Review paper

# From Equations to Geospatial Foundation models. What comes next for forest prediction?

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## Abstract

Predicting forest attributes and dynamics has long been a central objective of forestry, yet robust and transferable prediction remains challenging. Forest ecosystems are intrinsically heterogeneous, only partially observable, and shaped by interacting processes operating across multiple spatial and temporal scales. Over the past decades, predictive modelling has expanded across methodological paradigms that differ fundamentally in where predictive information is encoded and how it is learned. This perspective traces this evolution from equation-based models to machine learning, deep learning, and most recently, geospatial foundation models (GeoFMs). We do not view these paradigms as a succession of increasingly superior approaches, we examine them through the lens of environmental representation learning, with particular attention to how information about forest ecosystems is represented, learned, and transferred across tasks and contexts. GeoFMs extend this trajectory through large-scale self-supervised pretraining on Earth observation data, offering the potential to reduce dependence on task-specific labelled datasets and transfer learned representations across contexts and prediction tasks. However, much of this potential remains unrealized in forestry. The ecological meaning of learned representations remains poorly understood, their robustness across space and time is insufficiently established, and current applications largely focus on forest state inference rather than explicitly learning and predicting forest state evolution. We identify key research directions for addressing these limitations and propose a framework for guiding model choice across predictive paradigms. We ultimately position GeoFMs as complementary to, rather than replacements for, existing modelling approaches and argue that future advances in forest prediction may increasingly depend on how their respective strengths are combined.

## Keywords

Forest modelling, machine learning, deep learning, geofoundation models, representation learning, model transferability, earth observation

## Introduction

Forests cover nearly one-third of Earth's land surface, harbor a substantial share of the world's terrestrial biodiversity, and mediate major fluxes of carbon, water, and energy between the biosphere and atmosphere (Bonan 2008; FAO and UNEP 2020). Understanding and predicting the dynamics of forest ecosystems has been a central goal of forest ecology for more than a century yet anticipating forest dynamics remains challenging. Forests are complex adaptive systems shaped by interactions among biological, climatic, and anthropogenic processes operating across multiple scales of space, time, and biological organization (Levin 1992). Patterns observed at broader scales can emerge from localized interactions and selection processes operating at lower levels (Levin 2005; Messier et al., 2013). Historically, forest systems have been represented through state variables, such as biomass, stand density, and species composition, and process variables, including growth, mortality, and regeneration. These representations provided the basis for both inferring forest states and predicting their dynamics through time across different forest types and successional stages (Bugmann 2001; Purves and Pacala 2008).

Over the past few decades, however, the epistemological basis of forest attribute and ecosystem dynamics prediction has undergone a profound transformation. Approaches have evolved from statistical, heuristic, and theory-driven models toward increasingly data-driven methods (Reichstein et al. 2019; LaDeau et al. 2017), driven by a convergence of Earth observation (EO), proximal sensing technologies, flux tower networks, and large-scale forest inventories that now generate continuous, multidimensional observations at unprecedented spatial, temporal, and spectral resolutions (Schimel and Keller 2015; Pettorelli et al. 2014). Moreover, the objective of forest monitoring has expanded beyond traditional timber production to include biodiversity conservation, ecosystem restoration, and the broader provision of ecosystem services (Corona 2016). These developments have consequently shifted the challenge from the historical scarcity of observations to the capacity to transform large volumes of heterogeneous data into meaningful information, information into ecological knowledge, and knowledge into reliable predictions across an expanding range of forest attributes, ecosystem dynamics, and management objectives (Jung et al. 2020; Hansen et al. 2013).

Nevertheless, despite recognized advances in several key forest applications including growth prediction, species distribution modelling, and wildfire forecasting (Boukhris et al. 2025; Pecchi et al. 2019; Jain et al. 2020), forestry has not yet experienced the same degree of "predictive transformation" observed in adjacent environmental fields including for instance meteorology, hydrology, and climate science (Bauer et al. 2023; Kratzert et al. 2019). The complexity of biological and human interactions, the context-dependence of ecological processes, and the absence of universal laws like those governing physical systems, all constrain predictive generalization in forestry (Dietze 2017; Dietze et al. 2018). Forest prediction therefore remains largely contextual, modality-specific, and temporally constrained, with models often showing limited transferability across ecosystems characterized by different processes, disturbance regimes, and management contexts. In contrast, fields such as data-driven weather forecasting systems, have rapidly approached or exceeded the accuracy of operational physics-based forecasts at substantially lower cost, contributing to a broader transformation of the field (Lam et al. 2023; Price et al. 2025). These are not temporary obstacles that can be overcome by large volumes of data but reflect intrinsic properties of forest ecosystems that call for modelling paradigms capable of transforming heterogeneous observations into ecological understanding and, ultimately, into robust generalizable prediction.

It is within this context of persistent challenges in ecological prediction that foundation models (FMs) have recently emerged as a potentially important development (Sadel et al. 2025; Morera 2024). Rather than representing a discontinuity with previous approaches, their significance lies in a further redistribution of where predictive information is learned and encoded within the modelling process. FMs can learn reusable representations that may subsequently be adapted across ecosystems, sensing modalities, and prediction tasks. Their relevance for forestry therefore lies not only in predictive accuracy, but in the possibility of reusing learned environmental representations across locations and applications, potentially reducing dependence on task-specific models and labelled observations.

This perspective traces the historical evolution of predictive methods in forestry across key application domains, from equations-based models (EbMs) to machine learning (ML), deep learning (DL), and more recently geospatial foundation models (GeoFMs), examining how these modelling paradigms have changed the ways in which forest attributes and ecosystem dynamics are represented and predicted, while highlighting their respective strengths and limitations (see Figure 1 and Table 1). Rather than representing a linear succession in which one paradigm replaces another, this evolution reflects changing approaches to how predictive knowledge is specified, learned, and transferred. Finally, this perspective builds toward a framework for implementing GeoFMs within forestry. The goal is not to replace the ecological understanding accumulated over centuries of forest science, but to explore how this knowledge can be integrated with increasingly transferable representations to support the prediction and decision-making demands of the twenty-first century.

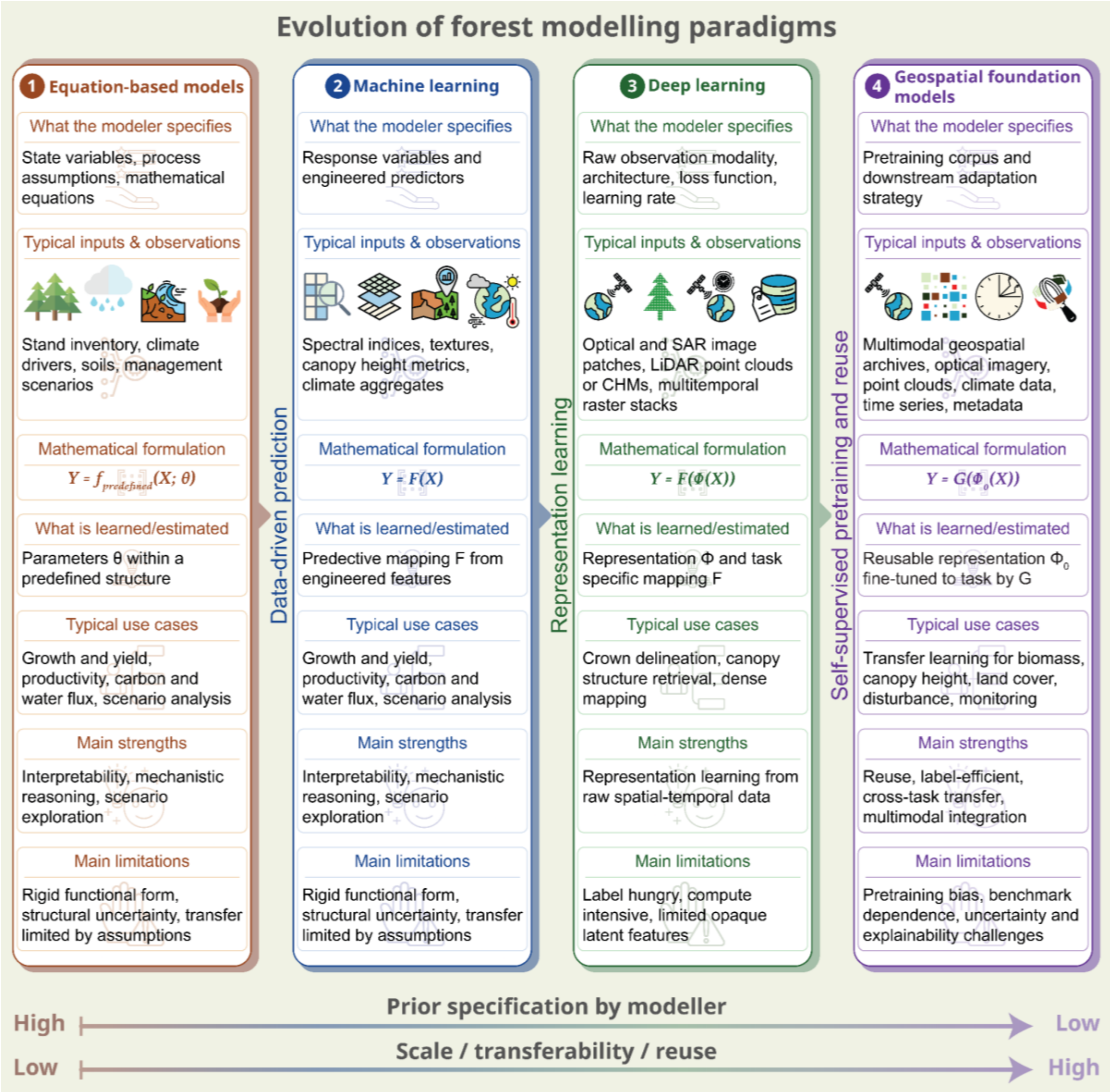


Figure 1: Evolution of predictive paradigms in forestry. The paradigm shift, across EbMs, ML, DL, and GeoFMs reflects a gradual change in how predictive and ecological knowledge is presented, specified, and learned. Across these paradigms, reliance on prior specification by the modeller decreases while representation learning, scalability, transferability, and model reuse increase. Each paradigm is characterized by distinct assumptions, data requirements, learning strategies, strengths, and limitations, and should therefore be viewed as complementary rather than strictly substitutive.

**Box: definition of key concepts**

Equation-based models (EbMs): Models that represent forest attributes or processes through explicitly specified mathematical relationships derived from empirical data, theory, or process understanding.

Machine learning (ML) models: Data-driven models that learn relationships between engineered predictors and target variables from training data without explicitly prescribing these relationships.

Deep learning (DL) models: A subset of ML based on multilayer neural networks that can automatically learn complex representations from data.

Geospatial foundations models (GeoFMs): Models pretrained on large and multimodal geospatial datasets to learn general-purpose representations that can be subsequently adapted to multiple downstream tasks.

Self-supervised pretraining: Training in which supervisory signals are derived from the data themselves, allowing representations to be learned without explicit labels.

Downstream task: A specific application to which a pretrained model or its learned representations are subsequently adapted.

## 2. State of the art of EM, ML, and DL in Forestry Sciences

### 2.1. Equation-based models (EbMs)

Systematic attempts to predict forest dynamics predate digital computation by more than a century. In the early nineteenth century, Georg Ludwig Hartig and Heinrich Cotta laid the foundations of modern forest yield science by introducing yield tables that quantified stand development and timber production, translating field observations into operational tools that could guide management decisions across stands and time periods (Assmann 1970; Pretzsch 2010). Meanwhile, naturalists documenting forest recovery after disturbances began recognizing recurrent successional patterns, early entomologists described the cyclical dynamics of insect outbreaks (Royama 2012; Raffa et al. 2008), and French engineers investigating catastrophic floods demonstrated the hydrological consequences of deforestation, promoting watershed restoration as both an ecological and engineering imperative ("Défense des Eaux et des Sols"). This conviction constitutes the intellectual origin of predictive forestry, not as a unified discipline, but as a recognized practice of extracting structured prediction from a recurrent ecological pattern (Messier et al., 2012).

The twentieth century brought a profound transformation with the rise of statistical methods and digital computation which did not replace earlier insights, but rather, formalized them. Regularities that had previously been expressed through tables, heuristics, or rules of thumb were translated into mathematical equations that could be systematically evaluated across stands and time periods (Vanclay 1994; Weiskittel et al. 2011) Prediction thus shifted from tabulated knowledge to computable relationships. This transition gave rise to what became the dominant paradigm of ecological prediction, i.e. “equation-based modelling”, in which the modeller specifies the mathematical structure of system behavior and empirical observations are used to calibrate its parameters (Levins 1966; Oreskes et al., 1994).

Within this framework, models differed primarily in the extent to which ecological mechanisms were explicitly represented. Some remained largely empirical, relating stand attributes directly to observed responses without explicitly representing underlying processes (Vanclay, 1994; Weiskittel et al., 2011). On the other hand, semi-empirical formulations incorporated theoretical relationships such as allometric scaling, light attenuation, or temperature response functions while retaining calibration from measurements (Landsberg and Waring 1997). As ecological understanding deepened, process-based models (PBMs) began to represent the internal functioning of forest ecosystems more explicitly, simulating carbon assimilation, water balance, competition, disturbance, and regeneration (Mäkelä et al. 2000; Fontes et al. 2010; Boukhris et al. 2025). This translated into hybrid approaches, that later combined mechanistic representations with empirical models to balance realism and tractability (Bugmann 2001; Kimmins et al. 1990; Mahnken et al. 2022). Despite differences in complexity and realism, all these approaches rely on explicitly specified model structures that embody prior ecological hypotheses, with observations serving primarily for parameter calibration and validation (Levins 1966).

This modelling tradition proved remarkably influential because it forged a powerful link between ecological understanding and practical prediction. By embedding hypotheses about system functioning into equations, EbMs enabled researchers and managers to explore scenarios, interpret ecological mechanisms, and extrapolate outcomes within known environmental conditions (Battaglia and Sands 1998; Mäkelä et al. 2000). Their transparency and interpretability made them indispensable tools in forest planning, ecosystem research, and resource management (Pretzsch 2010; Boukhris et al. 2025). However, the very feature that gives these models their explanatory clarity also introduces important constraints. Because relationships must be specified in advance, ecological responses are necessarily framed within predetermined mathematical forms, most often low-dimensional functions such as linear, polynomial, or logistic relationships. In complex ecological systems, however, processes are often nonlinear, context-dependent, and shaped by multiple interacting variables. Consequently, ecological complexity can become simplified, or even obscured, by the dictated structure of the model rather than revealed by the data.

Additional challenges arise during parameter estimation. Statistical calibration typically relies on assumptions about independence, variance structure, and error distributions that ecological datasets rarely satisfy. Spatial and temporal autocorrelation, hierarchical organization, and uneven sampling are common features of ecological data, complicating inference and increasing uncertainty (F. Dormann et al. 2007; Zuur et al. 2009). Moreover, increasing model realism often requires detailed prior knowledge of ecological processes. When such knowledge is incomplete, poorly understood mechanisms must be simplified or replaced by empirical approximations, introducing structural uncertainty into the model itself (Beven 2006; Luo et al. 2009). As a result, predictive performance is often strongest within the domain where the model was calibrated, while transferability to novel environmental or management conditions remains limited (Yates et al. 2018; Seidl et al. 2017). Finally, because parameter estimates depend directly on observational data, uncertainties related to measurement error, sampling design, or data quality can propagate through the predefined equations and influence model outputs (Clark et al. 2001; Dietze 2017).

These characteristics reflect a defining feature of equation-based modelling. Relationships among variables are specified a priori and subsequently calibrated against observations. Such specification is both a strength and a constraint. It allows established ecological knowledge and mechanistic hypotheses to be represented explicitly, enhancing interpretability and enabling predictions to be grounded in prior understanding. At the same time, predefined functional structures constrain the relationships that a model can express and may become increasingly difficult to formulate as ecological datasets expand, and the dimensionality of potential indicators increases. The central distinction from data-driven approaches is therefore not between models that contain assumptions and models that do not, but rather in how these assumptions and relationships are represented; explicitly through prescribed model structure or increasingly learned from observations. This challenge raises a fundamental question for ecological modelling regarding to what extent should model structure be prescribed in advance, and to what extent should it emerge from data? (Evans et al., 2012).

## 2.2. Machine Learning (ML)

The expansion of forest inventories, earth observation archives, and environmental databases created the conditions for a fundamentally different modelling strategy, one in which predictive relationships are inferred from data rather than being prescribed a priori by the modeller. Where EbMs require the functional forms of ecological relationships to be specified before calibration can begin, ML approaches estimate the mapping $Y=F(X)$ from paired observations of predictors $X$ and responses $Y$ without imposing explicit assumptions about the form of $F$. Model structure therefore emerges, to some extent, during training through optimization procedures rather than being defined in advance (Olden et al., 2008; Cutler et al., 2007). This represents a change in the underlying source of predictive structure. While EbMs encode ecological relationships through prior specification, ML relies more strongly on observations to infer these relationships empirically. The modelling challenge consequently shifts toward the choice and adequacy of the variables through which the forest is represented.

ML methods gained prominence in forestry primarily through remote sensing applications, where high-dimensional predictor spaces and complex nonlinearity challenged the structural assumptions of classical regression (Fassnacht et al. 2016; Wulder et al. 2008). Random forests, support vector machines, and gradient boosting algorithms proved particularly effective for biomass estimation, disturbance detection, and large-scale forest attribute mapping (Latifi et al., 2012; Maxwell et al., 2018). These developments positioned ML not only as a computationally convenient approach, reflecting a different basis for prediction in environmental science, in which relationships are learned primarily from observations rather than explicitly formulated from mechanistic understanding (Reichstein et al. 2019).

The ML approach has two important consequences. First, predictive validity becomes contingent on the stability of the joint distribution P(X,Y) between training and application contexts, where EbMs require statistical and mechanistic correctness, ML requires distributional consistency. Second, the flexibility that enables ML to approximate complex nonlinear interactions without prior ecological specification comes at the cost of reduced interpretability and limited process transparency (Dormann et al. 2012; Rudin 2019).

Moreover, transferability represents the most persistent operational limitation shared with the EbMs. ML models frequently perform well within the environmental space represented in the training data but degrade when extrapolated to novel climate conditions, disturbance regimes, or sensor configurations (Yates et al. 2018; Meyer and Pebesma 2021). This constraint is compounded by spatial autocorrelation and hierarchical data structures, as geographically clustered forest plots cause conventional random hold-out validation to systematically overestimate predictive performance, making spatial cross-validation necessary for realistic out-of-sample performance assessment. Under rapid environmental change, the distributional stability on which ML validity stands can no longer hold. The failure is not algorithmic but statistical as it reflects non-stationarity in the joint distribution P(X,Y), and no refinement of the learning procedure can compensate for a relationship that has itself changed.

A parallel constraint operates at the level of representation. Although ML learns functional mappings from data, the predictor variables themselves, vegetation indices, texture measures, canopy height metrics, aggregated climate variables, must still be constructed a priori through the so-called “feature engineering” (Belgiu and Drăguţ 2016; Maxwell et al., 2018). The modeller therefore retains the “intellectual responsibility” for defining how ecological information enters the model. This representational bottleneck is structurally like the specification bottleneck of EbMs in the sense that rather than prescribing the form of ecological relationships, the modeller prescribes the variables through which the system is described. If critical structural or physiological signals are absent from the engineered feature space, no learning algorithm can recover them, a constraint that becomes increasingly acute as remote sensing datasets grow in dimensionality and temporal depth (Reichstein et al. 2019).

ML thus represents an important shift in predictive modelling rather than a replacement for equation-based approaches. It relaxes the requirement to specify functional relationships in advance and enables complex, high-dimensional empirical prediction to be directly inferred from observations. Yet it displaces rather than dissolves the modeller's burden, shifting it from functional specification to the selection of informative predictors and ensuring their representativeness across the conditions in which predictions are made. This raises a natural question for the paradigm that follows, if neither relationships nor variables need be prescribed in advance, what remains for the modeller to define?

## 2.3. Deep Learning (DL)

DL is a subfield of ML that uses multilayer neural networks to jointly learn hierarchical representations of input data and the predictive mappings that operate on them (LeCun et al. 2015; Reichstein et al. 2019). While classical ML treats the predictor variables describing forest structure or physiology as given and learns only the function that maps them to a response, DL learns both, allowing the relevant features to emerge from raw observations during training. In epistemological terms, this shifts the modelling problem from designing ecological variables to learning representations of forest structure directly from data. Meaning, instead of approximating a function over predefined variables, DL models jointly infer hierarchical features and prediction rules from the data automatically (LeCun et al. 2015; Reichstein et al. 2019). Formally, ecological prediction can be expressed as $Y = F(\Phi(X))$, where the representation $\Phi(X)$ denotes a learned representation of forest structure and dynamics, capturing patterns that are not explicitly encoded in predefined ecological variables, and F maps that representation to a specific forestry task. DL can also infer latent descriptors of canopy geometry, vertical stratification, phenological stage, or disturbance patterns directly from data. This shift reflects a broader transition in environmental modelling from "feature engineering" to "representation learning". In this sense, the modelling task moves from selecting ecological descriptors to learning hierarchical abstractions of ecosystem structure and dynamics.

These applications have been enabled by advances in DL architectures designed to jointly process spatiotemporal data. Convolutional neural networks (CNNs) capture spatial organization in high-resolution imagery through local receptive fields and hierarchical feature extraction, allowing models to learn complex structural patterns from observations (Kattenborn et al. 2021). Recurrent architectures extend this capability to temporal sequences, enabling analysis of ecosystem dynamics in time series. More recently, transformer-based models capture long-range spatial and temporal dependencies and facilitate integration of multi-sensor observations across large regions (Vaswani et al. 2023; Dosovitskiy et al. 2021). Together these developments have shifted forest monitoring from statistical attribute estimation toward continuous observation of structural and functional change, where forest ecosystems are analyzed increasingly as spatiotemporal patterns rather than collections of predefined variables.

Therefore, the strength of DL lies in its capacity to exploit patterns inaccessible to handcrafted predictors, enabling consistent interpretation across heterogeneous landscapes. Hence, while ML reduces the need to prescribe the functional relationship between predefined variables, DL reduces the need to prescribe the variables themselves by learning representations directly from observations. This however does not eliminate prior assumptions, which change in nature; the architecture, training objective of the learning model, the data distribution, and target task remain specified by the modeller.

However, this flexibility introduces new challenges. Supervised training requires a substantial amount of manually labelled data, which remains scarce in many forest biomes, and the ecological meaning of learned representations is often implicit (Tuia et al. 2022). While models may reliably identify canopy states or disturbance events, their internal features are not directly linked to physiological processes such as growth allocation or carbon dynamics. Consequently, DL can describe forest patterns without necessarily explaining their mechanisms, highlighting the distinction between "predictive representation" and "mechanistic ecological understanding". Moreover, generalization still depends on training coverage, and novel environmental conditions or disturbance regimes may alter learned representations.

By constructing its own representation of ecosystem structure and dynamics from raw observations, DL has enabled unprecedented spatial and temporal detail in forest monitoring, yet it also weakens the explicit connection between prediction and ecological interpretation, and, critically, makes the construction of the representation $\Phi$ itself the central modelling challenge. The learned representations may have limited ecological interpretability. Rather, the principal question changes from which predictors should be engineered to which representations can be learned from the available observations. This raises a natural question consisting of whether $\Phi$ must be relearned from scratch for every new task and region, or can it be learned once, at scale, and reused across them?

These developments represent substantial methodological progress in extending the applicability of data-driven forest models. Yet, they address specific failure modes without resolving the underlying condition that produces them. That models learned within a specific domain, from a specific observational record, with representations shaped by that domain, cannot be straightforwardly generalized beyond the conditions of their construction. The collective trajectory of these advances, toward broader representations, richer temporal context, cross-modal integration, and reduced label dependence, points toward a qualitatively different modelling paradigm, one in which the representation $\Phi$ is not constructed for a specific task or region but learned across the full diversity of forest observations and applied wherever sufficient ecological signal exists. It is this architectural possibility that FMs are designed to realize.

## 3. Geospatial foundation Models: Opportunities and Challenges for Forestry Sciences

FMs extend the DL paradigm by addressing one of its central limitations, namely the need to train a separate representation $\Phi$ together with a task-specific mapping F for every new prediction task and region. An FM is, in operational terms, a single large neural network that is (i) pretrained on broad, heterogeneous data using self-supervised objectives, and (ii) subsequently adapted to many downstream tasks through fine-tuning or prompting. Self-supervision is the technical mechanism that makes this feasible. Rather than relying on human-provided labels, the model creates its own supervisory signal by predicting masked or corrupted parts of the input from the surrounding context, thereby learning statistical regularities directly from raw observations (He et al. 2022). At sufficient scale, such pretraining yields representations that exhibit emergent capabilities, i.e., generalization to tasks and conditions not seen during training, which is the property that distinguishes FMs from earlier instances of pretraining and transfer learning (Bommasani et al., 2021).

Formally, the modelling objective shifts from estimating a task-specific representation $\Phi$ together with its mapping F, $Y = F(\Phi(X))$, to first learning a shared representation $\Phi_0$ at scale during pretraining and then deriving task-specific predictions through mappings of the form $Y = G(\Phi_0(X))$. The primary modelling effort therefore moves from repeatedly training a new representation for each task to learning $\Phi_0$ once, in such a way that it captures environmental regularities such as spatial structure, temporal dynamics, and cross-sensor relationships that generalize across ecological contexts. Concretely, $\Phi_0(X)$ maps an input (e.g., a satellite tile, a multi-temporal image stack, a multi-sensor patch) to a compact vector representation, or "embedding", that summarizes its environmental content in a form that downstream task heads can exploit with minimal additional training.

In the context of earth observations, FMs trained on environmental and remote-sensing archives are increasingly referred to as GeoFMs (Jakubik et al. 2023; Yang et al. 2025). While conventional supervised deep learning trains a separate model per task, GeoFMs are trained as “generalists”, once, on broad data, without commitment to any specific downstream objective, and then are “specialized” many times. They are pretrained on large and heterogeneous environmental datasets (e.g. global satellite archives, multimodal earth observation data) to produce general representations of Earth-system dynamics that can subsequently be adapted to multiple downstream tasks (Jakubik et al. 2026; Ravirathinam et al. 2026).

The emergence of GeoFMs reflects the convergence of several developments. First, transformer-based architectures (Vaswani et al. 2023) made it computationally tractable to learn long-range dependencies across spatial and temporal data, and modern GPU and cloud computing infrastructures made large-scale pretraining feasible (Kaplan et al. 2020). Second, manual annotation of environmental datasets remains costly and geographically uneven, particularly for ecological variables such as biomass, species composition, or disturbance type. Moreover, annotations are often location-dependent, i.e. spectral signatures vary with atmospheric conditions, acquisition geometry, and phenological stage, limiting the transferability of models trained in a single region. Third, self-supervised pretraining circumvents this label bottleneck in the sense that techniques such as masked autoencoding (i.e., in which the model reconstructs masked portions of the input) and contrastive learning (i.e., in which the model learns to identify which observations correspond to the same physical location across time or sensors) extract regularities directly from large volumes of unlabeled data (Vincenzi et al. 2020; Ayush et al. 2022; Cong et al. 2023). These developments made it possible to train $\Phi_0$ at planetary scale and then reuse it across specific forestry tasks, which is the practical mechanism behind the FM paradigm.

### 3.1. Opportunities and implications for forest modelling

Capturing forest ecosystems often requires the integration of multiple observation sources, including optical imagery, synthetic aperture radar (SAR), LiDAR, forest inventories, ancillary data, and climatic information. This multimodal and heterogeneous information landscape makes forestry a particularly relevant domain for GeoFMs, which offer new opportunities to integrate and transfer information across data sources, tasks, and contexts (Wulder et al. 2012;

Fassnacht et al. 2016; Dubayah et al. 2020). At least four properties of GeoFMs are particularly relevant to addressing persistent challenges in forest prediction.

A first challenge concerns the scarcity and uneven distribution of labelled ecological data. Although global EO archives such as Landsat and Sentinel currently provide near-continuous observations of forest ecosystems (Crawford et al. 2023; Claverie et al. 2018), field measurements of aboveground biomass, species composition, disturbance history, and ecosystem functioning remain sparse and geographically biased. Establishing and maintaining forest inventories is financially and logistically demanding, that most forest regions in the world have not made and cannot afford to replicate, leading to major disparities in data availability across regions. Consequently, many forest modelling applications face an abundance of observations but a shortage of reliable labels. This imbalance is precisely one of the problems that self-supervised pretraining seeks to address. In this sense, GeoFMs may change the economics of forest modelling by reducing the amount of costly task-specific labelled data required to develop predictive models.

A second challenge concerns the multimodal nature of forest observation (Iheaturu et al. 2026). No single observation source captures all relevant dimensions of forest ecosystems. Optical imagery provides information on canopy reflectance and phenology but only limited information on vertical structure. LiDAR directly measures canopy height and structural complexity but remains spatially sparse. Radar observations are sensitive to vegetation structure, moisture conditions, and topography, but their interactions with forest properties are often complex. Forest inventories provide detailed ecological measurements, but only at a limited number of locations. Multimodal GeoFMs are particularly attractive in this respect because they can learn shared representations from heterogeneous observation systems, potentially combining complementary information within a common representation space (Hill et al., 2021).

A third challenge concerns transferability across ecological contexts. Forest ecosystems span broad gradients in climate, species compositions, canopy structure, and disturbance regimes, such that relationships learned in one region may not remain valid elsewhere. Limited transferability has long affected empirical, ML, and DL approaches, particularly when training data represent only a restricted portion of the environmental conditions encountered at prediction time (Ludwig et al. 2023). GeoFMs potentially address part of this limitation by learning representations from geographically extensive EO archives rather than exclusively from task-specific labelled datasets. However, geographically broad pretraining does not guarantee that either the learned representations or their downstream predictive relationships will remain stable across ecological domains (Madadikhaljan et al., 2026; Romero et al., 2026). Determining when GeoFMs representations can be transferred directly, and when regional adaptation remains necessary, therefore represents an important challenge for their applications to forests.

A fourth challenge concerns the representation of long-term forest dynamics. Forest ecosystems are fundamentally temporal systems in which succession, disturbance, recovery, and management operate over years to decades. However, many predictive approaches still rely on static snapshots of forest conditions. Long EO archives now make it possible to observe temporal trajectories of canopy development, disturbance, and regrowth directly. By pretraining on multi-temporal observations spanning large spatial extents, GeoFMs may learn representations that encode forest development and ecosystem change, thereby supporting applications that extend beyond static applications toward the modelling of dynamic forest processes (Klemmer et al. 2024; Q. Feng et al. 2025; Cong et al. 2023; Zhang et al. 2025).

Several GeoFMs proposed in recent years illustrate this potential. AlphaEarth Foundations (AEF), for example, is a self-supervised GeoFM pretrained on multimodal data from the Earth Engine Data Catalog, including optical, SAR, LiDAR, ancillary variables, and text embeddings (Brown et al. 2025). In tree-species classification, AEF embeddings achieved a weighted F1 score of approximately 0.83 compared with 0.80 using conventional Sentinel-1 and Sentinel-2 features, with particularly marked improvements in macro F1 (0.55 versus 0.50), indicating better discrimination of less represented species (Ball et al., 2026). Prithvi-EO-2.0, a transformer-based model pretrained on the Harmonized Landsat Sentinel-2 (HLS) archive (https://hls.gsfc.nasa.gov), showed a competitive performance across downstream tasks such as land-cover classification, wildfire mapping, burn-severity estimation, and aboveground biomass prediction, while maintaining similar performance under strong reductions in training labels (Szwarcman et al. 2026). For aboveground biomass estimation, its performance remained comparatively robust when the trained dataset was reduced from 6951 to 348 images (5%), resulting in only a 10.36% deterioration in performance, although a specialized task-specific model still achieved lower prediction error. TESSERA, a self-supervised model combining Sentinel-1 and Sentinel-2 time series, has likewise shown strong performance on forest-related applications including canopy-height estimation, aboveground biomass prediction, and tree-species classification, with particularly clear advantages under limited-label conditions (Z. Feng et al. 2026; Ball et al. 2026). In the latter task, TESSERA achieved a weighted F1 of approximately 0.83, with performance approaching saturation using 5% or less of the available labelled training parcels (Ball et al., 2026).

Although these models remain recent and their application to forestry is still evolving, they provide growing evidence that large-scale self-supervised pretraining can produce transferable geospatial representations relevant to forest monitoring. These developments indicate an emerging role for reusable environmental representations alongside task-specific modelling pipelines. .

### 3.2. Fine-tuning GeoFMs for forestry applications

For most forestry applications, GeoFMs will be adapted rather than pretrained from scratch (Figure 2). Pretraining uses large-scale Earth observation archives to learn general environmental representations, which can later be refined for specific downstream tasks using smaller labelled datasets (Chopra et al. 2023; Lu et al. 2025; Marti Escofet et al. 2026). This substantially reduces the data and computational requirements of downstream applications.

The practical application of GeoFMs therefore begins with the identification of an appropriate pretrained model and checkpoint. Public repositories increasingly provide access to GeoFMs pretrained on large Earth observation archives. Platforms such as Hugging Face (https://huggingface.co/), geospatial deep-learning libraries such as TorchGeo (https://github.com/torchgeo/torchgeo), and project-specific repositories hosted on platforms such as GitHub (https://github.com/) or GitLab (https://about.gitlab.com/) provide access to pretrained checkpoints and model configurations suitable for environmental applications (Wolf et al. 2020). When selecting a model, it is important to consider the compatibility between the pretraining domain and the downstream forestry task, including sensor modalities (e.g., multispectral imagery, SAR, or LiDAR), spatial resolution, and temporal sampling. A model pretrained on globally distributed EO may capture broad environmental regularities yet underperform in regions with specific phenology, canopy architecture, or disturbance regimes; an illustration of the same domain-shift challenge identified for EbMs, ML, and DL models in Sections 2.2, 2.3, and 2.4 (Meyer and Pebesma 2021). The distinction between model architecture and checkpoint is critical. The architecture defines the computational structure of the model, whereas the checkpoint contains the parameters learned during large-scale pretraining and therefore encodes environmental representations derived from the training data.

Once an appropriate pretrained model has been identified, the next stage concerns data preparation. Fine-tuning datasets must be harmonized with the expected input structure of the pretrained model, including spatial resolution, spectral bands, patch size, and temporal aggregation schemes. In forestry applications, this often involves integrating satellite imagery with reference data derived from field inventories, interpreted imagery, or existing forest information products (Fassnacht et al. 2016; Wulder et al. 2012). Data preparation typically relies on geospatial processing libraries such as GDAL (https://gdal.org/en/stable/), Rasterio (https://rasterio.readthedocs.io/en/stable/), and Xarray (https://xarray.dev/), as well as EO platforms including Google Earth Engine (https://earthengine.google.com/), which facilitate access to global satellite archives and environmental datasets (Gorelick et al. 2017).

The next stage involves model adaptation and optimization. Fine-tuning typically consists of adapting the pretrained model to a downstream task by replacing or modifying the task-specific prediction head and updating model parameters using a smaller labelled dataset (Zhuang et al. 2021). Depending on the available data and computational resources, several fine-tuning strategies can be adopted. A common approach is full fine-tuning, where all model parameters are updated during training. Alternatively, linear probing (or head-only training) consists of freezing the pretrained backbone and training only a newly initialized task-specific head, which allows evaluation of the quality of the learned representations with a minimal computational cost (Tomihari and Sato 2024).

The final stage concerns evaluation and interpretation. Model performance should be assessed using metrics matched to the task. Performance should also be assessed through the ability of the model to generalize across space, time, and ecological conditions, including different forest types, disturbance regimes, and environmental gradients. Spatial cross-validation is particularly important in environmental modelling because spatial autocorrelation can inflate apparent model skill when training and validation samples are geographically close (Roberts et al. 2017).

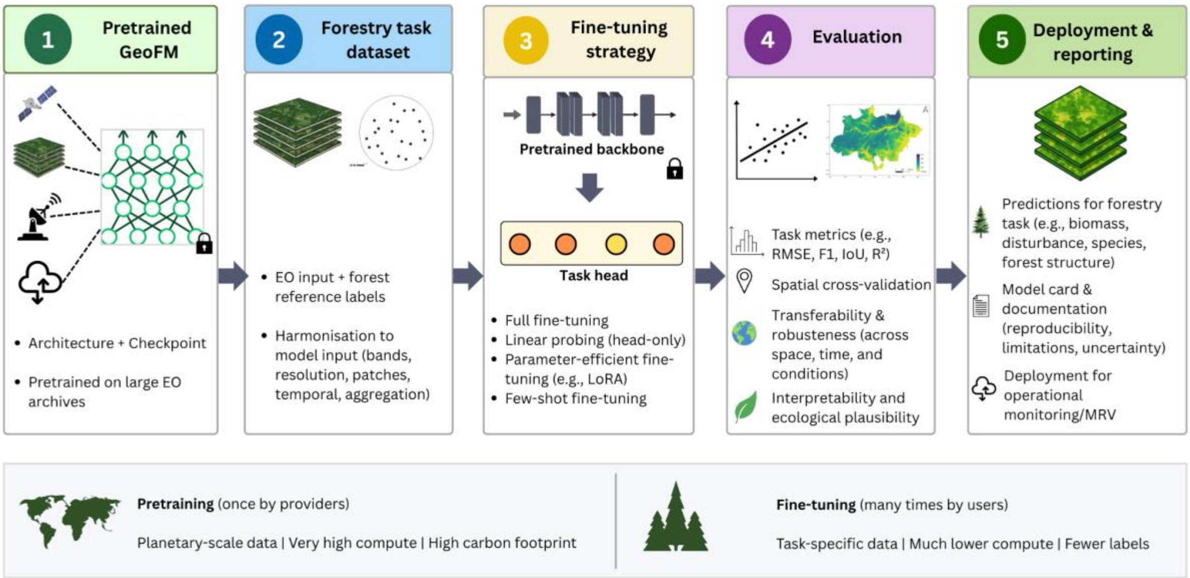


Figure 2: Workflow for fine-tuning GeoFMs for forestry applications. GeoFMs are first pretrained on large EO archives to learn general environmental representations and then adapted to specific forestry tasks using smaller labelled datasets through different fine-tuning strategies. Models are evaluated for predictive performance, generalization, and ecological plausibility before deployment with proper documentation to ensure transparency and reproducibility.

### 3.3. Future research directions for GeoFMs applied to forests

Current applications of GeoFMs in forestry largely demonstrate their ability to generate reusable representations for individual downstream tasks, such as AGB inference, wildfire monitoring, and species classification. While large-scale pretraining offers a means of exploiting heterogeneous EO archives and reducing reliance on task-specific labelled data (Xiao et al. 2025), successful performance on individual tasks is not sufficient to establish their broader value for forestry. Forest prediction requires models that can represent ecosystem change, remain robust across both space and time, provide ecologically interpretable outcomes, and complement well-established process-based modelling approaches. Whether current GeoFMs representations satisfy these requirements remains largely unresolved (Ma et al. 2024). We identify at least four research directions that are particularly important for moving from task-specific demonstrations toward a broader role for GeoFMs in forestry (Figure 3).

A first research direction concerns the transition from forest state inference to explicit representation and prediction of forest evolution/dynamics. Most current GeoFMs are primarily pretrained to learn representations from EO observations and have consequently been applied mainly to infer forest attributes or states at a given time (snapshots) (Szwarcman et al. 2026). Recent spatiotemporal FMs extend this approach by learning representations from satellite image series and capturing patterns that evolve across space and time (Qin et al. 2025). Temporal information may improve the representation of a current state without learning how that state evolves. For forestry, an important research frontier would therefore be the development of spatiotemporal FMs capable of representing transitions from a forest state at time t to its next state at t+Δt, conditional on relevant drivers and processes. The growing temporal depth of EO archives provides an opportunity to investigate whether self-supervised objectives can learn trajectories associated with growth, mortality, succession, disturbance and recovery, rather than solely exploiting temporal variability to improve state inference. Although spatiotemporal FMs are increasingly emerging in other Earth-system domains (Bodnar et al. 2025), their application to explicit forest state evolution remains comparatively under explored.

A second and closely related challenge concerns the spatial and temporal stability of learned representations and downstream models. Transferability across the temporal dimension cannot be assumed even for ecosystem attributes expected to remain relatively stable. For instance, (Ball et al. 2026) showed that tree-species classifiers trained on GeoFM embeddings from a given year experienced substantial performance degradation when applied to embeddings from the following year without fine tuning the model parameters. Such behavior may arise from differences in phenology, snow persistence, atmospheric conditions, acquisition characteristics, or changes in ecosystem states between the two years. Future research should therefore investigate the sources of spatial and temporal variability in GeoFM-based predictions and assess the extent to which learned representations and downstream models remain reliable across time. Such evaluation is necessary to distinguish apparent transferability with familiar conditions from generalization beyond the spatial and temporal contexts represented during model development phase.

A third direction concerns the ecological interpretability of learned representations. Although GeoFM embeddings can support accurate predictions of forest attributes (Muszynski et al. 2024; Ball et al. 2026), it remains unclear which ecological properties are represented within their latent features. For example, successful biomass prediction does not necessarily demonstrate that an embedding directly represents biomass or forest structure directly, as predictions may partly rely on correlated information related to climate, vegetation type, phenology, or geographic context. Recent evidence that individual GeoFM embedding dimensions can be associated with physically meaningful environmental variables suggests that systematic interpretation of these latent spaces is possible (Rahman 2026). Future research should therefore examine how specific forest attributes and processes are recoverable from GeoFM embedding spaces, which features drive downstream predictions, and whether these relationships remain consistent across forest types and environmental conditions.

A fourth direction concerns the integration of GeoFMs with scientific knowledge. PBMs encode physiological, biogeochemical, and demographic mechanisms that purely data-driven models are not explicitly designed to represent, while GeoFMs can learn environmental regularities from observations across large spatial scales. Growing work in ecological and Earth-system modelling has demonstrated, for instance, the potential of combining mechanistic models with machine learning (Reichstein et al. 2019; Wesselkamp et al. 2024; Pichler and Käber 2026). Drawing on this broader literature, several forms of GeoFM-PBM integration can be envisaged. GeoFMs could provide spatially explicit information for initializing or constraining model states and parameters; mechanistic knowledge could be incorporated as physical or ecological constraints during learning; and learned models could emulate computationally expensive process modules or characterize systematic models' residuals (Dagon et al. 2020). Rather than replacing mechanistic modelling, such approaches could establish a complementary relationship between learned environmental representations and process understanding, providing a pathway toward forest predictions that are both observationally informed and ecologically constrained.

These directions suggest that the next generation of forest GeoFMs should not be defined simply by larger architectures or more pretraining data. The more consequential challenge is to develop representations that are dynamically informative, spatially and temporally transferable, ecologically interpretable, and compatible with the current mechanistic knowledge.

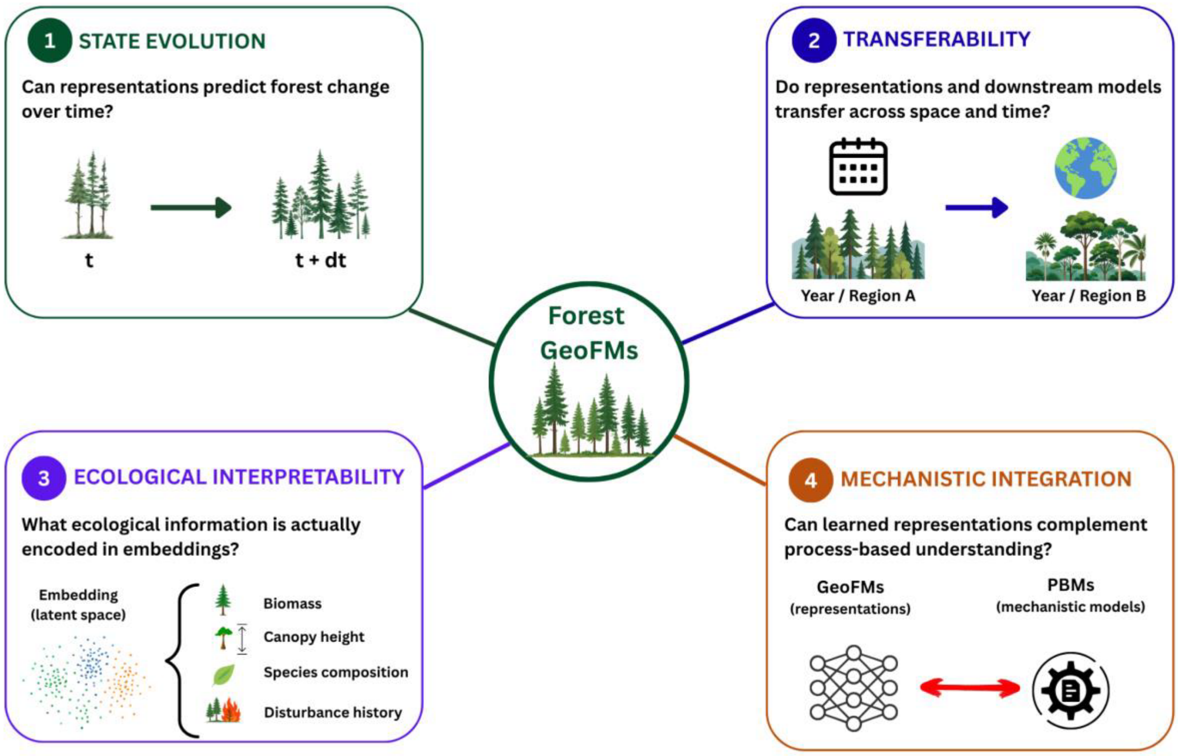


Figure 3: Key research challenges for advancing GeoFMs in forestry. Realizing this potential of GeoFMs requires moving beyond their use as transferable feature extractors for individual downstream tasks. Four priorities are highlighted: predicting forest state evolution through time instead of providing snapshots; assessing the spatial and temporal transferability of learned representations and downstream models; determining the ecological information encoded in embedding spaces; and integrating learned representations with mechanistic; process-based understanding.

## 4. Toward an integrated framework for forest prediction

The development of predictive approaches in forestry has expanded the ways in which ecological knowledge and observational data can be used for prediction. The different approaches we discussed extensively in Sections 2 and 3 differ not simply in their computational complexity, but also in how predictive relationships and representations are specified or learned.

In EbMs, ecological understanding is explicitly embedded by the modeller through mathematical equations describing statistical relationships or mechanistic knowledge. Observations primarily serve to calibrate parameters within these predefined structures. ML differs in that functional relationships do not need to be specified a priori. Instead, the modeller defines the predictor space, while the learning algorithm infers the relationships linking observation to ecological responses. In DL, this learning extends to the representations of forest structure and dynamics to be learned directly from raw observations. GeoFMs broaden this paradigm by learning transferable environmental representations at planetary scale through self-supervised pretraining, enabling the same representation to be reused across multiple ecosystems, sensing modalities, and downstream tasks. These differences in how predictive relationships and representations are specified or learned underpin the distinct assumptions, strengths, and limitations of each modelling paradigm, which are summarized in Table 1.

**Table 1:** Core hypotheses, limitations, and bottlenecks addressed across predictive modelling paradigms in forestry.

| **Model category** | **Core hypothesis** | **Main limitation** | **Bottleneck addressed** |
|---|---|---|---|
| **EbMs** | Ecological relationships can be represented through predefined mathematical equations grounded in prior ecological knowledge or statistical significance | Functional relationships must be specified a priori, becoming difficult to formulate as interactions and predictor spaces grow in complexity | Provides explicit simple and interpretable representation of ecological knowledge and process/relationships |
| **ML** | Predictive relationships can be inferred from observations without prescribing their functional form in advance | Performance depends on the quality/representativeness of engineered features and labelled observations, transferability beyond the training distribution remains limited | Relaxes, to some extent, the need to prescribe functional relationships and enables flexible learning from high-dimensional predictors |
| **DL** | Both predictive relationships and useful representations can be learned directly from raw or minimally processed observations | Requires substantial data, learned representations can remain task- and domain-specific and difficult to interpret | Reduces dependence on manual feature engineering by learning hierarchical representations directly from observations |

| | | | |
|---|---|---|---|
| **GeoFM** | Large-scale self-supervised pretraining can produce transferable geospatial representations reusable across locations, sensors, and downstream tasks | Requires substantial computational resources. Ecological interpretation, temporal generalization, and mechanistic grounding remain limited | Reduced dependence on task-specific labelled datasets and independently trained representations through reusable pretrained representations |

This paradigm evolution should not, however, be interpreted as a progression toward a universally superior modelling paradigm. What constitutes a better model depends on the prediction problem itself. Improvements in predictive accuracy, flexibility, or transferability may come with trade-offs in interpretability, computational demand, temporal robustness, or ecological consistency. EbMs, ML, DL, and GeoFMs are consequently better understood as an expanding set of modelling capabilities rather than a succession in which each new paradigm renders the previous one obsolete. Recognizing this complementarity also requires considering the conditions under which each modelling paradigm may be most appropriate. We propose an orienting framework that relates model choice to how predictive relationships and representations are specified or learned, and to whether learned representations are intended for reuse beyond a specific prediction problem (Figure 4). When predictor-response relationships can be specified *a priori*, either from established statistical relationships or ecological process understanding, EbMs provide a natural choice. When these relationships cannot be predefined, but informative predictors can be specified by the modeler, ML provides a flexible alternative. Where representations themselves need to be learned from complex observations, DL becomes particularly relevant, while GeoFMs offer an additional option when reusable representations and their transfer across tasks, regions, time periods, sensors or modalities are central to the problem. These directions provide an initial orientation rather than strict boundaries between model classes. Other considerations, including data and label availability, interpretability requirements, computational resources, prior ecological knowledge, and the availability of suitable pretrained models, may further refine the choice, as summarized in Table 1.

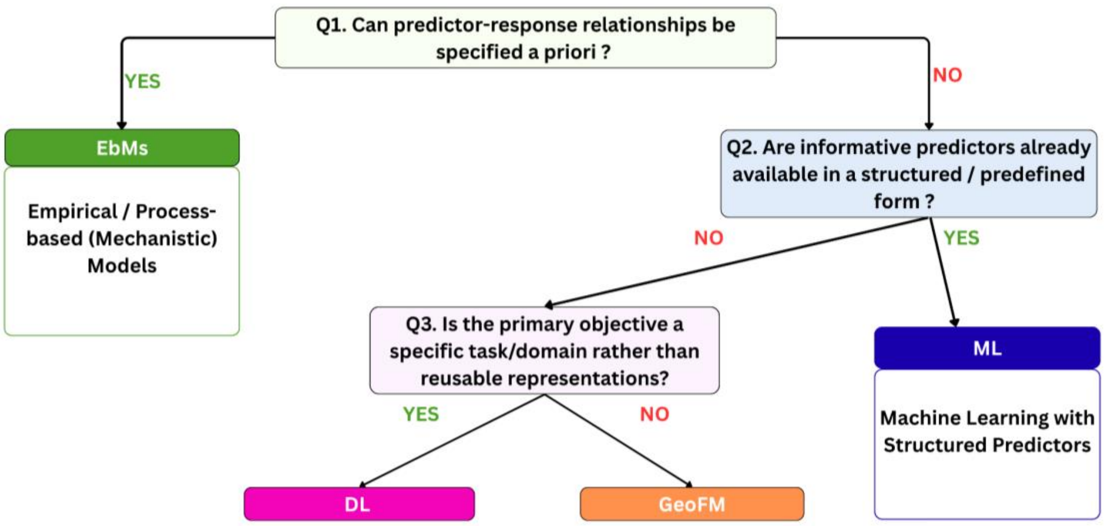

Figure 4: Conceptual framework orienting the choice among EbMs, ML, DL, and GeoFMs for forest prediction. The decision pathways reflect differences in how predictive relationships and representations are specified or learned and in the intended reuse of learned representations.

The future of predictive forestry will therefore not be determined by the replacement of one modelling paradigm by another. Their different capabilities are better viewed as complementary than competing. The question is no longer which paradigm will dominate future forest science, but how their respective strengths can be brought together to build predictive systems that are accurate, transferable, interpretable, computationally sustainable, and ecologically grounded. The next advance in forest prediction may therefore come not from another modelling paradigm, but from learning how to make the existing ones work together.

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