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Review

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Mechanisms and scales in modeling forest responses to changing disturbance regimes

Author for correspondence:
Xiangtao Xu
Email: xx286@cornell.edu

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Xiangtao Xu[1], Cameron Scholl[1], Yixin Ma[1], Evan Gora[2], Maria Uriarte[3], William R. L. Anderegg[4,5], Yanlan Liu[6], Tao Han[1], Yiqi Luo[7], Charles D. Koven[8], Winslow D. Hansen[2] and Douglas C. Morton[9]

[1]Department of Ecology and Evolutionary Biology, Cornell University, Ithaca, NY 14850, USA; [2]Cary Institute of Ecosystem Studies, Millbrook, NY 12545, USA; [3]Department of Ecology Evolution & Environmental Biology, Columbia University, New York, NY 10027, USA; [4]School of Biological Sciences, University of Utah, Salt Lake City, UT 84112, USA; [5]Wilkes Center for Climate Science and Policy, University of Utah, Salt Lake City, UT 84112, USA; [6]Department of Geography, University of California, Los Angeles, CA 90025, USA; [7]Soil and Crop Sciences Section, School of Integrative Plant Science, Cornell University, Ithaca, NY 14853, USA; [8]Climate and Ecosystem Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA; [9]Biospheric Sciences Laboratory, NASA Goddard Space Flight Center, Greenbelt, MD 20771, USA

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Summary

Natural disturbances are major drivers of large-scale forest dynamics. However, the representation of forest disturbances remains oversimplified and poorly constrained in terrestrial biosphere models, compromising predictive performance under rapidly changing disturbance regimes. In this review, we first summarize the general mechanisms underlying vegetation responses to major disturbance agents across spatio-temporal scales, including occurrence regimes, immediate structural impacts, post-disturbance community reorganization, and long-term ecosystem feedbacks. Predictable patterns of the processes provide the ecological foundation of disturbance modeling. Subsequently, we synthesize progress and challenges toward more mechanistic disturbance modeling, organized by three generic modules: occurrence, impact, and post-disturbance dynamics. Future model developments should implement dynamic disturbance regimes, model lethal and nonlethal structural damage with trait-based hazard functions, and represent key ecological processes determining post-disturbance ecosystem dynamics – including different regeneration strategies, trait plasticity in response to rapid microenvironmental changes, and disturbance legacy effects. Finally, we discuss observational constraints on mechanistic disturbance models. Model

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parameterization and development can benefit from advancing disturbance detection and attribution via multi-modal and multi-platform remote sensing, ground measurements, and disturbance manipulation experiments. Altogether, mechanistic, scalable, and observation-constrained simulation of disturbance is essential for reducing uncertainties in forecasting global change impacts on ecosystems and carbon cycle feedbacks.

I. Introduction

Natural disturbances damage individual trees, create forest gaps, alter community structure and composition, and have long-lasting impacts on forest ecosystems (Pickett & White, 1985; Turner, 2010; Gough *et al.*, 2024). Spatial heterogeneity in natural disturbances explains a large share of the variation in forest biomass, carbon fluxes, and functional composition (Pugh *et al.*, 2019), and shapes forests and their ecosystem services globally (Thom & Seidl, 2016). Novel disturbance regimes (see Box 1) under climate change, such as more frequent and intense fires, droughts, hurricanes, forest pest outbreaks, and their co-occurrence, are of increasing concern because of their potential to push ecosystems beyond historical resilience thresholds and trigger ecosystem regime shifts (Turner & Seidl, 2023).

The ecosystem modeling community has long recognized the importance of disturbances – an early model intercomparison project concluded '*Improved consideration of disturbance is a key "next step" for spatial ecosystem models*' (Schimel *et al.*, 1997). Predicting forest responses to natural disturbances and changing disturbance regimes, however, remains a grand challenge due to knowledge gaps in disturbance occurrence, ecosystem impact, and post-disturbance recovery (McDowell *et al.*, 2020; Sturtevant & Fortin, 2021; Seidl *et al.*, 2022). First, models often represent discrete disturbance events through probabilistic or dynamic occurrence frameworks, but spatio-temporal patterns of major forest disturbance agents and their covariance are not well quantified (Luo *et al.*, 2015; Seidl *et al.*, 2017; Ridder *et al.*, 2020; Turner & Seidl, 2023). Second, forest structure, plant functional traits, and microenvironment interact to regulate disturbance exposure and resistance, resulting in varying severity under similar intensity (Richards *et al.*, 2022; Han *et al.*, 2026). The challenges of capturing these complex interactions contribute to uncertainty and biases in disturbance impact modeling. Third, modeling forest recovery is complicated by a wide range of observed community reorganization pathways, driven by interactions between disturbance severity, plant functional diversity, ecological and evolutionary legacies from previous disturbances, and chronic shifts in climate and ecosystem resources (Buma, 2015; Johnstone *et al.*, 2016; Seidl *et al.*, 2022). While post-disturbance ecosystem biomass recovery appears moderately predictable, generally following a saturating function of time with parameters varying across biomes and climatic gradients (Anderson-Teixeira *et al.*, 2013; Luo *et al.*, 2015; Poorter *et al.*, 2016), predicting changes in forest structure and composition is far more difficult.

These knowledge and observational gaps have left disturbances problematically oversimplified within terrestrial biosphere models (TBMs, see Box 1). Seidl *et al.* (2011) reviewed approaches for modeling forest disturbance and recommended more mechanistic process-oriented disturbance modeling. The past decade has seen substantial progress in mechanistic modeling of some disturbance agents, particularly fire and drought (Anderegg *et al.*, 2015a; Hantson *et al.*, 2016). However, TBMs remain much better at capturing spatial variation in productivity than in biomass turnover (Pugh *et al.*, 2020), and correspondingly, Earth System Models (ESMs) predict very little dynamic response of biomass turnover under climate change (Koven *et al.*, 2015). Meanwhile, process-based TBMs increasingly incorporate trait-based parameters and more detailed forest structure (Fisher *et al.*, 2018; Xu &

Box 1 Key concepts and definitions in forest disturbance used in this review

Disturbance: A discrete event that can result in plant structural damage to one or more individuals in a forest, thereby changing resource availability and competition within plant communities.

Disturbance regime: Spatial and temporal patterns of disturbance attributes, including but not limited to intensity, severity, timing, temporal duration, spatial extent, and impact patch size distribution. Disturbance regimes emerge from climate–vegetation–human interactions. Novel disturbance regimes might increase the risk of ecosystem regime shifts (Turner & Seidl, 2023).

Intensity vs severity: Intensity refers to the strength of the disturbance agent, such as wind speed in a storm or the level of water deficit in a drought. Severity refers to the magnitude of impact on vegetation and ecosystem states and is often measured by tree mortality rate or loss of biomass. Plant functional diversity and landscape heterogeneity can regulate plant resistance and exposure to disturbances, leading to different degrees of severity under similar disturbance intensity.

Hazard function: A hazard function measures the rate or risk of event occurrences at a given time. It is widely used in modeling tree mortality. In disturbance impact modeling, hazard functions estimate the risk of damage based on time-varying disturbance intensity together with plant resistance and exposure to disturbances (Fig. 4). The sensitivity of hazard to intensity can be related to plant traits that influence disturbance resistance, such as hydraulic safety, structural stability, and flammability.

Community reorganization: The different post-disturbance ecosystem response pathways based on how forest structure and composition change (*sensu* Seidl *et al.*, 2022), including resilience (no changes in structure and composition), reassembly (only composition changes), restructuring (only structural changes), replacement (changes in both structure and composition), and regime shift (transition to nonforest).

Vegetation model: A computational tool for predicting vegetation dynamics. Vegetation models include stand models (also called gap models) focusing on simulating individual trees in one stand, forest landscape models focusing on simulating how different stands evolve and interact over large areas, terrestrial biosphere models (TBMs, also referred to as dynamic global vegetation models or DGVMs) focusing on global-scale simulations that can be coupled to atmospheric models.

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Trugman, 2021). This structural evolution of models enables more mechanistic and accurate representation of disturbance-related processes from individual trees to landscapes, and supports assimilating novel data from field-based observational networks, manipulative experiments, and remote sensing observations. Therefore, a modern synthesis of forest disturbance modeling is much needed to advance predictions of global forest dynamics and guide model development.

The review is structured into three sections, each organized around the generic modules of disturbance modeling – occurrence, impact, and post-disturbance recovery and feedback. First, we establish the ecological foundation of forest disturbance modeling through a synthesis of the general mechanisms underlying forest responses to different disturbances. Second, we compare common disturbance modeling frameworks, describe the current representation of major natural forest disturbances, and summarize progress and challenges toward more mechanistic representation of forest disturbances. Third, we review recent advances and persistent challenges in observations that can constrain disturbance modeling. We conclude with recommendations for future research directions. While the review focuses primarily on vegetation processes, other components of forest ecosystems, particularly soil biogeochemistry and microbial communities, are also shaped by disturbances and are important for accurately predicting disturbance effects (Bowd *et al.*, 2019).

II. Ecological foundations of forest disturbance modeling

Forest disturbances arise from different agents and occur at varying spatio-temporal scales. *Wildfire* is a major driver of global forest loss (van Wees *et al.*, 2021) and wildfire severity has increased globally in recent decades (Bowman *et al.*, 2020). *Drought and heatwaves* often interact to elevate soil water deficit and atmospheric water demand, inducing stomatal closure, xylem cavitation, leaf shedding, and tree death (Brodribb *et al.*, 2020). Shifting drought regimes under climate warming are threatening forest ecosystems (Hammond *et al.*, 2022). *Wind disturbance* causes tree mortality and stand replacement across global forests (Forzieri *et al.*, 2020; Urquiza-Muñoz *et al.*, 2024), driven by cyclonic storms (Kropf *et al.*, 2025) and localized convection and tornadoes (Peterson, 2000; Gora *et al.*, 2025). For example, in Amazon forests, convective storms are estimated to account for 30–60% of tree biomass mortality (Gora *et al.*, 2025). *Lightning* preferentially strikes the tallest trees with the largest crowns. Lightning-induced large tree mortality has cascading effects on forest structure, biomass turnover rates, and biomass stocks, particularly in tropical forests (Gora *et al.*, 2020a). *Forest pests and pathogens* are a major threat to forest health and biomass that can result in extensive canopy defoliation and forest die-off (Hicke *et al.*, 2012). Host specificity and complex interactions among host tree species, pests, and pest-specific pathogens or parasitoids can produce patchy spatial patterns (Barbosa *et al.*, 2012).

Beyond these globally important agents, cold extremes and ice storms induce physiological and physical stress for trees in temperate and boreal forests. Late spring freezes can also impose substantial damage to leaf buds and flowers, occasionally leading to tree mortality (Chamberlain *et al.*, 2019). In riparian and floodplain forests, flooding and sea level rise elevate tree mortality and hinder recruitment (Friedman & Lee, 2002). Submergence and saltwater intrusion trigger mortality and create ghost forests in coastal regions (Kirwan & Gedan, 2019). In montane and alpine forests, natural hazards such as landslides and avalanches severely disrupt the physical landscape, often leading to stand-replacing forest disturbance (Guariguata, 1990; Bebi *et al.*, 2009).

Despite their diverse origins, forest responses to these disturbances follow a set of common ecological mechanisms. Predictable patterns of disturbance occurrence, immediate structural damage, post-disturbance community reorganization, and long-term responses and feedbacks serve as the foundation for modeling forest disturbances across scales (Fig. 1).

1. Occurrence regime

Individual disturbance events are stochastic in space and time. While modeling historical forest disturbances can rely on past records, future disturbance events can hardly be predicted deterministically. At appropriate temporal and spatial scales, however, individual events aggregate into statistically regular regimes that can be used for predictions.

Two common metrics to describe a disturbance regime are the size distribution of event extents (or patch sizes) and the associated average return interval because forest responses to disturbances are sensitive to both disturbance frequency and spatial context. Across many agents and biomes, patch sizes follow an approximately power-law or Pareto distribution, where small events vastly outnumber large ones (Espírito-Santo *et al.*, 2014; Hantson *et al.*, 2015; Senf & Seidl, 2021a). Return intervals span several orders of magnitude, from less than a decade for small windthrow gaps and spongy moth outbreaks (Liebhold *et al.*, 2000; Espírito-Santo *et al.*, 2014) to a century or more for stand-replacing fires and megadroughts (Williams *et al.*, 2020; Jones *et al.*, 2022). The two metrics are also coupled: larger disturbances generally have longer return intervals, but the rare largest events can disproportionately shape long-term forest structure and biogeochemistry (Turner, 2010). In addition, event intensity, timing, duration, and other dimensions of disturbance regime are increasingly considered given their importance for impact modeling.

Occurrence statistics vary along climatic gradients and are expected to shift as climate changes (Seidl *et al.*, 2017; Turner & Seidl, 2023). The mechanistic pathways linking climate to occurrence span a hierarchy of complexity and uncertainty. For abiotic agents such as drought and storms, occurrence is governed primarily by atmospheric dynamics and large-scale land-atmosphere feedback. For others, occurrence is shaped by climate–vegetation interactions, such as the joint control of ignition, weather, and fuel moisture on wildfire risks (Hantson *et al.*, 2016). Biotic disturbances usually entail greater complexity, because climate simultaneously modulates insect or pathogen population dynamics, host physiology and chemical defense, and interactions across trophic levels, including natural enemies (Raffa *et al.*, 2008). Prognostic modeling of changing disturbance

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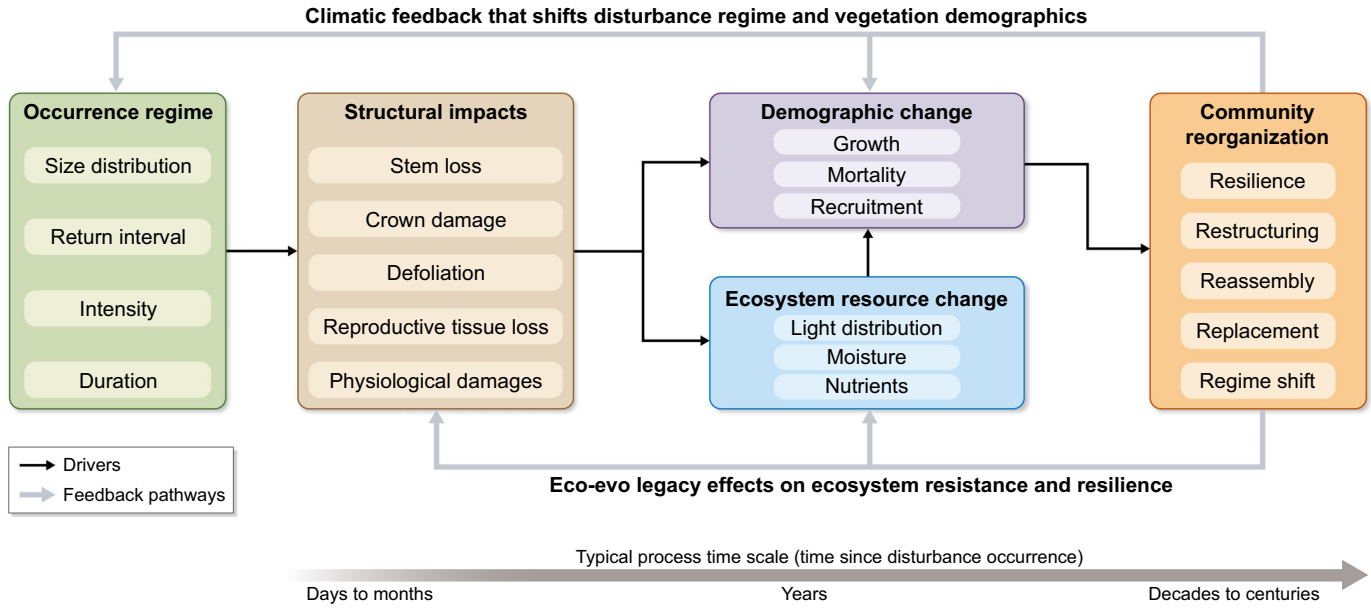

Fig. 1 Mechanisms of forest responses to natural disturbances. Occurrence of disturbance events follows a statistical regime. Physical and physiological stresses induced by disturbance events result in structural damage. These short-term impacts lead to demographic changes, driven by tree physiological responses to damages and post-disturbance changes in ecosystem resources. Patterns of demographic changes reorganize forest communities, leading to long-term shifts in forest structure and composition and potential regime shift to nonforest states (see Seidl *et al*., 2022 for more details). These long-term shifts in turn regulate forest responses to future disturbances through influencing ecosystem resistance and resilience to disturbances due to ecological and evolutionary legacy effects (see Johnstone *et al*., 2016 for more details). Large-scale community reorganization can also lead to environmental feedback to climatic and disturbance regimes.

occurrence regimes requires representing these agent-specific mechanisms, which remains a principal source of uncertainty in projections of future forest dynamics (McDowell *et al*., 2020; Turner & Seidl, 2023).

2. Structural impacts

Complex ecosystem responses to disturbances are initiated by acute structural damage (Fig. 1, second box). Stand replacement and stem loss from extreme physiological and physical stress receive the most attention because they are easier to measure and directly affect forest structure, carbon stocks, and many other ecosystem functions. Nevertheless, nonlethal structural damage is also common and consequential. Branch losses caused by disturbance contribute substantially to forest biomass turnover globally (Marvin & Asner, 2016; Leitold *et al*., 2018; Zuleta *et al*., 2023; Lim *et al*., 2024). Defoliation, irreversible xylem dysfunction, and partial canopy loss decrease photosynthetic capacity, incur tissue repair or regrowth costs, and elevate tree mortality risk (Zuleta *et al*., 2022; Reed & Hood, 2024; Tanzer *et al*., 2025). While rarely documented at large scales, climate extremes such as late spring freezes, droughts, and hurricanes can also induce reproductive tissue loss that may affect recruitment (Chang-Yang *et al*., 2016; Zimmerman *et al*., 2018).

The types and severity of structural damage vary across disturbance agents and are determined by disturbance intensity as well as forest structure and composition. Stem density, canopy structure, and tree height jointly regulate forest exposure and resistance to drought and storms (Bennett *et al*., 2015; Ankori-Karlinsky *et al*., 2025). Functional diversity in plant traits associated with disturbance resistance, for example bark thickness for fire (Staver *et al*., 2020), crown shape and allometry for wind (Jackson *et al*., 2024), and xylem hydraulic traits for drought (Anderegg *et al*., 2016; Greenwood *et al*., 2017), produces heterogeneous impacts across the landscape during a single disturbance event. Ideally, modeling disturbance impacts should account for both intensity heterogeneity and plant functional diversity. Yet, observations to constrain them are rare beyond a few intensively monitored sites.

3. Post-disturbance community reorganization

Tree growth, mortality, and recruitment respond to both immediate disturbance impacts and subsequent changes in ecosystem resources, such as understory light and temperature, soil moisture, and nutrient cycling. Together, these demographic responses determine whether a forest recovers toward its prior state or is pushed into a new one (Fig. 1, boxes of the right two columns). Variability in post-disturbance demographic rates across species and tree size classes leads to a spectrum of community reorganization outcomes as categorized by Seidl *et al*. (2022).

Increases in light and nutrient availability promote tree recruitment and seedling growth immediately following disturbance, especially for early-successional and opportunistic colonists (Comita *et al*., 2009). However, recruitment after large-scale and high-severity disturbances can be limited by species-specific

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germination rates, microclimatic stressors to seedling establishment, and the absence of seed bank and seed dispersal (Comita *et al.*, 2009; Nolan *et al.*, 2021). Resprouting is a common ecological strategy for overcoming such regeneration limitations (Bond & Midgley, 2001; Clarke *et al.*, 2013; Nolan *et al.*, 2021). For example, in US Appalachians, recruitment from sprouts constituted 26–87% of early gap regeneration (Dietze & Clark, 2008). Some species also develop disturbance-adapted reproduction strategies, such as serotinous cones in pine species (Schwilk & Ackerly, 2001). When recruitment is successful, high stem density can in turn elevate tree mortality due to self-thinning under intense resource competition. The timescale of self-thinning ranges from a few years in tropical forests to a few decades in temperate biomes (Comita *et al.*, 2009; Turner *et al.*, 2016).

Like new recruits, surviving trees can benefit from competitive release and exhibit enhanced growth (Tanner *et al.*, 2014; Silva Pedro *et al.*, 2016; Gough *et al.*, 2021). However, nonlethal damage to surviving trees can reduce growth and lead to delayed mortality. The degree of partial tree crown damage was a dominant mortality risk factor across several tropical forest sites (Zuleta *et al.*, 2022). In an Amazonian tropical forest, over 50% of wind-damaged trees died within 4 yr with mortality rising further when compounded with fire disturbance (Silvério *et al.*, 2019). At the global scale, tree-ring records suggest that growth may take several years to recover after drought (Anderegg *et al.*, 2015b, but see Zuidema *et al.*, 2025 for counter-evidence in tropical forests). Mechanistically modeling these demographic responses likely requires representing neighborhood competition and plant carbon allocation responses to nonlethal damage (Uriarte *et al.*, 2004; Anderegg *et al.*, 2015a).

Beyond individual tree responses, post-disturbance recovery also shows predictable patterns at the ecosystem scale. Spatial variation of secondary forest regrowth rates is correlated with temperature and precipitation (Anderson-Teixeira *et al.*, 2013; Poorter *et al.*, 2016). Biomass regrowth and compositional recovery can also be limited by soil nutrient availability or soil substrate types (Rastetter *et al.*, 2013; Mekonnen *et al.*, 2019; Martinuzzi *et al.*, 2022), but the degree of nutrient limitation varies across sites, species, and tree size (Wright *et al.*, 2011; Li *et al.*, 2018; Wong *et al.*, 2024). Compared with climatic effects, our understanding of how edaphic factors shape demographic rates appears less coherent.

4. Long-term response and feedbacks

Eco-evolutionary legacies and environmental feedbacks (Fig. 1, open arrows) become essential when predicting ecosystem dynamics under repeated disturbances, compound disturbances, and changing disturbance regimes over longer timescales (Bond-Lamberty *et al.*, 2014; Buma, 2015; Johnstone *et al.*, 2016).

Disturbance-induced changes in tree physiology, forest structure, composition, and ecosystem resources become ecological legacies that influence ecosystem resistance and resilience to future disturbances (Johnstone *et al.*, 2016). For example, disturbance preferentially removes vulnerable trees while sparing tolerant ones, leaving the forest more tolerant to subsequent disturbances of the same type and intensity (Medvigy *et al.*, 2025). Fire effects on soil nutrient concentrations can last for decades, shaping long-term plant community changes (Bowd *et al.*, 2019). Furthermore, post-disturbance legacies can shape interactions with other disturbance agents. In a Puerto Rican tropical forest, community composition shifted toward more early-successional species after a severe hurricane, increasing forest vulnerability to subsequent drought (Smith-Martin *et al.*, 2022). On evolutionary time scales, repeated disturbance can drive plant life-history trait adaptation, creating evolutionary legacies tied to a given disturbance regime.

Large-scale disturbances also alter the hydrological cycle, surface energy balance, and ultimately land-atmosphere interactions, with consequences for local, regional, and global climate (Randerson *et al.*, 2006; Lawrence & Vandecar, 2015). These environmental feedbacks alter disturbance regime characteristics and modify local climate conditions, with consequences for future ecosystem responses. Meanwhile, quantifying and incorporating these feedbacks can be difficult, contributing to uncertainties in long-term model simulations.

III. Toward more mechanistic forest disturbance modeling

Existing vegetation models adopt a variety of schemes for disturbance occurrence, impacts, and recovery (e.g. models reviewed by Seidl *et al.*, 2011; Sturtevant & Fortin, 2021; Bugmann & Seidl, 2022; Díaz-Yáñez *et al.*, 2024), balancing model realism, parsimony, and scalability across space and time. In the 24 active vegetation models reviewed in Bugmann & Seidl (2022), half of them explicitly incorporate fire disturbances; a third have biotic disturbances and only a quarter represent wind disturbances. The level of disturbance module complexity is usually constrained by the predictive goal of each model (e.g. carbon, forest structure, or composition) and the data available for calibration and benchmarking. It is also constrained by the structure of the host vegetation model. For example, TBMs without explicit representation of forest structure tend to adopt more parsimonious disturbance schemes (Pugh *et al.*, 2020; Sitch *et al.*, 2024). Fig. 2a presents the modules that directly or indirectly influence the disturbance module in a modern TBM. Interactions of these modules across timescales determine simulated long-term ecosystem responses and feedbacks.

Table 1 summarizes common representations of major forest disturbance agents in current vegetation models following schemes categorized in Fig. 2b. Drawing on these model implementations, the remainder of this section discusses future directions for improving the modeling of occurrence, impact, and recovery, with an emphasis on TBMs targeted for regional to global simulations.

1. Toward dynamic disturbance occurrence modeling under changing climate

Disturbance occurrence modeling aims to predict the spatial and temporal variations of disturbance intensity (see Box 1 for the distinction between intensity and severity). Given that novel disturbance regimes under climate change increasingly threaten

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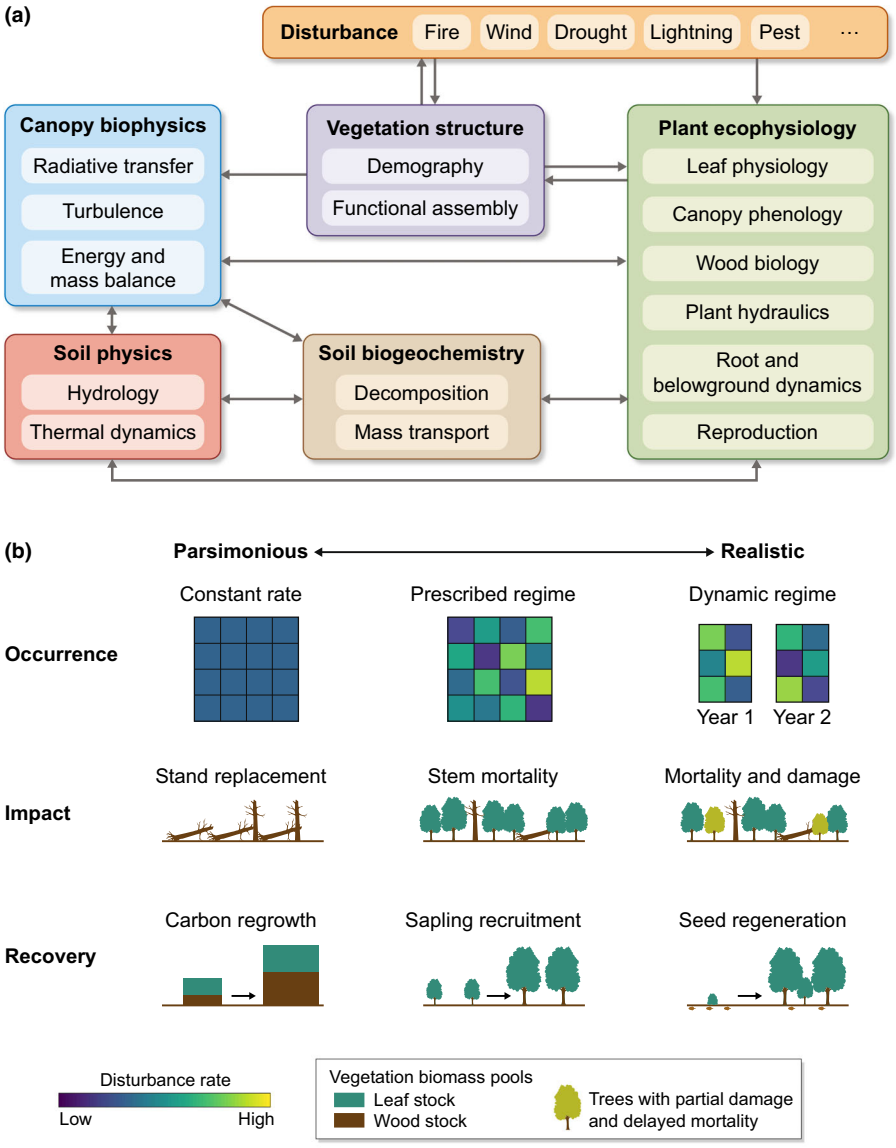

Fig. 2 Representations of disturbance and its impact on forest dynamics in models. (a) Key modules related directly or indirectly to disturbance modeling in modern trait-based terrestrial biosphere models (TBMs). Post-disturbance ecosystem responses and long-term eco-evo and environmental feedback emerge from the interactions across all modules. The TBM module diagram and color scheme are adapted from Fisher & Koven (2020), licensed under CC BY 4.0 (http://creativecommons.org/licenses/by/4.0). (b) Schematics showing the different approaches for disturbance occurrence, impact, and recovery in current vegetation models and TBMs. Ecological realism and model complexity increase from left to right. See Section III for detailed discussions of these approaches. Arrows in the Recovery panel indicate evolution of time.

global forest ecosystems, a key task of occurrence modeling is to capture how climate drives disturbance intensity and how landscape heterogeneity modulates the climate effect, so that spatially varying and temporally evolving disturbance regimes emerge. However, current occurrence modeling schemes suffer from oversimplification and uncertainties (Table 1). We categorize these approaches based on their mechanistic complexity (Fig. 2b). The simplest occurrence scheme applies a constant background rate, often calibrated to long-term biomass turnover rates. A more complex scheme prescribes spatially varying but temporally constant disturbance rates. The most mechanistic scheme predicts dynamic regimes prognostically from climate, vegetation, and land surface properties. Below, we discuss these model limitations and development directions for major disturbance agents.

Fire occurrence modeling is likely the most sophisticated among all disturbance agents. Prognostic fire occurrence models such as SPITFIRE and its successors consider ignition, fuel, and fire spread and have been coupled with many TBMs (Hantson *et al.*, 2016; Shuman *et al.*, 2024). These schemes generate dynamic fire regimes from climate–vegetation–human interactions, using a mix of statistical and process-based approaches. Nevertheless, parameter uncertainties in these complex processes challenge their scalability and accuracy. A recent analysis of fire-enabled CMIP6 models found that they underestimated global burned area and failed to reproduce observed spatial and inter-annual variability in burning (Li *et al.*, 2024). Better representation of anthropogenic and natural ignition probability and of fuel load and moisture dynamics is particularly needed to capture climate sensitivities of fire regimes in TBMs (Hantson *et al.*, 2016; Oberhagemann *et al.*, 2025).

Occurrences of climate extremes are largely modeled outside of TBMs. Their climatic sensitivities arise from internal dynamics of ESMs and the historical observations used for calibrating them. Drought and heatwaves are often represented as prescribed regimes embedded in the climate forcing. However, biases and uncertainties exist in climate forcing derived from ESM model predictions or reanalysis data (Sillmann *et al.*, 2017). For example, the estimated

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Table 1 Synthesis of current states, future development recommendations, and observational needs for modeling disturbance occurrence, impact, and recovery.

	Current model representation*	TBM development recommendations	Observational needs
Occurrence	Highly depends on disturbance agents: *Fire*: Dynamic regime driven by ignition, fuel, and fire spread. These processes are influenced by climate–vegetation–human interactions[1] *Drought and heatwaves*: Prescribed regime when forced by climate data; Dynamic regime when coupled with Earth System Models *Wind and lightning*: Constant rate in most models[2]; Prescribed regime in some models based on wind speed patterns[3] or lightning strike density[4,5] *Pests and pathogens*: Prescribed regime or missing in most models[6]	Replace constant rates with prescribed or dynamic regimes for wind, lightning, and pests Estimate climate sensitivity of disturbance regimes to parameterize dynamic regime modeling Improve mechanistic representation of plant-pest interactions for more robust dynamic regimes in biotic disturbances Incorporate sequential and co-occurring disturbances in modeling using statistical or mechanistic approaches	Attribute satellite-based disturbance detections across space and time Combine ground census with airborne and unmanned aerial vehicle remote sensing to constrain occurrence regimes for smaller yet abundant disturbance events
Impact	Highly depends on vegetation model structure and scale: *Global models without demography*: Increased biomass turnover[7] *Demography-explicit models*: functional-type-specific or species-specific stem mortality for demography-explicit models and stand models[1,2,8]. Partial crown damage other than defoliation and its legacy effects are relatively rare (but see Needham *et al*., 2022)	Develop trait-based hazard functions to integrate intensity, exposure, and plant resistance to capture heterogeneous disturbance impacts Simulate plant stress variables, such as plant water potential and nonstructural carbohydrates, which can more robustly predict impacts	Quantify fine-scale impacts beyond tree cover changes from high-resolution remote sensing across global forest biomes Leverage manipulative experiments to establish and calibrate hazard functions for disturbance impacts.
Recovery	Highly depends on vegetation model structure and scale: *Global models without demography*: Biomass regrowth[7] *Demography-explicit global models*: Sapling recruitment[9,10] *Spatially explicit stand or landscape models*: Both sapling recruitment and seed regeneration[9]	Represent seed dynamics and diversity in reproductive strategies Incorporate trait plasticity in response to rapid changes in post-disturbance microenvironment Model legacy effects from short-term nonlethal structural damage	Collect and analyze high-resolution remote sensing data following large-scale disturbance events Conduct rapid-response field campaigns after disturbance events Maintain long-term ecological monitoring in natural and experimental sites

[1]Hantson *et al*. (2016).
[2]Bugmann & Seidl (2022).
[3]Seidl *et al*. (2014).
[4]Krause *et al*. (2025).
[5]Medvigy *et al*. (2025).
[6]Kautz *et al*. (2018).
[7]Sitch *et al*. (2024).
[8]Pugh *et al*. (2020).
[9]Díaz-Yáñez *et al*. (2024).
[10]Eckes-Shephard *et al*. (2025).
*Refer to Fig. 2b for different categories of model representations.

area impacted during the 2015–2016 ENSO drought in the Amazon basin varied by over 1.5 million square kilometers across different rainfall data sets with substantial differences in drought epicenters (Papastefanou *et al*., 2022). Fundamental improvement of modeling these climate extremes relies on integrative efforts from the broad ESM community.

By contrast, wind and lightning disturbances are usually implicit in models, contributing to background disturbance rates. In TBMs, disturbance other than fire is generally implemented as a fixed turnover time, a random stand replacement rate, or background stem mortality rates (Pugh *et al*., 2020). Recent model developments have started to explicitly consider wind extremes and lightning in TBMs (Zhang *et al*., 2022; Shi *et al*., 2024; Krause *et al*., 2025; Medvigy *et al*., 2025). Emerging data sets on global storm and lightning patterns (Fig. 3) also enable representation of spatially varying wind and lightning disturbance regimes and the inference of their climate sensitivities. As an example, the frequency of mesoscale convective systems (MCSs) varies spatially in correlation with convective available potential energy (CAPE), an atmospheric variable that can be calculated from climate model output (Wu *et al*., 2026). This correlation may therefore be used to statistically model dynamic regimes for storms. However, extrapolation of such spatial relationships to temporal changes warrants caution, especially when climate goes beyond the range of historical variability.

Modeling dynamic occurrences of forest pest outbreaks can be more complicated than abiotic disturbances. Forest pest outbreaks are driven by multi-trophic interactions among plants, pests, and

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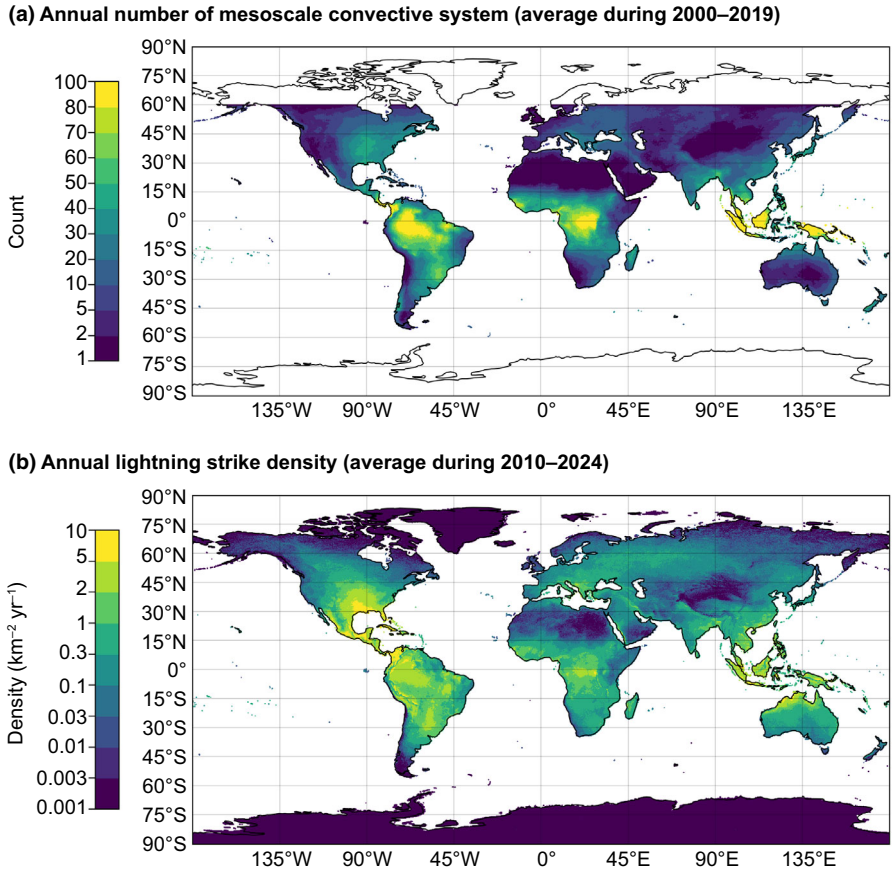

Fig. 3 Storms and lightning strikes are ecologically important but under-represented disturbance agents in current models. Global patterns of (a) annual number of pass-by mesoscale convective systems (MCS, Feng *et al*., 2021; data limited to 60° N–60° S) and (b) estimated lightning strike density as the number of lightning strokes detected by the World Wide Lightning Location Network system of sensors (Kaplan & Lau, 2021) demonstrate large spatial variations of these disturbance agents.

pest bio-controls (e.g. fungal and virus disease and predators of pests), all of which are sensitive to climate conditions (Dukes *et al*., 2009). Moreover, observations on pest populations are not commonly available at large scales, making it difficult to calibrate prognostic models. Therefore, biotic disturbances such as bark beetles and defoliators are more commonly modeled in site-level or regional simulations, often as prescribed regimes parameterized by available data records (Kautz *et al*., 2018; Foster *et al*., 2026). While TBMs would benefit from mechanistic representation of forest pest population dynamics, semi-empirical schemes may be a more practical near-term model development direction. Recent studies have used statistical risk models to estimate insect suitability and host susceptibility based on climate and stand characteristics (Marie *et al*., 2024). Some models further incorporate factors, such as temperature-driven insect lifecycle development and infection rates to predict biotic disturbance dynamics (Bentz & Jönsson, 2015; Robbins *et al*., 2022).

Finally, linked (sequential) and compound (co-occurring) disturbances should be better represented in occurrence modeling. Such correlated disturbance regimes can naturally emerge when models consider mechanistic processes underlying each agent, such as drought-fire interactions through dry fuel availability (Guion *et al*., 2022) and drought-pest interactions through reduced plant defense under stress (Anderegg *et al*., 2015a). When mechanistic understanding of disturbance interactions is lacking, statistical covariance between disturbance agents based on historical records can also provide useful constraints (Ridder *et al*., 2020).

2. Toward trait-based hazard functions in disturbance impact modeling

Disturbance impact modeling translates disturbance intensity into severity. The simplest scheme only considers total biomass loss after disturbance, often implemented as increases in biomass turnover rates (Fig. 2b). Models that explicitly track individual trees or tree cohorts usually allow for selective stem mortality as a function of tree size, functional traits, and stress levels. The most mechanistic scheme adds nonlethal damage that reduces growth or elevates delayed mortality risk.

The structure and complexity of impact modeling depend more on the spatial granularity of the hosting vegetation models than on the specific disturbance agent. Across vegetation models, fire impact schemes range from fractional biomass loss in burnt area to stem mortality parameterized for each plant functional type (PFT), and partial crown and cambial damage regulated by bark thickness and tree height (Hantson *et al*., 2016; Trugman *et al*., 2018). Generally, TBMs focusing on carbon dynamics simplify impact as increased biomass turnover, while demography-enabled models allow for variable impacts at the scale of individual trees or tree cohorts (Pugh *et al*., 2020; Sitch *et al*., 2024). Spatially explicit forest landscape models can additionally represent microenvironment and neighborhood interactions such as the forest-edge effect on wind damage in the iLand model (Seidl *et al*., 2014). Nonlethal damage has been less commonly modeled despite its importance for forest demographics and carbon cycling. Canopy defoliation

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triggered by plant water stress or forest pest outbreaks is the most widely implemented nonlethal damage (Powell *et al.*, 2013; Kautz *et al.*, 2018; Foster *et al.*, 2026). Needham *et al.* (2022) extended the partial canopy damage module in the FATES model to include structural biomass pools.

Regardless of host model granularity and complexity, the core of disturbance impact modeling is hazard functions (Box 1). Hazard functions for disturbance damage can be viewed as a generalization of stress-driven tree mortality functions in current vegetation models (Bugmann *et al.*, 2019). Disturbance hazards are jointly determined by disturbance intensity, plant resistance, and disturbance exposure. The sensitivity of hazard to intensity is higher for plants with lower resistance or with higher exposure to the disturbance agent (Fig. 4). Given that plant traits strongly regulate both resistance and exposure, hazard functions for all disturbance agents will benefit from linking parameters to traits. For example, bark thickness and tree height have already been used to model differential fire susceptibility across PFTs. Evidence is also mounting that modeling drought-driven tree mortality must consider plant hydraulic trait variations, such as rooting depth (Matheny *et al.*, 2017; Agee *et al.*, 2021; Chitra-Tarak *et al.*, 2021), stem hydraulic vulnerability (Adams *et al.*, 2017; Powers *et al.*, 2020), and tree size (Bennett *et al.*, 2015; Stovall *et al.*, 2019). Plant exposure and resistance to wind extremes and lightning strikes are regulated by tree size and canopy structure, although it remains unclear what traits determine tree size effect variations across species and sites (Uriarte *et al.*, 2019; Gora *et al.*, 2020b). Plant chemical traits underlying constitutive and induced defense as well as carbon allocation regulate hazards to biotic disturbances (Raffa *et al.*, 2008; Anderegg *et al.*, 2015a). Therefore, replacing constant or PFT-specific parameters with trait-based parameterization offers a more mechanistic and likely more robust path forward for hazard functions (e.g. stem mortality hazard function proposed in Camac *et al.*, 2018).

Hazard functions also benefit from using mechanistic plant stress metrics. For drought impacts, tracking plant hydraulics and using plant water potential as a stress variable has improved model performance compared with only using soil moisture (Xu *et al.*, 2016; Eller *et al.*, 2018; De Kauwe *et al.*, 2020). Interactions between traits and microenvironment should also be considered. Notably, subsurface hydrology and its interplay with plant rooting depth are important to modeling drought disturbance impacts because deep soil moisture supply can help plants survive or even benefit from drought (Goulden & Bales, 2019; Chen *et al.*, 2024).

3. Toward enhanced ecological realism in post-disturbance recovery modeling

The key goal of post-disturbance modeling is to predict how immediate disturbance impacts evolve through the complex interactions between biophysical, biogeochemical, and ecophysiological modules in TBMs (Fig. 2a). Like the disturbance impact module, recovery modeling schemes (Fig. 2b) also hinge on the host vegetation model structure. The simplest scheme tracks only bulk carbon or biomass regrowth. Demography-enabled models represent regrowth through sapling recruitment, usually

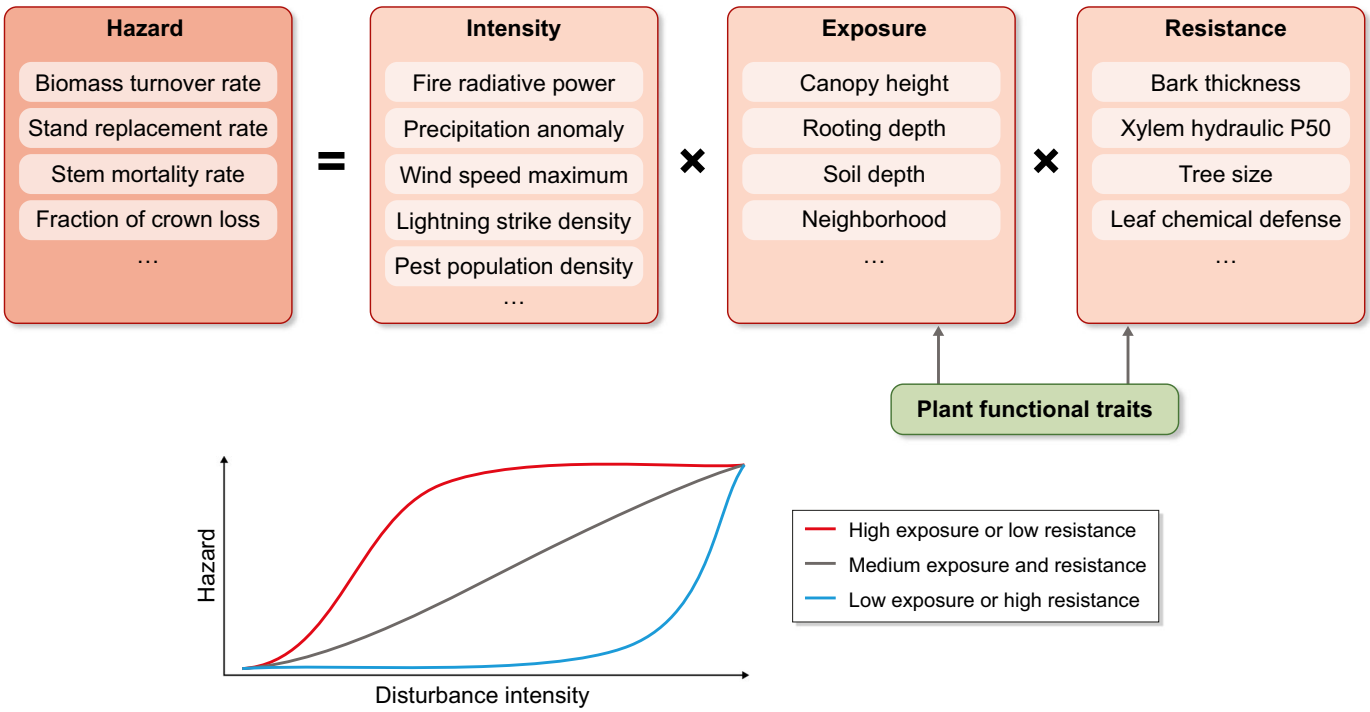

Fig. 4 Schematic diagram showing the joint effects of disturbance intensity, plant exposure, and plant resistance to the risk of disturbance damage, that is, hazard. Plant functional traits regulate plant resistance and exposure while the local environment is also important for disturbance exposure. Example metrics and model variables are given for each term.

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determined by reproductive carbon allocation or prescribed seed rain, which allows forest structural and compositional changes along the recovery trajectory. The most mechanistic scheme explicitly represents reproduction and seed regeneration, which can capture recruitment limited by seed availability and dispersal distance.

A major challenge of recovery modeling is to capture heterogeneous recovery patterns across space, time, and disturbance agents. In addition to multiple community reorganization pathways categorized based on forest structural and compositional recovery (Seidl *et al.*, 2022), forests may fail to recover after high-severity disturbances under changing climatic regimes, resulting in a landscape transition to a nonforest state (Gough *et al.*, 2016; Davis *et al.*, 2019; Batllori *et al.*, 2020). Here, we focus on several processes pivotal to capturing post-disturbance dynamics across disturbance agents.

First, seed bank dynamics, dispersal, and germination are critical to forest regeneration but are absent or highly simplified in TBMs. While stand- and landscape-level forest models tend to better represent reproduction and seed dynamics (Díaz-Yáñez *et al.*, 2024), global models implement recruitment as carbon regrowth or sapling establishment calculated from plant internal carbon pools or prescribed external seed rains (Eckes-Shephard *et al.*, 2025). For example, plant reproductive adaptations to fire regimes are represented in some models, such as serotinous cones in iLand (Hansen *et al.*, 2018), but are rarely considered in global models. TBMs are beginning to implement more realistic recruitment frameworks that consider microenvironment (e.g. understory light and soil moisture), seed dispersal, and key reproductive traits, such as seed size (Hanbury-Brown *et al.*, 2022; Wiegand *et al.*, 2025). Meanwhile, sprouting or vegetative reproduction, another important reproductive process for post-disturbance regeneration (Bond & Midgley, 2001), is largely missing in models. Adapting model reproductive parameterization offers one feasible path forward. For example, di Porcia e Brugnera *et al.* (2019) considered vegetative reproduction of lianas by significantly increasing the reproductive carbon allocation for the PFT.

Second, post-disturbance recovery is often characterized by rapid changes in microenvironment and ecosystem resources. Plant phenotypic plasticity to these environmental changes could be critical to modeling plant growth and mortality. Yet, trait plasticity is represented to only a limited extent in current models (Berzaghi *et al.*, 2020; Xu & Trugman, 2021). Several recent modeling studies (Ma *et al.*, 2025; Needham *et al.*, 2025) have demonstrated that incorporating light-driven plasticity of leaf traits can significantly improve simulated forest structure and composition during secondary regeneration in tropical forests. Implementing trait plasticity also requires developing and constraining other TBM modules, such as canopy radiative transfer and soil biophysics and biogeochemistry due to their importance in simulating post-disturbance microenvironment changes (Fig. 2a). In addition, knowledge gaps in the time scale, magnitude, and cost of trait plasticity limit the parameterization of plasticity schemes.

Third, models need to improve the representation of legacy effects from short-term nonlethal structural damage. When partial damage is implemented in models, it is straightforward to track carbon costs to regrow leaves and shoots and opportunity costs of reduced photosynthetic capacity (Needham *et al.*, 2022). These disturbance-induced carbon costs can reduce growth and increase mortality risk during recovery. While accurately modeling the carbon cost and legacy effects requires a deeper understanding in plant physiology, particularly nonstructural carbohydrate dynamics (Dietze *et al.*, 2014; Anderegg *et al.*, 2015a), phenomenological metrics can be leveraged. For example, Foster *et al.* (2026) used cumulative crown loss to predict delayed mortality from defoliators in the LANDIS-II model.

4. Managing complexity in disturbance model development

Dynamic disturbance regimes, trait-based hazard functions, and process-based recovery simulations increase model realism and flexibility so that models can better capture heterogeneity in disturbance impacts. However, they also carry the cost of higher model complexity. Managing model complexity is a well-recognized challenge across different components of land surface modeling (Fisher & Koven, 2020).

For increased complexity related to plant functional diversity, trade-offs and coordination among traits, such as the widely observed growth-mortality, growth-defense, and stature-reproduction trade-offs in forest ecosystems (Fine *et al.*, 2006; Rüger *et al.*, 2020; Kambach *et al.*, 2022), can be leveraged to reduce the parameter space dimensionality and help manage model complexity. It is also useful to organize trait diversity according to different strategies to deal with disturbances, similar to Grime's C-S-R framework (Grime, 1974). Plant traits and thus model parameters are coordinated to achieve life-history strategies, spanning stress avoidance (e.g. deep roots and drought deciduousness), stress tolerance (e.g. large hydraulic safety margin, flexible stems, and high reproduction rates), and stress escaping (e.g. sprouting).

For increased complexity related to spatial granularity (e.g. tracking individuals or cohorts), it has been demonstrated that tracking tree cohorts and sub-grid patches organized by age since last disturbance is a promising way to aggregate fine-scale processes to the landscape level (Moorcroft *et al.*, 2001; Fisher *et al.*, 2018). A few tens of dynamic patches can preserve first-order ecosystem heterogeneity generated by disturbances within each model grid and achieve grid-level dynamics comparable with averaging hundreds of ensembles. However, tracking spatial interactions is more difficult in TBMs. Sub-grid modeling units such as tiles or patches are generally spatially implicit. Horizontal interactions across grids are also limited (Fisher & Koven, 2020). Therefore, it is not straightforward to simulate contagious disturbance spread (e.g. fire, wind, pest and pathogen) and neighborhood interactions in demographic responses (e.g. seed dispersal or post-disturbance stem thinning). One naive strategy is to use finer spatial grains and explicitly model their horizontal interactions; however, this will incur geometrically increasing computational cost. McCabe & Dietze (2019) proposed a second-order spatially implicit framework to scale sub-grid contagious processes by tracking spatial adjacency matrices. This is a promising and computationally efficient approach for capturing spatial heterogeneity in disturbance modeling.

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IV. Detection and attribution of forest disturbances to constrain modeling

Model parameterization is a major source of prediction uncertainty in forest disturbance modeling and in TBMs in general (Bonan & Doney, 2018; Luo & Schuur, 2020). Moving toward more mechanistic disturbance models often comes with increased data needs for parameterization. Detection and attribution of forest disturbances from observations, especially at large scales, are fundamental to calibrating and validating models (He *et al.*, 2024).

Advances in spaceborne remote sensing in the last few decades have made large-scale disturbance detection possible (Frolking *et al.*, 2009; Rodríguez Paulino *et al.*, 2024). A milestone study by Hansen *et al.* (2013) estimated annual global forest cover change at 30 m spatial resolution using Landsat data, demonstrating how satellite data can inform forest disturbances modeling. Recent studies have further characterized disturbance regimes and their changes (Senf & Seidl, 2021a). Meanwhile, the accumulation of ground-based observations, near-surface remote sensing, and manipulative experiments provides rich information to constrain impact and recovery in models (Table 1). In this section, we discuss observational advances and remaining needs for constraining mechanistic disturbance modeling across three areas.

1. Integrating multi-scale observations to constrain disturbance regimes

High-quality data on agent-specific disturbance patterns are critical for modeling dynamic disturbance regimes. Building on advances in disturbance detection, recent studies have rapidly improved in disturbance attribution based on temporal–spatial–spectral features of satellite data. However, attribution accuracies vary among disturbance agents, with generally better performance for anthropogenic than for natural disturbances (Curtis *et al.*, 2018; Stahl *et al.*, 2023; Qiu *et al.*, 2025; Sims *et al.*, 2025). Except for hurricanes, large fires, and severe droughts, accurate attribution of natural disturbances is challenging because there are usually no accompanying high-resolution records of plant stress levels. Compound disturbances further complicate the attribution. For example, during drought events, it can be difficult to determine whether forest mortality detected from remote sensing data is directly driven by water stress, biotic attacks, or other coinciding factors (Aleixo *et al.*, 2019).

Integrating multiple data sources is needed to address this challenge. High-quality and expansive ground data on disturbance causes are valuable for attributing satellite-based disturbance events and to train statistical or machine learning models to predict disturbance cause (Senf & Seidl, 2021b). Yet, stand-scale censuses typically follow multi-year cycles, making it difficult to acquire timely pre- and post-disturbance information for attribution. Annual or rapid-response sampling strategies may alleviate this and allow better attribution (Arellano *et al.*, 2021). However, such ground campaigns are not easily scalable beyond existing forest plot networks, and limited spatial footprints can amplify uncertainty in estimating disturbance impacts, particularly for rare events, such as large tree mortality (Gora & Esquivel-Muelbert, 2021). The increasing use of unmanned aerial vehicles (UAVs) for ecological monitoring can help to bridge the scale gap between ground and satellite observations. Repeated UAV flights successfully quantified canopy disturbance across 1500 hectares of forest in Central Panama, capturing crown-level damage patterns useful for attribution and driver analyses (Cushman *et al.*, 2022; Araujo *et al.*, 2025).

2. Detecting disturbance impacts and recovery beyond tree cover change

Satellite-based disturbance products mostly report tree cover changes or landscape severity indices (Hansen *et al.*, 2013; Senf & Seidl, 2021a). While these metrics can characterize stand-replacing or other high-severity disturbance events, they do not easily translate into response variables used in disturbance hazard functions, such as biomass loss and stem mortality (Fig. 4). Furthermore, disturbances such as drought, wind, lightning strikes, and biotic attacks by forest pests and pathogens tend to operate at individual-canopy scales, particularly in ecosystems with higher species diversity. The spatially sporadic death of large canopy trees can lead to significant biomass loss at the ecosystem scale and create heterogeneous ecosystem resources. For example, the vast majority of biomass mortality in tropical forests occurs in < 0.1-hectare disturbance events (Espírito-Santo *et al.*, 2014). Yet, such individual-level disturbance impacts are difficult to detect even with 10–30 m remote sensing data.

Crown and sub-crown level observations are critical to quantifying fine-scale disturbance impact. A prime example is NASA G-LiHT airborne campaigns over Puerto Rico, including data before and shortly after Hurricane Maria in 2017. Repeated RGB imagery at *c.* 3 cm resolution provides finer detail on hurricane damage than Landsat and MODIS satellite images (Fig. 5), allowing for crown-level damage analysis that can be used to calibrate disturbance hazard functions (Ankori-Karlinsky *et al.*, 2025; Han *et al.*, 2026). In addition to optical data, repeat airborne lidar data (Fig. 5, last column) can track forest structural changes in crown height, size, and volume, as well as crown-level post-disturbance recovery. Regional-scale studies with airborne images and lidar data have offered important insights into the frequency of canopy turnover events, gap formation rates, and their associated carbon fluxes (Leitold *et al.*, 2018, 2022; Dalagnol *et al.*, 2021).

At the global scale, where sub-crown resolution remote sensing images are not readily available, an alternative approach is to leverage multiple data streams to infer ecologically meaningful variables other than tree cover. For instance, nonphotosynthetic vegetation fraction changes estimated from satellite data with spectral unmixing analysis have been used to predict stand-level tree mortality following severe wind disturbances (Chambers *et al.*, 2007; Negrón-Juárez *et al.*, 2011). Temporal autocorrelation of vegetation greenness time series has also been proposed as a good predictor of biomass mortality rate during drought (Liu *et al.*, 2019; Wu *et al.*, 2022). Recently, vegetation optical depth (VOD) calculated from microwave remote sensing products has been widely used to estimate landscape-scale biomass changes,

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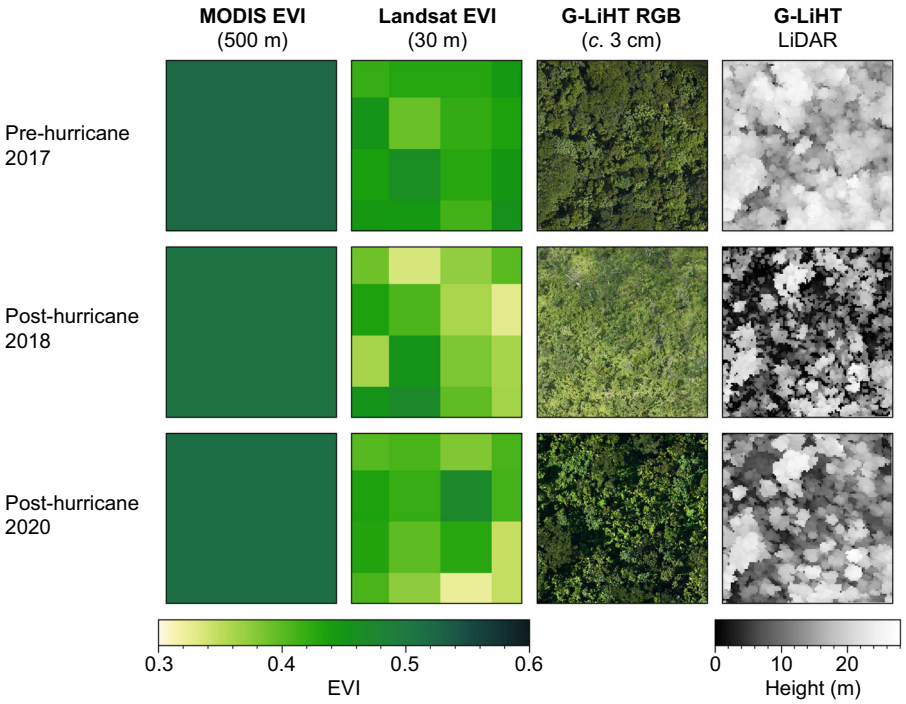

Fig. 5 Disturbance impacts and recovery for Hurricane Maria at the Luquillo Forest Dynamic Plot (LFDP) in Puerto Rico assessed from different remote sensing platforms. Observations for Enhanced Vegetation Index (EVI) were calculated from MODIS NBAR (first column, 500 m spatial resolution) and Landsat 7/8 Collection 2 data products (second column, 30 m spatial resolution) using the median observation over a one-year period immediately prior and post-Hurricane Maria and the corresponding period 3 yr after. Data from NASA Goddard's Lidar, Hyperspectral, and Thermal (G-LiHT) Airborne Imager highlight fine-scale details from stereo air photographs (third column, 3 cm spatial resolution) and lidar-based canopy height models (fourth column, 1 m spatial resolution). High resolution and timely observations help to detect heterogeneous hurricane damages that are critical to model impacts and post-disturbance recovery. G-LiHT data collection was supported by the USDA Forest Service International Institute of Tropical Forestry and NASA. See Leitold *et al*. (2022) for additional details.

particularly in response to regional droughts (Wigneron *et al*., 2020). Finally, data fusion of multi-modal and multi-platform sensors (lidar, radar, optical, and hyperspectral) can combine their complementary information, providing high-resolution and continuous data products to parameterize and evaluate large-scale forest disturbance modeling (Silva *et al*., 2021; Tang *et al*., 2023).

3. Leveraging manipulative experiments

In addition to observational approaches, manipulative ecosystem experiments that measure multi-scale forest responses to controlled disturbances are highly valuable for constraining mechanistic sub-modules in disturbance modeling. For instance, experimental drought in Tapajós National Forest, Brazil, served as a critical benchmark dataset for dynamic vegetation models (Fisher *et al*., 2007; Powell *et al*., 2013), which motivated a series of throughfall exclusion experiments across forest ecosystems globally. Controlled tree damage and removal experiments, such as the Hurricane Simulation Experiment at Harvard Forest (Cooper-Ellis *et al*., 1999), the Canopy Trimming Experiment in Puerto Rico (Shiels *et al*., 2014), and the Michigan FASET experiment (Gough *et al*., 2022), provide observations on post-disturbance dynamics of forest structure and demography under different disturbance severities. Other experiments target disturbance interactions, such as the drought-fire experiment in the southern Amazon (Brando *et al*., 2014) and wind-fire experiment in the southeastern United States (Cannon *et al*., 2019). Model development should leverage these rich datasets and develop model intercomparison and perturbation studies targeting these manipulative experiments (e.g. Powell *et al*., 2013; Holm *et al*., 2023; Haber *et al*., 2025).

V. Conclusion

Our review highlights the ecological foundation of disturbance modeling and summarizes practice and challenges in modeling occurrence, impact, and recovery from individual trees to community and ecosystem levels. Although much progress has been made over the past decades, especially for fire and drought, representation of disturbance remains oversimplified in models. Building on this synthesis, we propose the following priority research directions for the forest disturbance modeling community:

(**1**) Move beyond a simple background disturbance rate in occurrence modeling and develop disturbance regime datasets that can be readily used as model input to represent spatially and temporally varying disturbance rates. Such datasets should also be used to infer climatic sensitivities of disturbance regimes to enable dynamic occurrence modeling. Major forest disturbance agents, such as fire, drought, storms, lightning, and forest pests, should be separated and their occurrence covariance estimated.

(**2**) Implement disturbance hazard functions for both tree mortality and nonlethal damage, leveraging accumulated data from natural disturbances and manipulative experiments. Parameters of these hazard functions should be linked to traits (tree size, wood density, hydraulic safety margin, etc.) and plant physiological variables (nonstructural carbohydrates and plant water potential) measurable from ground and remote sensing.

(**3**) Improve recruitment and regeneration processes in models by more explicitly considering seed dispersal, seed germination, and sprouting. These processes are essential for predicting post-disturbance community reorganization. Trait plasticity in response to rapid changes in post-disturbance microenvironment, and the legacy effects of partial damage on forest demography, should also be included.

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(4) Integrate efforts and knowledge across the modeling, field, and remote sensing communities with the iterative Model-Experiment integration approach. Model evaluation should also go beyond ecosystem-level metrics (e.g. carbon and water fluxes) and include demographic rates and forest structural changes as in recent effort by Díaz-Yáñez *et al.* (2024) and Eckes-Shephard *et al.* (2025).

Changing disturbance regimes are increasingly threatening global forest ecosystems alongside chronic climate change. Mechanistic simulation of disturbance, building upon ecological principles and observations across scales, is essential for reducing uncertainties in forecasting global change impacts on ecosystems and carbon cycle feedbacks.

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Competing interests

None declared.

ORCID

William R. L. Anderegg https://orcid.org/0000-0001-6551-3331
Evan Gora https://orcid.org/0000-0002-0537-5835
Tao Han https://orcid.org/0000-0001-9164-284X
Winslow D. Hansen https://orcid.org/0000-0003-3868-9416
Charles D. Koven https://orcid.org/0000-0002-3367-0065
Yanlan Liu https://orcid.org/0000-0001-5129-6284
Yiqi Luo https://orcid.org/0000-0002-4556-0218
Yixin Ma https://orcid.org/0000-0002-4454-8559
Douglas C. Morton https://orcid.org/0000-0003-2226-1124
Cameron Scholl https://orcid.org/0000-0002-5216-5021
Maria Uriarte https://orcid.org/0000-0002-0484-0758
Xiangtao Xu https://orcid.org/0000-0002-9402-9474

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