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Review

Forest Dynamics Models for Conservation, Restoration, and Management of Small Forests

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Abstract: Globally, there are myriad situations in which people aim to conserve, restore, or manage forest ecosystems at small spatial scales of 50 ha or less. To inform management, forest dynamics models provide an increasingly diverse and valuable portfolio of tools for projecting forest change under different management and environmental conditions. Yet, many models may not be appropriate or feasible to use in small forest management because of their design for larger-scale applications, the information needed to initialize models, or discrepancies between model outputs and information relevant for small forest management objectives. This review explores the suitability of 54 existing forest dynamics models to inform the management of small forests. We evaluated the characteristics of each model using five criteria with implications for small forest management: spatial resolution, number of species the model can simulate, inclusion of spatial structure, modeling approach, and mechanistic detail. While numerous models can be suitable under certain conditions, the review criteria led us to conclude that two models offered the broadest versatility and usability for small forest contexts, SORTIE and FORMIND. This review can help orient and guide small forest managers who wish to add modeling to their forest management efforts.

Keywords: simulation models; mixed-species models; spatially explicit models; empirical models; process-based models; mechanistic models

Citation: Benson, D.L.; King, E.G.; O'Brien, J.J. Forest Dynamics Models for Conservation, Restoration, and Management of Small Forests. *Forests* **2022**, *13*, 515. https://doi.org/10.3390/f13040515

Academic Editors: Guy R. LaRocque, Weifeng Wang, Herman H. Shugart and Vladimir Shanin

Received: 15 February 2022
Accepted: 23 March 2022
Published: 26 March 2022

1. Introduction

Trends of increasing forest fragmentation [1,2], parcellation [3], devolution of forest stewardship [4], and forest cover gains in fragmented landscapes [5] are seen around the world—all of which can result in more forest fragments and parcels being managed at smaller scales [6]. In the United States, for instance, forest land area has remained relatively stable for several decades [7–9], but the mean size of individual forest parcels has steadily decreased due to continued parcellation, land conversion, and fragmentation [10]. Forests that exist or are managed as parcels less than 50 ha in size have thus increased in number [11,12] and make up about 95% of the nation's privately owned forests [13]. In addition to private properties, small forests are also found as green spaces in urban and residential areas, in nature reserves and state parks, and as woodlands or woodlots in other fragmented landscapes.

While fragmentation and parcellation are significant threats to the ecological integrity of forested landscapes [2], people are increasingly recognizing the value of small forests for the host of ecosystem services and benefits they offer [14–19]. In both urban and agricultural landscapes, small forests provide ecosystem functions including nutrient cycling, soil stabilization, water purification, flood control, and carbon sequestration. Small forests can also offer an array of recreational or economic opportunities including walking trails and timber production. Some contain rare species, communities, and ecosystems or are prized for the biological or cultural heritage they represent. Many small, forested lands are

managed to preserve historical landmarks and educate its visitors. In urban areas, forested greenspaces can significantly improve individual and community well-being and public health by providing desired aesthetics, reducing noise and heat, improving air quality, or offsetting carbon dioxide emissions [17,18]. Furthermore, while fragmentation is generally detrimental to service provision, the persistence of small forests within a fragmented landscape can still promote landscape biodiversity by providing habitat connectivity for pollinators, birds, and other wildlife [20].

In addition to the aims of maintaining or enhancing these benefits, many small forest managers must also face concerns about the future of the small areas they manage. Environmental changes and anthropogenic stressors such as climate change, altered land use, pests and invasive species, and limiting resources can directly alter forest tree density, composition, and structure [15,16,21]. Natural disturbances (or lack thereof) including storms, drought, and fire can result in undesired effects on forest health and function [18,21,22]. In addition, managing forest composition or structure for multiple uses often requires complex coordination with governmental agencies, forest users, and other stakeholders to meet management objectives and optimize benefits. This is especially evident in urban greenspaces and parks as forest managers balance recreational use and aesthetic value with forest ecological integrity and habitat quality [17,18,23]. As one forest parcel can influence the potential of another, coordination with managers and stakeholders of adjacent lands may also be necessary [14,18,19,23].

The types and extent of benefits that small forests provide depend on the attributes of the structure and composition, ecosystem functioning, and landscape-level context of forest parcels [16]. Understanding how these attributes of forests will change through time as a result of internal community dynamics, succession, feedbacks with ecological processes, management interventions, disturbance, and other environmental factors, is vital for restoring, sustaining, and enhancing desired ecological services and benefits [21,24,25]. For instance, altered surface hydrology and invasive plants can result in population declines of valued tree or plant species, or reduced resilience to natural disturbances [21]. As a consequence, the management concerns of small forest stewards tend to focus on how forest structure/composition, ecosystem function, and landscape-scale attributes will change under the influence of different drivers, and how different management alternatives can direct that change [26,27]. Forest dynamics models have become increasingly valuable tools for simulating and projecting change in forest attributes through time based on current conditions or knowledge about forest structure and behavior [25,27]. There are many forest dynamics models available, each developed to predict certain forest attributes at a specified spatial resolution. Among them, models with outputs relating to forest composition and structure, ecosystem functions, and landscape-level changes can potentially inform many common small forest management concerns (Figure 1). Yet, some small forest management concerns, such as faunal diversity, visitor accessibility, or stream health, may not be directly informed from using forest dynamics models, unless coupled with additional ecological knowledge to predict these conditions from modeled forest attributes [28].

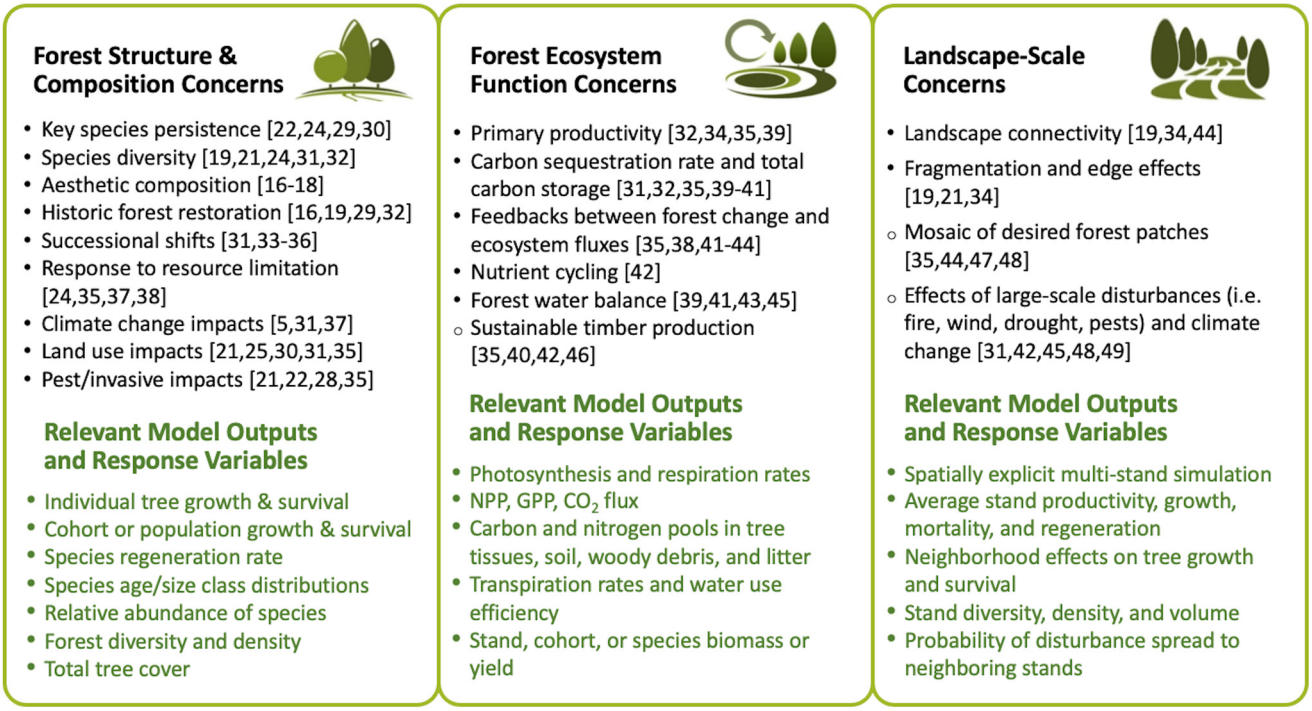

Figure 1. Small forest management concerns that can be informed by forest dynamics models, and the types of forest dynamics model outputs and response variables that can help address them. They are grouped in columns as issues related to forest structure and composition, ecosystem function, and landscape-scale patterns and processes. Management concerns with closed bullets may be relevant for many types of small forests, including urban forests, parks, isolated forest fragments, and small parcels within contiguous forested landscapes. Open bullets, which relate to timber production and larger forested matrices, are generally not relevant for urban forests. Superscripted citations provide examples from the literature [5,16–19,21,22,24,25,28–49].

Despite the broad utility of forest dynamics models, some may not be appropriate for small forests or the particular forest attributes of interest in a given management context. Each model entails assumptions and simplifications. The model's representation of ecological dynamics and outputs must align with the complexity and level of detail required to inform specific management concerns, in a number of important ways [24,31,50,51]. First, models that simulate dynamics at large spatial scales may not help address particular small forest management concerns such as local species turnover during succession or regeneration and competition in single treefall gaps [25,28,52]. Second, models developed for single tree species or specific forest types may not be informative for managers of multi-use, mixed small forests, who are often concerned with multi-species community structure and dynamics that contribute to the forest's desired ecosystem services [26,27]. Third, because of the smaller spatial scale, it is more critical to understand localized ecological interactions that depend on the explicit spatial relations among trees, often at the level of individual trees [53]. Fourth, managers are often striving to anticipate the consequences of environmental change or novel ecological conditions; models that simulate forest change based on underlying processes rather than past empirical observations will be better able to predict novel dynamics and outcomes [28,54]. Lastly, however, models that simulate underlying processes may require detailed physiological data to parameterize, which are rarely available for non-commercial tree species and may be technically difficult or impossible for small forest managers to obtain themselves [28]. Managers or model users may opt to use simpler models to avoid the extensive input information or complex calculations [24,27,55]. Choosing a model is therefore dependent on aligning the specific information needs for a given small forest management context with the data requirements and relevance of model outputs.

Based on the reasoning above, these five issues of alignment between model characteristics and the particular concerns of small forest managers can serve as a useful set of criteria for evaluating the suitability of forest dynamics models to inform small forest management. The purpose of this review is to evaluate different existing forest dynamics models—including models of individual tree species, communities, succession, and ecosystem processes—to assess their applicability to address common small forest management concerns. To do so, we arranged the five identified issues—(1) spatial resolution, (2) species the model can simulate, (3) spatial structure, (4) approach for modeling ecological processes, and (5) mechanistic detail—as a tiered hierarchy of criteria that can be queried based on model characteristics (Figure 2). The following section provides a detailed explanation of each criterion, describing the different model characteristics affecting their suitability for modeling small forests. We then applied the tiered criteria to evaluate 54 existing forest dynamics models to address the central question of which available models are the most suitable for addressing the concerns of small forest managers. The Results section describes how the evaluation narrowed the pool of suitable models at each step. Ultimately, two models, SORTIE and FORMIND, were found to have the strongest and broadest suitability characteristics.

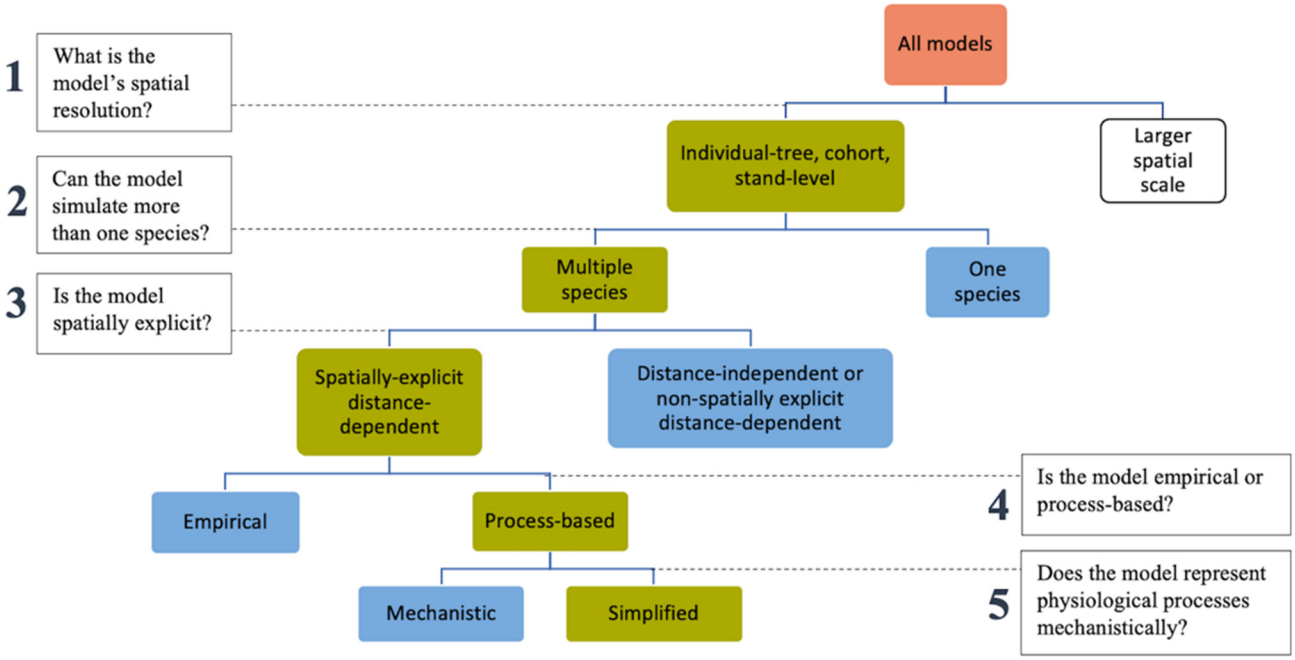

Figure 2. Tiered series of evaluation criteria used to assess the suitability of 54 forest dynamics models for informing small forest management concerns. Characteristics that are more relevant and appropriate for small forests are in green. Characteristics with weaker relevance, or narrow applicability to specific management concerns, are in blue. Characteristics that will not help inform small forest management are in white.

This review aims to provide small forest managers with a convenient guide to facilitate the selection and adoption of appropriate models to inform their management efforts. To that end, the Discussion section has three subsections. The first distills the key findings of the model suitability evaluation for small forests, and why SORTIE and FORMIND were most favorable, given the criteria, constraints, and tradeoffs. The second subsection discusses additional considerations that managers and modelers may face when applying a model specifically in a new context—including technical feasibility aspects, software accessibility, and the reliability and usefulness of outputs—and how those issues can be navigated when using SORTIE and FORMIND in particular. The discussion concludes with some practical recommendations for getting a new modeling endeavor successfully underway.

2. Five Criteria for Assessing Model Suitability for Small Forests

The suitability criteria focus on attributes of models that have been previously used to classify forest dynamics models. We adopted and modified a common typology following [24,27,38] and other published works [33,34,47,54,56] to define differences among model attributes that are specifically relevant for small forests. Similar to other existing typologies, we organized the suitability factors hierarchically, allowing us to conduct our subsequent evaluation of models by applying the tiered set of five criteria for small forest suitability, illustrated in Figure 2: (1) What is the model's spatial resolution, (2) how many species can the model simulate, (3) is the model spatially explicit, (4) is the model's approach empirical or process based, and (5) does the model represent physiological processes mechanistically?

2.1. What Is the Model's Spatial Resolution?

Forest dynamics models can be classified by their spatial resolution, defined as the smallest spatial unit at which the model evaluates forest dynamics or reports outcomes. Spatial resolution determines the types of forest attributes the model can simulate or project, and thus the types of management issues the model can inform [24,36]. Forest dynamics models are broadly categorized into four spatial resolutions: individual-tree, cohort or size-class, stand, and landscape [27,38]. Individual-tree models consider each tree as a unit, and they help explore how individual trees compete with one another for sunlight, nutrients, and other resources. Cohort models simulate aggregates of trees as separate groups, which can be defined by species, functional types, diameter or height size classes, or ecological layers [38]. Typically, cohort models apply one representative set of characteristics to all trees within a group [53,57]. Separating groups by specific characteristics can help study the variation and relative performance between species, cohorts of the same species, and other size classes [58].

Most stand and landscape models, on the other hand, have less resolution and treat large forest patches as a single unit, within which species age and composition are assumed to be uniform [36]. Stand models represent one or more forest patches that typically correspond to management units [36] and can be applied to study mosaics of forest patches with different compositions. When stand models represent the interactions of a stand and neighboring patches, they can help understand how litter decomposition, water cycling, and other environmental processes in one patch can influence an adjacent patch [24]. Stand models can therefore provide useful outputs for issues relating to ecosystem function as well as landscape-level management issues (Figure 1). Landscape-scale models, also called forest landscape simulation models (FLSMs), can simulate similar processes that drive change but at a much larger spatial resolution [44]. Landscape models tend to focus on carbon and water balance over large, homogeneously represented areas, and thus better address broader-scale management concerns such as regional or global effects of climate change [25,44]. Forest landscape models such as LANDIS PRO and LANDCLIM typically lack species differentiation or size differentiation that finer-resolution models have [49,59]. Although some forest landscape models may simulate succession at a stand or larger scale, they are unable to simulate interspecific competition or heterogeneity in tree growth and survival at an individual or plot level [59].

Individual-tree, cohort, and stand models are likely to be more useful when simulating small forest dynamics [36] compared to landscape models because their smaller scale resolution can inform many common issues concerning forest structure and composition, including the persistence of specific tree species, rates and trajectories of succession, and fine-scale responses to environmental change (Figure 1). When choosing a suitable spatial scale for a model, managers should consider whether the required parameterizing data are available or feasible to obtain, and also whether the resolution of outputs will provide enough detail to answer management questions [36]. The subsequent evaluation criteria consider these decision points further.

2.2. Can the Model Simulate More than One Species?

This tier distinguishes forest dynamics models by how many species and what types of species they can simulate. Single-species models treat the entire forest as one species, using a single set of species-specific parameters, such as average growth rate or adult height, to simulate forest dynamics [27,53]. Most single-species models were developed to estimate timber production in monoculture forestry of commercially important native or exotic tree species, so their outputs are typically yield estimates such as total biomass or productivity [25,27]. Other single-species models were designed for natural forests that contain only one species or one dominant species [60]. Single-species models have been applied to multi-species forests by simulating each species' dynamics separately as a monoculture without considering tree–tree interactions and combining these simulation outputs proportionally to species abundance in the forest [25,27]. On the other hand, there are a growing number of multi-species models with species-mixing capabilities, which use different sets of growth, mortality, and resource allocation parameters for more than one tree species. Multi-species models may also account for interspecific interactions, either abstractly using competition indices or more explicitly by modeling the processes or mechanisms through which trees interact [27].

Choosing between single- or multi-species models depends on management needs and the forest under observation. Single-species models can be more beneficial when managing total tree cover for timber production, carbon storage, or aesthetic value (Figure 1) [42,61,62]. When addressing these concerns, treating a multi-species forest as a monoculture may not necessarily compromise the usefulness of model outputs if managers are seeking aggregate stand-level predictions [42]. However, increased interest in the dynamics of mixed-species, multi-use forests has made multi-species models a vital tool for forest management. Most tree species differ in how they photosynthesize, grow, and allocate resources [27], which will influence the relative abundances of individual trees, species, and cohorts over time [24]. Thus, multi-species models can better inform many small forest management concerns because they can simulate changes in forest composition and structure, patch and landscape heterogeneity, and species-specific environmental responses (Figure 1).

Some single-species and multi-species models were primarily developed for a particular species, site, or region to serve specific needs [25,27,60], and modifying them to apply to other species and regions may be difficult or impossible for small forest managers in different contexts. For example, the individual-tree, single-species model FOREGEM uses a set of allometric rules or equations derived from species- and site-specific parameters to simulate the forest response to environmental change [62]. To parameterize the model for a different species or site, the model user must have knowledge of physiological parameters and phenotypically plastic traits, including the timing of bud burst, pollen dispersal distance, or relation between stomatal conductance and water stress, which may not be known for non-commercial tree species [27,53,62,63]. On the other hand, the individual-tree, multi-species model FORMIND can be more readily adapted to different contexts because it classifies species into functional groups and then uses physiological parameters and allometric equations that generally represent each functional group [31]. When choosing between single- and multi-species models, small forest managers should consider not only the specific management concerns, but also the inputs necessary to run the model and the type of trees it was designed to simulate in order to select the simplest model that can generate relevant outputs. Multi-species models are likely to satisfy these considerations for a broader range of small forest management concerns.

2.3. Is the Model Spatially Explicit?

Individual-tree, cohort, and stand models differ in terms of whether and how they represent the spatial location or distribution of trees. Most distance-independent models are stand models that do not specify the locations of individual trees, cohorts, or species. Instead, they often treat the entire stand as one unit, implicitly assuming that all individual trees within the stand have the same growing space (Figure 3A). These models abstractly

infer intra- and interspecific competition using stand-level variables of density or basal area [64,65].

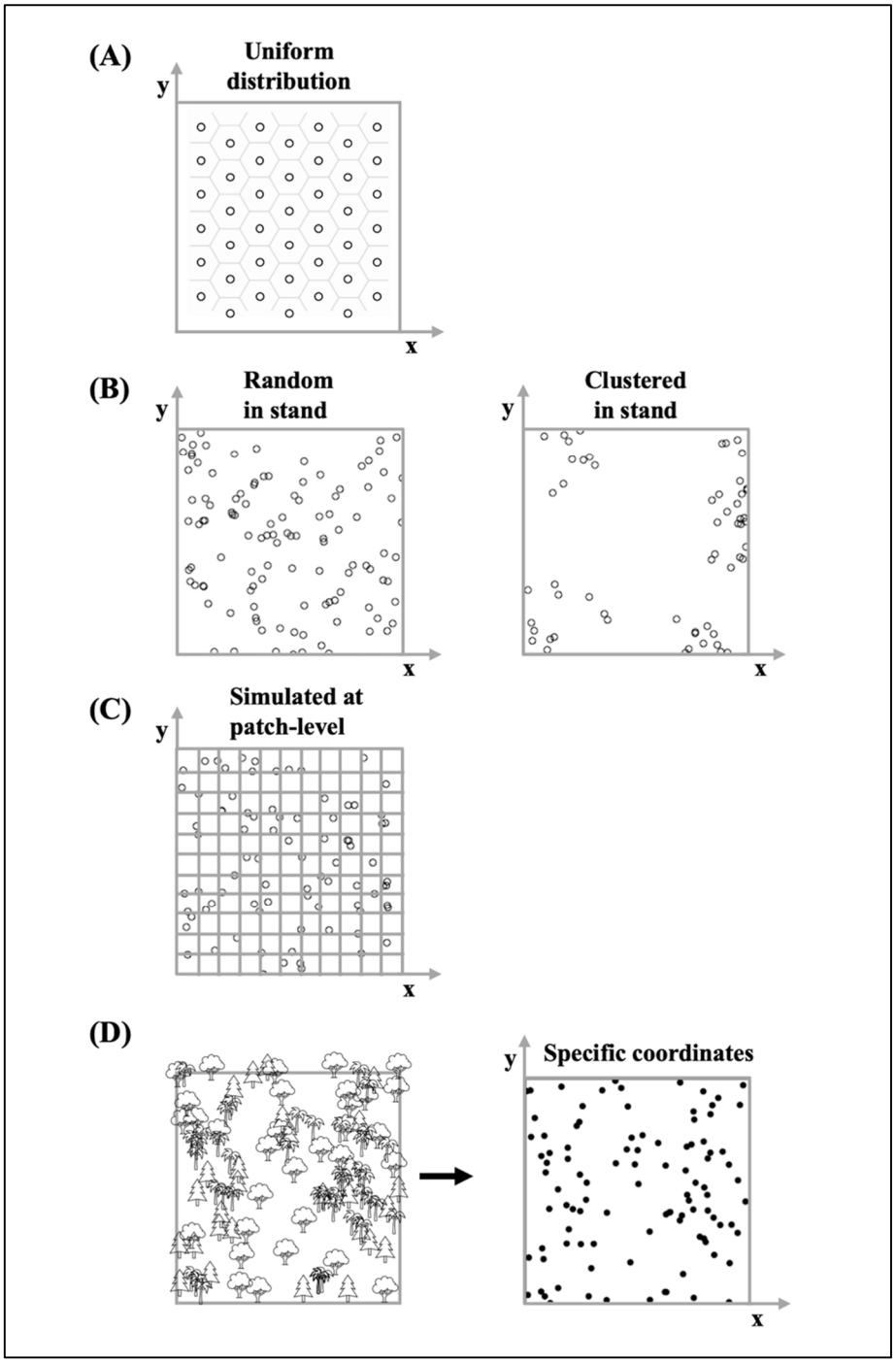

Figure 3. Representation, or implied representation, of tree distributions in different model types. Distance-independent models do not specify locations in space; they implicitly assume all trees have equal space, which would imply an equidistant lattice if represented spatially (**A**). Distance-dependent, non-spatially explicit models assume different statistical distributions of distances between individual trees across a stand. Examples of distributions, realized spatially for illustrative purposes, include random and clustered (**B**). In distance-dependent spatially explicit models, the locations of individual trees are typically simulated within a forest gap (represented by grid cells) (**C**) or are mapped as (x, y) coordinates within a stand (**D**) [64].

Distance-dependent models do not assume all trees within a stand have the same growing space. Instead, they implicitly or explicitly describe tree–tree competition by incorporating intra- and interspecific interactions into model functions [27]. Distance-dependent models can be further classified as either spatially explicit or non-spatially explicit, with the classification depending on the spatial resolution of model inputs and outputs. Most non-spatially explicit models are stand or cohort models that use a statistical approach when representing spatial distributions by assuming a random or clustered distribution of individual trees or species within a stand or grid cell [24,64,66] (Figure 3B). They use competition indices or multipliers within the model's algorithms to estimate individual-tree, species-specific, or stand growth and mortality at the stand level as a function of assumed distance to neighbors. Stand structure is therefore a feedback loop between species-specific competition indices and multipliers, tree growth and mortality, and stand growth [27], and outputs mostly represent stand-level attributes. Spatially explicit models, on the other hand, are often individual based. They can generate tree locations either by simulating them within a forest patch or plot based on distance or distribution statistics (Figure 3C), or they can use full stem maps of (x, y) coordinates to recreate an observed distribution of individual trees across a stand (Figure 3D) [66]. In gap models, forest patches spatially represent the influence zone of a large, mature tree, and tree species and size classes compete for resources within that patch. Spatially explicit models describe horizontal spatial structure at a higher resolution and provide individual-tree or cohort and size class information as model outputs, whereas non-spatially explicit model outputs provide stand-level attributes [53,64,66,67].

Both distance-independent and -dependent models can help guide small forest management planning. Most distance-independent models and non-spatially explicit, distance-dependent models provide stand outputs such as total stand growth, biomass yield, and density [43,68,69], which can prove useful when managing timber production or estimating carbon and nutrient pools and fluxes (Figure 1). However, many small forest management concerns require acknowledgement of within-stand spatial heterogeneity to predict the relevant attributes of future forest composition and structure [24,64]. Although distance-dependent models typically have higher data input requirements to represent variable tree spacings, they can better predict how individual trees' interactions with one another can influence forest change and are thus more broadly useful for informing small forest management concerns [27,40]. For example, the initial design of the stand-level, distance-independent model FOREST-DNDC requires biomass per unit area but no spatial information inputs, and assumes monospecific characteristics at the grid level, including survival rate and mean tree height [40]. In contrast, the distance-dependent cohort model CABALA can incorporate the effects of within-stand tree spatial distributions in biophysical processes and outcomes of management actions because it requires tree spacing information within and between grid cells [42]. In a study comparing *Eucalyptus* forest growth estimates from different models, FOREST-DNDC overestimated forest growth because of its spatial simplification of competition and growth processes while CABALA provided the most accurate predictions [40]. Thus, FOREST-DNDC is often used to simulate stand-level information such as photosynthesis, respiration, and carbon and nitrogen pools and fluxes when there is little concern about local tree competition and resources to parameterize and calibrate are limited.

Distance-dependent models can be useful when studying smaller, mixed-species forests because they contain the spatial relationships required to simulate how trees of different species interact with one another and the local environment [37], which is especially beneficial to small forest managers concerned with species assembly, succession, invasion, or responses to limiting resources (Figure 1). Simulating a mixed-species forest without considering more specific tree, species, or cohort distributions can lead to unrealistic predictions about small forest dynamics, such as how light competition influences the age structure and species composition of a forest [27,64]. The CABALA example demonstrates how accounting for spatial distribution of individual trees or species can result in more

reliable model projections in a single-species forest. For multi-species forests, incorporating distance dependence becomes even more valuable to account for the effects of spatial pattern on both intra- and interspecific interactions. Spatially explicit models are particularly well suited for simulating the localized effects of intra- and interspecific interactions.

2.4. Is the Modeling Approach Empirical or Process Based?

Two modeling approaches, empirical and process based, differ in the way that biological processes or physical mechanisms are incorporated into the model and how they influence tree growth [27,28,34]. Empirical models typically use correlations between repeated measurements of tree species, age, diameter, and height and observed environmental parameters from forest inventories to derive allometric equations and growth functions [25]. The models then simulate forest dynamics by applying those relationships deterministically or probabilistically [36,52]. Process-based models, on the other hand, simulate forest dynamics via the biological and physical principles and processes and that govern tree growth and forest development, with varying degrees of mechanistic detail (discussed in Tier 5) [54,66,70]. Both modeling approaches have their advantages and disadvantages for addressing different management concerns related to small forest growth, succession, and responses to environmental change. Each approach is also constrained by data availability—empirical models by the availability of inventory data relevant to the species and conditions to be modeled, and process-based models by the detailed environmental and physiological data needed to parameterize them.

Projecting tree and forest growth may be valuable to small forest managers concerned with timber production, carbon sequestration, or rates of recovery from disturbance. Empirical models can provide simple and accurate projections of forest growth, but only if the species and conditions used to derive allometric relationships are well matched to the scenario being modeled [36,71]. However, data needed to describe allometric growth relationships for non-commercial, multi-species forests are generally rare and highly site specific. In contrast, process-based models predict tree growth by simulating the underlying physiological processes, which allows these models to predict forest growth under a range of conditions for which there may be no empirical growth data. This advantage comes at a cost in terms of model complexity and data needs, however. For instance, in order to project change in tree biomass, many models simulate the process of photosynthesis mechanistically, which requires the accurate parameterization of several physical variables such as radiation, rainfall, vapor pressure deficit, and soil type, as well as species-specific physiological traits [28].

Empirical and process-based models have the potential to inform small forest managers' concerns regarding compositional change over time, such as the persistence of certain tree species, shifts toward or away from desired forest composition, or the restoration of historic forest communities. Historically, empirical models were developed primarily to project single-species timber production after harvest, but their outputs and more recent multi-species variants can also inform site-specific questions about the succession and trajectories of forest composition change [25]. To achieve this, empirical models often predict stand-level community change by linking successional stages through probabilistic or deterministic state-and-transition pathways. However, establishing the patterns and rates of shifts in species composition requires extensive prior observational data of stand-level changes in relative species abundance over time or tree-level transition probabilities [36]. Competition for light is a dominant driver of forest composition change. Empirical models represent this process phenomenologically, usually through gross correlations between neighborhood or stand density and species-specific growth [36], which limits realism and resolution. Process-based models offer advantages for modeling community change, especially for representing light availability as a driver, because growth is modeled via the process of photosynthesis, which is driven by light availability [24]. Process-based models at gap and individual tree levels calculate light availability as a dynamic function of the surrounding tree canopy structure when simulating tree growth, mortality, and recruitment

to project forest compositional change [66]. To achieve this, however, these models introduce additional complexities and data requirements [28,52] regarding canopy structure and light attenuation, species-specific photosynthesis–light response curves, and additional physiological parameters in more mechanistic models.

For many small forest management concerns, incorporating responses to environmental change is vital because many small forests experience continuous change due to their size and proximity to humans, and novel suites of environmental factors will create different future states of a forest [34]. Empirical models are generally limited in their ability to simulate responses to a changing environment. Because empirical models use fixed relationships fitted to direct forest observations, they are often referred to as "static" [25,36,38]. Accurate projections are limited to the suite and range of environmental conditions that were measured during inventories used to build the model [27,71], and these models often offer no reliable way to account for disturbances or the effects of climate change [28,36,70], which are common small forest management concerns (Figure 1).

Most process-based models can account for responses to environmental change dynamically because they contain one or more sub-models or behaviors that interact with one another to simulate the effects of environmental conditions on photosynthesis and thus tree growth from basic physical and physiological principles [27,33]. The most commonly modeled environmental processes that influence photosynthesis are climate, soil and site conditions, including soil texture and nitrogen content, and water balance [27,28]. However, including these additional processes greatly increases computational complexity and demand for accurate atmospheric, soil, and hydrological parameter values. Because inaccurate parameter estimates can be compounded when coupling processes and scaling up, these models are more often used to study underlying processes in research, rather than to make reliable projections for informing management [36]. Process-based models are better suited for understanding forest ecosystems and simulating different management or climate scenarios than providing absolute predictions of future forest composition and structure [35,54,72]. Other seasonal or episodic changes of relevance to small forest managers, such as altered storm, fire, and pest disturbance regimes, are not as easily represented or parameterized in model structures [27,28].

Empirical and process-based models represent two ends of a modeling approach spectrum [72]. So-called hybrid models couple together various components of empirical and process-based approaches to take advantage of both physiological and empirical data to span scales from leaf-level metabolism to forest-level change [34,36]. In practice, most individual-tree and gap process-based models must rely on at least some empirical tree-level data in order to scale up physiological processes, even if not fully coupled to an empirical model [70]. In choosing a modeling approach, small forest managers should ask what input and output details are necessary to answer their management question or concern. If a manager has sufficient inventory data that span the environmental conditions of interest, an empirical model may sufficiently and accurately provide the desired projections of forest change [36]. Otherwise, process-based models can simulate many relevant dynamics, including projections that account for environmental change and light competition, but they require at least some physiological information for the species to be modeled. If a forest manager wishes to pursue forest dynamics modeling but lacks both appropriate empirical allometric data and physiological parameters, the latter can usually be obtained or estimated from existing forests, whereas allometric relationships require time-series inventory data collected over many years. Thus, from a pragmatic stance, the data limitations of process-based models may be more easily overcome than limitations for empirical models.

2.5. Does the Model Represent Physiological Processes Mechanistically?

Although all process-based models simulate forest dynamics via the underlying biological and physical processes that govern tree growth and forest development, some employ more mechanistic representations of these processes than others. As models vary in their

degrees of mechanism and abstraction, so do different scholars' terminologies and criteria for categories [27,28,58,66]. Herein, we distinguish between mechanistic and simplified process-based models, as this has relevant implications regarding model complexity and usability for small forest managers. So-called mechanistic process-based models explicitly simulate tree growth as a function of species-specific physiology, morphology, and/or architecture using established equations [60,73]. These physiological equations, with those for photosynthesis and respiration being the most common [54,66], entail numerous input parameters at the tree organ or (sub-)cellular level such as stomatal density, photosynthetic photon flux density on a leaf, and potential electron transport rate [24,54,60,73].

Process-based models that require less mechanistic information and feature simpler parameterization protocols are often called simplified process-based models because they use simpler metabolic relationships to represent more detailed biochemical and biophysical mechanisms [53,66]. These models still simulate the processes that are the underlying causes of tree growth, competition, and mortality, but do so via coarser relationships between tree or species allometry and organ-specific photosynthesis and respiration rates [66]. For instance, the cohort-model FORMIX simulates tree growth using a carbon balance approach that calculates carbon assimilation from photosynthesis–light response curves and canopy allometric relationships. This is an example of a simplified process-based models because it incorporates the underlying causes of tree growth but does not calculate photosynthesis and respiration at a mechanistic level. In addition to the core behaviors of growth and mortality as simplified functions of light availability and photosynthesis, some simplified process-based models allow model users to include additional degrees of mechanistic and environmental detail. For example, the individual-tree models SORTIE and FORMIND provide optional sub-models to simulate processes that directly affect growth dynamics, including precipitation, harvest and disturbance, and dispersal functions [74].

In principle, both physiological and simplified process-based models can help address small forest management questions regarding changes in forest structure and composition through time. Their outputs can project the age or size class distributions of individual species and relative abundances of different species or functional groups (Figure 1). Because mechanistic process-based models often include more physiological, phenotypical, and genetic information as inputs and model parameters [28,75] and describe eco-physiological feedbacks at a (sub-) cellular level, they can increase our understanding of forest and tree function [73,75]. However, generally speaking, as a model's mechanistic detail increases, so does the difficulty of measuring, estimating, and validating the detailed, species- and size-class-specific biophysical parameters and abstract coefficients their equations require [33]. This can render them nearly impossible to use for small forest managers studying non-commercial trees for which these parameters are unknown. In addition, few attempts have been made to create or calibrate physiological process-based models beyond the study systems for which they were developed, so the pool of models that can be feasibly adopted to project forest structure and composition in a new context is limited [28].

Simplified process-based models have much greater potential feasibility for small forests. Their simplified representation carbon assimilation and allocation still simulate forest growth processes dynamically, yet they require more easily obtainable data and are computationally less complex [54,66,76]. Simplified process-based models provide information to help small forest managers answer questions about individual tree growth, forest structure, and species composition at appropriately local scales (Figure 1), while decreasing uncertainty in model parameters relative to mechanistic models.

3. Methods

To compile a set of models to evaluate, we first used Google Scholar and Web of Science to gather publications that developed or used forest dynamics models. We used search terms "forest" and "model" with other terms, including "dynamics", "growth", "allometric", "simulation", "stand", "gap", and "tree". For each publication, we identified the name of the model used, its general purpose (i.e., modeling timber production, change in

forest composition, etc.), and the specific management question asked. The search identified several review papers, from which we tabulated the set of models covered in the review. Among the publications we gathered, one review by Pretzsch and others [27] covered a sufficiently complete, representational, and recent set of 54 foundational models, which were compiled from other literature searches and reviews [27,28,77]. This set included a wide range of models that varied in how they represent forest function, structure, and environmental processes. Furthermore, Pretzsch and others [27] summarized several common model attributes that were relevant to our criteria of applicability to small forests, including spatial resolution, species-mixing potential, spatial structure, modeling approach, and mechanistic complexity. In this study, we re-assessed the 54 models reviewed in Pretzsch et al. [27] specifically to evaluate their suitability for small forests according to our tiered series of evaluation criteria. At each tier, we evaluated whether each model had characteristics that are suitable for small forests, as described in Section 2. Those models that were deemed most likely to be useful for informing small forest management were forwarded for evaluation at the subsequent tier level.

4. Results

The tiered small forest evaluation criteria (Figure 2) consider five model characteristics: (1) spatial resolution, (2) number of species the model can simulate, (3) whether spatial structure is incorporated, (4) modeling approach used, and (5) mechanistic detail. At each tier, we considered each of the 54 reviewed model's attributes in light of their suitability to address the potential management concerns that small forest managers may have. Below we describe the outcomes of the model attributes evaluations.

4.1. Tier 1: What Is the Model's Spatial Resolution?

All 54 models that we evaluated simulate forest dynamics at an individual, cohort, or stand level. In effect, this first tier suitability criterion was applied in our initial selection of models to review. Small forest managers do frequently have landscape-scale concerns, such as habitat connectivity and the broader-scale spread of invasive species or pests. However, landscape-scale forest dynamics models on their own may not be the most appropriate tools to evaluate these effects. These concerns would be more readily addressed by incorporating outputs of stand-scale or finer simulations into geospatial analyses of the matrix surrounding the focal small forest [35]. Additionally, forest dynamics models can be coupled with regional hydrological models to capture important feedbacks between forest change and water availability [78], which is another salient concern for many small forest managers.

4.2. Tier 2: Can the Model Simulate for More than One Species?

Of the 54 models evaluated, 38 can simulate more than one species. Some of the multi-species models were developed for specific species. For instance, COMMIX was designed to study two species, *Fagus sylvatica* (European beech) and *Pseudotsuga menziesii* (Douglas fir) [79]. FINNFOR evaluates three different species native to Finland: *Picea abies* (Norway spruce), *Pinus sylvestris* (Scots pine), and *Betula pendula* (Silver birch) [28]. These models would likely require extensive re-parameterization to simulate other tree species. Therefore, small forest managers may find these models less convenient when studying forests that contain species other than those. Other multi-species models, including SORTIE, FORMIND, FORMIX, and 3-PG, are more flexible and can generally be applied to various species and forest types [27,47,53,58].

4.3. Tier 3: Is the Model Spatially Explicit?

For each of the 38 multi-species models identified in Tier 2, we assessed whether they were distance dependent, and if so, whether they were spatially explicit and at what resolution. We found that 10 models can incorporate horizontal spatial structure at an individual-tree or patch level and provide individual-tree, cohort, and size-class information as model

outputs (Table 1). FORMIX is a distance-dependent but non-spatially explicit size-class or cohort model, and the other nine models are spatially explicit individual-tree models.

Table 1. Model characteristics of the 10 reviewed distance-dependent, multi-species models that simulate tree coordinates of more than one tree species at an individual-tree or patch level. Characteristics include spatial resolution, species capacity, (horizontal) spatial explicitness of distance-dependence, modeling approach, and whether the model represents physiological processes mechanistically.

Model Name	Spatial Resolution [27]	Potential # of Species [27]	Spatial Explicitness	Approach (Empirical, Process-Based, or Hybrid) [27]	Use of Physiological Mechanisms to Simulate Processes
BALANCE	Individual	5	Explicit, individual-tree coordinates [28,80]	Process-based	Yes [28,80]
BWIN PRO, TreeGrOSS	Individual	Several	Explicit, individual-tree coordinates [81,82]	Empirical	No [83]
COMMIX	Individual	2	Explicit, individual-tree coordinates [79]	Process-based	Yes [79]
EFIMOD	Individual	3	Explicit, individual-tree coordinates [28,84]	Hybrid	Yes [27,28]
FORMIND	Individual	Several	Explicit, individual-tree coordinates [31,85]	Process based	Not required [85]
FORMIX	Cohort	5 groups	Explicit, statistical distribution at patch or plot level [58,66]	Process based	Not required [28,66]
MAESTRO/MAESPA	Individual	Several	Explicit, individual-tree coordinates [86,87]	Process based	Yes [86,87]
MOSES	Individual	4	Explicit, individual-tree coordinates [30]	Empirical	No [30,88]
SILVA	Individual	5	Explicit, individual-tree coordinates [35,58]	Hybrid	Not required [35]
SORTIE/BC	Individual	Several	Explicit, individual-tree coordinates [66,74]	Process based	Not required [74]

4.4. Tier 4: Is the Modeling Approach Empirical or Process-Based?

We evaluated each of the 10 distance-dependent, spatially explicit models according to their modeling approach (Table 1). Empirical models include BWIN PRO/TreeGroSS and MOSES. Hybrid models EFIMOD and SILVA contain both empirical and process-based components. The remaining six models use a process-based approach. Although empirical models such as BWIN PRO/TreeGroSS and MOSES and the hybrid models with empirical components can accurately predict forest structure and composition, they lack a dynamic approach to account for changing environments. Because models with process-based components vary in their degrees of mechanistic detail, they pose different tradeoffs between biological realism and data requirements. In Tier 5, we explore the implications of these differences for the eight process-based and hybrid models.

4.5. Tier 5: Does the Model Represent Physiological Processes Mechanistically?

The evaluation at Tier 5 identified three simplified process-based models, SORTIE, FORMIX, and FORMIND, and three fully mechanistic process-based models, COMMIX, BALANCE, and MAESTRO/MAESPA. Two hybrid physiological models, EFIMOD and SILVA, statistically simulate tree growth based on empirically fitted physiological parameters for sub-organ- and organ-level mechanisms in the most basic model versions [27]. The Tier 5 attributes of these models, and other model characteristics from previous tiers, are summarized in Table 1. Figure 4 summarizes the tier-by-tier evaluation of all models.

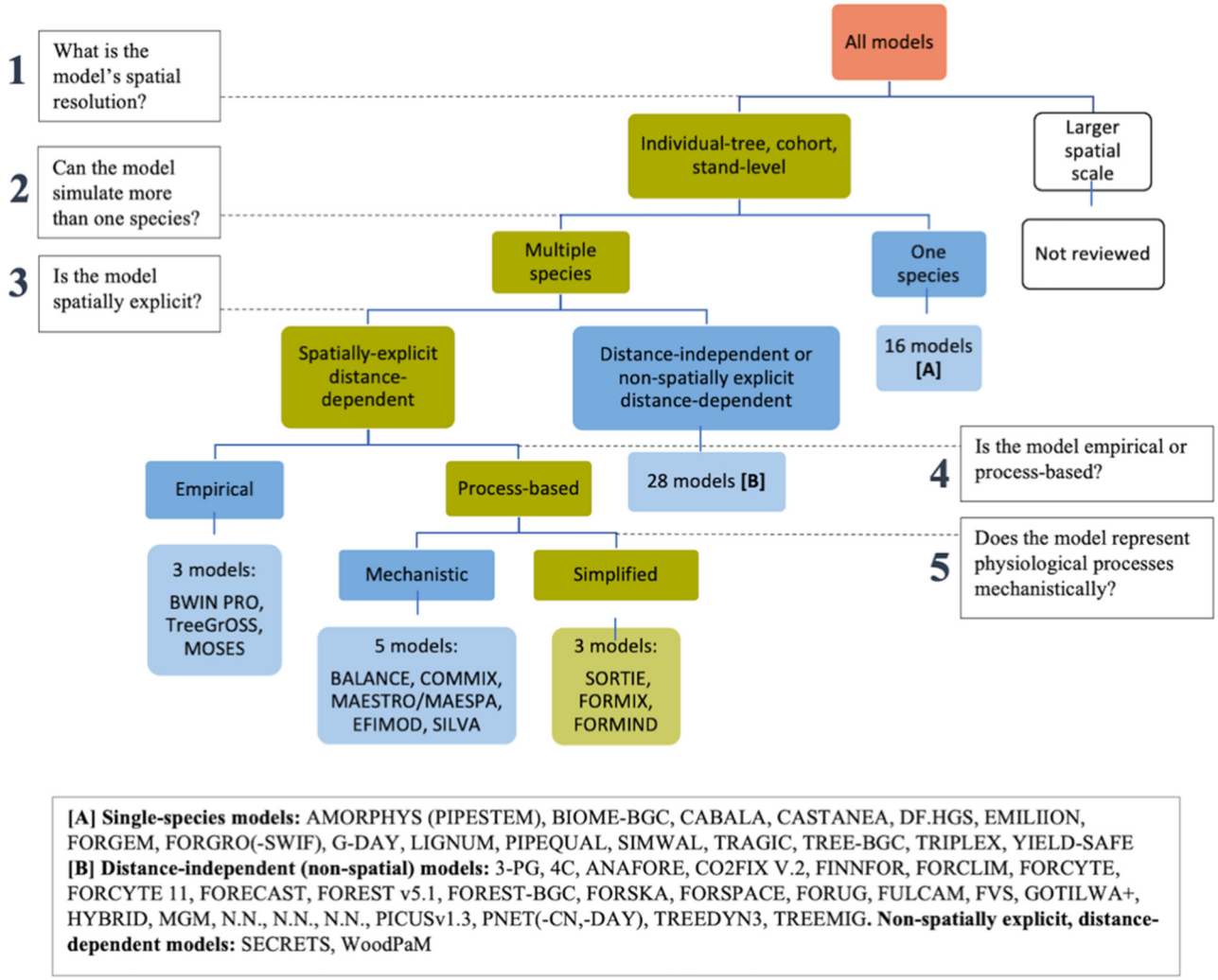

Figure 4. Tiered series of evaluation criteria used to assess the suitability of 54 forest dynamics models for informing small forest management concerns. Characteristics that are more relevant and appropriate for small forests are in green. Characteristics with weaker relevance, or narrow applicability to specific management concerns, are in blue. Characteristics that will not help inform small forest management are in white. Models that best met small forest evaluation criteria include SORTIE, FORMIX, and FORMIND.

As simplified, process-based, multi-species models, SORTIE, FORMIX, and FORMIND have the broadest potential application to small forest management out of the models we evaluated. FORMIND and FORMIX are highly cited models [58,66] and have primarily been used by the research team that developed them to evaluate forest change in species-rich tropical regions [85]. They have similar model structures and algorithms [58]. However, FORMIX is cohort based and not fully spatially explicit at an individual-tree resolution, while FORMIND is an individual-tree, spatially explicit model. The most recent versions of FORMIX (i.e., FORMIX3 and FORMIX3-Q) contain improved equations that more accurately describe tree productivity [58,89–91], but FORMIND has the capacity to address finer-scale interspecific interactions that influence forest structure and composition issues of concern to small forest managers as well as more adaptable equations that have been calibrated for various forest types. Like FORMIND, SORTIE is also an individual-tree, spatially explicit model, and it has evolved (the most recent version being called SORTIE-ND) to become more adaptable across ecosystems and can help inform small forest management for different regions. Because of their spatially explicit simulations and potential portability to other systems, SORTIE and FORMIND are thus deemed the most suitable, flexible, and

potentially applicable models for informing small forest management goals and concerns, particularly in new modeling contexts. In the discussion, we explore additional practical aspects and offer guiding recommendations for new implementations of SORTIE or FORMIND in small forests.

5. Discussion

5.1. Key Findings from the Model Suitability Evaluation

The five-tiered suitability criteria assess different aspects of model scale, structure, and approach, from which we inferred their potential suitability of 54 forest dynamics models for informing several common small forest management issues. Tiers 1 and 3 focus on spatial resolution; we concluded that models that simulate forests at the stand level or finer resolution are most suitable, with spatially explicit models affording more nuanced treatments of environmental effects and interspecific interactions. Tier 2 evaluates model design in terms of number of tree species represented; except in the contexts of small forests dominated by a single well-studied species, models with the capacity to represent multiple species can inform a broader the range of small forest management concerns. Tier 4 examines empirical versus process-based models; we found that both have their own forms of data availability limitations, yet process-based models offer the advantage of simulating dynamic environmental effects and growth dynamics beyond those measured empirically in the past. Lastly, Tier 5 assesses the level of mechanistic detail in process-based models, and we posited that because of the difficulty of parameterizing highly mechanistic models, simplified process-based models are likely to be much more feasible for small forest management applications. Of the three simplified models identified in this final tier, we concluded that SORTIE and FORMIND have advantageous combinations of spatially explicit individual-tree simulations and flexible model designs to address a range of potential processes that influence small forest dynamics (Table 2).

Table 2. Summary of advantageous attributes of SORTIE and FORMIND, in terms of criteria for (**A**) suitability for small forests and for (**B**) application in new contexts.

Suitability Criteria		SORTIE and FORMIND Attributes	Advantages
A. Suitability for small forest management concerns			
1.	Spatial resolution	Individual tree	Aligns with small spatial scale concerns and localized processes
2.	Number of species	Multiple	Broadest applicability across diversity of small forest contexts
3.	Spatial explicitness	Explicit	Captures effects of heterogeneous environments and local interactions
4.	Empirical or process-based	Process based	Better suited for modeling dynamic and novel environments
5.	Mechanistic or simplified processes	Simplified	Reduces technical complexity and need for hard-to-measure physiological parameters
B. Suitability for application in new contexts			
1.	Data needs and availability	Tree size attributes plus establishment, mortality, light-growth rates	Requires multiple data sources, but less demanding for site-specific and physiological data than other models
2.	Model portability	Simplified, process-based multi-species simulations	Facilitates transfer to new systems without detailed physiological parameterization
3.	Range of application conditions	Numerous optional modules	Modules can be added to address different applied management scenarios and questions

Table 2. *Cont.*

	Suitability Criteria	SORTIE and FORMIND Attributes	Advantages
4.	Software availability	Freely available, well-documented	User-friendliness lowers obstacles for use in new contexts and by new or novice modelers
5.	Model robustness	Highly parameterizable	Tailoring parameters improves robustness but assumptions and uncertainties should be explored with sensitivity analyses

5.2. Considerations for Implementing Models in New Contexts

The tiered criteria fruitfully address a range of factors particularly relevant to management concerns in small forests, as well as some factors relevant to new contexts, by which we mean forest units, conditions, and/or management contexts that have not been modeled previously. Because this review is intended to orient and inform forest managers who are not yet using forest dynamics models, the pragmatic feasibility of implementing a model in new contexts is an especially important topic, as emphasized in other forest model reviews [92,93]. We highlight five key issues for model suitability in new contexts, which were previously identified (but categorized slightly differently) by Monserud and others [92] and Monserud and Robinson [92]. The tiered criteria already provide a lens for considering three key pragmatic issues: (1) input data needs and availability, (2) model portability, and (3) range and extendibility of application conditions. Two other key issues have not been addressed explicitly thus far and warrant further evaluation: (4) technical accessibility of modeling software, and (5) the reliability, or robustness, of model outputs.

Input data needs are determined by model structure and design, but input data *availability* is determined by the extent of research and monitoring efforts applicable to the new forest context [93]. In each tier, we discussed both data needs and likelihood of adequate data availability. The latter was a key factor in determining model suitability in Tiers 4 and 5, where we concluded that data availability for both empirical models [27,71] and mechanistic models [28] is expected to be prohibitively low for most novel small forest applications, leading to our recommendation for simplified process-based models. At their basic model structures, SORTIE and FORMIND require relatively easily obtainable information about size attributes of different life history stages such as height, diameter, and crown characteristics (Figures 5 and 6) [74,85]. However, some physiological and environmental knowledge—notably, species-specific establishment, mortality rates, and growth responses to varying light conditions—is required [66]. Because the models are process based, these characteristics do not need to be site specific, but they should be species specific [66]. If estimates are unavailable, parameterization and calibration will prove difficult, and the usefulness of model outputs will be limited.

Model portability, or the ease at which a model can be calibrated for an intended use, is largely determined by model design [58,93]. Portability to both small forests and new forest contexts was addressed in Tiers 2, 4, and 5. These evaluations found that single-species and empirical model designs require prior information about species- and site-specific growth rates, and most models of those types were developed for specific forest types [27]. These factors limit their portability to other forests with different species and environmental conditions. In the Tier 5 evaluation, we concluded that simplified process-based models are more portable to new contexts than heavily mechanistic models because they can simulate growth under novel conditions based on relatively simple light-growth relationships [58]. In particular, SORTIE and FORMIND have a history of sequential applications to new contexts and also have modules that can expand the range of forest processes that models can represent, which strengthens their portability and expandability [53,58,74,85].

Application conditions refer to a model's ability to simulate management-relevant factors such as environmental change, disturbance, and management actions when projecting

future forest conditions, and *extendibility* refers to the ease of adding more sub-models or behaviors [93]. Application conditions were key considerations when assessing models' suitability for small forest issues (Figure 1) in Tiers 3, 4, and 5. The arguments in Tier 4 and 5, regarding the advantages of process-based models to simulate novel environmental conditions, also relate to new forest contexts. Because process-based models simulate environmental effects via underlying processes instead of via previously observed growth responses, they are more suitable than empirical models for informing a wider range of application conditions in new contexts as well. While mechanistic process-based models also generate useful outputs for many application conditions, the data needs and availability for parameterizing such application conditions in new forest contexts presents a larger obstacle, as discussed in Tier 5.

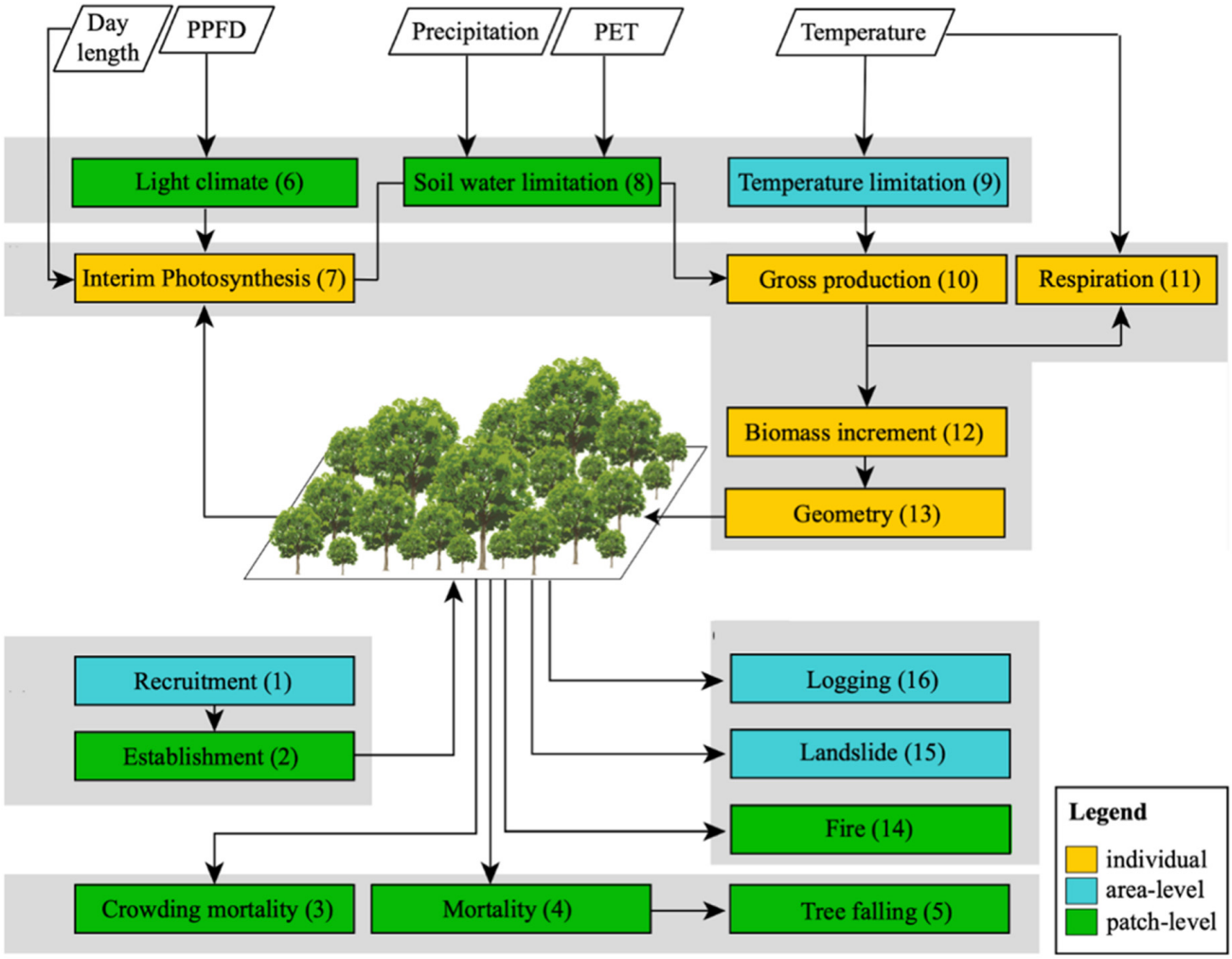

Figure 5. Schematic of the FORMIND model. Main processes are in white, and parallelograms indicate climatic parameters, some of which are required to run the model (abbreviations: PET—potential evapotranspiration; PPFD—photoactive photon flux density). Yellow, blue, and green boxes show physiological, demographic, and optional extensions including logging, harvesting, and fire at different spatial scales. Numbers in parentheses indicate scheduled flow of individual processes within the model, and grey frames underlying boxes group them according to their processes and chapters associated with the FORMIND handbook. Reprinted from [85] with the author's permission and under Creative Commons license.

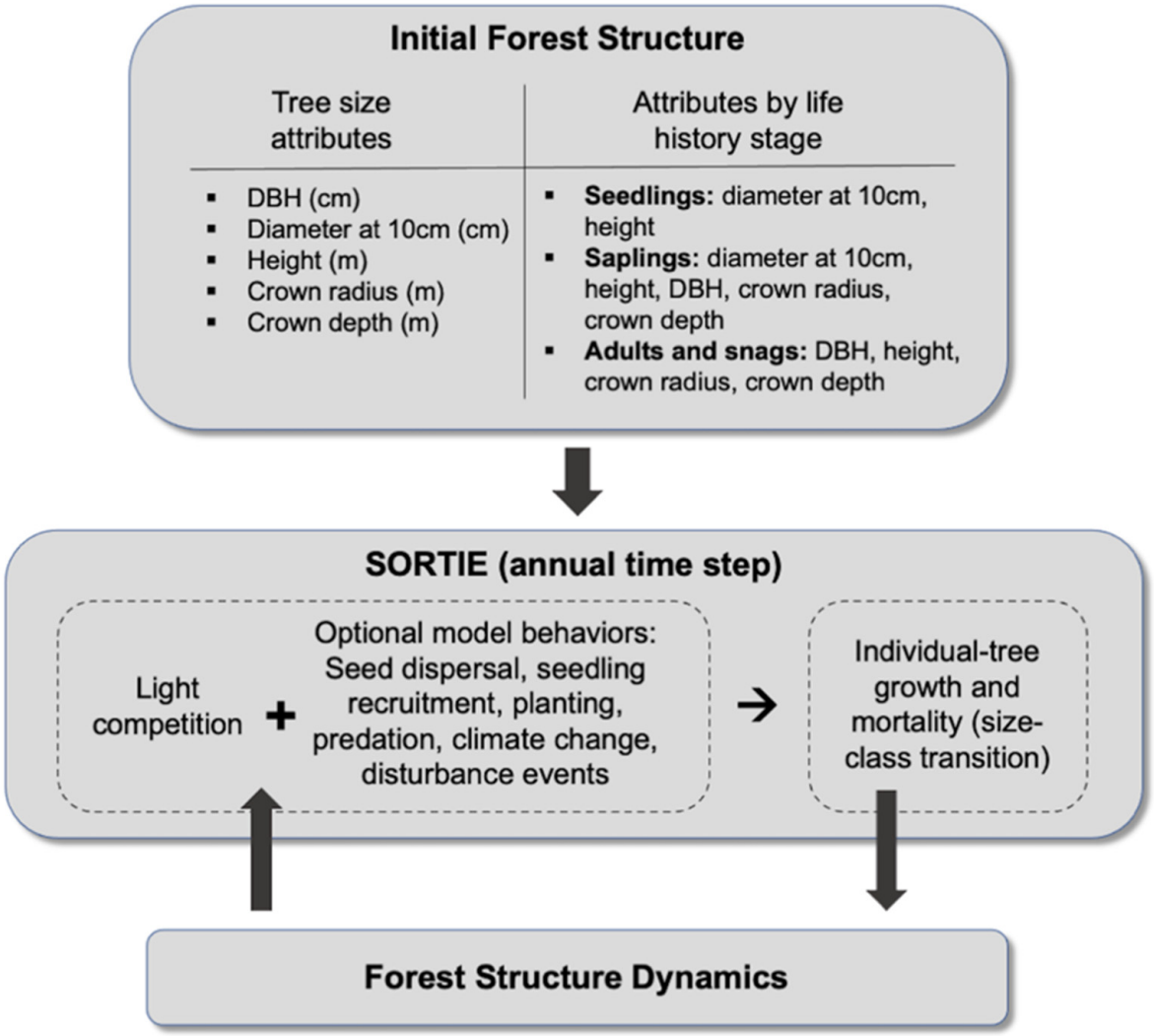

Figure 6. Basic schematic of the SORTIE model. Initialization requirements include tree size attributes of four different size classes or life history stages (i.e., seedlings, saplings, adults, and snags). In each annual timestep, neighborhood density and light–growth relationships drives individual-tree growth and mortality. SORTIE is pre-loaded with growth parameters for eight North American tree species, and users can upload values for additional species. Optional sub-models can be coupled at each timestep to account for other factors that influence forest community change. After SORTIE annually projects individual-tree growth and mortality, the resulting forest structure determines light that is available for the next annual time-step. Information source: [17].

Although both SORTIE and FORMIX were originally designed for specific application conditions, they contain adaptable equations that are calibrated for various forest types across the world [53,58,74,85,94], and they can simulate the effects of a variety of management scenarios through optional model behaviors and sub-models (Figures 4 and 5) [74,89,95]. These options extend both the portfolio of useful model outputs as well as the applications conditions that the models can simulate. For example, SORTIE and FORMIND have been used to study logging and harvesting [90,96,97], climate change scenarios [98,99], and insect, pathogen, and herbivore intensity [100,101] in tropical, temperate, and boreal forests. Many forest management studies have also incorporated other environmental processes like water balance, nitrogen deposition, and natural disturbances into the model process [74,102,103]. FORMIND is one of the few forest dynamics models that has a sub-model called ForFire (Figure 5) that can simulate the impact of fire events [104–106]. However, many of the

optional functions within FORMIND and SORTIE that are relevant to new management contexts cannot be parameterized without additional data collection [94].

Technical availability of modeling software, an issue we have not yet addressed in this review, includes both source code availability and adequate documentation to guide its use [93]. This is critical to the feasibility of implementing a forest dynamics model for a new context. SORTIE and FORMIND are widely used internationally and have free source code that is available online [53,58,74,85]. Thus, they meet the essential criterion of technical availability. However, the utility of SORTIE and FORMIND to small forest management is still heavily influenced by the number of parameters that can be estimated within the source code. Simply supplying these models with only DBH or other more easily obtainable data leaves little room for calibrating many of the allometric equations required to provide accurate model predictions [94]. Without existing forest inventory data, a substantial data collection effort may be required to get reliable model outputs.

Therefore, the last issue, which is a perennial concern in all modeling work, is *model robustness*—the model's ability to provide accurate and reliable estimates [58,92,93]. Model robustness does not depend on model complexity but on the variability and uncertainty of model inputs and parameters [58]. This is a limitation in any modeling context, but parameter uncertainty is likely to be particularly high for small forests due to the lack of well-studied analogs. Uncertainty or inaccuracy in parameter estimates do not all have proportional effects on the robustness of model outputs. Rather, model outputs tend to be more sensitive to uncertainties in some parameters, and more robust to others. Thus, it is important to evaluate the reliability of functional relationships within the model structure and model outputs through sensitivity analyses. Sensitivity analyses systematically alter model inputs and parameters through multiple simulations to identify those that contribute the most to model fluctuations outputs [54,107]. This technique offers small forest managers a way to identify model limitations and also recognize highly influential ecological information that can be prioritized during parameterization and calibration [54,107]. For instance, it often recommended to focus on light competition variables when applying a simplified process-based model [94]. For SORTIE and FORMIND, the most basic light competition variables include tree crown geometry and estimates of size-dependent growth rates [17,78]. These variables can be derived for a large number of tree species, and studies have generally found the models' community-level predictions to be rather robust to uncertainties in those parameters. However, if forest community change is driven by factors other than light competition, and relevant available sub-models are other major drivers not incorporated, SORTIE and FORMIND and other simplified process-based models can generate unrealistic or inaccurate estimates [94]. Model calibration, validation, and sensitivity analyses are thus particularly important if quantitative model estimates are used as the basis for making management decisions [58,107]. When model robustness is limited due to the novelty of a new context, an alternative use of model outputs for forest management is more qualitative evaluations of management alternatives, and to explore the relative influence of different factors that can affect the trajectory of forest change. Sensitivity analyses of both SORTIE and FORMIND have helped researchers make both quantitative and qualitative inferences from model outputs, as appropriate given parameter uncertainties [108]. Thus, SORTIE and FORMIND do not offer immunity to this challenge of model robustness or the previously discussed issues that arise when implementing a model in a new context, but since they were designed for wide adoption and user friendliness, they offer options, advantageous attributes, and documented implementation examples that can help minimize obstacles (Table 2B).

5.3. Recommendations

Choosing a model ultimately depends on alignment between management concerns, the information needed to answer that question, and the generation of robust outputs to inform management [24]. SORTIE and FORMIND are accessible, relevant, and relatively user-friendly tools that can address a wide range of small forest management concerns,

as summarized in Table 2. They are often seen as alternatives to one another [94] because they both have similar input parameters, requiring at minimum initial stand structure, tree geometries, and species-specific tree growth rates (Figures 4 and 5) [74,85,94]. SORTIE has been more frequently applied in temperate forests, and FORMIND in tropical forests, but they are not constrained to those contexts. Rather, selection should be guided by alignment between the salient management concerns, the likely ecological importance of available sub-model options, and the usefulness of available simulation outputs. When resources and information are limited, we recommend starting with the simplest forms of the model and structuring management questions to compare management actions and alternatives instead of depending solely on quantitative model estimates. Combining different sources of information and collaborating with modelers, research organizations, ecological forestry consultants, academic institutions, and other partners and scientists of different disciplines can also help fulfill model requirements and data needs, facilitate implementation, and build capacity and management effectiveness through multi-directional knowledge sharing [30,35,66,94].

Collaborating with decision-support experts can also help small forest managers relate model outputs to particular management actions. Model outputs can feed a decision-support tool, framework, or system to help landowners, small forest managers, and stewards transfer scientific knowledge to practical forest management actions to meet their objectives [84]. For example, a SORTIE model was built to incorporate climatic and management prescription data, creating an array of future forest projections that served as a decision-support tool to evaluate how different forest management actions and climate change scenarios may affect ecosystem services [109]. Other decision tools are not specific to any forest dynamics model and can incorporate model outputs describing future forest structure and composition. As decision-support tools that require information about forest structure and composition are becoming more popular for forest management [84,109–112], they are a potential resource for many small forest managers to couple with forest dynamics modeling when addressing forest benefits and concerns.

6. Conclusions

Although forest dynamics models have become increasingly vital when answering management questions, their appropriateness for simulating the dynamics of management concern in smaller forested areas had not been systematically explored. In this literature review, we evaluated the suitability of 54 existing forest dynamics models to small forest management using five criteria. All models had some drawbacks. However, two, SORTIE and FORMIND, offered the most suitable balance of scale appropriateness, forest type flexibility, structural definition, management relevance, model dynamism and simplicity, plus portability, robustness, and pragmatic usability for application in new, small forest contexts. Establishing a robust implementation of either of these models in a new, small forest context, including those of varying agricultural and urban influences, is likely to proceed incrementally as model calibration improves and environmental factors are incorporated. While full model validation may be an unrealistic near-term goal in most small forest contexts, sensitivity analyses provide useful, accessible techniques for gaining insights regarding achievable conditions and the potential impact of management actions. Each of these models have their advantages and can therefore be applied to different management scenarios [38] whether preserving key tree species, conserving a particular forest structure and composition, restoring historical tree communities, or managing a forest for multi-use.

These findings will hopefully inform small forest managers about the suite of available forest dynamic models available to them and which models to use for specific research questions and help them make sound management decisions. As more and more forests globally exist and are managed at smaller spatial scales, guidance through modeling is also becoming increasingly relevant, feasible and accessible through models like SORTIE and FORMIND.

Author Contributions: Conceptualization, D.L.B., E.G.K. and J.J.O.; methodology, formal analysis, data curation, D.L.B.; writing—original draft preparation, D.L.B. and E.G.K.; writing—review and editing, D.L.B., E.G.K. and J.J.O.; visualization, D.L.B.; supervision, E.G.K.; project administration, funding acquisition, D.L.B. and E.G.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by a Jekyll Island Authority Research Grant, National Institute for Food and Agriculture (U.S.) McIntire-Stennis Grant number GEOZ0184-MS, and Golley Memorial Scholarship at the University of Georgia's Odum School of Ecology.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors are grateful for constructive feedback from Dan Johnson and Clint Moore during project conceptualization and analysis.

Conflicts of Interest: The authors declare no conflict of interest.

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