

A new index for monitoring non-linear trends in passive forest recovery at regional scale

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ABSTRACT

Passive rewinding is an important restoration strategy that promotes ecosystem recovery in meaningful areas with little or no human intervention. To assess the success of this approach toward biodiversity conservation aims, new monitoring tools should be developed based on the understanding that ecosystem recovery is not a linear process either in space or time. Considering that native forests are primary targets of passive rewinding strategies due to their potential to promote biodiversity and ecological resilience, we propose a spatially explicit index of passive forest recovery that integrates the concepts of ecosystem complexity and successional dynamics. Land cover class was an indicator of ecosystem complexity, increasing from non-woody ecosystems to heathlands-shrublands and native forests. Land cover transitions allowed the assessment of successional dynamics. The index was implemented using an enhanced multi-temporal series of CORINE land cover data (1990–2018) and tested in the Spanish Ibero-Atlantic Region. Spatial patterns of passive forest recovery were evaluated using patch-level landscape metrics, while socio-ecological drivers were explored with decision tree regression models. We found that 12.71 % of the study area experienced passive recovery (annual average rate of 302 km²) and 9.90 % suffered one to three regressions along the successional dynamics. Passive forest recovery varied along geographic gradients, with patches strongly aggregated according to recovery trends, and was driven by geographic position, human accessibility and climate. The index developed here provides a tool for understanding spatio-temporal patterns of rewinding in temperate regions under rural restructuring and for integrating this complexity in conservation policies at regional scale.

1. Introduction

Passive rewinding occurs spontaneously after farmland abandonment or extensification, providing important opportunities to re-establish lost native habitats (Meli et al., 2017; Song et al., 2018; Broughton et al., 2021). Consequently, ecological values and key ecosystem services, as climate regulation, carbon sequestration or hydrological flow (Filoso et al., 2017; Bastin et al., 2019; Mo et al., 2023), can be enhanced with little or null human direct intervention over significant tracts of degraded lands (Perino et al., 2019; Pettorelli et al., 2019; Carver et al., 2021). In this context, the recovery of native forests (hereafter passive forest recovery) is a primary target of passive rewinding strategies due to their potential to promote biodiversity and long-term ecological

resilience in a changing world (Crouzeilles et al., 2017; Burton et al., 2018; Wilson et al., 2024). Important advantages of passive forest recovery strategies are: (i) preservation of local genetic diversity (Morel et al., 2020), in contrast to tree plantations that are often focused on a few non-native species (44 % of the cases; FAO, 2020); (ii) prevention of alien species introduction, diseases and pests from imported saplings; (iii) improvement of climate change regulation (Kirschbaum et al., 2024); (iv) higher resilience to disturbances, as extreme forest fires (Keesstra et al., 2024); and, (v) cost-effective management (Rodwell and Patterson, 1994). Nevertheless, some drawbacks can also be recognized, as this is a slow process that cannot be guaranteed because tree colonization can be prevented by biotic (e.g. competition, herbivory and lack of dispersal or facilitation mutualisms) and abiotic (e.g. climate or soil

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conditions) constraints in early stages of the ecological succession (Prach and Pyšek, 2001; Martínez and García, 2017).

Passive forest recovery is highly complex and varies non-homogeneously across space and time depending on multiple factors, such as biogeographic context (Suárez-Seoane et al., 2002), land use legacy (e.g., cropping and grazing history; Álvarez-Martínez et al., 2014), landscape attributes (e.g. proximity to forest patches acting as a source of propagules; Hewitt and Kellman, 2002) or susceptibility to natural and/or anthropogenic disturbances (Pereira and Navarro, 2015). Then, to become a successful strategy that can be included in ecological restoration agendas, patterns of passive forest recovery need to be explored in depth (Frei et al., 2024). Although many authors have monitored general trends of passive forest recovery over recent decades, both at regional (e.g. Turubanova et al., 2023) and landscape (e.g. Broughton et al., 2021) scales, only a few studies have developed approaches accounting for the multi-dimensional nature of this process in space and time (e.g. Elphick et al., 2024). In this sense, long-term restoration of ecosystem structure and function requires moving beyond traditional biodiversity and functional assessments to a broader perspective that considers key ecological dimensions of ecosystems as complexity and successional dynamics (Moreno-Mateos et al., 2020). On the one hand, complexity determines the diversity, resistance and resilience of ecosystems in the face of disturbances and, therefore, their natural balance (Parrott, 2010). On the other, the short-term dynamics, resulting from the interaction between ecological succession and disturbances, regulates extinction-colonization processes and determines the persistence of species (Amos et al., 2012; García et al., 2021).

The development of improved monitoring tools at large scale is a top priority for land managers and other stakeholders involved in the design of adaptive actions aimed at preserving landscape values or minimising potential trade-offs between ecosystem services (Pérez-Silos et al., 2021). The implementation of such indicators at regional scale would allow for a more accurate assessment of passive forest recovery in the face of the uncertainty generated by other scientific approaches based on the downscaling of global trends that may lack typological resolution (e.g. not discriminating between native forests and plantations of exotic species; Palmero-Iniesta et al., 2021), as well as by the social narrative about land abandonment and secondary forest regrowth that shapes the perceptions of local stakeholders (Frei et al., 2020). To be effective, monitoring tools should meet several requirements: (i) They should provide an accurate description of the state of the system under evaluation. In this sense, most of the forestry data available at European level (e.g., FAO, 2020) are not useful to monitor passive forest recovery since they do not discriminate between native forests and tree plantations of exotic species (e.g. *Eucalyptus* spp.). This entanglement can be associated to many factors, such as the huge variety of forestry policies among European countries or the lack of a clear conceptual framework to classify tree-dominated ecosystems (Chazdon et al., 2016). (ii) They require the definition of meaningful starting and ending points. Those reference points are critical to assess the progress and completeness of the target process and should be stated by both historical and expert knowledge according to ecological attributes as complexity, recovery speed, rate of change, deviations in the trajectories or persistence over time (Beyers and Sinclair, 2022). (iii) They need to be operative, cost-effective and synthetic, accounting for meaningful combinations of indicators of pressure (describing the forces exerted by human activities) and state (accounting for the quantity, condition or characteristics of the process under evaluation) that optimize the trade-off between simplicity and accuracy. (iv) Finally, they should be spatially explicit to allow the definition of critical areas for land management.

The main aim of this study is to develop a new spatially explicit index that integrates the concepts of ecosystem complexity and successional dynamics to explore non-linear trends of passive forest recovery at biogeographic scale, using the Spanish Ibero-Atlantic biogeographical region as the case study. Specifically, we intend: (i) to disentangle spatio-temporal patterns of passive forest recovery, identifying

important areas according to the prevalence of this process to guide land managers acting in degraded landscapes; and, (ii) to recognize the main socio-ecological drivers explaining the observed trends.

2. Material and methods

2.1. Study area

The Spanish Ibero-Atlantic biogeographical region covers 69,282.23 km² in the northern part of the country (Fig. 1; González-García et al., 2024). The climate is Oceanic, with a mean annual temperature of 11.5–14.5 °C and an annual precipitation over 1000 mm distributed uniformly throughout the year (AEMET-IMP, 2011). Elevation ranges from the sea level up to 2650 m a.s.l. Topography and soil vary at short scale (García-Manteca et al., 2024), strongly influencing landscape patterns. Dominant land cover classes are pasturelands and croplands in lowlands, heathlands and shrublands in midlands, deciduous forests of *Fagus sylvatica*, *Betula celtiberica*, *Quercus robur* and *Q. petraea* in northern mountain slopes, and *Q. pyrenaica*, *Q. rotundifolia* and *Q. orocantabrica* on the southern slopes. Coastal areas are mostly dominated by plantations of *Eucalyptus* spp. and *Pinus* spp. (López-Sánchez et al., 2021). Within the study area, the Cantabrian Mountains stand out as a biodiversity hotspot for European habitats and species (e.g. they include more than 2300 native plant species), many of them endemics (García-Llamas et al., 2019; Jiménez-Alfaro et al., 2021).

As in other European mountain ranges, socio-economic changes have been accelerated in recent decades in this biogeographical region, leading to a complex reorganisation of land uses (González-Díaz et al., 2019). The intensification of agroforestry and livestock farming practices (i.e., fewer but larger livestock farms and large-scale productive forestry actions on private lands) is combined with the abandonment or extensification of the most marginal lands, at the edge of economic viability (Marey-Pérez and Rodríguez-Vicente, 2009; Lasanta et al., 2017), where native vegetation expands quickly due to a high rate of primary production favoured by climate, soil conditions and biodiversity (i.e., remnants of native vegetation serving as propagules) (Álvarez-Martínez et al., 2014; Paquette et al., 2018). Consequently, in this region, passive forest recovery can be considered as a Nature-based Solution (NbS) that promotes socio-ecological sustainability in the face of climate change (García et al., 2023), since it can be related to high levels of carbon sequestration and storage in aboveground biomass (Castaño-Santamaría et al., 2013) and soil (Doblas-Miranda et al., 2013).

As a result of the aforementioned land-use transitions, the disturbance regime has undergone important changes, particularly regarding forest fire dynamics. In the Ibero-Atlantic region, fires have been historically frequent, but small in scale and low in severity, mainly affecting shrublands and heathlands (San Miguel-Ayanz et al., 2022). However, in recent decades, land abandonment (Morán-Ordóñez et al., 2013) and the spread of monospecific plantations (López-Sánchez et al., 2021) have altered the structure and composition of forest stands, which, together with climate change promoting longer periods of drought (Castañeda and Reyes, 2014), has led to a higher prevalence of large and severe fires (Nunes et al., 2005; Suárez-Seoane et al., 2024).

2.2. Land cover data: sources and accuracy assessment

The input data comprised a multi-temporal series (1990, 2000, 2006, 2012 and 2018) of land cover maps derived from the CORINE Land Cover (CLC) dataset, a flagship product of the Copernicus Land Monitoring Service used in the European Union's land cover inventory (<http://land.copernicus.eu/pan-european/corine-land-cover>). Originally collected in vector format at a scale of 1:100,000, this dataset was rasterised to a 30-m spatial resolution, since this level is consistent with the resolution of the satellite imagery used to develop CLC products and is effective for assessing land cover changes at regional scale (García-Llamas et al., 2016). CLC data offer a hierarchical classification system

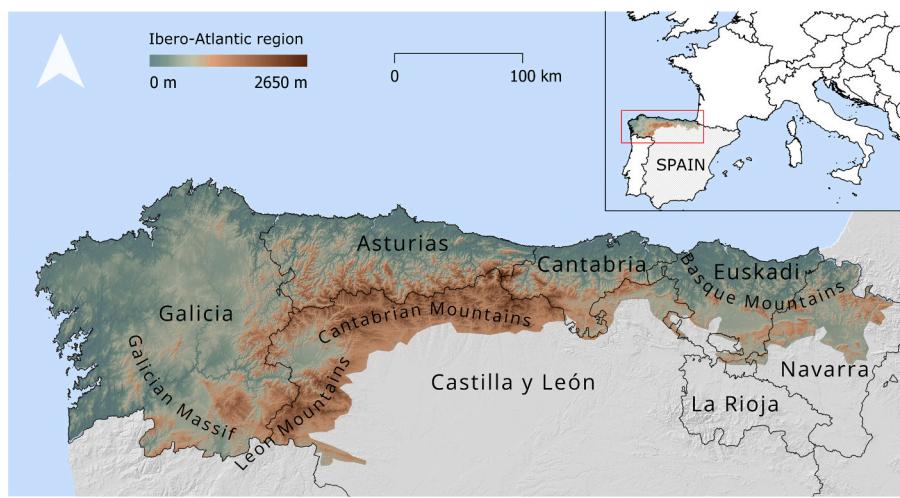


Fig. 1. Ibero-Atlantic biogeographical region in Spain. The administrative boundaries of the Spanish regions (autonomous communities) are shown, as well as the main mountain systems.

of 44 land cover classes, at the most detailed typological resolution (level 3), that is based on biophysical descriptions of the earth's surface, combining environmental and human components (Bossard et al., 2000; Kosztra et al., 2017). CLC presents important advantages for the purpose of this study against other available datasets, such as comprehensive spatial cover, wide accessibility for users and easy interpretation. Nevertheless, several inaccuracies related to the delimitation of certain classes have been pointed out, which are particularly noticeable for some years. For instance, the 1990 dataset covers a broad period (1985–1996), so classes are chronologically heterogeneous (e.g., Feranec et al., 2007). In our study area, findings from García-Llamas et al. (2016) allowed the identification of two major constraints related to the misclassification of urban areas and the lack of discrimination between broadleaved native forests and broadleaved plantations of non-native tree species (mostly *Eucalyptus* spp.). To sort out both problems and enhance the classification reliability, the CLC time-series was combined with two extra datasets: a settlement map (available from the Spanish Geographic Institute (www.ign.es) at 1:5000 resolution) and the Spanish national forest map that provides accurate information on tree plantations (available with a decadal coverage (period 1996–2021) at 1:50,000 to 1:25,000 scale, with uneven spatial readiness; <https://www.miteco.gob.es>). This enhanced CLC time-series was reclassified into seven primary categories to improve its operational efficiency and reduce the classification uncertainty. Therefore, the final land cover (FLC) time-series included the following categories (Table S1 and Fig. S1, Supplementary Material): (1) urban areas, (2) water bodies (i.e., wetlands and both inland and marine waters), (3) sparsely vegetated lands (i.e., mountain grasslands and bare rocks), (4) agricultural lands, (5) heathlands and shrublands, (6) tree plantations of conifers and eucalyptus, and (7) natural and seminatural native broadleaf forests (dominated by oaks, beeches, birches or sweet chestnuts, but also by holm oaks or bay laurels). Land cover classes 1 and 2 were considered non-variant throughout the study period and, therefore, were not included in subsequent analyses of landscape change.

The classification accuracy of the FLC time series was measured with an independent random sample of 350 points (50 per class) per year, that were distributed throughout the study area and separated more than 500 m to minimize spatial autocorrelation (in consistency with the average grain size of the landscape). Points were visually inspected using aerial imagery for each corresponding period. We calculated the following indicators: (i) Overall accuracy as the percentage of sampling points correctly classified, representing the overall quality of the map. (ii) Kappa coefficient that measures the agreement between the classified and the reference maps, correcting for the agreement that could

occur by chance. (iii) Producer's accuracy which is the number of correctly classified samples of a given class divided by the true number of samples of that class. It provides the probability that a sample of a given class is assigned as the same class in the classification map. (iv) User's accuracy or the number correctly classified samples of a given class divided by the number of classified samples of that class. It provides the probability that a particular map location of a given class is also the same class in truth. A high producer's accuracy means a low proportion of omission errors, whereas a high user's accuracy means a low proportion of commission errors. (v) F-score, a composite measure that combines producer and user accuracies to assess the reliability of the classification (Eq. 1).

$$Fs = \frac{2 \cdot PA \cdot UA}{PA + UA} \quad (1)$$

where: Fs = F-score, PA = producer's accuracy and UA = user's accuracy.

FLC time series had overall accuracies above 0.8. The final classification obtained for the most recent year in the series (2018) had an accuracy of 0.94, a Kappa value of 0.93 and a F-score above 0.87. Producer and user accuracies were higher than 0.82 and 0.88, respectively (Table S2, Supplementary Material).

2.3. A bi-dimensional and spatially explicit index to monitor passive forest recovery

The Passive Forest Recovery Index (PFRI) was parametrized from the FLC classification built at 30 m of spatial resolution for the period 1990–2018 along two ecological dimensions: ecosystem complexity and successional dynamics.

Ecosystem complexity describes the state of an ecosystem and is linked to ecological integrity, diversity and resilience (Levin, 1998). There is a range of approaches to measure ecosystem complexity from geospatial data but, given the high dimensionality of ecosystems, none of them provide a complete picture (Parrott, 2010). Here, we used land cover as an indicator of ecosystem complexity because it is a proxy for the physical configuration and organization of ecosystems in space and time that relates well to taxonomic, structural and functional diversity (August, 1983). In this framework, the first PFRI dimension was defined as the net increase in ecosystem complexity ($iEC_{i,j}$) resulting from long-term passive forest recovery between year i (1990) and year j (2018). This measure encompassed land cover transitions leading not only to the establishment of native forests, but also to earlier successional stages, such as heathlands and shrublands, and was derived using land cover

transition matrices and maps (Debussche et al., 1976). The value of $iEC_{i,j}$ ranged from 1 to 3 according to the magnitude of the change ($iEC_{i,j} = 1$ when agricultural and sparsely vegetated lands changed to heathlands-shrublands; $iEC_{i,j} = 2$ when heathlands-shrublands changed to native forests; $iEC_{i,j} = 3$ when agricultural and sparsely vegetated lands changed to native forests; Fig. 2a). Land cover transitions nonrelated to passive forest recovery were not considered to calculate PFRI.

Along the long-term passive forest recovery processes, the potential linear increase in ecosystem complexity due to ecological succession

may be disrupted at short term by ecological regressions caused by disturbances, ultimately affecting ecosystem stability (van der Wurff et al., 2007; Donohue et al., 2016). In fact, ecological succession should not be conceptualized as a deterministic progression toward a stable climax, but rather as a dynamic and contingent process shaped by disturbances, among other factors. Regressions are therefore intrinsic components of the successional dynamics and must be integrated into theoretical frameworks. Recognizing the possibility of non-linear transitions is essential for understanding ecosystem trajectories under both

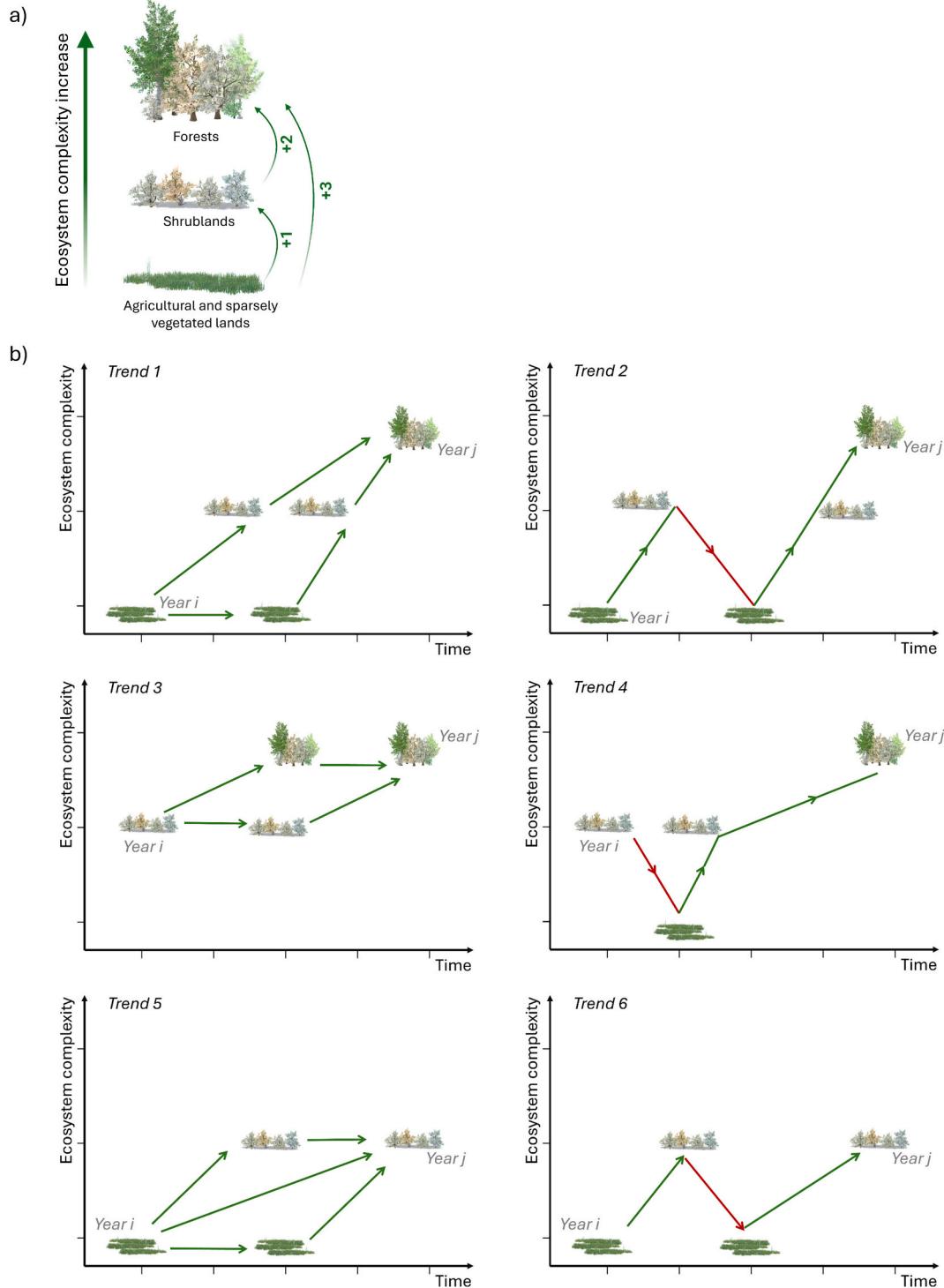


Fig. 2. Ecological dimensions of the PFRI: (a) Net increase in ecosystem complexity ($iEC_{i,j}$) from year i to year j due to passive forest recovery. (b) Successional dynamics ($SuDi,j$) within the period $i:j$; the figure illustrates different dynamics for similar net increases in complexity.

natural and anthropogenic pressures (Holling, 1973). To calculate the second dimension of the PFRI, non-linear trends of successional dynamics (SuD_{i-j}) within the study period were explored with land cover transition maps and matrices, considering the years 1990, 2000, 2006, 2012 and 2018 as the time chain links. For pixels where ecosystem complexity increased in the long term, the number of ecological regressions leading to a state of lower complexity in the short term was quantified. Pixels scored at maximum ($SuD_{i-j} = 1$) when no disturbance caused ecological regression along the succession process between 1990 and 2018, with this score decreasing as the number of regressions increased. Successional dynamics were then quantified according to Eqs. (2) and (3).

$$SuD_{i-j} = \frac{R_{max} + 1 - R}{R_{max} + 1} \quad (2)$$

where: $SuD_{i,j}$ = successional dynamics, R = number of detected ecological regressions and R_{max} = maximum number of possible regressions in the time-series.

$$R_{max} = Y - \lfloor \frac{Y}{LCC} \rfloor - 1 \quad (3)$$

where: Y = number of time chain links considered in the analysis (in this study case, five), and LCC = number of land cover classes involved in passive forest recovery (in this study case, three).

Fig. 2b summarizes the most likely scenarios of passive recovery in the study area. Trends 1 and 2 represent different transitions from agricultural and sparsely vegetated lands (year 1990) to native forests (year 2018). In both cases, the net increase in ecosystem complexity scores equally ($iEC_{1990-2018} = 3$). However, successional dynamics scores different, with trend 1 representing a linear recovery trajectory in which no ecological regression occurs ($SuD_{1990-2018} = 1$) and trend 2 showing a non-linear trajectory, in which a regression occurs ($SuD_{1990-2018} = 0.75$). Trends 3 and 4 represent transitions from heathlands and shrublands to native forests. Therefore, $iEC_{1990-2018} = 2$ in both cases, while $SuD_{1990-2018}$ scores 1 and 0.75, respectively. Finally, trends 5 and 6 represent changes from agricultural and sparsely vegetated lands to heathlands and shrublands. Then, $iEC_{1990-2018} = 1$ and $SuD_{1990-2018}$ equals 1 and 0.75, respectively.

The parametrization of PFRI is shown in Eq. (4).

$$PFRI = \frac{iEC}{iEC_{max}} \cdot \frac{R_{max} + 1 - R}{R_{max} + 1} \quad (4)$$

where: PFRI = Passive Forest Recovery Index; iEC = net increase in ecosystem complexity in the long term (period $i-j$) due to ecological succession; iEC_{max} = maximum increase in complexity, this value depending on the number of land cover classes involved in forest recovery (in this case, three); R = number of detected ecological regressions; R_{max} = maximum number of potential regressions in the time-series, (Eq. 3).

The index takes continuous values that vary from 0 (no passive forest recovery) to 1 (maximum ecosystem complexity driven by ecological succession, with no ecological regressions). To facilitate the interpretation of the PFRI, output values were classified into three categorical levels: low (0.1–0.3), intermediate (0.3–0.7) and high (> 0.7), with these thresholds being set in the two-dimensional space defined by the PFRI, according to Fig. 3. In specific, PFRI scores were compared for the three classes of increase in ecosystem complexity (Fig. 2a) and then the number of regressions for which these scores matched were identified. The thresholds would then represent equilibrium zones where the same PFRI value can be reached through different ecological pathways. For example, an intermediate PFRI value may result from a strong increase in ecosystem complexity under moderate disturbance or from a lower complexity increase in absence of disturbance.

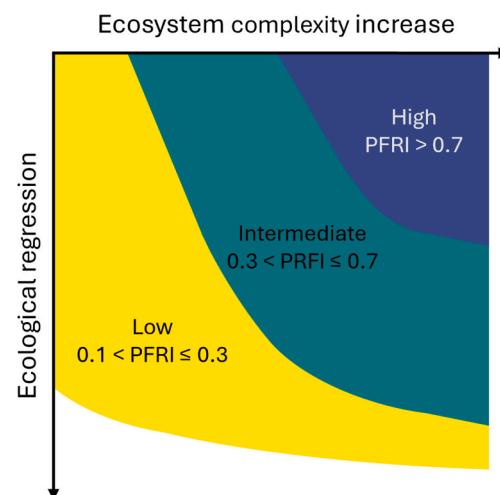


Fig. 3. PFRI scores estimated according to the increase in ecosystem complexity and the number of ecological regressions. The index varies continuously between 0 (no passive forest recovery) and 1 (ecological succession drives to maximum ecosystem complexity, with no ecological regression). Values were grouped into three levels according to the following thresholds: $0.1 < PFRI \leq 0.3$ (low); $0.3 < PFRI \leq 0.7$ (intermediate); $PFRI > 0.7$ (high).

2.4. Spatial patterns and drivers of passive forest recovery

Spatial patterns of passive forest recovery were quantified using different landscape metrics (number, size, perimeter and aggregation index) calculated at patch-level. Patches arise from the adjacency of pixels categorized by an equivalent PRI level (low, intermediate and high levels; Fig. 3). The aggregation index quantifies the spatial clustering of each class by comparing the number of adjacent cells with the theoretical maximum, values ranging from 0 (maximum disaggregation) to 100 (maximum aggregation) (He et al., 2000).

Finally, we explored the role of a set of socio-environmental variables with potential influence on passive forest recovery, according to our expertise. To this aim, 1789 sampling points, separated at least 1200 m to avoid spatial autocorrelation (in consistence with the spatial resolution of climate data) and stratified according to the three PFRI levels (low, intermediate and high levels; Fig. 3), were randomly distributed across the study area. For each point, the continuous PFRI values were extracted, together with the following set of variables: (i) geographic position: longitude (coordinate X), latitude (coordinate Y) and elevation (Z, data from a NASA SRTM digital elevation model at 30 m resolution; Farr et al., 2007); (ii) climate: annual maximum temperature (bio5), annual range of temperature (bio7) and annual precipitation amount (bio12), all downloaded from CHELSA database version 2.1 (period 1981–2010) at 30 arc sec (~ 1 km) (<https://chelsa-climate.org>; Karger et al., 2017); (iii) topography: slope (in percentage), derived from the NASA DEM; (iv) accessibility and population: distance to the nearest settlement, distance to the nearest road (both calculated from the settlement map available from the Spanish Geographic Institute at 1:5000 resolution) and change in population density (inhabitants/km²) between 1990 and 2018 (obtained from the Spanish Digital Atlas of Urban Areas, 1:5000). Then, the Moran's I test was calculated, showing a value of 0.033 that confirms the absence of significant spatial autocorrelation patterns for the PFRI index (Moran's $I < 0.1$; Diniz-Filho et al., 2012). Additionally, the pairwise Pearson correlations between predictors were verified to be lower than 0.75, which reduce interpretability issues in subsequent modelling analyses. To assess the relationships between passive forest recovery and this set of potential drivers, we ran univariate linear models and decision trees based on regression models (Loh, 2011). This is a sequential approach that simulates the branching structure of a tree, generating a collection of

internal and terminal nodes where entropy measures the uncertainty of each binary decision. The algorithm will automatically select the category of the variable that predicts at best the dependent variable, rejecting all other classes (Loh, 2011). The performance of the models was measured by the coefficient of determination (R^2) and the significance of each variable as the increase in the mean square error (% IncMSE), where the model prediction error increases by randomly substituting the value of each predictor. A 10-fold cross-validation (repeated three times) was applied to evaluate the results, averaging the values of R^2 and RMSE (root mean square error) on each out-of-fold prediction. This validation allows for controlling the optimal size of the decision tree. Finally, the partial dependencies of each variable in the model were plotted, keeping the effect of the other variables constant.

All analyses were conducted in QGIS v.3.36.2 and R software v.4.3.2, including Landscapemetrics v.2.1.1 (Hesselbarth et al., 2019), rpart (Milborrow and Milborrow, 2019) and caret (Kuhn, 2008) packages.

3. Results

During the period 1990–2018, ecosystem complexity increased in 12.71 % (8775 km²) of the study area due to ecological succession, with an average rate of 302.55 km² per year, this pattern being non-spatially homogeneous (Fig. 4a). In specific, a 6.15 % (4247 km²) of the area transitioned from agricultural and sparsely vegetated lands to heathlands-shrublands, a 3.41 % (2352 km²) from heathlands-shrublands to native forests and a 3.15 % (2176 km²) from

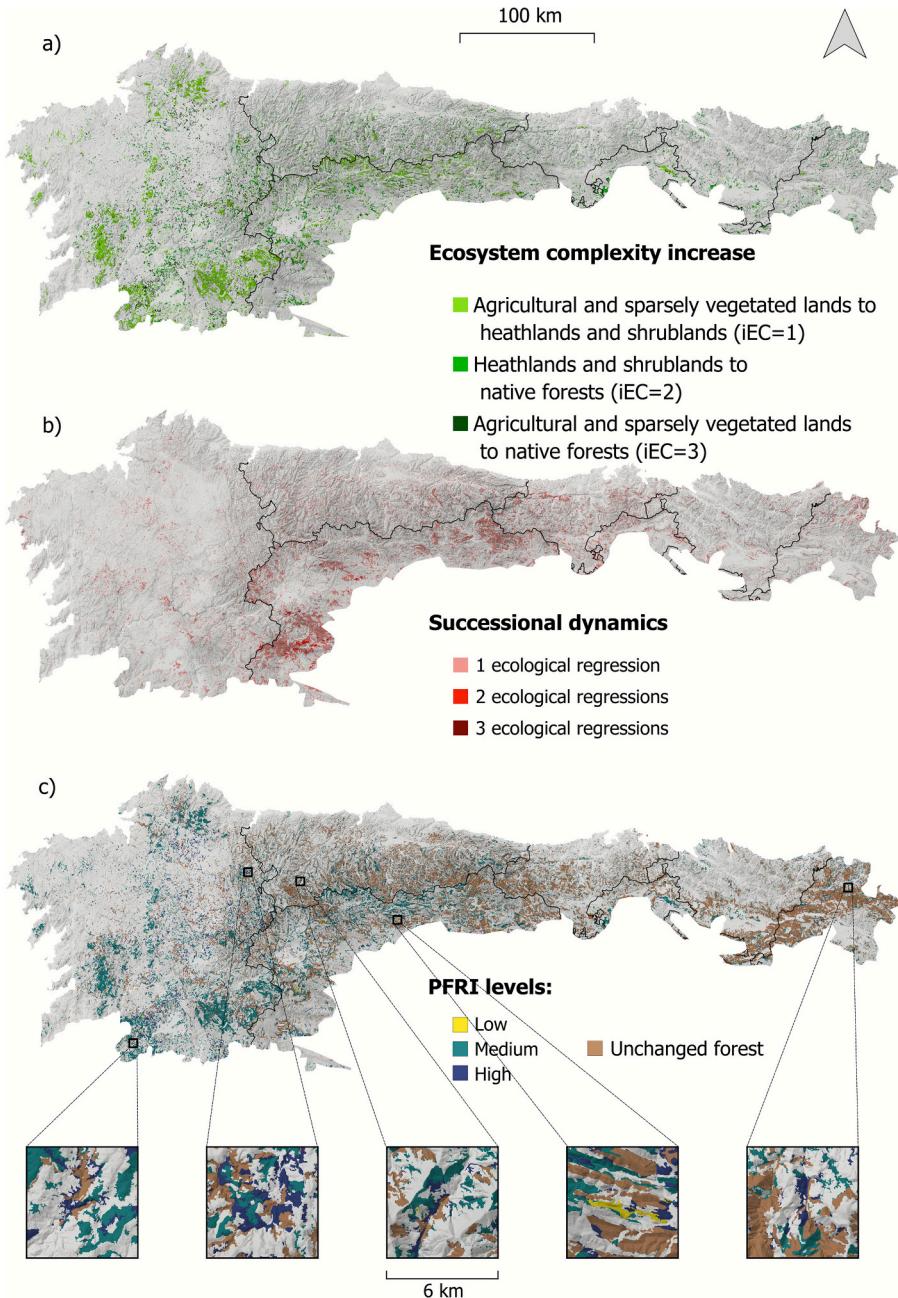


Fig. 4. (a) Net increase in ecosystem complexity in the long term due to ecological succession during the study period (1990–2018). (b) Number of ecological regressions driving to non-linear recovery trends. (c) PFRI parameterized based on the increase in ecosystem complexity and the successional dynamics, with values ranging from 0 (no recovery) to 1 (maximum increase in complexity and no regressions within the study period), reclassified into low, medium and high levels. The figure includes some examples of passive recovery patterns (native forests that remained unchanged throughout the whole period are referred to as “unchanged forest”).

agricultural and sparsely vegetated lands to native forests (Table S3, Supplementary Material). The 9.90 % (6862 km²) of the study area was affected by ecological regression: 9.70 % (6723 km²) suffered a single regression, 0.20 % (138 km²) two and 0.01 % (<0.01 km²) three (Fig. 4b).

The PFRI showed a scattered spatial pattern, with the westernmost (Galicia) and central (Cantabrian Mountains) parts of the Spanish Ibero-Atlantic region being the most relevant areas for passive forest recovery (Fig. 4c). Patches with the lowest PFRI values were less numerous and smaller, but more irregular in shape than those with high or intermediate PFRI values, which were the largest and most compact in shape. Aggregation was strong at all levels (AI >77 %), particularly for patches with the highest PFRI values (Table 1, Fig. 4c).

All of the socio-environmental predictors tested were significantly correlated with PFRI, except for the change in population density (1990–2018) (Table S4). The adjusted decision tree regression model explained 26.17 % of the variance and showed significant differences in the relative importance of these variables as drivers of passive forest recovery (Fig. 5 and Fig. 6). The most relevant predictor of PFRI was elevation, present at both the first and second hierarchical levels of splitting identified in the tree. Additionally, the distance to settlements was identified as a meaningful driver at the second tree level, while the longitude (coordinate X), the distance to roads and the annual amount of rainfall (bio12) had a significant effect at the third level. The highest values of PFRI were found in lowlands (≤ 820 m a.s.l.), close to settlements (≤ 417 m; nodes 4 and 5). The average values of R² and RMSE coefficients obtained by 10-fold cross-validation for this model were 0.22 and 0.27, respectively.

4. Discussion

4.1. Conceptual advance and applied relevance of the PFRI

The index proposed in this study introduces a novel framework to quantify spatio-temporal trends in passive forest recovery at large scale through the integrated assessment of ecosystem complexity and successional dynamics, thereby capturing ecological dimensions that conventional indicators may overlook. Most studies of forest recovery have focused on the comparison of land cover transitions between the initial and the final year of the study period, typically mapping areas where agricultural lands have reverted to shrublands or forests and quantifying recovery in terms of net forest-cover gain over time (e.g. Solano et al., 2021). These approaches evaluate direct land cover transitions without considering the intermediate years within the period of analysis (usually several decades). Consequently, they may neglect relevant short-term changes resulting from disturbances that disrupt the general trend of increasing ecosystem complexity throughout ecological succession. The explicit consideration of such complex dynamics into integrated indices of passive forest recovery, as PFRI, allows to move beyond static snapshots of land cover.

The PFRI supports a wide range of ecological applications associated with distinct types of functional outcomes in the fields of biodiversity conservation and land-use planning and management. These include the assessment of species persistence in heterogenous and changing landscapes, which depends not only on the amount and connectedness of suitable habitat patches, but also on the temporal dynamics of those patches at different scales. In fact, in many cases (e.g., habitat-specialist

species), temporal features, such as patch longevity or the time during which a patch is suitable or not (Ellner and Fussmann, 2003), are even more important for species persistence than structural features, such as the number of patches (Keymer et al., 2000) or the distance between them (Fahrig, 1992). In this sense, the index can be used to identify habitat patches resulting from long-term transitions toward structurally complex vegetation types (i.e., areas with high PFRI values), such as forests, which are particularly relevant for specialist species that depend on stable and continuous forest cover. The PFRI can also help map recovering mosaics of shrublands and young forests (i.e., areas with intermediate PFRI values) that facilitate species movement and buffer more established habitats. Furthermore, the PFRI may be relevant to identify emerging areas across the landscape where passive recovery leads to forest with high aboveground biomass, thereby contributing significantly to increased carbon sequestration and storage (Castaño-Santamaría et al., 2013), which is particularly important for climate change mitigation. The recognition of these forests is also of significant relevance in the Ibero-Atlantic region, given their demonstrated resilience to forest fires (Cruz et al., 2024), reducing fire-line intensity by up to five times, even under extreme weather conditions (Oliveira et al., 2023).

4.2. Spatial patterns of passive forest recovery and drivers

The spatial patterns revealed by the PFRI underscore the role of landscape configuration in passive forest recovery. We found a predominance of high and intermediate PFRI values throughout the study area that were aggregated into large and compact patches. In contrast, low PFRI values were found in relatively small patches, reflecting isolated spots of recent encroachment that have not persisted or larger areas still under active use. Overall, passive forest recovery showed a high spatial aggregation (>77 %), which indicates that new forest patches are clustered, rather than spreading diffusely. This aggregation pattern for tree cover is consistent with the observed previously in the study area (Cantabrian Mountains) for beech and oak forests (García et al., 2005) and also in other European regions. In this sense, Schulte to Bühne et al. (2022) reported that passive rewilder in Great Britain tends to progress in contiguous patches, identifying higher increases in primary productivity in passive rewilded core areas that declined toward surrounding buffer zones. At continental scale, forest expansion has been associated with reduced patch numbers and increased spatial aggregation (Palmero-Iniesta et al., 2020). Our findings confirm that passive forest recovery often proceeds by “nucleation” of wooded patches that expand and coalesce, resulting in a patchy yet aggregated landscape of native forests and shrublands.

The strong spatial variations in the PFRI and its components (ecosystem complexity and succession dynamics) observed across the Spanish Ibero-Atlantic Region can be associated with territorial identity (different autonomous communities), which, in turn, is related to the specific socio-environmental characteristics evaluated in this study (explaining 26.17 % of the variance), but also with socio-political factors not considered despite they may also contribute significantly to shaping the landscape. Elevation and human accessibility (proximity to settlements) emerged as key passive forest recovery drivers. Notably, the highest PFRI values did not occur in remote uplands, contrary to broader European trends that often associate land abandonment with high-elevation or marginal farms (Kuemmerle et al., 2016). Instead, the

Table 1

Patch metrics for different levels of the passive forest recovery index (high: PFRI >0.7, intermediate: 0.3 < PFRI \leq 0.7 and low: 0.1 < PFRI \leq 0.3).

PFRI	Number of patches	Mean area (ha)	Range area (ha)	Mean perimeter (m)	Range perimeter (m)	Perimeter-area ratio (m/ha)	Aggregation index (AI)
High	84,944	2.6	0.1–773.4	774.2	120–90,836.8	297.8	87.8 %
Intermediate	82,359	7.9	0.1–28,196	360.0	120–1,201,278	45.6	77.4 %
Low	7560	1.2	0.1–454.6	347.3	120–25,979.1	289.4	78.0 %

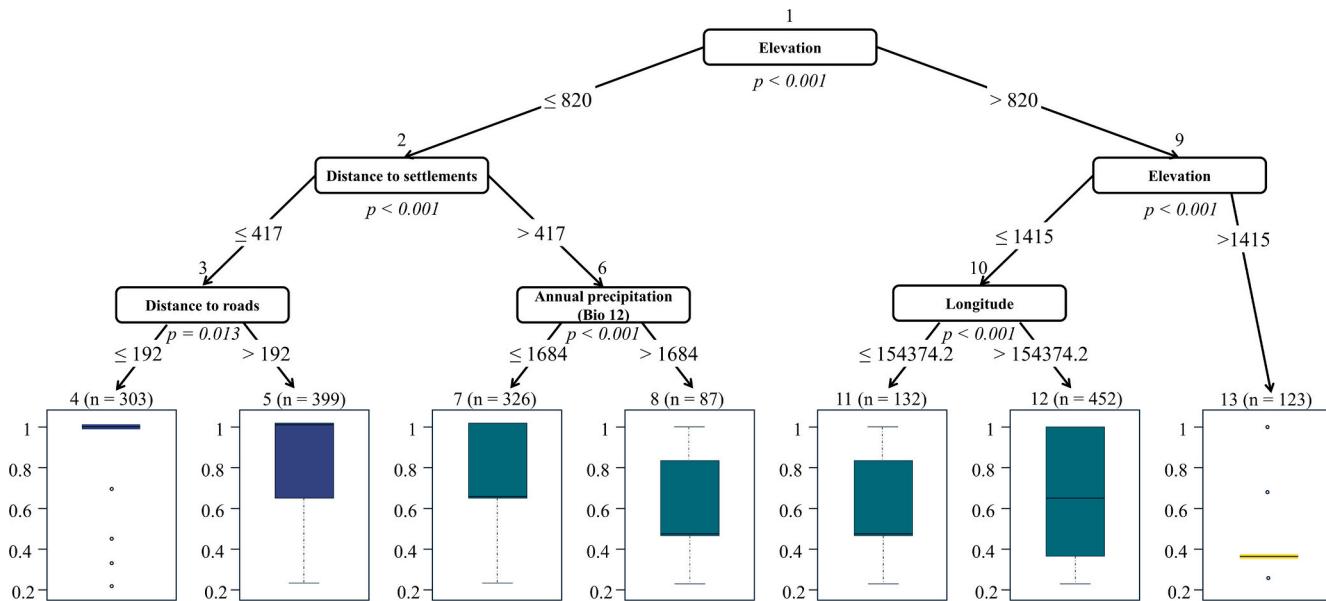


Fig. 5. Decision tree regression model showing the socio-environmental drivers of passive forest recovery (PFRI): elevation, distance to the nearest settlement, distance to the nearest road, annual precipitation and longitude (coordinate X). For each terminal node, a boxplot of PFRI value is displayed, together with the number of samples corresponding to each one.

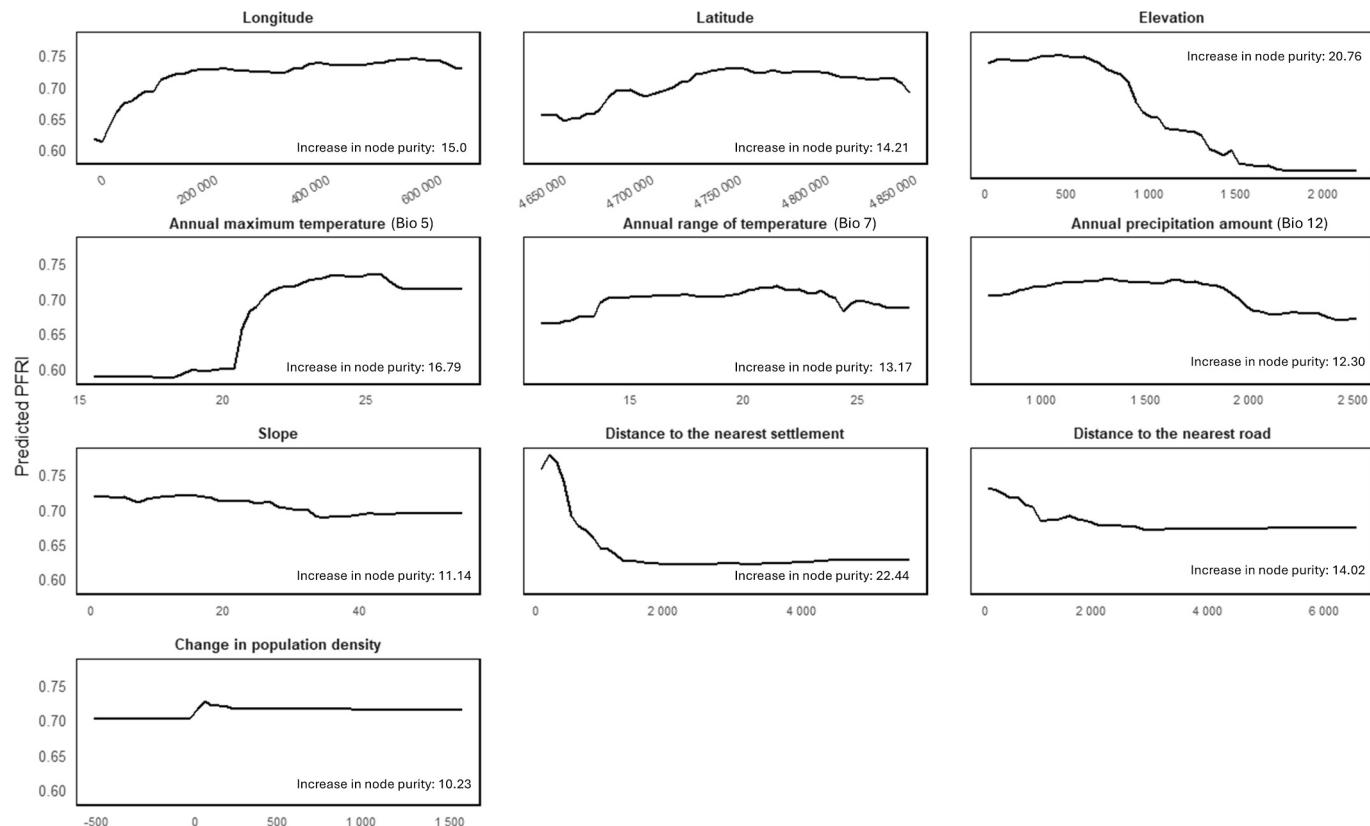


Fig. 6. Partial dependence plots showing the relationship between the passive forest recovery (PFRI) and the socio-environmental drivers considered in the study. Plots display how each predictor affected PFRI, keeping constant the effect of the other variables.

strongest passive forest recovery was concentrated at mid-elevations, often near depopulated villages. This pattern reflects the historical regional pattern characterised by a high density of rural settlements, where land abandonment typically occurs near numerous small nuclei rather than in isolated upland areas (SADEI, 2021). This observation reveals that passive forest recovery is especially pronounced around

areas affected by rural exodus in recent decades, in consistency with broader European patterns of forest expansion at mid-elevations between 500 and 1000 m a.s.l. (Palmero-Iniesta et al., 2020). In the Spanish Ibero-Atlantic biogeographical region, passive forest recovery is not solely a remote upland phenomenon, but a peri-settlement one. This is consistent with a broader, generalized trend, highlighted by recent

reports on passive rewetting (García et al., 2023). However, such patterns are not universal and may vary depending on regional socio-ecological contexts, therefore they cannot be extrapolated to other areas and scales.

4.3. Limitations of the PFRI

Although the PFRI framework provided consistent and likely robust results at broad scales, several drawbacks may be identified: (i) The index design assumes that forest is the universal endpoint of succession in abandoned lands. However, this assumption is context-dependent since, in the Spanish Ibero-Atlantic biogeographic region, forest is not the potential vegetation everywhere, for instance at elevations above 1600–1800 m a.s.l. (3.2 % of the territory) or in areas with specific edaphic constraints (González-García et al., 2024; González Le Barbier et al., 2025). (ii) The PFRI is a measure of landscape change and successional stage, but it does not provide an assessment of ecosystem quality, condition or functional integrity (Pettorelli et al., 2018), similar to other land-cover based studies at large scale. (iii) Another limitation lies in the evaluation of the short-term successional dynamics, which is based on the absence of ecological regressions (i.e., land cover changes toward classes of lower ecosystem complexity), overlooking non-stand replacing disturbances (i.e., events that modify ecosystem structure but do not result in the complete removal of vegetation; Brown et al., 2025). For instance, a site undergoing a meaningful structural change (e.g., thinning of forest canopy from natural tree fall) and yet remaining a forest would be counted by PFRI as fully stable, even though its structure and species composition changed. (iv) The analysis was constrained by the use of Corine Land Cover (CLC) data, which comes with well-known limitations for monitoring landscape dynamics (Castanho et al., 2021), especially when it is applied in heterogeneous and highly changing systems (Álvarez-Martínez et al., 2011). Among these limitations, we can mention: a lack of availability for meaningful time periods, an inconsistency in the classification resolution across the time series due to methodological changes implemented in 2012 (García-Álvarez and Camacho, 2017) and the inherent characteristics of the data set (e.g., typological resolution) that may limit the understanding of the ecological processes, since it has been developed for other specific aims (Eigenbrod et al., 2010).

5. Conclusions and future recommendations

The PFRI here proposed complements the existing pool of rewetting monitoring indicators by adding a lens on the short-term successional dynamics, then offering a more holistic tool that can support decision-making in the fields of biodiversity conservation and land planning and management. The spatial pattern of passive forest recovery identified at biogeographical scale reveals a strongly aggregated mosaic where human legacies, especially settlement distribution and land-use history, strongly govern where and how passive forest recovery unfolds on the landscape. Our approach and results may be useful for understanding the spatio-temporal patterns of rewetting in other temperate regions affected by rural restructuring.

Given the above-mentioned limitations of the data used to perform the PFRI, further research should be done using more detailed information and advanced monitoring techniques. Longer time-series of high or moderate spatial resolution satellite imagery (e.g., Landsat) could be analysed using continuous change detection algorithms (e.g., Zhu and Woodcock, 2014) to identify more accurately land cover changes. Also, the consideration of finer classifications at more detailed typological resolution could reveal other relevant land cover transitions, with the optimal level of detail remaining uncertain and context dependent. Future work should embrace these improvements, using PFRI or similar approaches as a stepping stone toward increasingly accurate and detailed monitoring of passive forest recovery across dynamic landscapes in the face of global change.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used Microsoft Copilot in order to improve readability. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Daniel Pfitzer-López: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Rubén Ramírez-Rodríguez:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Jose Valentín Roces-Díaz:** Writing – review & editing, Writing – original draft, Visualization, Validation. **Jose Manuel Álvarez-Martínez:** Writing – review & editing, Conceptualization. **Mario Quevedo:** Writing – review & editing, Funding acquisition, Conceptualization. **Daniel García:** Writing – review & editing. **Borja Jiménez-Alfaro:** Writing – review & editing, Conceptualization. **Susana Suárez-Seoane:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecolind.2025.114532>.

Data availability

Data will be made available on request.

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