzsch et al. (2015) and Bravo et al. (2019), one of the following four principles can be used to predict the growth of mixed-species forests: (1) by applying weighted means of monocultures, (2) multipliers, (3) species-specific growing space competition indices or (4) process-based representation of mixing effects. Most common single-species YM can be used to predict growth in mixed-species forests by simple weighted means of species growth predicted in

monocultures. This approach does not consider interspecific competition, and thus, it is less suitable to simulate the future growth of mixed-species forests. Individual-based empirical growth simulators often include inter-tree and interspecific interactions by means of various distance-dependent competition indices (Pretzsch et al. 2002, 2015; Fabrika 2005). The use of empirically based multipliers or more advanced competition indices used in ES often assumes that interactions do not change over time. However, a few competition indices use tree dimensions in the calculation and thus consider competition changes over time. PMs have the potential to overcome the shortcomings of ES by modelling species interactions in a mechanistic way. PMs differ in which processes are considered to be affected by species-mixing effects, i.e. radiation, water, phenology, nutrients and structure (Pretzsch et al. 2015). However, only a few PMs and LDMs consider species interactions in most of the processes to simulate the growth of mixed forests more realistically (Rötzer et al. 2010; Seidl et al. 2012; Temperli et al. 2012; Forrester and Tang 2016; Huber et al. 2018). Also, in this case, it is challenging to better understand how the species composition affects carbon allocation within the tree and among the trees belonging to different species and social positions, and its comprehension would dramatically improve the prediction ability of PMs.

7.3.5 Integrating Silvicultural Prescriptions and the Induced Treatment Responses into Growth Models

Forest management, specifically silvicultural treatments applied over the rotation period, can modify species composition and canopy structure, which in turn can influence forest response to environmental change, including direct effects of warming and drying or other disturbances caused by various factors, such as wind, snow, game and ice (Seidl et al. 2011; Mausolf et al. 2018). The effects of silvicultural interventions and past natural and human-induced perturbations should be correctly considered in forest growth simulation studies, especially in the case of intensively managed European forests (Spiecker 2003; Fontes et al. 2010). Silvicultural techniques influence not only the productivity (and so the carbon sequestration) of the forest stand but also carbon allocation among the tree and stand components, forest vertical and horizontal structure, crown morphology, forest stability and vitality, which alter the resistance of forest to various types of disturbances (Noormets et al. 2015). For example, “heavy thinning from below” applied in some European countries removes all suppressed trees and keeps dominant trees that are all directly exposed to macroclimate (Bosela et al. 2016c). On the other hand, vertically more diversified forests after “thinning from above” may be more resistant under predicted future climate change conditions. Applied silvicultural treatments, including different regeneration methods, have a significant role in creating more complex forests that are expected to be more resistant and resilient to changes in environmental conditions and natural disturbances (O’Hara 2006; Puettmann 2011; O’Hara and

Ramage 2013; Lafond et al. 2014; Fahey et al. 2018). Forest microclimate, altered by different silvicultural treatments, will probably have a crucial role in buffering extreme weather events in the future (Zellweger et al. 2020).

Several models consider silvicultural treatments as a very important component of future growth predictions (Fontes et al. 2010; Fabrika et al. 2018). The most common management intervention employed in growth models is thinning, which can vary by type, intensity and timing. Different types of thinning are implemented mostly in individual-tree process-based models, functional-structural plant models, distance-dependent and distance-independent empirical tree models, tree and cohort gap models or distribution stand models (Fabrika et al. 2018). Other management prescriptions rather rarely applied in growth models are early stand treatments (weeding, cleaning), fertilisation often combined with thinning and harvesting (Weiskittel et al. 2011).

Up to now, less than one-third of all existing growth models consider species-mixing effects and can be directly applied to mixed forests (Pretzsch et al. 2015). The present tendency in silvicultural prescriptions to convert monospecific to multispecies stands or establish new mixed forests is very much favoured, considering matching species composition to site conditions, and requires the development and implementation of appropriate silvicultural strategies for mixtures into growth models (Bravo et al. 2019).

Despite the importance of silvicultural treatments on stand productivity and climate sensitivity of tree species, forest growth models are not always capable of simulating the effects at individual tree level. This limited capacity is because some of the models operate at a stand or biome level and thus are unable to consider inter- and intraspecific competition or facilitation (Jucker et al. 2014). Stand- and biome-scale distance-independent models can simulate the growth under varying stand densities (Horemans et al. 2016), whereas individual-tree distance-dependent ESs/SESs and PMs are well placed to simulate the growth of individual trees and forest stands under different silvicultural treatments and/or forest disturbances (Pretzsch et al. 2002; Fabrika 2005; Seidl et al. 2012; Mina et al. 2017). Other constraints of the wider application of silvicultural methods in growth models include the quality and quantity of experimental data available and appropriate determination of temporal resolution (Weiskittel et al. 2011).

Nevertheless, much effort needs to be invested to improve the existing forest growth models to include an entire portfolio of silvicultural strategies and forest management that would address global climate change (D'Amato et al. 2011).

7.3.6 Effects of Genetic Structure on Forest Growth

Postglacial migrations have altered the genetic diversity of organisms (Hewitt 2004). Evidence has suggested that the populations in refugial areas are typically genetically more diverse and the allelic richness may gradually decline along the

migration routes (Hewitt 2000; Petit et al. 2003). A certain level of genetic diversity is required to allow populations to adapt to changing conditions (Howe et al. 2003). A recent study showed the impact of postglacial migration on genetic diversity of European silver fir, *Abies alba* Mill. (Liepelt et al. 2009), which might have had strong effects on the growth and climate responses of the species (Bosela et al. 2016a). Climate-driven natural selection also leads to local adaptation if the climate remains static over at least one tree generation. It may be questioned whether this was ever the case in any tree species' history since the last glaciation in Europe. Tree populations usually exhibit moderate to strong local adaptation; however, fast environmental change may cause local populations experience conditions to which they are not yet adapted (Howe et al. 2003; Wang et al. 2010). Therefore, the higher the genetic diversity is at the population level, the more chance for populations to adapt to the changing environmental conditions (Howe et al. 2003). Consequently, recommendations have stressed the importance of high genetic variability of forest plant material for uncertain futures (Eriksson et al. 1993; Yousefpour et al. 2017). Strong selection, especially among seedlings, would play a crucial role for local selection in natural forests, and varying adaptation effects would recur and act differently in time and space (at different locations and on each tree generation). How far such effects also come to bear on plant material raised under optimal conditions in nurseries and planted under growth-promoting forest management measures remains an open question (Namkoong 1998). Co-occurring tree species can develop quite different adaptive strategies under identical environmental conditions. Contrasting genecological patterns reported for spruce and fir (strong climate-related differentiation in spruce vs. modest differentiation in fir) suggested that spruce can be considered an adaptive specialist while fir is more an adaptive generalist (Frank et al. 2017).

Strong latitudinal clines in the bud burst of tree species (Kramer et al. 2015), which depends on critical temperature sums specific to the climate a provenance is adapted to, and the effects of genetic diversity on tree growth (Bosela et al. 2016a) suggest (successful) genetic adaptations to local environmental conditions in the standing tree generation. However, the bud burst response of, e.g. European beech (*Fagus sylvatica* L.) to temperature sums proved to be plastic (Kramer et al. 2017), which further complicates the evaluation of the issue. Despite that the effects of intraspecific genetic variability on the responses to local climate conditions were ascertained (Neale and Wheeler 2019), still only a very few forest growth models address this aspect (Kramer et al. 2015; Berzaghi et al. 2020). It is important to stress that strongest selection/adaptation effects are experienced by tree populations in the seedling stage (when individuals are most vulnerable to extreme conditions) or in the event of catastrophic disturbances that kill the less resilient individuals. Ignoring the above effects in predicting future adaptive responses of tree species may under- or overestimate the potential of species under changing environmental conditions. Moreover, phenotypic plasticity and adaptive capacity of tree species may be significantly modified by epigenetic variation (Bräutigam et al. 2013).

7.4 Source of Data to Parameterise, Calibrate and Validate Growth Models

In this section, we review different sources of forest data, including national and stand-wise forest inventories, long-term research plots, eddy covariance system, dendrochronological networks (e.g. ITRB), climate and soil databases and remotely sensed data that can be acquired or are available to be used for forest growth models.

7.4.1 *National Forest Inventory*

It was as early as in the 1910s and 1920s when the European Nordic countries, namely, Norway, Sweden and Finland, launched the first sample-based national forest inventories (NFIs) as a response to the increasing importance of forests and wood for their economy (Vidal et al. 2016a). However, sample-based inventories were not initiated in the rest of Europe until after World War II. Since then, their importance has increased, and the country-scale inventories were launched in France (1958), Austria, Spain, Portugal and Greece (1960s), followed by Switzerland, Italy, Germany (1980s) and other countries. Nowadays, almost all countries in Europe conduct their NFI (Vidal et al. 2016a).

NFIs represent the main source of information about the state and changes of wood resources primarily at a national scale, but in some cases also at a regional scale. However, varying sampling designs among the European countries due to varying policy needs in the past limited the use of European NFIs for international reporting. Recent international activities were successful in harmonising the outputs of the European NFIs at European scale (Vidal et al. 2008, 2016a, b; Bosela et al. 2016b; Fischer et al. 2016; Gschwantner et al. 2016; Alberdi et al. 2020).

NFIs are valuable sources of data for parameterisation and calibration of forest growth models and simulators, because they often provide repeated measurements, representative of a region, landscape and country (McCullagh et al. 2017). They cover a broad range of site conditions, where tree species grow. Data from NFIs have been successfully used to calibrate and validate empirical growth simulators (Fabrika 2005; McCullagh et al. 2017). In Switzerland, the NFI-based forest management scenario model MASSIMO is, among others, successfully used to simulate future harvesting potentials, forest-related carbon budgets and forest reference levels used in greenhouse gas reporting (Stadelmann et al. 2019). In Germany, the NFI-based forest model WEHAM is used to evaluate the sustainability of potential future forest policy scenarios (Seintsch et al. 2017). Similarly, the Cãldis system was recently used to evaluate climate-smart management scenarios in terms of standing biomass and carbon as well as soil carbon based on the data of the Austrian NFI (Jandl et al. 2018). NFI data were also used to parameterise or calibrate physiological forest development models (van Oijen et al. 2013; Gutsch et al. 2018; Minunno et al. 2019).

Recently, NFI data of 23 European countries have been used to prepare future projections of the forest growing stock, above-ground carbon and harvesting until 2040 (Vauhkonen et al. 2019). The European Forest Dynamics Model (EFDm) was parameterised using NFI data, and future development of forest resources was simulated under business-as-usual forest management. Further, the large-scale European Forest Information Scenario model (EFISCEN) (Schelhaas et al. 2007) uses data of European NFIs and has been applied to evaluate the development of forest resources in the future under various management scenarios (Verkerk et al. 2011). These modelling activities suggest that European NFIs are suitable to serve the increasing information demands from national to international levels. As they are statistically sound and sufficiently cover the European forest area, NFIs can become the main source of data to aid in sustaining the resilience and climate smartness of the European mountain forests. However, the shortcoming of NFI data is that stand history is not known, and extreme densities and treatments are often insufficiently represented, although these are of special importance for model parameterisation and evaluation. The strength and limitation of NFI-derived CSF indicators, as well as an example of their application in two case studies, are presented in Chap. 4 of this book (Temperli et al. 2021).

7.4.2 *Stand-Wise Forest Inventory*

Stand-wise inventory, or inventory by compartments, is the assessment of wood resources of the forest stand defined as “geographically contiguous parcels of land whose site type and growing stock is homogenous” (Koivuniemi and Korhonen 2006). The first stand-wise forest inventories were often local and conducted by timber producers to estimate timber resources (Tomppo et al. 2010). For Central and Eastern European countries (especially the former socialistic countries with centrally planned economy), it has been typical to collect forest data at a stand level for management planning. State administration used these data to strictly regulate the use of forest resources at stand and forest district levels. In many Central-Eastern European countries (including the Czech Republic, Slovakia, Romania, Poland, Slovenia, etc.), stand-level inventories continue to be the main source of data for strategic management planning and regulation, despite the fact that the countries have already launched their sample-based NFIs. However, stand-wise inventory data are not available in most European countries. Moreover, stand-wise inventories are often conducted as surveys of forest managers and include expert assessments of forest characteristics, such as species composition, of unknown or limited precision, which strongly limits their use for scientific investigations (Grīnvalds 2014). Stand-wise inventory data are also limited in the spectrum of provided variables. They often only include mean stand variables, such as mean stand diameter and height, growing stock and stand density. The stand (compartment) area largely varies and often changes over time, which also limits the use of these data for temporal studies.

7.4.3 Long-Term Research and Monitoring Plots

Long-term research or monitoring plots are a unique source of data that can be used to either build empirical models or to calibrate and validate available growth models and simulators (Pretzsch et al. 2014; Pretzsch 2020). Compared to tree-ring data, long-term plots usually include mortality data and thus provide information on the true development of forest stands. The spectrum of variables assessed and measured in the plots depends on the aims of monitoring but is often reduced to dendrometric characteristics, which limits their use for assessing the indicators of SFM and CSF. Long-term monitoring plots often include only simple diameter and height measurements, because volume stock estimation was the main purpose of establishing such plots in the past, and thus bring uncertainty when scaling to estimations of biomass and carbon stocks and fluxes. However, the European network of forest condition monitoring plots (International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests, ICP Forests) provide an example of the long-term monitoring plots (from national to European scales) that go beyond the measurement of basic dendrometric characteristics (Michel et al. 2019). The biggest advantages of long-term monitoring plots are the long time period they cover (often several decades and in few cases more than 100 years) and the known management treatments. In an actual example, such data were used for estimating parameters of the process-based 3-PG model (Landsberg and Waring 1997) in conjunction with other data sources such as NFI data (Trotsiuk et al. 2020). Zell (2018) used data from long-term experimental forest management plots to parameterise an empirical climate-sensitive stand development model that includes an empirical management module. Thanks to long-term data, the capacity of forest gap-models to simulate accurate forest management prescriptions has greatly increased over the past decade (Rasche et al. 2011; Mina et al. 2017). A shortcoming of long-term plots is their uneven spatial distribution, covering only a small portion of the range of site conditions and only a few tree species. These include mostly productive sites and commercially interesting tree species, for studying the growth of which long-term plots have historically been set up. Moreover, monitoring plots that span across centuries are scarce and missing for most regions. However, establishing long-term monitoring plots across the range of site conditions is crucial to calibrate and validate growth simulators under changing climatic conditions and to support climate-smart forest management decision-making (Thrippleton et al. 2020). In Chap. 5 (Pretzsch et al. 2021), the design of a smart network of observational forest plots across European mountain regions is described, and a discussion on their relevance for monitoring growth patterns in monospecific European beech and mixed-species stands of Norway spruce, European beech and silver fir is provided.

7.4.4 Eddy Covariance Measurements

The eddy covariance (EC) technique is an atmospheric measurement technique based on measuring vertical turbulent fluxes within atmospheric boundary layers. It is one of the most appropriate ways to measure local turbulent fluxes of CO₂ (Wang et al. 2009). The technique is used to estimate seasonal fluctuations in carbon exchange between the forest and the atmosphere (Baldocchi 2003). This technique has been successfully used to estimate the net ecosystem productivity (NEP). EC measurements are often used for calibration and validation of NEP estimated by growth simulators (Kramer et al. 2002; Mo et al. 2008; Meyer et al. 2018). However, using the EC technique (but not only EC) includes two potential sources of uncertainty: measurement error and representativeness error (Lasslop et al. 2008; Youhua et al. 2016). Measurement error can be minimised by, for example, the calibration of the instruments. However, representativeness error depends on surface roughness and thermal stability, which further depends on the vegetation heterogeneity (Youhua et al. 2016). EC measurements are more accurate when the atmospheric conditions are steady, the terrain is flat and the surrounding vegetation is homogeneous (Baldocchi 2003). Hence, in the mountainous areas, i.e. in highly complex terrain, and in forests strongly affected by natural disturbances (e.g. fire, diseases, insect infestation), the precision of EC estimates of NEP strongly decreases. The more complicated orography and vegetation heterogeneity were likely the reason for different findings from nearly no link to the high correlation between biometric data and EC measurements (Rocha et al. 2006; Zweifel et al. 2010; Babst et al. 2014b). The distance between the forest under study and the nearest EC tower is another factor affecting the coherence between biometric and EC data (Babst et al. 2014b). A recent study based on a 5 km × 5 km gridded EC measurements revealed large variability in the representativeness of single EC towers to estimate NEP (Youhua et al. 2016).

7.4.5 Remote and Proximal Sensing

Remotely sensed data, such as Landsat or Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery, are increasingly used to estimate gross or net primary productivity (GPP, NPP, Neumann et al. 2016) and NEP or to derive vegetation indices further used in large-scale ecological studies, including the characterisation of forest disturbance regimes (Yuan et al. 2010; Jin and Eklundh 2014; Liang et al. 2015; Hart et al. 2017; Liu et al. 2018; Yang et al. 2020). Light-use efficiency (LUE), defined as the amount of carbon produced per unit of absorbed

photosynthetically active radiation (APAR), has been successfully used to quantify the dynamics in GPP. The models to estimate LUE, and therefore GPP, are usually based on normalised difference vegetation index (NDVI), photosynthetically active radiation (PAR), fraction of PAR, air temperature, moisture and other environmental conditions (Yuan et al. 2010). There are, however, various definitions of LUE used in developing LUE models, which have implications for the estimation of forest productivity (Gitelson and Gamon 2015). Ecosystem respiration (ER) is an essential component of water and energy budgets and is used to estimate NPP of forest ecosystems by its subtracting from GPP. It is, however, the most difficult component to estimate because of the heterogeneity of the landscape, soil properties and topography, among other factors (Yuan et al. 2010; Zhang et al. 2016). NDVI is a remotely sensed vegetation index frequently used to assess leaf phenology or changes in the canopy due to disturbances, such as bark beetle outbreak or wind storms (Jönsson et al. 2009; Meddens et al. 2013; Jin and Eklundh 2014). Although it is popular because of its robustness against noise, in some forest types, the index is too sensitive to snow cover and much less sensitive to growth of close-canopy forests (Jönsson et al. 2009). Canopy nitrogen content and chlorophyll light-absorbance variables, used as indices to nutrient cycling and maximum photosynthetic capacity, can be estimated using both aerial and satellite optical hyperspectral imagery. Variables, such as above-ground tree height and vertical and horizontal distribution of tree crowns, used for the model parameterisation, can be computed using light detection and ranging (LiDAR) data and interferometric synthetic aperture radar (SAR). Other vegetation indices used in ecological studies include the enhanced vegetation index (EVI), normalized difference water index (NDWI), wide dynamic range vegetation index (WDRVI), phenology index (PI) and leaf area index (LAI). To obtain the remotely sensed data, the MODIS instrument aboard the Terra satellite is often used. MODIS is viewing the entire Earth's surface every 1 to 2 days and acquires data in 36 spectral bands, or groups of wavelengths. The spatial resolution of MODIS images is 250 m (bands 1–2), 500 m (bands 3–7) and 1000 m (bands 8–36). To increase the spatial resolution of MODIS-derived indices, a combination of MODIS and Landsat time series (available at finer 30 m resolution) provides a solution (Yang et al. 2020). Another promising remote sensing-based data sources are the Sentinel-1 and Sentinel-2 SAR data that can be collected independently from daylight or weather conditions and were recently used for rapid detection of windthrows (Frampton et al. 2013; Rüetschi et al. 2019).

There are various models able to utilise remote sensing data in different ways, but the satellite-driven version of the 3-PG model (Physiological Principles in Predicting Growth), developed by Landsberg and Waring 1997 and Waring et al. 2010 is probably the most known and used. The physiological variables used in the model can be estimated from remote-sensing measurements of factors that influence those variables. In the model, GPP is ultimately a function of the APAR and the canopy quantum use efficiency.

It is worth mentioning that recent data assimilation (DA) techniques have been used to estimate forest stand data by sequentially combining remote sensing-based estimates of forest variables with predictions from growth models (Nyström et al. 2015). DA provides a way of blending the monitoring properties of remotely sensed data with the predictive and explanatory abilities of forest growth models (Huang et al. 2019). Input to the data assimilation may be canopy height models, obtained from airborne laser scanning (ALS) data or from image matching of digital aerial images at different time points during the growth season. With this approach, the prior forecast is updated to the posterior forecast when a new estimate is considered. This kind of approach needs modification of the existing growth models that would allow data assimilation and also requires the possibility to interrupt the model simulations before the end and use remote sensing data to update specific characteristics.

7.4.6 Tree-Ring Time Series

Annually resolved TRW series represent a valuable source of information on past growth dynamics of individual trees and forests (Babst et al. 2018, 2019; Klesse et al. 2018). Over the past century, TRW data have been collected across the globe for many different purposes, and a high portion of these data has been archived in the International Tree-Ring Data Bank (ITRDB) managed by Paleoclimatology Team of National Centers for Environmental Information and the World Data System for Paleoclimatology. ITRDB now includes TRW series from over 4000 sites and six continents. Tree-ring networks were frequently used to reconstruct past climate as well as to investigate responses of forest trees to variation in environmental characteristics to assess species vulnerability to changing conditions (Babst et al. 2013). Recently, TRW data have been successfully applied to predict future forest growth and climate responses (Charney et al. 2016; Dorado-Liñán et al. 2019). TRW data have also been used to reconstruct regimes of windthrow, bark beetle, storm and other disturbance regimes (Veblen et al. 1994; Svoboda et al. 2014). Explaining relationships between climate and disturbance dynamics (Hart et al. 2014) forms the basis to parameterise models of disturbance dynamics under climate change (Temperli et al. 2015; Thom et al. 2017). However, using TRW data for detecting long-term growth trends and species climate responses must follow purpose-oriented sampling designs (Nehrbass-Ahles et al. 2014) and appropriate detrending methods (Peters et al. 2015) to minimise potential prediction biases (Klesse et al. 2018).

7.5 Conclusions and Perspectives

Expected rapid climate change will likely challenge the adaptation capacity of many forest ecosystems. Forest growth models represent a promising tool to predict the effects of different climate change scenarios on the growth of individual trees and forest stands as well as the future distribution of forest tree species under changing conditions and thus to support forest managers and policymakers in developing long-term strategies. Available forest growth models largely differ from each other in many ways due to which they provide a large range of future growth estimates. A multi-model averaging technique has been found a good way to avoid biased estimates of single models due to shortcomings of individual modelling approaches (Picard et al. 2012; Hlásny et al. 2014; Dormann et al. 2018). Although modelling the relationships between forest production and future climate is complex and intrinsically uncertain, forest growth models may help to guide climate-smart strategies aimed at overcoming mitigation, adaptation and production gaps. For example, synergies and trade-offs between biodiversity conservation and timber production can be assessed, and user-friendly interactive decision support tools can be developed, ensuring that all stakeholders envisage the risks of adapting their management strategies to changes in climate and society and anticipate the consequences of environmental disturbances.

Past constraints that limited the capacity to model forest dynamics, such as the availability of data for model calibration and validation, the computing capacity, the model applicability to real-world problems and the ability to integrate biological, social and economic drivers of change, have become less restrictive. For this, the role of models for predicting forest growth and yield under changing environments is now central in applied decision-making. For that, to ensure their role, great attention is required to evaluate the performance, to expand the driver of changes and to incorporate variables as input social and economic trends and needs.

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Appendix

Annex 7.1 Identification of ability of selected growth models (representing the model groups defined in Fig. 7.3) to address the indicators of climate-smart forestry (indicator list based on (Bowditch et al. 2020))

Indicator	Specific indicator	Yield tables	PROGNAUS	SIBYLA	Biome-BGC	iLand
1.1 Forest area		Not provided	Input and output	Not provided	Not provided	Input and output
1.2 Growing stock		Output	Input and output	Output	Derived from output	Output
1.3 Age structure and/or diameter distribution	Age structure	Input and output in the form of mean stand age	May be obtained as output	Input and output	Stand age as a parameter driving the start of normal simulation	Input and output
	Diameter distribution	Not internally considered	Input and output	Input and output	Not considered	Input and output
1.4 Carbon stock	Carbon stock in forest biomass	Not provided, may be derived from growing stock	Not provided, may be derived from growing stock	Output	Output	Output
	Carbon stock in forest soils	Not provided	Not provided	Not provided	Output	Output
	Carbon stock in harvested wood products	Not provided, may be derived from model output if coupled with assortment model	Not provided, may be derived from model output if coupled with assortment model	Can be derived from model output	Not provided, may be derived from model output if coupled with assortment model	Not provided, may be derived from model output if coupled with assortment model
2.1 Deposition of air pollutants	Carbon dioxide	Not considered	Not considered	Input	Input	Input
	Nitrogen deposition	Not considered	Not considered	Input	Input	Input
	Sulphur deposition	Not considered	Not considered	Not considered	Not considered	Not considered
	Other (CO, O ₃ , ...)	Not considered	Not considered	Not considered	Not considered	Not considered

(continued)

Annex 7.1 (continued)

Indicator	Specific indicator	Yield tables	PROGNAUS	SIBYLA	Biome-BGC	iLand
2.2 Soil condition	pH	Not considered	Not considered	Not considered	Not considered	Not considered
	CEC = cation exchange capacity	Not considered	Not considered	Not considered	Not considered	Not considered
	C/N	Not considered	Not considered	Not considered	Can be derived from model output	Input
	Organic C	Not considered	Not considered	Not considered	Output	Output
	Base saturation (percentage of CEC occupied by bases (Ca ²⁺ , Mg ²⁺ , K ⁺ and Na ⁺))	Not considered	Not considered	Not considered	Not considered	Not considered
	Soil type	Not considered	Input	Not considered	Not considered	Not considered
	Soil fertility	Not considered	Not considered	Input	Not considered	Not considered
	Soil moisture	Not considered	Input	Input	Output	Output
	Site index	Input	Not considered	Input	Not considered	Not considered
	Growth region	Input	Input	Input	Not applied	Not applied
2.3 Defoliation		Not considered	Not considered	Not considered	Not considered	Not considered

2.4 Forest damage	Wind	Not considered	Not considered	Output	Not internally considered, can be approximated by modifying mortality rate	Input of windstorm characteristics (length, severity) and output/simulated spatially and explicitly at landscape scale
	Fire	Not considered	Not considered	Output	Input (annual fire mortality rate) and output	Input and output
	Bark beetle	Not considered	Not considered	Output	Not internally considered, can be approximated by modifying mortality rate	Output
	Defoliators	Not considered	Not considered	Output	Not considered	Not considered
3.1 Increment and fellings	Annual increment in volume, biomass or carbon stock	Output	Output	Output	Output	Can be derived from model output
	Annual felling of wood volume, biomass or carbon stock	Output	Output	Output	Output	Output
3.2 Roundwood	Quantity of roundwood	Output from assortment yield tables	Output	Output	Not considered, may be derived from model output if coupled with assortment tables	Can be derived from model output
	Market value of roundwood	Not considered, may be derived from assortment yield tables	Can be derived from model output	Output	Not considered	Can be derived from model output

(continued)

Annex 7.1 (continued)

Indicator	Specific indicator	Yield tables	PROGNAUS	SIBYLA	Biome-BGC	iLand
3.5 Forests under management plans	Forests under FMP	Not considered	Input and output if provided by a user	Not considered	Not considered	Input
4.1 Tree species composition	Number of tree species	Not considered by individual models	Input and output	Input and output	Not internally considered	Input and output
4.2 Regeneration		Not considered	Output	Input and output	Not considered	Input and output
4.3 Naturalness		Not considered	Can be derived from model output	Not considered but can be derived from model output	Not internally considered, but the degree of naturalness (not area) can be considered as input information affecting simulation set-up (past management specification)	Not considered but can be derived from model output
4.4 Introduced tree species		Not considered	Not considered	Not considered	Not considered	Input (seeds or planting) and output
4.5 Deadwood	Volume of deadwood	Not considered	Output	Output	Can be derived from model output	Output
	Carbon stock in deadwood	Not considered	Can be derived from model output	Can be derived from model output	Output	Output
4.6 Genetic resources		Not considered	Not considered	Not considered	Not considered	Not considered
4.7 Landscape pattern		Not considered	Not considered	Not considered	Not considered	Not considered but can be derived from model output
4.8 Threatened forest species		Not considered	Not considered	Not considered	Not considered	Not considered

4.9 Protected forests	Not considered	Input and output if provided by a user	Not considered	Not considered	Input
5.1 Protective forests – soil and water	Not considered	Input and output if provided by a user	Not considered	Not considered	Not considered
6.7 Wood consumption	Not considered	Not considered	Not considered	Not considered	Not considered
6.8 Trade in wood	Not considered	Not considered	Not considered	Not considered	Not considered
6.9 Energy from wood resources	Not considered	Not considered	Not considered	Not considered	Not considered
6.10 Accessibility for recreation	Not considered	Input and output if provided by a user	Not considered	Not considered	Not considered but can be derived from model output
Management system	Predefined	Input	Input	Input	Input
Slenderness coefficient	Can be derived from mean stand values	Output	Output	Not considered	Input, can be derived from output as well
Vertical distribution of tree crowns	Not considered	Output	Output	Model input – simplified two-layer structure	Included in model simulations but without any output information
Horizontal distribution of tree crowns	Output	Output	Output	Not considered	Input and output
	Not provided	Output	Output	Not considered	Included in model simulations but without any output information

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