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Reconciling short- and long-term predictions for ecosystem management

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Abstract:

1. Management plans grounded in scientific evidence can be used to limit the impacts of ongoing global changes on socio-ecological systems. In this framework, modeling tools play a crucial role in informing and supporting management strategies.
2. While the urgency of implementing evidence-based actions directed most scientific efforts towards short-term ecological forecasting (ranging from days to decades), we argue that long-term projections (longer than a few decades) can be as important as short-term forecasts. Complex ecological feedbacks and long-term ecosystem dynamics can have effect over decades if not centuries, possibly leading to undesired management outcomes. In this viewpoint, we highlight the need to incorporate long-term ecosystem responses into decision-support studies and discuss the technical requirements and current limitations of state-of-the-art modeling frameworks and datasets.
3. We recommend defining the prediction horizon based on intrinsic ecosystem timescales and studying ecological legacies at biogeographical levels higher than the landscape, such as ecoregions. Combining information from different sources could provide complementary data layers with varying resolution, detail, and uncertainty. Integrating and leveraging these information layers across different spatiotemporal scales represents a key step towards reconciling short- and long-term predictions.
4. *Policy implications.* We emphasize the necessity of routinely integrating short- and long-term predictions. To this end, we envisage international communities that foster the convergence of transdisciplinary knowledge and expertise, also engaging with stakeholders, to generate timely and reliable ecological predictions aiming at assisting management planning through a mutual learning loop.

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1 Introduction

Unprecedented global changes are posing significant challenges to ecosystems (Kerr et al., 2025), ultimately altering the yield of essential ecosystem services to human society (Cardinale et al., 2012). Management actions and policies - coordinated from the local (e.g., building fire-resilient landscapes; Thacker et al., 2023) to the global scale (e.g., meeting the 30x30 biodiversity goal; Harris et al., 2024) - typically aim at mitigating the effects of global changes on socio-ecological systems, limiting the loss of biodiversity, ecosystem functioning and human lives (IPBES, 2024). Predictive models are essential support tools for ecosystem management and restoration actions as they provide insight into how ecosystems may function and how they may respond to environmental changes, thus allowing to evaluate alternative management strategies (Geary et al., 2020).

The urgency to implement management actions, devised to face multiple environmental crises, has encouraged the use of near-term ecological forecasting to make decisions on actionable timeframes (Dietze et al., 2024). While recognizing that short-term forecasts are essential, here we argue that long-term predictions can also be important for specific processes. Such dual needs in ecosystem modeling – that is, immediate forecasting to provide timely suggestions to managers, and long-term projections to ensure reliable outcomes and durable management interventions – brings modelers at a crossroads. Here, we set out to provide a roadmap to reconcile and integrate short- and long-term ecological predictions, with the main goal to assist management practices, stressing the advantages as well as challenges of such endeavor.

2 Why consider long timeframes?

Daily to decadal timeframes are appropriate for modeling several ecological processes - such as the spread of invasive species (e.g., Baker et al., 2018; Mitchell & Dominguez Almela, 2025), soil organic carbon decomposition (e.g., Diele et al., 2022; Schiedung et al., 2023), or wildlife movements (Finch et al., 2020). Yet, this time horizon might be too short to provide decisive information about other processes. For instance, planning management actions to prevent high impact, rare events (that are however becoming increasingly hazardous), such as wildfires or insect outbreaks in boreal forests, requires timeframes longer than decadal to observe a significant number of events and build robust statistics on which choices can be based (e.g., Aakala et al., 2023; Dondini et al., 2025). Long-term studies can also help testing the stability of model predictions, avoiding for example unrealistic model behavior on long timescales (Kelder et al., 2022; McIntire et al., 2022). In addition, when the ultimate purpose of management practices is to achieve unassisted ecosystem recovery (e.g., for conservation purposes; Buisson et al., 2022; Moreno-Mateos et al., 2020), the long-term effects of interventions must be considered to assess the actual achievement of and the time required to attain the targeted recovery phase. Furthermore, differing legacies or disturbances may lead to tipping points and result in permanent ecosystem shifts, also known as "alternative ecosystem states" (e.g., Dakos et al., 2019; Pausas & Bond, 2020). A shift between different ecosystem states may for instance emerge from climatic events (e.g., coral bleaching after exceptionally high summer sea temperature, Donner et al., 2005), land-use changes (e.g., nutrient input in shallow lakes (Scheffer et al., 2001) or afforestation (Dlamini et al., 2025)), infrastructure works (e.g. dam construction, . and overfishing (Möllmann & Diekmann, 2012), among others, and then self-reinforce over time (Suding et al., 2004). Therefore, long-term studies are necessary to predict whether and for how long shifts might persist. In all those cases, we stress that considering long timeframes entails both digging in the past to understand present conditions (Blondel, 2006; Haddad et al., 2015; Mariani et al., 2022; Vallejo et al., 2012) and looking far ahead in the future to account for long-term consequences of management practices (e.g., Abelson et al., 2022).

3 How long are 'long timeframes'?

We highlight that the selection of the appropriate prediction timeframe should be based on the intrinsic system timescales. In general, intrinsic system timescales are given by the characteristic time of all the ongoing processes, including ecological processes (e.g., the time to achieve the expected late-successional community state), abiotic processes (e.g., lake water turnover time), as well as those related to human management and activities (Berger et al., 2019). Parts of these processes are excluded during model development, as modeling representation results from trade-offs between detail, specificity, interpretability, computational resources, and validation potential (Larsen et al., 2016). Hence, building models requires making choices based on the specific research goal(s), and by so doing the range of relevant scales is also reduced.

We therefore suggest that the longest timescale among those considered key defines the time horizon that the model should be able to represent, that is the study timeframe. Recognizing that ecological timescales are often hard to define, one may adopt a "rule-of-thumb" approach. For instance, a common rule of thumb is to consider the turnover time of individuals of the longest-lived species in the ecosystem (Connell & Sousa, 1983). Another approach suggests using 4–5 "community characteristic times", which represent how long it takes for species richness to change significantly in communities affected by huge perturbations (Ontiveros et al., 2021). In many of these rules, included the above ones, the identification of the longest timescale depends on the specificities of the study system. As an example, the generation length of a relatively small vertebrate group such as mammals, may vary between 129 days of *Microtus* voles to approximately 9,000 days of the Sumatra orangutan (*Pongo abelii*) (Pacifici et al., 2013). Hence, using the first rule-of-thumb listed above, the orangutan generation length would set the modeling timeframe when both orangutans and voles are studied, whereas the vole generation length may set the timeframe in areas where only this genus is present. Similarly, when adopting the community perspective, the characteristic species turnover time may vary of several order of magnitude in different communities. For instance, within the bacterial kingdom it varies between few days for human bacteria to about 3 years for soil or Alpine-lake bacteria (Ontiveros et al., 2021), and also in these cases the longest turnover time should be used. For plants, this task may become even more challenging; for example, age estimation in clonal plants (for which recognizing the individual is already difficult) constitutes an unresolved matter, still there are indications that genetic individuals may extend tens of thousands of years (e.g., Pineau et al., 2024). Notwithstanding these challenges, we illustrate the advantages of applying one of these rules of thumbs with a practical example, namely predicting the effects of exotic *Eucalyptus* spp. plantations in the Mediterranean Basin (Badalamenti et al., 2018; Silva-Pando & Pino-Pérez, 2016). Individuals of *Eucalyptus* spp. can indeed live more than 200 years (England & Attiwill, 2006), and species used in afforestation projects are usually fast-growing (high ability to acquire and use resources) and very good resprouters (Cerasoli et al., 2016). When becoming naturalized, these plants may impact biodiversity, ecosystem nutrient cycling and fire regimes for a few centuries; however, predictions in the Mediterranean Basin are generally limited to decades or a century at most (e.g., Morán-Ordóñez et al., 2021), which therefore call for longer-term predictions.

4 What are the main steps and challenges in reconciling short- and long- term predictions?

The technical requirements for producing reliable predictions across different time horizons often diverge, yet some may also overlap. The short-term behavior mostly depends on initial (i.e., present-day) conditions, reflecting the legacy of past natural and human disturbances (e.g., Hastings et al., 2018; Hurtt et al., 2010; Tappeiner et al., 2021). In contrast, the dynamics over longer times are mostly dependent on the overall biogeographic and climatic scenario considered, with future climate scenarios that may diverge significantly at regional scales (Fernández et al., 2019; Fronhofer et al., 2023). In long-term modeling frameworks, assessing the effect of different initial conditions is also instrumental when evaluating the ability of the model to reproduce ecosystem tipping behaviors. From dynamical system theory, the occurrence of tipping points can be detected by running long enough simulations, with different initial conditions and parameter values to explore a wide range of scenarios (Ashwin et al., 2012; Dietze, 2017; Hastings et al., 2018). Hence, accurate estimation of initial condition is crucial for predictions on different time horizons.

For both short- and long-term predictions, we suggest considering possible initial conditions observed at biogeographical levels higher than the landscape, such as ecoregions (Olson et al., 2001). While management goals are set at different scales (global, national or regional), interventions are typically implemented by local authorities, such as protected area managers, at the landscape level (e.g., Dalmonech et al., 2022). Therefore, many management-oriented models focus on the dynamic of (terrestrial or marine) landscape(s). Despite landscapes consisting of interconnected patches that can differ in terms of biotic (e.g., species) and abiotic (e.g., soil) composition or spatial arrangement (Turner 2001, 2005), these might not include the whole variety of possible ecosystem states emerging for given climatic and environmental conditions. To overcome this issue, one should identify the ensemble of landscapes experiencing similar eco-evolutionary bioclimatic and abiotic conditions, that may be considered as replicates (e.g., Mariani et al., 2024) running over different temporal trajectories. This ensemble is thus composed of a set of different instances of the same system, possibly starting with different initial conditions and experiencing different disturbances and management regimes. We expect this exercise to provide three essential pieces of information: i) a collection of snapshots that might represent possible future states of the target ecosystem, potentially allowing to observe the consequences of different legacies (Moreno-Mateos et al., 2020); ii) an evaluation of the transferability of modeling results (Lewis et al., 2023; Yates et al., 2018); iii) a set of initial conditions useful for both short- and long-term predictions, as discussed above.

Another important step, and a challenge, is the integration of available data differing in space and time (Zipkin et al., 2021). While observations provide essential insights into past and present landscape dynamics, limited data availability remains a major constraint for reconstructing the past, hindering the possibility of model calibration and validation. The wealth of remote-sensing and *in-situ* data produced in recent decades (Cavender-Bares et al., 2022; Wood et al., 2024) provides a solid ground to build short-term forecasts (Fer et al., 2021). Conversely, information covering long timeframes may be obtained mostly studying proxies from natural archives (e.g., tree rings, pollen, charcoal, biological macro-remains; Ancillotto et al., 2025; Mariani et al., 2024), which allow reconstructing century- or millennium-long landscape dynamic. This information might, however, not be available within the target landscape, further corroborating the necessity to resort to higher biogeographical levels. Integrating information from both scientific and non-academic sources (e.g., herbaria, forest inventories, documentary archives, land-use and management maps; Daru, 2025) may partially compensate for data scarcity in past times and is essential when dealing with management planning. We envision this as a crucial step towards reconciling short and long timeframes (Figure 1).

5 What to expect from state-of-the-art frameworks?

Even when assembling data from different sources, the level of detail (i.e., the number of components, attributes, interactions, processes; Larsen et al., 2016) captured in available records typically shrinks moving back in time (shadow bar in Fig. 1). Similarly, the finest scale represented in the dataset inevitably coarsens, i.e., the spatial and temporal resolution decreases (solid line in Fig. 1). In the present and recent past, advanced field measurement techniques have enabled the collection of detailed information on a wide range of ecosystem features with high spatial and temporal resolution. These include, for instance, the characterization of deep ecosystems (Aguzzi et al., 2024) or nearly real-time single-leaf photosynthetic rate (Siebers et al., 2021), potentially supporting detailed and high-resolution models (e.g., Lyu et al., 2024). When looking further back in the remote past, paleo-data can inform about vegetation communities, herbivore density, insect outbreaks or fire events, going back thousands of years. Such data provide quantitative information across different spatial scales - from tens of meters to the whole watershed - with temporal resolution ranging from seasons to decades in lake, ice and tree-ring records (Zolitschka et al., 2015; but see improvements offered by new co-registered proxies Garcés-Pastor et al., 2023). In turn, the reduction in the level of detail and spatiotemporal resolution of data across past times increases the level of uncertainty about system dynamics (dotted line in Fig. 1; e.g., Simmonds et al., 2024).

Data availability also constrains the model characteristics. As models generally have constant spatiotemporal resolution and level of detail across the study timeframe, mismatches in data resolution and detail limit the possibilities of model calibration and validation (but see Boukhris et al., 2025). Hence, high-detail and high-resolution models can be implemented, and are reliable, over short timeframes, whereas their uncertainty (e.g., caused by parameter estimation, assumptions in modeling representation or uncertainties in future scenarios, Schuwirth et al., 2019) increases over longer timescales, making prediction meaningless (Dietze et al., 2024). Instead, over long timeframes models based on low-detail and low-resolution data can be important tools to support decision-making processes. We stress that, if prediction uncertainties and model approximations are properly acknowledged and communicated to stakeholders (Fischhoff & Davis, 2014), even simplified, low-resolution models can produce useful qualitative information, describing system tendencies (Magnani et al., 2023) or help defining constraints on model predictions (Foley et al., 2013). Considering the most informative and reliable predictions theoretically available at a given future point, we expect the pattern of model detail, uncertainty, and resolution as shown in Fig. 1.

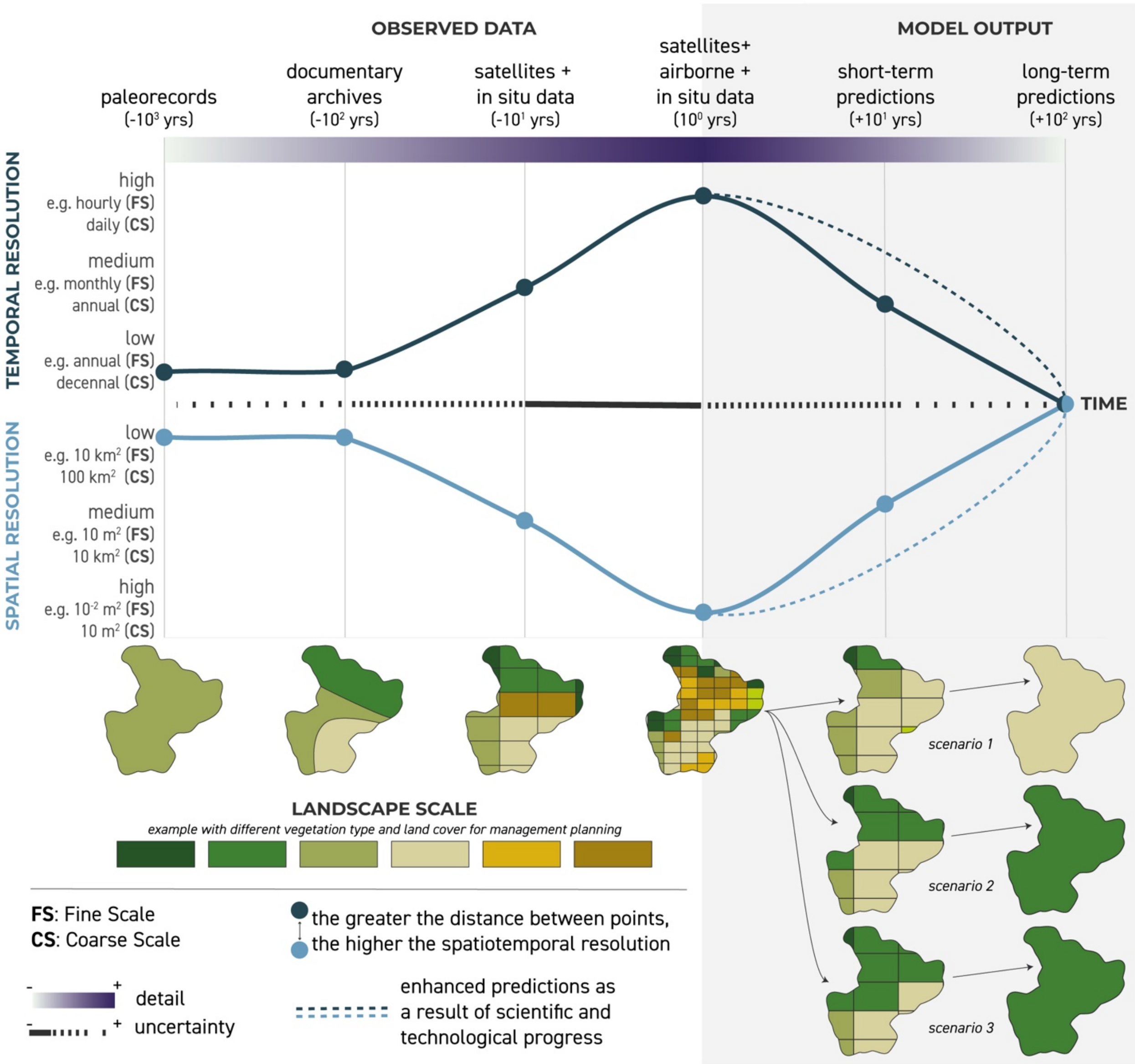

Figure 1. Schematic representation of the state-of-the-art level of information across spatiotemporal scales for observations (left) and future model predictions (right). The solid line represents the coarser level of spatiotemporal resolution in past observed data, while it corresponds to the forecast horizon (sensu Petchey et al., 2015) in future predictions; with scientific progress enhancing the forecast horizon in the near future (dashed line in Fig. 1).

6 Conclusions

We argue that just as management actions not informed by sound scientific evidence have led to undesired outcomes (Sutherland et al., 2004), inappropriate modeling frameworks may result in interventions having inefficient or even detrimental impacts. To this end, we emphasize that long timeframes can be as important as short timeframes to support decision-making processes and verify the sustainability and effectiveness of management plans. We therefore envision the flexible spatiotemporal framework proposed here as a stimulus for further refining evidence-based management planning. We also recognize that producing both short-term forecasts (or nowcasts) and long-term projections using a single model or within a single study might be a challenge. In this sense, the situation is similar to that of "seamless predictions" in climate dynamics, aiming at using models that can cope with all timescales, from seasonal to multi-decadal predictions (Palmer et al., 2008). While seamless predictions call for using the same type of model on differing timescales, sometimes this strategy is not feasible, and different models are needed for different space and time scales. The challenge of coupling short- and long-term predictions could be tackled by "communities of practice" (Wenger, 1999), such as the Ecological Forecasting Initiative, that foster the convergence of experiences from different disciplines. We stress that such communities - already advocated by Dietze et al. (2024) for advancing short-term ecological forecasting – should also include long-term projections. These communities may involve not only interdisciplinary, but also transdisciplinary teams (i.e., also engaging stakeholders, such as landscape managers, local and regional agencies, rangers, local communities) sharing knowledge, expertise, and aiming at mutual learning (Lang et al., 2012). Such transdisciplinary integration could start with the identification of specific addressable goals, continue with the decision of study methods and type of intervention(s), and should also include the monitoring and success-evaluation of the interventions (e.g., Danovaro et al., 2025), to possibly adjust the ongoing management plan (adaptive management; Holling, 1978; Walters, 1986). We are convinced that this integration would form a learning and information loop, in which modeling predictions are bound by governances and laws, that may in turn adapt policies to emerging scientific evidence.

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Authors' contributions:

MM and MB conceived the original idea, wrote the first draft of the manuscript and led the integration of all contribution; GO, PF and AP contributed to the development and refinement of the manuscript idea with inputs on the conceptual framework as well as on the drafting; LA, AC, DD, FD, GF, SBG, CM, CR, RS and GV contributed to the contextualization of the original idea in their field of expertise. All authors contributed to revising the manuscript.

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