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Support for forest conservation imperatives: A robust approach for multi-dimensional, spatially explicit resilience assessment

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ABSTRACT

Forest ecosystems are ecologically, socially, and culturally valuable, and are essential to global sustainability, yet climate change and altered disturbance regimes are threatening the future of forests around the globe. Policies and regulations pertaining to forest conservation require reliable and informative measures of condition and management effectiveness to sustain these investments, but standardized methods for characterizing management impacts on multiple ecological resources are still lacking. Composite indicators provide a promising approach for quantifying forest resilience across scales, yet their development is often inconsistent, lacking theoretical rigor and sensitivity to ecological context. This study presents two transparent, scalable pathways for constructing composite indicators of ecosystem resilience, with a focus on forest resilience in California's Sierra Nevada. We operationalize the Ten Pillars of Resilience (TPOR) framework and apply two core metric selection methods: Real Core Metrics (RCM) via hierarchical clustering and Synthetic Core Metrics (SCM) via factor analysis, both combined with climate-based ecological stratification, fuzzy logic-based normalization, and optimized metric weighting. Composite indicators were developed using both compensatory and non-compensatory aggregation techniques. Results show that stratified, optimized approaches (RCM and SCM) outperformed a traditional, landscape-wide theoretical model by better capturing ecological variability and avoiding bias from outliers. The SCM approach produced more symmetric and statistically elegant indicators, while RCM indicators retained interpretability through direct ties to tangible forest attributes. We introduce an Information Retention Index (IRI) to quantify the amount of information preserved by the composite indicators and conduct a Monte Carlo-based sensitivity analysis to assess the stability of indicator outputs across methodological choices. Our pathways advance the rigor, transparency, and ecological relevance of composite indicator development, providing a robust foundation for spatially explicit resilience assessments that support adaptive management and conservation investments.

1. Introduction

Forest ecosystems provide and support a wealth of ecosystem services and their conservation has long been recognized as critical to the future of global sustainability and quality of life (Salim and Ullsten, 1999; Payn et al., 2023). Forests in western North America and around the globe are experiencing unprecedented stress from the confluence of climate change and altered disturbance regimes, leading to widespread concerns about their long-term resilience (Hessburg et al., 2019) and sustainability of the many critical ecosystem services (e.g., water, carbon, biodiversity, wood products) provided by forest ecosystems (Aznar-Sánchez et al., 2018). Recent declarations and commitments to forest conservation, such as the Kananskis Wildfire Charter (Group of Seven, 2025), the EU's Forest Monitoring Law (Resco de Dios and Boer, 2025), and the Global Biodiversity Framework (Burgess et al., 2024) call for near-term progress (next 5 years) across multiple metrics and ecosystem facets as critically important to the future of forests and global sustainability. Motivating these commitments is the need for meaningful and actionable metrics to characterize ecosystem conditions and change over time toward enhancing conservation finance mechanisms and investments (e.g., Lawler et al., 2020; Waldron et al., 2013).

To be successful, conservation programs need to provide quantitative, transparent and defensible assessments of multidimensional conditions and threats to forest resilience (Brand, 2009; De Leo and Levin,

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1997) to quickly inform effective conservation action (e.g., Elsen et al., 2020) and show measurable results to justify and motivate investments (e.g., De Groot et al., 2013; zu Ermgassen and Löfqvist, 2024). The complexity of socio-ecological systems necessitates multi-metric approaches to capture the multidimensional nature of resilience and its implications for providing ecosystem services (e.g., de Jonge et al., 2012; de Juan et al., 2018). The large scale of the processes governing system dynamics is such that these assessments require individual metrics (e.g., tree density) to be characterized at high-resolution across large spatial extents, and then summarized along with other metrics associated with facets of forest ecosystems (e.g., forest structure) to make inferences about higher order conditions (e.g., forest health; McDonald and Lane, 2004) in a robust and repeatable manner. A clear pathway to quantifying status and change across multiple metrics and ecosystem facets that are potentially scalable across continents and the globe is lacking.

Many of the barriers to accessing and integrating high-resolution spatially explicit data into environmental applications have been removed in recent years. However, with big data can come big problems due to the "curse of dimensionality" (Altman and Krzywinski, 2018), which impacts the ability to make meaningful and actionable decisions due to the inherent complexity of data. The crux of the issue is finding a balance between including enough information (e.g., number of individual metrics) to adequately characterize the system of interest while ensuring the analysis is easily interpretable to the large and potentially diverse end-user base. Forest conservation and land management programs remain challenged with inconsistent and potentially underperforming approaches that can effectively support investment and measure progress. In most cases, metrics are normalized (aka scored) and then those scores are simply summed or averaged, or the range of values are presented in some form (e.g., bar charts) and shifts in conditions within and among metrics are summarized (Gorman et al., 2024; Keene and Pullin, 2011). These approaches, despite their widespread use, frequently are inadequate to the task of incisively informing strategic investments in forest restoration and conservation, and the unintended bias in these approaches can make them less stable and reliable measures of condition, two fundamental requirements for bolstering market demand and financial investment (e.g., "bridging conservation funding gap"; Clark et al., 2018; Gonon et al., 2024; Perino et al., 2022; Thompson, 2023).

Composite indicators offer a valuable solution by integrating two or more metrics into a single value that reflects a facet of the landscape (e.g. forest resilience), which can be applied similarly across multiple facets of the landscape to reflect the status and change of complex ecosystems (Briguglio et al., 2009; Sharifi and Yamagata, 2016; Tate, 2012). These indicators are particularly useful in comparing and ranking conditions across various domains such as the intersection of forest resilience with biodiversity conservation, carbon sequestration, water security, and economic justice over space and time (Nardo et al., 2008). They allow for the quantification of resilience at multiple scales, offering a more comprehensive and balanced view of system response to disturbances (Cutter et al., 2014). For example, the integration of ecological indicators (e.g., biodiversity, soil quality) with social factors (e.g., governance capacity, community adaptation) can provide critical insights into how resilience is distributed across landscapes and communities and the degree to which they are interdependent (Liggs et al., 2015).

Environmental composite indicators are not new, but they are largely limited to singular resource areas. Most applications have resulted in indices (spatially explicit or not) assessing the current and/or future state of a system to address specific resource outcomes, such as ecological suitability, habitat quality, hazard exposure, management opportunities, stability under climate change, and facets of social well-being tailored to particular places. Examples of such applications include the assessment of sustainability of agriculture practices (Gómez-Limón et al., 2020; Talukder and vanLoon, 2017), quality and stability of biodiversity habitats (de Castro-Pardo et al., 2022; Klausmeyer et al., 2011; Riedler et al., 2015; Suraci et al., 2023; Yu et al., 2017), prioritization of forest management strategies (Brovkina et al., 2017; Lin, 2020; Marín et al., 2021; Pert et al., 2012; Tarasewicz and Jönsson, 2021), land use and land cover degradation (Benini et al., 2010; De Montis et al., 2020; van Oudenhoven et al., 2012), productivity of marine and coastal ecosystems (Campos et al., 2024; Yamada et al., 2021; Ye and Link, 2023), resilience or vulnerability to environmental hazards and climate change (Ferrier et al., 2020; Flensborg et al., 2023; Hiete et al., 2012; Kotzee and Reyers, 2016; Lung et al., 2013; Salvati et al., 2013, Thakur and Mohanty, 2025), and water security (Chung and Lee, 2009; Lü and Lü, 2021; Molinos-Senante et al., 2014).

Creating useful and reliable composite indicators is a complex process that requires careful consideration to ensure accuracy, relevance, and representation (Nardo et al., 2008). Four primary components to the development of composite indicators and their evaluation include: 1) selecting a strong theoretical framework that explicitly defines the concept being represented (Booysen, 2002); 2) selecting metrics that have individual appeal but also make strong contributions to representing complex systems on the whole; 3) putting metrics on a common scale through a normalization process that does not bias their representation; and 4) summarizing conditions across metrics without losing the inherent variability among metrics in the composite representation. The importance of a theoretical framework lies in its ability to provide a coherent structure upon which the composite indicator is built. This, in turn, guides the selection of metrics and their respective influence and interpretation (Greco et al., 2019). Without a sound theoretical foundation, the resulting composite indicator may lack validity and could mislead users regarding the true nature of the phenomenon being represented (Burgass et al., 2017; Nardo et al., 2008).

This study presents two transparent and repeatable methodological pathways for deriving robust composite indicators to represent forest ecosystem conditions in an unbiased and geospatially integrated manner using a relatively new theoretical framework for socio-ecological systems. The two methodological pathways were designed to compare and contrast the strengths and sensitivities of the proposed pathways to core metric selection and weighting to derive composite indicators of forest resilience. We also present a novel method of characterizing the 'information capture' accomplished by a given multi-metric representation and use the method to evaluate the effectiveness of the indicators generated by each of the two methodological pathways we explore. These pathways can be adopted by and applied to multiple ecosystem facets (not limited to forest resilience) and any conservation and restoration program at any scale, making them highly versatile. Finally, we demonstrate how it can be used to address multiple ecosystem facets to make inferences about overall landscape resilience across the Sierra Nevada ecoregion (California, United States).

2. Methods

2.1. Demonstration study area

The Sierra Nevada is a large and diverse landscape, extending approximately 650 km from north to south, and ranging in elevation from 200 to 4400 m, spanning multiple vegetation zones from foothill oak woodlands to subalpine and alpine ecosystems (Fig. 1). The region is known for high levels of endemism and biological diversity, including 13,000 different plant species, 27 species of conifers, and more than 40 different vegetation associations (Sawyer et al., 2008). Although dominated by forested public lands, the Sierra Nevada has a diversity of land ownerships, ranging from National Parks to private industrial timber lands to a wide range of urban environments. Accordingly, the Sierra Nevada provides a strong test of the efficacy and performance of composite indicator methodologies.

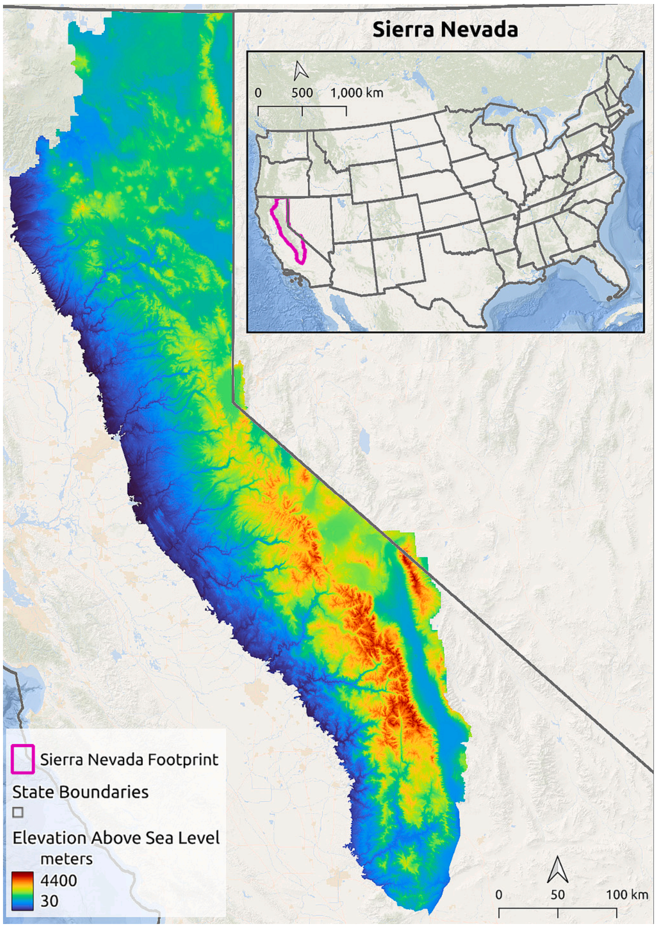

Fig. 1. The Sierra Nevada, California, demonstration landscape.

2.2. *Socio-ecological system TPOR framework*

We used the Ten Pillars of Resilience Framework (TPOR Framework) as the theoretical foundation for our composite indicator work (Manley et al., 2023). The TPOR Framework integrates both social and ecological values through ten "pillars": (1) forest resilience, (2) fire dynamics, (3) fire-adapted communities, (4) carbon sequestration, (5) air quality, (6) biodiversity conservation, (7) water security, (8) wetland integrity, (9) economic diversity, and (10) social and cultural well-being. Each pillar is comprised of one or more core *elements* (e.g., forest resilience is partitioned into structure, composition, and disturbance), which in turn are described by *metrics* that represent individual components of landscape conditions, which in turn are quantified using spatially explicit data (e.g., raster or vector data). The relationship between pillars, elements, and metrics is hierarchical (one or more metrics are nested within a given element, one or more elements are nested within a given pillar); however in application the intermediate level of organization - the 'elements' - may or may not be included in making inferences about the overall socio-ecological system. This framework has proven useful in several landscape assessments performed at various scales to inform landscape planning and management (Manley et al., 2023; Manley et al., 2025; Povak et al., 2024).

We applied our composite indicator pathways to the forest resilience pillar of the TPOR Framework and evaluated their performance. The Sierra Nevada is a heavily forested area, and reliable spatial data on a range of forest metrics are widely available. The breadth of available data and metrics on forest conditions provided a strong test of the composite indicator pathways. Finally, we demonstrated the hierarchical application of our pathways under the TPOR lens. We achieved this through a comprehensive assessment that incorporates metrics across all 10 pillars into a multi-pillar indicator of ecosystem resilience. Fig. 2 shows a schematic representation of the general workflow, including the proposed pathways to build composite indicators.

2.3. *Forest resilience example application*

Characterizing complex systems requires selecting a comprehensive set of metrics that adequately defines the study system while also considering model parsimony to ensure outputs are easily interpreted by the end users. The selection of metrics used in our example reflect that compromise as the metrics were picked from a larger pool of remotely sensed data for the state of California. Metric selection derived from interactions among scientists, practitioners, and government and non-government interest holders to determine those metrics that best represented landscape conditions, had direct application for management, and were easily communicated to users. Correlation analyses were also conducted (data not shown) among the larger set of metrics to eliminate redundant metrics while forming the final set (Table 1). These metrics also aligned with several laws, charters, and initiatives that have recently been implemented within the United States and across the globe. In sum, the metrics included in the current assessment represented not only a bottom-up approach where selection was driven by regional scientific knowledge and community engagement but also addressed larger national and global imperatives at larger scales.

Following these criteria, we represented the forest resilience pillar using ten metrics associated with each of three elements (structure, composition, and disturbance; Table 1). Five metrics related to forest structure, including basal area, tree density, density of large trees ($>$ 75 cm diameter at breast height (dbh)), stand density index (SDI), and canopy fractal dimension index. Three metrics related to forest composition, including the proportion of the landscape in early and late seral stages, and the density of large snags ($>$ 75 cm dbh). And, two metrics related to disturbance, including tree mortality and the time since the last disturbance. Each of the ten metrics were evaluated to determine if they met assumptions of a normal distribution, and statistical transformation was applied to those with the highest bias associated with skewness and outliers (Table 1).

2.4. *Pathways for constructing composite indicators*

We explored two complementary pathways for constructing composite indicators of socio-ecological resilience (cluster analysis and factor analysis) and then demonstrated their application to forest resilience. These pathways have different strengths and sensitivities that are determined in part by the breadth and substance of metric representation but also determined by the character of individual metrics and their relationship with one another. The selection process reflected a balance between data availability with the need to accurately represent the target phenomenon. The aim is to ensure that the chosen metrics effectively captured the multidimensional aspects of the ecosystem component or overall ecosystem. Accordingly, metrics were selected based on their relevance to the theoretical framework and their contribution to the information presented through the composite indicator (Booysen, 2002; Dale and Beyeler, 2001; Freudenberg, 2003; Li et al., 2012).

We could have constrained the aggregation process for the forest resilience pillar to each level of the TPOR hierarchy – first aggregating metrics to their associated element and then aggregating the three elements to the pillar (Fig. 3) – but we chose to bypass elements and aggregate all the metrics to represent the pillar. We bypassed elements in our analysis for two reasons: 1) working with a greater number of metrics provided a more robust comparison of the performance of each pathway, and 2) it was an opportunity to directly compare the outputs of these pathways to the outputs of the TPOR Framework as the theoretical foundation.

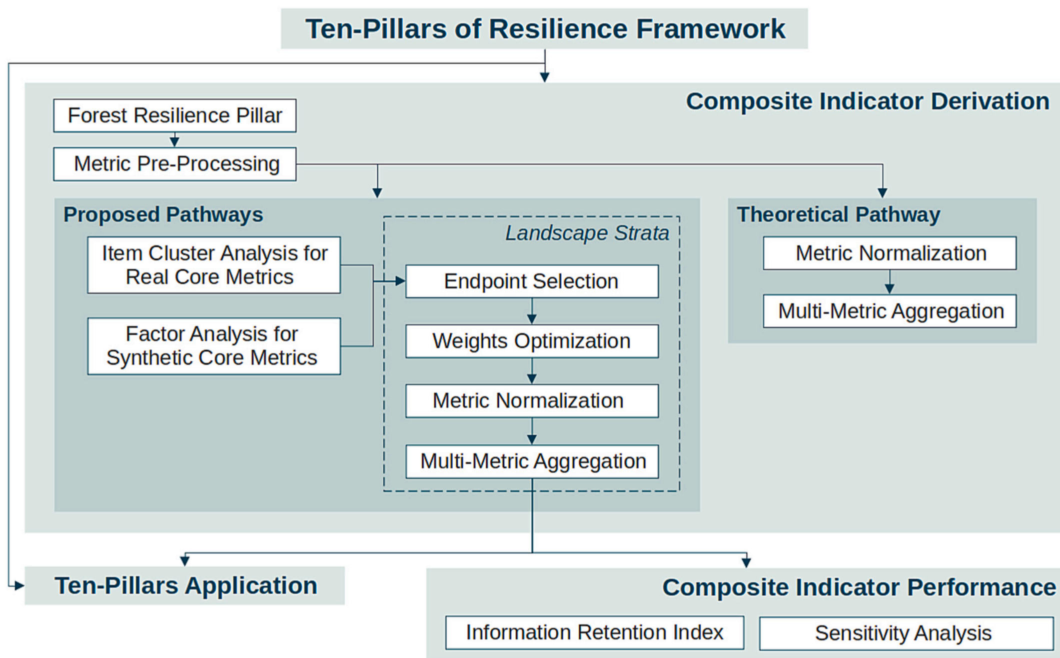

Fig. 2. Schematic representation of the proposed workflow to build composite indicators of forest resilience based on two analytical pathways. The first pathway is based on hierarchical cluster analysis to select 'core' metrics from a large pool of initial metrics. The second pathway has the same objective but it employs factor analysis to build 'synthetic' core metrics. These two pathways include landscape stratification to constraint endpoint selection based on outlier detection, mathematical weight optimization, metric normalization based on fuzzy logic, and metric aggregation via compensatory or non-compensatory means. The composite indicator performance is assessed through a spatially-explicit information retention index and sensitivity analysis. A third (theoretical) pathway is presented for comparison purposes.

Table 1
Metrics and elements of the forest resilience pillar as per the Ten Pillars of Resilience (TPOR) Framework (Manley et al., 2023).

Short Name	Description	Data Source	Pre-Processing	Element	A Priori Interpretation	Normalization Method
BA	The cross-sectional area of tree trunks measured at diameter breast height (dbh). Expressed in square feet per acre.	Imputation of FVS runs on FIA plot data (Huang et al., 2018)	Square root transformation	Structure	Lower is better	Negative, piecewise linear slope
TPA	The number of trees per acre, commonly used to assess forest structure and habitat condition.	Imputation of FVS runs on FIA plot data (Huang et al., 2018)	Logarithmic transformation	Structure	Lower is better	Negative, piecewise linear slope
TPA30	The number of large trees, defined as those with diameters at breast height (dbh) >30 in., per raster pixel.	Imputation of FIA plot data and allometric equations	Logarithmic transformation	Structure	Higher is better	Positive, piecewise linear slope
SDI	Relates the current stand density to an equivalent density in a stand with a quadratic mean diameter of 10″ (Reineke, 1933).	Imputation of FVS runs on FIA plot data (Huang et al., 2018)	None	Structure	Lower is better	Negative, piecewise linear slope
FDI	A measure of canopy shape complexity, ranging from 1 (simple, continuous canopy) to 2 (highly complex, interrupted canopy).	Canopy height model analysis (Chamberlain et al., 2023)	Range clamping at percentile 99.5	Structure	Higher is better	Positive, piecewise linear slope
eSE	Proportion seedlings (dbh < 1″) and saplings (1″ < dbh < 6″) in a stand.	Imputation of FVS runs on FIA plot data (Huang et al., 2018)	None	Composition	Lower is better	Negative, piecewise linear slope
lSE	Proportion of medium to large trees (dbh > 24″) in a stand.	Imputation of FVS runs on FIA plot data (Huang et al., 2018)	None	Composition	Higher is better	Positive, piecewise linear slope
Snag40	Number of snags per acre from all species and all decay classes with diameters of 40″ dbh and greater.	Imputation of FVS runs on FIA plot data (Huang et al., 2018)	Logarithmic transformation	Composition	Higher is better	Positive, piecewise linear slope
Mort	The dead tree canopy cover fraction change between 2017 and 2021, considering insect and disease causes only.	Segmented dynamic detection algorithm (Koltunov et al., 2020)	Logarithmic transformation	Disturbance	Lower is better	Negative, piecewise linear slope
TSD	Time in years before 2021 since the most recent disturbance of at least 25% canopy cover loss per 30 m pixel.	Segmented dynamic detection algorithm (Koltunov et al., 2020)	Majority filter (4-cell radius)	Disturbance	Higher is better	Positive, piecewise linear slope

2.4.1. Real core metric pathway

The Real Core Metric (RCM) pathway is most applicable when few, possibly interrelated metrics are available, when the overall dimension encompassed by these metrics is not large enough to be subject to the derivation of a synthetic representation of metrics (as described in 2.4.2), or when the application calls for metrics based on real measured

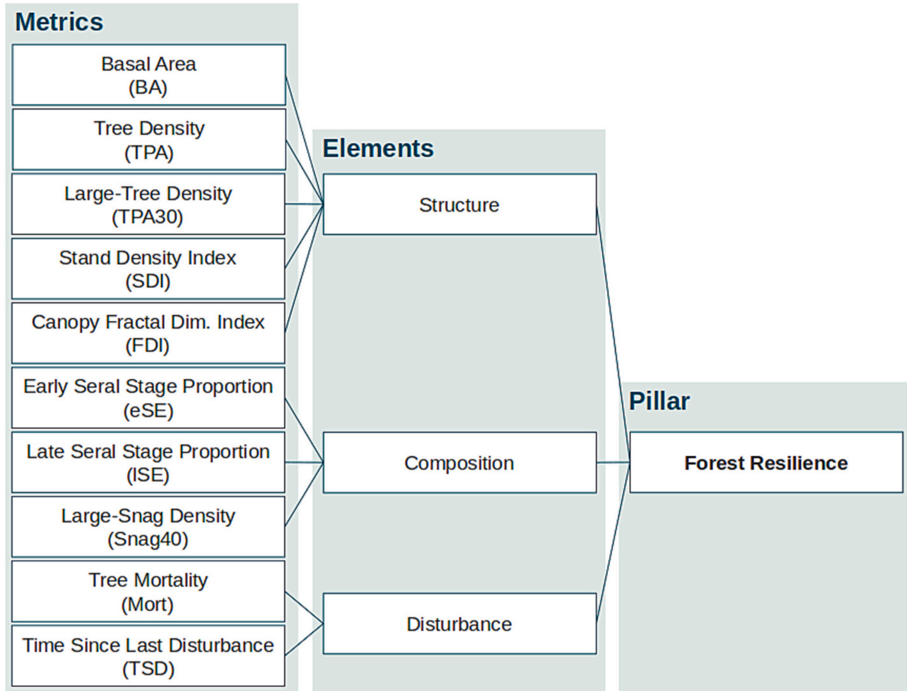

Fig. 3. Ten metrics of forest resilience used to demonstrate composite indicator methodologies. They represent the three elements of the forest resilience pillar of the TPOR Framework, and illustrate the hierarchical structure of the pillar that served as the theoretical foundation for building the composite indicator.

or estimated values (e.g., trees per unit area) such as for policy or regulatory purposes. This pathway is based on the Item Cluster Analysis (ICLUST) technique proposed by Revelle (1979). Unlike standard factor analysis, ICLUST builds a hierarchical structure of metrics using two complementary reliability coefficients: coefficient Beta (β), the worst split-half reliability (a measure of general factor saturation or homogeneity), and coefficient Alpha (α), the average split-half reliability (a measure of internal consistency). While high α indicates that metrics are correlated on average, it does not guarantee unidimensionality, that is, a cluster can be reliable but multidimensional ("lumpy") if β is low (Revelle, 1979). The function *ICLUST* of the R package *psych* (Revelle, 2025) was used to perform the metric clustering.

We generated the full ICLUST hierarchy using permissive defaults ($\alpha = 3; \beta = 1$) and then traced the clustering chain to identify the specific hierarchical node where β began to diverge distinctively from α. This divergence signals the point where distinct sub-constructs are forced into a broad composite, maintaining high internal consistency only through metric aggregation rather than structural unity. We restricted our final dimension selection to the clusters immediately preceding this divergence, ensuring that every identified forest resilience cluster possessed reasonable factorial homogeneity ($\alpha \approx \beta$). Note that we optimize the initial number of clusters (k) to find through ICLUST by testing multiple numbers and by selecting the maximum number of clusters that would still prevent a single metric from forming its own cluster.

Once homogeneous forest resilience clusters were isolated, we applied a two-step filter to select the single most representative RCM for each cluster. First, we pruned "late-joining" metrics, which we defined as those merging at the hierarchy's periphery. This pruning aimed at eliminating specific variance while maximizing stability, as late-joining metrics would result in lower factor saturation. Second, we selected a single RCM from the remaining metrics using ICLUST's pattern matrix. Unlike standard cluster loadings, which can be inflated by variance shared between oblique clusters, pattern coefficients represent standardized regression weights that partial out inter-cluster correlations (Revelle, 1979). Conceptually, the pattern matrix is equivalent to the loading matrix from a factor analysis (Revelle, 1979). We selected the metric with the highest absolute pattern coefficient. This selection was validated through ecological reasoning and a priori knowledge of the statistical properties of the input metrics (distribution, compositional nature, etc.).

2.4.2. *Synthetic core metric pathway*

The Synthetic Core Metric (SCM) pathway is based on factor analysis (FA), and it is proposed for those scenarios where a large number of (interrelated) metrics are initially available. FA is a multivariate statistical technique commonly used to reduce the dimensionality of a set of observed metrics by identifying a smaller number of unobserved latent factors that explain the correlations among them. In the context of composite indicator analysis, FA serves as a tool to extract the underlying structure of the data, simplifying complex, high-dimensional metrics into interpretable synthetic indicators. FA operates on the principle that the observed metrics (X) are linear combinations of common factors (F) and unique variance (E), expressed by the fundamental model (Eq. 1):

$$X_j = \sum_{k=1}^{p} l_{jk} F_k + E_j$$

where l_{jk} represents the factor loading of the j-th metric on the k-th factor. The goal is then to identify a set of factors that effectively reproduces the original correlation structure, allowing for a parsimonious interpretation of the data's underlying dimensions. In general terms, the FA procedure begins with the variable correlation matrix (R), which is then decomposed to find a factor loading matrix (L) that best reconstructs R (i.e., $R \approx LL'$). The extraction of factors is guided by their eigenvalues ($\lambda_k = \sum_j l^2{}_{jk}$), which represent the amount of variance explained by each factor. Typically, only factors with eigenvalues greater than one are retained. The proportion of each variable's variance explained by these retained factors is its *communality* ($h^{2_j} = \sum_k l^2{}_{jk}$). To enhance interpretability, the initial loading matrix L is often subjected to an orthogonal or oblique rotation (e.g., Varimax). This process achieves a "simple structure" where each variable loads strongly on only one factor, clarifying the meaning of the underlying constructs without altering the overall variance explained.

Note that we didn't perform metric selection by removing metrics with a low loading (e.g., < 0.4) on their main factor (Howard, 2016). We did this in order to favor the representation of metric information over rigid adherence to simple-structure heuristics (Howard and Henderson, 2023; Sass and Schmitt, 2010). However, we applied the 0.2 cutoff rule to the difference between the loading of a metric on its main factor and its alternative factor loadings (i.e., cross-loadings) (Howard, 2016; Howard and Henderson, 2023) for metric removal if needed. This pathway assumes that the latent factors represent underlying, interpretable constructs of some aspect of socio-ecological conditions (forest resilience in our application). Furthermore, we argue that these factors retain only the most relevant, non-redundant information that drives the variability in the initial pool of metrics. We refer to these latent factors as *synthetic core metrics*. The R package *psych* (Revelle, 2025) was used to conduct FA with estimation of the optimal number of factors via random parallel simulation.

2.5. Metric normalization and landscape stratification

The numerical representation of the metrics selected to create a composite indicator must be normalized to ensure comparability across different units of measurement (Mazziotta and Pareto, 2016). Normalization is the means by which original or transformed (e.g., log-transformed) values of a metric are converted to a uniform range (Wang and Cumming, 2011), which for this study was set from 0 to 1. Normalization facilitates the aggregation of data that would otherwise be inherently incomparable. Without normalization, adding together metrics measured in different units would result in a composite indicator that is difficult to interpret and potentially misleading (Nardo et al., 2008). A normalization process is also needed for applications that evaluate the conditions based on targeted outcomes, which requires users to score conditions based on an a priori notion of "favorable" or "unfavorable" values expressed by a given metric (Czúcz et al., 2021).

2.5.1. Normalization approaches

Although necessary in the context of developing composite indicators, normalization of spatially explicit metrics across large spatial extents and/or heterogeneous landscapes should be approached with caution. Normalization of metric values without an ecological context can limit the effectiveness of a composite indicator in accounting for regionalized, intrinsic ecological productivity and other sources of variance in ecological potential. The most used normalization and standardization methods rely on the observed range and distribution of metric values as the basis for scoring, such as scaling by *Z*-score (mean of zero and a standard deviation of one) and min-max scaling (min set to zero, max set to one and a linear gradient in between). The min-max method is popular because it preserves the relationships among indicators and is easy to interpret (Brunet, 2000). However, both min-max and Z-score normalization methods are sensitive to outliers, leading to biased or skewed composite indicators (Tarasewicz and Jönsson, 2021). Furthermore, any normalization approach that is influenced by the range and distribution of values implicitly imposes the full range of values across all sites, however biophysical constraints affect the potential range of values, and the resulting extreme values and outliers can lead to skewed scores and reduced variability of metric values across the landscape (Tarasewicz and Jönsson, 2021).

The reference values method can be independent of the existing range and distribution of values, as they are user-defined scores based on proximity to one or more reference values (aka, target values) (El Gibari et al., 2018; Saisana and Saltelli, 2011; Talukder and vanLoon, 2017). The proximity measure can be constrained to a specific range outside of which proximity values immediately become (e.g.) zero or one. Moreover, the proximity measure can be forced to follow certain mathematical functions, which result in this measure having a particular 'shape'. Some of the mathematical functions commonly used to score metrics using reference values are the membership functions (MF), which are widely applied in fuzzy logic. Fuzzy logic, originally introduced by Lotfi Zadeh in 1965, is a mathematical framework for dealing with uncertainty and vagueness (Zadeh, 1965). Fuzzy logic extends classical binary logic (true/false) by allowing variables to have a degree of truth ranging between 0 and 1. Practically speaking, endpoints (e.g., metric values representing full support (1) and no support (0) for a proposition) can be set by the analyst or the end user to represent ecologically meaningful values, or set these values based on some distributional criteria (e.g., 10th and 90th percentile values). This feature makes fuzzy logic particularly suitable for situations where precise boundaries between ranks, classes, or categories are difficult to define (Zani et al., 2013).

In the context of composite indicators, a MF maps a given metric into a continuous space where the proximity of each metric value to one or more reference values is quantified. The number and interpretation of reference values dictates the shape of membership function to use, and thus, the parametrization (Munda, 1995). Examples of these functions include the following: (i) s-shaped function (increases from 0 to 1 between the reference values x and y); (ii) z-shaped function (decreases from 0 to 1 between the reference values x and y); (iii) triangular function (increases from 0 to 1 between x and y, and then decreases from 1 to 0 between y and z); (iv) trapezoidal function (similar to triangular function but with a flat top achieved by including a fourth reference value); and, (v) non-linear variants of these functions based on Gaussian and sigmoid curves (Iliadis et al., 2010). A "higher is better", "lower is better", etc., reasoning of reference values is commonly used to select the shape and parametrization of membership functions to score metrics (Kouikoglou and Phillis, 2011).

2.5.2. Climate-based strata

For our application, we addressed the ecological context for normalization by 1) creating climate-based ecological strata across the Sierra Nevada to reflect variability in biophysical constraints by geographic zones (Povak and Fuentes., *in press*; Fig. 4), and 2) using a combination of range-based and reference-based metric interpretations for normalization and weighting. We followed an ecological stratification approach based on climate characteristics, similar to the one proposed by Jeronimo et al. (2019). These authors based their approach on the climate analogs concept (Churchill et al., 2013) to cluster climatic variables into climate strata. We used the Basin Characterization Model (BCM) (Flint et al., 2021) dataset to construct 30-year normals (1981–2010) of actual evapotranspiration (AET), climatic water deficit (CWD), minimum annual temperature (Tmin), and maximum annual temperature (TMax). We selected these variables as representatives of biophysical factors that affect vegetation productivity, moisture stress, regeneration and growth (Dobrowski et al., 2013; Jeronimo et al., 2019; Lutz et al., 2010).

The climate strata were created by agglomerative nesting (i.e., hierarchical clustering) of the climate variables based on the Ward method. The climatic variables were rescaled using the z-score method (mean = 0, StDev = 1) prior clustering. We evaluated the clustering dendrogram, the corresponding scree plot, and the silhouette index (Rousseeuw, 1987) to select the optimal number of climate strata. The cluster analysis resulted in five climate strata (Povak and Fuentes., *in press*) that generally conformed to elevation bands along the western slope of the Sierra Nevada (Fig. 4; see Section 3.5 for more details). We conducted a PERMANOVA to test the significance of the resulting climate strata and as a post-hoc validation of the selected number of clusters. Hierarchical clustering requires a pairwise distance matrix, which can become computationally prohibitive as the number of observations increases. Consequently, we performed stratified random sampling based on the multivariate joint distribution to select a representative subset of observations from the rescaled climatic variables. The C5.0 algorithm (Kuhn, 2008) was used to project the discrete cluster assignments (i.e., climate strata) from the sampled data points back onto the entire continuous raster landscape. The model was trained using the

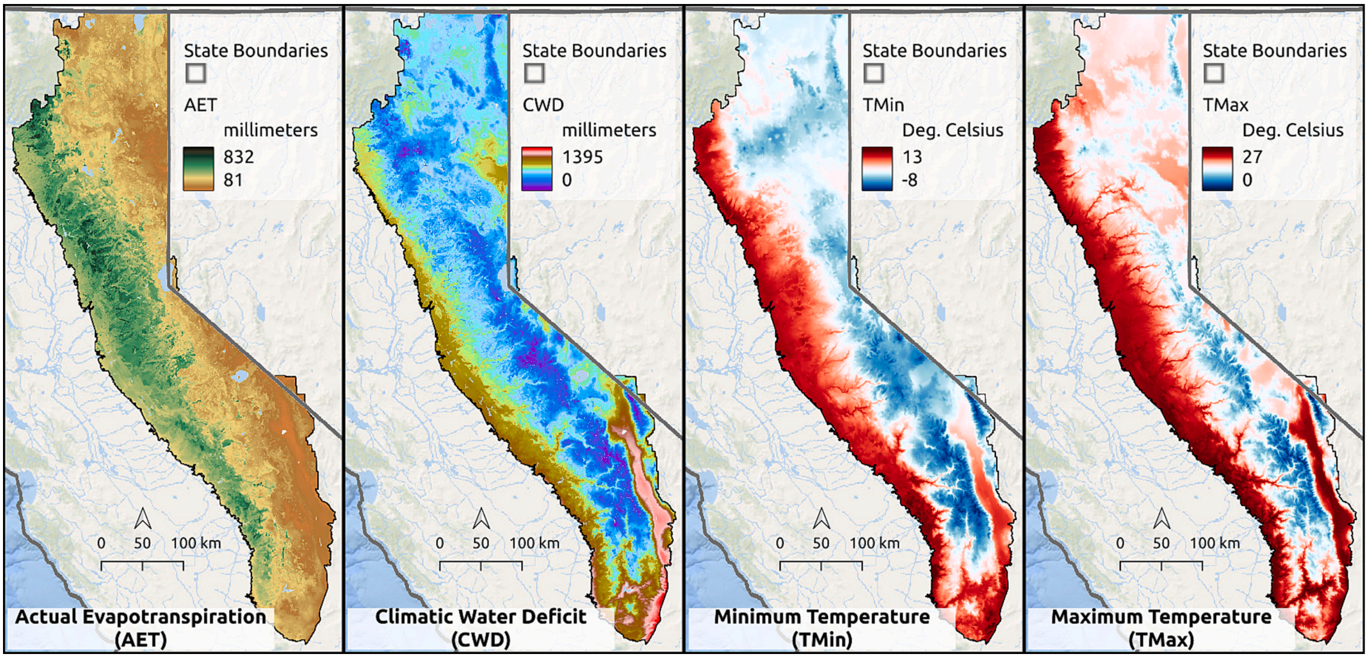

Fig. 4. Maps of the four variables used in a cluster analysis to generate climate strata for the Sierra Nevada, California: a) actual evapotranspiration (AET in millimeters), b) climatic water deficit (CWD in millimeters), c) minimum annual temperature (TMin in centigrade), and d) maximum annual temperature (TMax in centigrade). Data values represent 30-year normals (1981–2010; Flint et al., 2021).

sampled dataset where the four climate variables (AET, CWD, TMin, TMax) served as the predictor variables and the resulting stratum ID served as the categorical response variable. The cluster analysis, PERMANOVA, and C5.0 modeling were conducted in R using the packages cluster (Maechler et al., 2025), vegan (Oksanen et al., 2025), and C50 (Kuhn, 2008), respectively. The R package terra (Hijmans, 2025) was used as the backend of spatial analysis including data interoperability (e. g., conversion of spatial rasters to numerical matrices and vice versa).

2.5.3. Normalization by climate strata

The normalization of metric values for multi-metric aggregation was performed by climate strata and first entailed the elimination of outliers and the identification of endpoint values based on the remaining range across the climate stratum. The endpoint values were selected based on univariate outlier detection. The R package univOutl (D'Orazio, 2022) was used to detect outliers based on the following equation (Eq. 2):

$$S_{\text{left}} = (P50th - P10th)/1.2816; S_{\text{right}} = (P90th - P50th)/1.2816$$

where S_{left} and S_{right} are robust scale estimates based on percentiles (10th, 50th, and 90th) that account for skewness at both tails of the distribution. Note that if no outliers were found, the corresponding minimum or maximum value was used as the endpoint value.

The metric normalization then followed a reference value approach (El Gibari et al., 2018; Saisana and Saltelli, 2011; Talukder and vanLoon, 2017) coupled with a priori notions of "favorable" and "unfavorable" metric conditions (Czúcz et al., 2021) (Table 1, Fig. 5). The endpoint values served as reference values, and the proximity measure was based on fuzzy membership. The a priori notion of a metric guided the selection of the membership function. For instance, if the a priori notion of a metric was "higher is more favorable", a linear s-shaped membership function was selected. Conversely, if the a priori notion of a metric was "lower is more favorable" a linear z-shaped function was selected. The endpoint values were used to parametrize the fuzzy membership function for a given metric within a given stratum. The equations of the linear s-shaped (a) and the linear z-shaped (b) membership functions are shown below (Eq. 3 and Eq. 4, respectively).

$$f(x, E_1, E_2) = \left\{ \begin{array}{cc} 0 & \text{for } x < E_1 \\ \dfrac{x - E_1}{E_2 - E_1} & \text{for } E_1 \leq x \leq E_2 \\ 1 & \text{for } x > E_2 \end{array} \right\}$$

$$f(x, E_1, E_2) = \left\{ \begin{array}{cc} 1 & \text{for } x < E_1 \\ \dfrac{E_2 - x}{E_2 - E_1} & \text{for } E_1 \leq x \leq E_2 \\ 0 & \text{for } x > E_2 \end{array} \right\}$$

where x is the metric value for a given raster cell, E_1 is the lower endpoint value, and E_2 is the upper endpoint value.

2.6. Weighting and aggregation

The aggregation process involves combining the individually normalized metrics into a single composite indicator. The aggregation of normalized metrics into a composite indicator includes two critical steps: (a) the definition of a weighting scheme, and (b) the selection of an aggregation function. The choices made for these two steps determine the relative influence each metric has on the composite indicator score, and consequently the interpretations and management implications drawn from it (Becker et al., 2017). If aggregation is done at multiple levels of an information hierarchy (e.g., metrics to element, elements to pillar, pillars to ecosystem) and/or spatial scales (e.g., pixels to subwatershed, subwatersheds to watershed, watersheds to landscape), these steps will apply to each aggregation, ideally using a consistent approach across the hierarchy.

2.6.1. Weighting scheme

Weights can be assigned to metrics based on various criteria, such as ecological importance, management objectives, policy relevance, or to reach a more equitable degree of influence among metrics (Gan et al., 2017; Suraci et al., 2023). As such, it is important to explicitly address how metrics are weighted (intentionally or otherwise) in aggregation. Some examples of weighting schemes include: (i) equal ("naive")

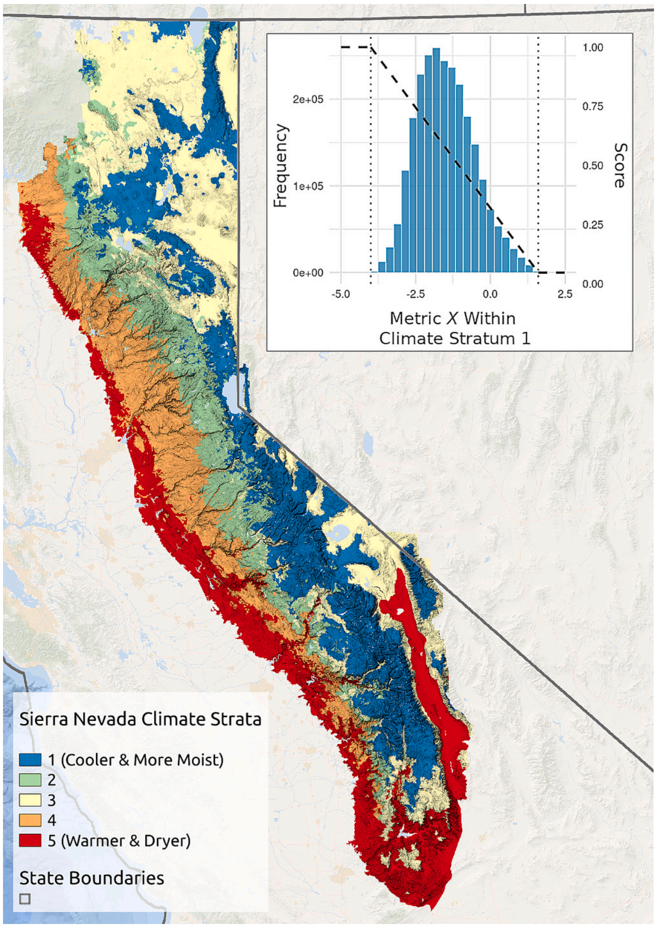

Fig. 5. A schematic representation of the stratified normalization process for ten metrics of forest resilience based on fuzzy logic and endpoint values. The dotted, vertical bars in the inset histogram represent the lower (left) and upper (right) endpoint values for a given metric *X* within the climate stratum 1 (cooler and more moist). The z-shaped dotted line in the same inset represents the fuzzy logic membership function used for stratum-wise, endpoint-constrained metric normalization.

weighting, (ii) analytic hierarchical process (AHP), (iii) statistical weighting, and (iv) optimized weighting. These weighting schemes are discussed next.

Intuitively, the aggregation of normalized metrics using equal weights (i.e., no assigned weight) would lead to a balanced, symmetrically distributed representation of metric variability by the final composite indicator (Suraci et al., 2023). However, distributional properties like outliers, skewness, and metric inter-correlation can cause certain metrics to have a stronger influence on the composite indicator (Becker et al., 2017; Paruolo et al., 2012; Suraci et al., 2023).

AHP weighting involves the systematic, pairwise comparison of metrics to determine relative importance (Singh et al., 2007). This process is useful when empirical data support the assignment of weights, but it becomes complex as the number of metrics increases (Gan et al., 2017).

Statistical weighting uses techniques like PCA and FA to assign weights proportionally to the amount of variance that a metric explains for a given component or factor (i.e., component or factor loadings). This scheme can help reveal the underlying structure of the data (Paruolo et al., 2012). However, weights derived through PCA and FA might reflect statistical properties of the data rather than the true importance of each metric according to the theoretical framework as the conceptual basis for composite indicator analysis (Hermans et al., 2008).

In contrast, optimized weighting is intended to balance the influence of metrics on the composite indicator. Optimized weighting is particularly valuable when subsets of metrics are correlated, effectively reinforcing each other, which leads to an implicit increase in their combined influence (Becker et al., 2017). Additionally, metrics with higher variance, more extreme values (e.g., a skewed distribution), or metrics normalized using larger ranges, can have a disproportionate impact on the composite score, even if all metrics are equally weighted (Nardo et al., 2008).

We adopted a modified version of the indicator-weight optimization method proposed by Becker et al. (2017), which serves to equilibrate the influence each metric has on the aggregated composite score. While Becker et al. (2017) optimized weights using a nonlinear Pearson correlation ratio estimated via Gaussian Processes and penalized splines, we employed a weight optimization routine based on an inverse regression framework. Treating the composite indicator as a latent ecological construct representing forest conditions, we modeled each metric as a non-linear function of the composite using Generalized Additive Models (GAMs) with thin-plate regression splines. Metric contribution was quantified as the explained deviance extracted from these models, ensuring that importance was defined by the composite's ability to faithfully represent the variance of each underlying ecological dimension (i.e., metric) rather than by linear correlation alone.

The optimization was executed using the Nelder-Mead simplex algorithm (Nelder and Mead, 1965), initialized with equal weights and manually constrained to sum to unity. The algorithm iteratively adjusted weights to minimize an objective function defined as the log of the mean square error between the normalized explained deviances and a target vector of perfect equality. At each iteration, a new version of the composite indicator is constructed using the adjusted weights. The logarithmic loss function imposes a steep penalty on variance imbalance, pushing the algorithm to converge on a solution where the composite indicator captures the information of all input metrics as balanced as possible, regardless of their statistical distributions. This approach alters the weight (decreasing or increasing) of a particular metric to balance the explained deviance of all metrics by the composite indicator. A balanced explained deviance across metrics suggests equalized contribution of the metrics on the composite indicator. We have included the full mathematical formulation of the weight optimization routing as part of the supplementary material (Appendix 1).

2.6.2. Aggregation method

Several aggregation functions have been proposed in the literature depending on the conceptual reasoning of the composite problem, i.e., compensatory versus non-compensatory (Greco et al., 2019; Munda, 2005). The difference between these two types of reasoning is that the compensatory (most commonly used) approach assumes that a higher score on one metric can offset a low score on another (Munda and Nardo, 2009), whereas the non-compensatory approach reflects no such assumption.The most common compensatory aggregation function is the linear aggregation of metrics, which is equivalent to a weighted average when the sum of the metric weights is not equal to one, or to a weighted sum when the sum of the weights is equal to 1 (Saisana and Tarantola, 2002). The assumption of compensatory effects may not be appropriate when metrics represent fundamentally different dimensions that functionally do not offset one another. Alternatively, the geometric mean is a non-compensatory aggregation (Burgass et al., 2017; Van Puyenbroeck and Rogge, 2017). In the geometric mean, metrics are multiplied after being raised to the power of their corresponding weight. If the sum of the weights is not equal to one, the final product is rescaled by raising it to the power of the inverse of the sum of the weights (Ebert and Welsch, 2004).

For each pathway, we first employed the optimized weighting methods described above and then explored two mathematical approaches to combine metrics to derive the final composite indicator: (a) compensatory, and (b) non-compensatory. The compensatory aggregation was based on the weighted arithmetic mean, calculated as (Eq. 5):

$$C_a = \sum_{i=1}^{n} (w_i x_i)$$

where C_a represents the compensatory composite indicator score, x_i is the normalized value of the i-th metric (i.e., the metric score), and w_i denotes the *optimized weight* assigned to each metric, with the sum of the weights being equal to 1. This arithmetic approach averages values among metrics, thereby enabling high values for one metric to compensate for low values in another in the aggregated composite indicator score.

In contrast, the non-compensatory aggregation was based on the weighted geometric mean, defined as (Eq. 6):

$$C_g = \prod_{i=1}^{n} \left(x_i^{w_i}\right)$$

where C_g represents the non-compensatory composite indicator score, x_i is the normalized value of the i-th metric (i.e., the metric score), and w_i denotes the *optimized weight* assigned to each metric, with the sum of the weights being equal to 1. This geometric approach reduces the compensation among metrics, significantly penalizing composite indicator scores when one or more metrics have low values, thereby inferring that the aggregate composite indicator is only as strong as its weakest member, and emphasizing balance (i.e., evenness) across metrics.

It is important to note that the selection of endpoint conditions, normalization, weighting and aggregation was performed independently for each climate stratum. This stratified approach explicitly incorporates local biophysical constraints, and thereby the resulting value of the composite resilience indicator reflects the intrinsic ecological productivity across the landscape of interest.

2.7. Composite indicator performance

2.7.1. Information retention index

The practical utility of composite indicators depends on their ability to accurately represent the dimensions of the phenomenon it seeks to measure. A composite indicator without a sound theoretical framework risks being a misleading abstraction, detached from the actual state of the phenomenon it is meant to represent. In the context of our forest resilience composite indicator, this means the final score is only as meaningful as its ability to reflect the underlying ecological axes of forest structure, composition, and disturbance dynamics. The process of metric selection is therefore not a mere technical step of dimensionality reduction but is a critical stage in ensuring the indicator's ecological representativeness. Accordingly, we developed an information retention index (IRI) to quantify the amount of information that is preserved by each selected core metric (RCM or SCM). The IRI is based on the coefficient of determination (R^2) between each core metric and every other metric in the initial pool, weighted by the variance of those initial metrics. Higher IRI values suggest a more effective preservation of the original information, and it provides a quantitative method for evaluating the trade-off between the RCM and SCM pathways in terms of metric representation.

Let the initial pool of metrics be a set X with n individual metrics (Eq. 7):

$$X = \{X_1, X_2, \ldots, X_j, \ldots, X_n\}$$

Let the selected subset of core metrics (from either the RCM or SCM pathway) be a set C with p core metrics (Eq. 8):

$$C = \{C_1, C_2, \ldots, C_k, \ldots, C_p\}$$

First, compute the total variance of the original dataset by summing the individual variances of all n initial metrics (Eq. 9), which represents the total amount of information available to be explained.

$$Var_{total} = \sum_{j=1}^{n} Var(X_j)$$

Next, for each individual core metric C_k in the selected subset C, calculate its specific IRI. This is done by quantifying how much of the total variance (Var_{total}) is explained by this single core metric. This is achieved by summing the variance-weighted coefficients of determination between C_k and every initial metric X_j. The formula for the IRI of a single core metric C_k is (Eq. 10):

$$IRI_k = \frac{\sum_{j=1}^{n} \left[R^2(C_k, X_j) \cdot Var(X_j)\right] * 100}{Var_{total}}$$

where $R^2(C_k, X_j)$ is the coefficient of determination between the core metric C_k and the initial metric X_j, and $Var(X_j)$ is the variance of the initial metric X_j. Finally, the overall IRI for the entire selection pathway (RCM or SCM) is calculated by taking the average of the individual IRI values for all p core metrics in the pathway (Eq. 11):

$$IRI_{pathway} = \frac{1}{p} \sum_{k=1}^{p} IRI_k$$

This final value represents the average proportion of total information from the initial pool of metrics that is retained by the selected set of core metrics, providing a single, quantitative measure of the composite index representativeness. The calculation of the IRI for each pathway was made spatially-explicit by calculating its focal values using a wall-to-wall moving window. Specifically, for a given cell in the output raster layer (i.e., the focal cell), the IRI value was calculated using a square neighborhood of 9-by-9 cells centered on the focal cell. The core metrics and the initial pool of metrics were resampled from 30-m to 300-m cell size to make the IRI calculation computationally feasible across the study area.

2.7.2. Sensitivity analysis

The process to construct composite indicators involves a series of decisions, such as the selection of input metrics, scoring function and reference values, weighting scheme, and aggregation reasoning. Consequently, the sensitivity of a composite indicator to these methodological criteria is often quantified to assess its reliability and stability. Sensitivity analysis based on techniques like Sobol indices, coupled with resampling techniques like bootstrapping, can be used to elucidate the contribution of each criterion (e.g., reference values, weights, aggregation method) to the overall variance in the composite indicator (Saisana and Tarantola, 2002). Sensitivity analysis is particularly important in non-compensatory composite indicators, where poor performance in one dimension cannot be offset by good performance in another (Munda and Nardo, 2009; Munda and Saisana, 2011).

We conducted a comprehensive sensitivity analysis using the COINr package in R (Becker et al., 2022) to assess the robustness of our forest resilience composite indicator to methodological choices. Specifically, we evaluated the sensitivity of our composite scores to variations in three critical criteria: (1) the position of lower and upper endpoint values along the full range of metric values, (2) the balance (or lack thereof) of normalized metric weights for aggregation, and (3) the aggregation method (compensatory arithmetic mean vs. non-compensatory geometric mean). For each of these methodological components, we defined discrete alternative scenarios within COINr sensitivity analysis construct. We performed Monte Carlo simulations ($N = 1000$ iterations) to systematically vary these methodological criteria and quantified their impact on the composite indicator scores. The sensitivity analysis was aimed at providing uncertainty ranges and global sensitivity indices, highlighting the manner and degree that each criterion influenced the composite indicator scores and performance. A detailed explanation of the sensitivity analysis construct adopted by COINr can be found in Saisana et al. (2005).

3. Results

3.1. Core metric selection and assignment of normalization function

3.1.1. Real core metrics

The item cluster analysis (ICLUST) suggested 3 clusters of correlated metrics (Fig. 6), roughly equivalent to the Disturbance, Composition, and Structure elements of the forest resilience pillar in the TPOR framework (Fig. 3). The first cluster was disturbance centric and included the metrics Time since Last Disturbance (TSD), Early Seral Stage (eSE), and Tree Mortality (Mort). The metric-composite Pearson's correlation coefficient (r) had the same magnitude for these 3 metrics ($r = 0.43$), but it was positive for TSD and negative for eSE and Mort. The second cluster was composition centric and included the metrics Late Seral Stage (lSE) and Snags >40″ dbh (101.6 cm) (Snag40), which were both positively correlated with their composite ($r = 0.73$). The third cluster was structure centric and included the metrics Fractal Dimension Index of Vegetation Cover (FDI), Reineke's Stand Density Index (SDI) (Reineke, 1933), Basal Area (BA), Trees per Acre (TPA), and Trees >30″ dbh (76.2 cm) per Acre (TPA30). Overall, high metric intercorrelation in this subset resulted in higher metric-composite correlation as compared to the other cluster. The high metric intercorrelation was expected since metrics like SDI are formulated as the outputs of equations that include other metrics as parameters (Reineke, 1933; Curtis and Marshall, 2000). All the metric-composite correlations in this subset were positive, except for FDI. Fig. 6 shows the result of the ICLUST, including the metric-composite correlation coefficients.

The metrics eSE, Snag40, and SDI were selected as real core metrics from cluster 1, 2, and 3, respectively (Fig. 6). The pattern matrix output from ICLUST (Table S1) suggested these metrics as those most representative of the disturbance, composition, and structure clusters, respectively. This purely data-driven selection was validated using the following criteria: (a) the metric suitability for composite analysis (e.g., eSE is a continuous variable whereas TSD is discrete), (b) the metric inherent composite nature (e.g., SDI is calculated using the quadratic mean diameter and TPA, with the former being calculated using the quotient of BA and TPA), and (c) the metric uniqueness considering direct or inverse relationships with metrics from other clusters (e.g., Snag40 being preferred over lSE since lSE and eSE were part of the same compositional variable). A normalization function was assigned to each real core metric based on its metric-composite correlation direction (negative vs positive) within its cluster and based on the interpretation of its cluster. A linear s-shaped function was selected as normalization function for Snag40, while a linear z-shaped membership function was assigned to SDI and eSE. The metric-composite correlation of Snag40 was positive, and its cluster was considered as representative of stable phases of vegetation succession, which are characterized by the co-occurrence of large trees and large woody debris (both desirable indicators of forest composition) (Barry et al., 2017). The core metric SDI was positively correlated with its cluster, which was considered representative of highly dense and homogeneous structural conditions. These conditions were deemed undesirable given the importance of structural complexity for forest resilience (Felipe-Lucia et al., 2018, Reich et al., 2022). The correlation between the core metric eSE and its cluster was negative, but the conditions represented by the cluster were deemed desirable. This cluster was considered as representative of recovery

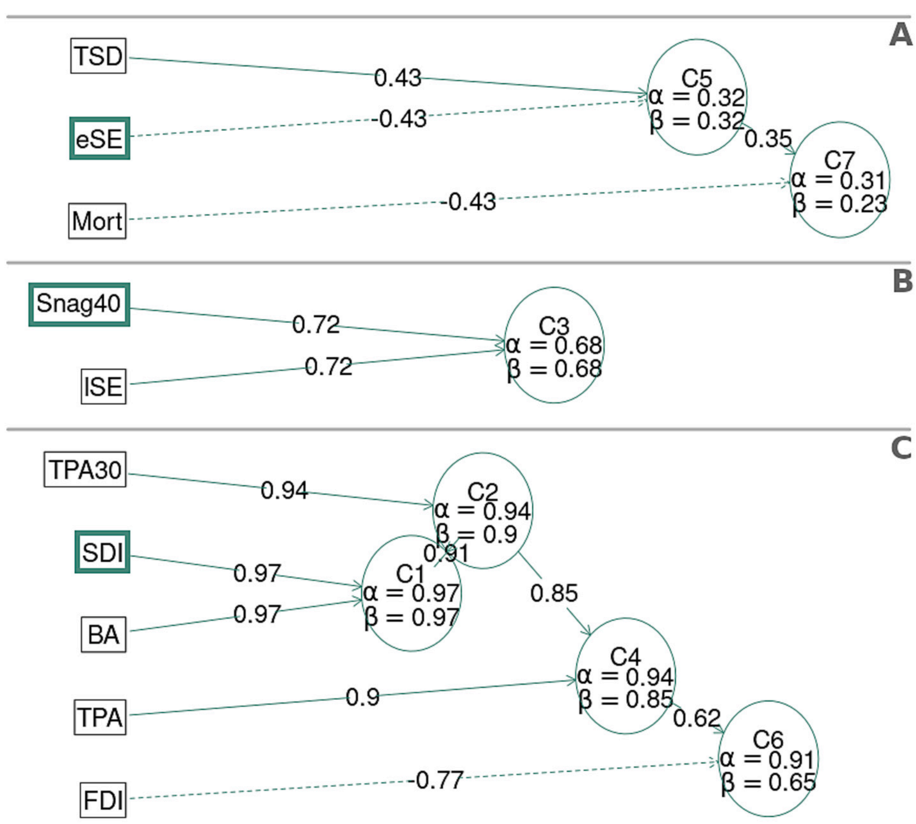

Fig. 6. Results of the item cluster analysis (ICLUST) (Revelle, 1979) performed to select real core metrics (RCM) from the ten metrics of forest resilience across the Sierra Nevada, California. The terminal nodes (left) represent the initial metric pool. ICLUST reports coefficient Alpha, representing internal consistency, and coefficient Beta, representing homogeneity. The analysis identifies the 'Real Core Metric' dimensions by focusing on the node immediately preceding the divergence of these coefficients. The arrows indicate the flow of the clustering hierarchy, and their values indicate the loading of one metric or cluster on the next one. The subsets A, B, and C, represent the three metric clusters found through ICLUST (disturbance-centric, composition-centric, and structure-centric, respectively). The bold frames denote the forest resilience metrics selected as core metrics for each cluster based on ICLUST pattern matrix.

processes mainly driven by time after disturbance events and successful tree recruitment (Sturtevant et al., 2014).

3.1.2. Synthetic core metrics

The factor analysis coupled with random parallel simulation suggested including three factors (i.e., synthetic metrics) to represent the dimensionality of the input metrics (Fig. 7). Good agreement was again found between the full hierarchy of the TPOR framework for the forest resilience pillar (metric-element-pillar linkages; Fig. 3) and the factors (i.e., synthetic core metrics derived from the factor analysis) (Fig. 7). The first synthetic metric (Synth1) was structure centric, being heavily loaded by metrics related to forest density and complexity, including SDI (loading = 0.86), BA (0.79), and TPA (0.78), with a strong negative loading from the FDI (0.64). This factor was interpreted as a gradient toward forest density and structural simplicity, which suggested a linear z-shaped membership function as adequate for normalization. The second synthetic metric (Synth2) was composition centric, defined by high positive loadings from metrics indicative of mature forest characteristics, namely Snag40 (0.76), TPA30 (0.75), and lSE (0.68), representing a late-successional and old-growth dimension. The third synthetic metric (Synth3) was disturbance centric, with moderate loadings from TSD (0.39) and a negative loading from eSE (−0.50), capturing a dimension of post-disturbance recovery. A linear s-shaped membership function was assigned for the normalization of these two synthetic metrics given the overall desirability of their greater values. For all the input metrics, the difference between their loading on the main factor and alternative factor loadings was greater than 0.2. Therefore, no metric removal due to cross-loading was needed (Table S2).

3.1.3. Correspondence between real and synthetic core metrics

Overall, the ecological dimensions elucidated by the factor analysis corroborated the groupings identified through the ICLUST technique. Both statistical methods independently converged on the same fundamental data structures, which aligned with our theoretical TPOR framework elements of Disturbance, Composition, and Structure. In both analyses, the Structure groupings captured the greatest variation in conditions across the Sierra Nevada, followed by the Composition groupings, and with Disturbance capturing the least variation across the ecoregion. This convergence provided robust, multi-faceted evidence for the underlying relationships between the metrics and validated the selection of eSE, Snag40, and SDI as the real core metrics that effectively represent these distinct ecological dimensions.

3.2. Landscape stratification and normalization

3.2.1. Climate-based strata

The hierarchical clustering of four key climate variables – actual evapotranspiration (AET), climatic water deficit (CWD), and minimum and maximum annual temperatures (Tmin, Tmax) - produced five distinct climate-based strata (Fig. 8). This number of classes was justified by the silhouette index being the highest at k = 5 (Fig. 8). We evaluated these strata based on the within-stratum distribution of the climate variables and built the following interpretation:

Climate Stratum 1 represents the coldest environments, mainly located in high-elevation areas. This stratum has the lowest median minimum and maximum temperatures (TMin = −1.6 °C; TMax = 12.5 °C), but it still experiences notable seasonal water stress (Median CWD = 470.6 mm). Climate Stratum 2 is interpreted as a transitional, mid-elevation stratum. This stratum has warmer temperatures than Stratum 1 (Median TMax = 15.4 °C) and higher water stress (Median CWD = 508.8 mm). Productivity in Stratum 2 remains high (Median AET = 412.7 mm). Climate Stratum 3 shows a mix of cool temperatures similar to Stratum 2 (Median TMax = 16.1 °C) with a significantly higher climatic water deficit (Median CWD = 666.9 mm). These conditions may explain the much lower productivity (Median AET = 222.7 mm) across this stratum. Climate Stratum 4 is characterized by warm

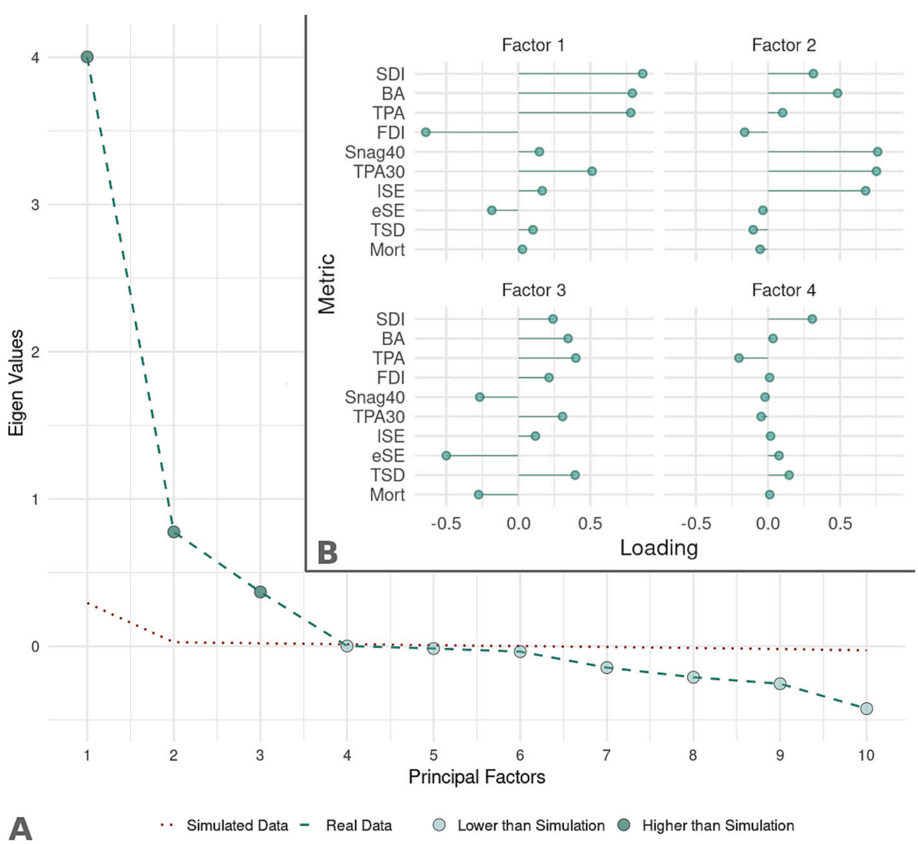

Fig. 7. Factor analysis of ten metrics of forest resilience across the Sierra Nevada, California, including the random parallel simulation and factor loadings.

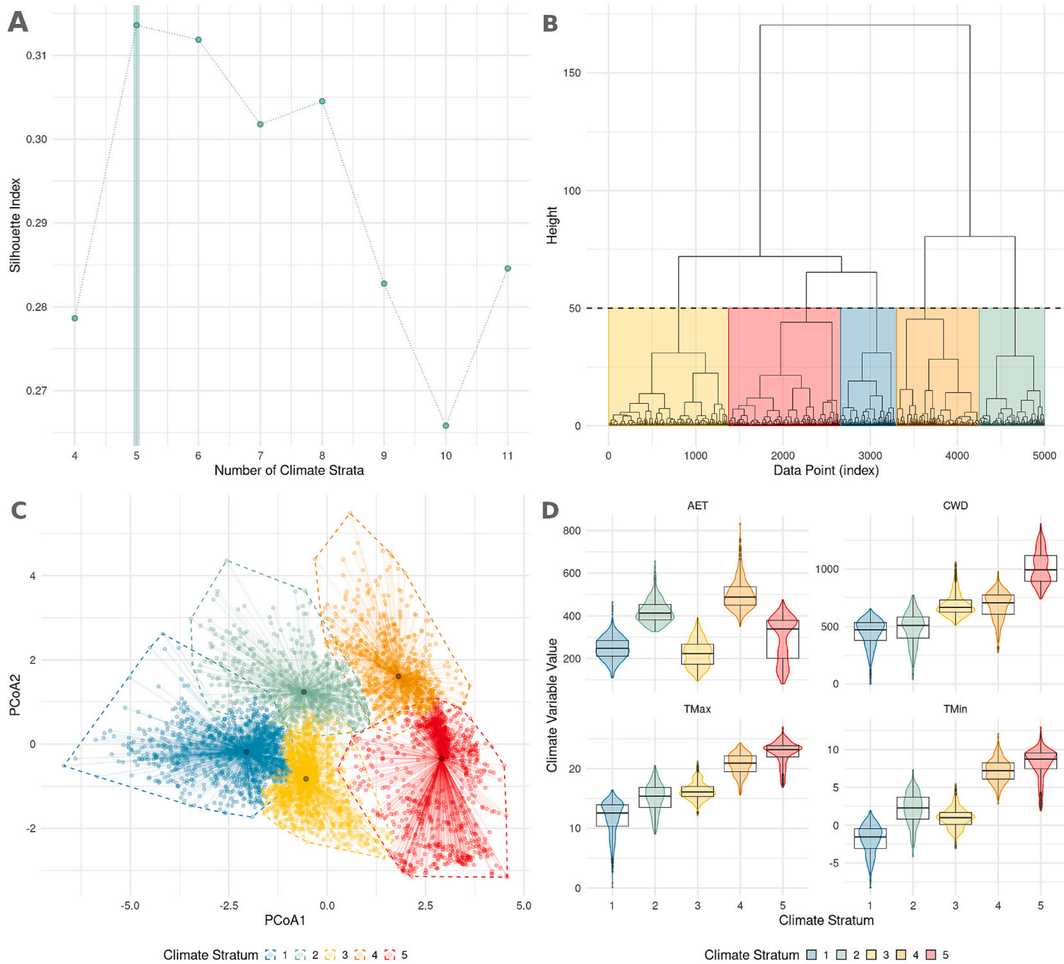

Fig. 8. Silhouette index for a chain of hierarchical cluster analysis with different number of clusters (k, i.e., climate strata) (A), dendrogram partitioned at the clustering solution with the highest silhouette index value ($k = 5$) (B), Projection of the points sampled for cluster analysis onto the first two principal coordinate axes (C), and stratum-wise boxplots and violin plots of the input climate variables for cluster analysis (D).

temperatures (Median TMax = 20.9 °C) and the highest productivity of all strata (Median AET = 488.1 mm). Water deficit is the second highest across all strata (Median CWD = 706.7 mm), but water may still be available enough to support the high productivity. Lastly, Climate Stratum 5 represents the most extreme conditions. This stratum is defined by the highest maximum temperatures (Median TMax = 23.2 °C) and the most severe climatic water deficit (Median CWD = 993.1 mm). Consequently, it has very low productivity (Median AET = 338.5 mm) compared to the similarly warm Stratum 4.

A subsequent PERMANOVA test confirmed that these 5 climate strata were statistically significant (F = 3810.62, $p < 0.001$) and explained a substantial portion of the climatic variance across the study area ($R^2 = 0.75$) (Fig. 8). The high degree of statistical significance and the large amount of variance explained validated the value of using a climate-based stratification approach to selecting endpoints for normalization. It also demonstrated that the landscape could be effectively partitioned into ecologically meaningful regions based on variables that govern primary productivity, moisture stress, and vegetation growth.

3.2.2. *Endpoint selection for normalization*

Following the selection of core metrics and landscape stratification, our next step was to normalize the metric data in a way to make their distributions free from outliers and sensitive to regional ecological differences (Tables S1 and S2). Within the climate strata, the distributions for eSE and Snag40 were highly skewed and leptokurtic. These non-normal distributions, characterized by extreme outliers, confirmed that a standard normalization would cause most data points to be compressed into a small portion of the 0–1 range, disproportionately weighting the rare, extreme values. Removing outliers prior to data normalization mitigated this issue, ensuring that the fuzzy membership functions were parameterized based on the effective and most common range of values for each metric. This allowed for a more stable and representative indicator and validated the landscape stratification.

The endpoint values selected for each core metric varied significantly across the climate strata, reflecting different intrinsic ecological potentials (Fig. 9). For instance, the upper endpoint for real core metric Snag40 was 0.70 (log of snags per acre; Table 1) in the cool-moist-high Stratum 1 but was −0.68 in the hot-dry-low Stratum 5, indicating a fundamentally different expectation for the presence of large snags (Table S3). Similarly, the upper endpoint for eSE ranged from 0.35 in Stratum 1 to 0.60 in Stratum 3 (Table S3). This variability demonstrated that a single, landscape-wide normalization scheme would have failed to capture the unique ecological context of each region for at least some metrics. By constraining the normalization process to stratum-specific endpoint values, the resulting composite indicator evaluated conditions relative to a local baseline, making it a more precise and ecologically defensible tool for informing management. Table S3 shows summary statistics of the real core metrics and their endpoint values selected through the outlier-detection approach. Fig. 9 shows boxplots with quantile marks and the region within the endpoint values to denote the metrics distribution and outlier-detection results.

As expected, we found that the synthetic core metrics were generally

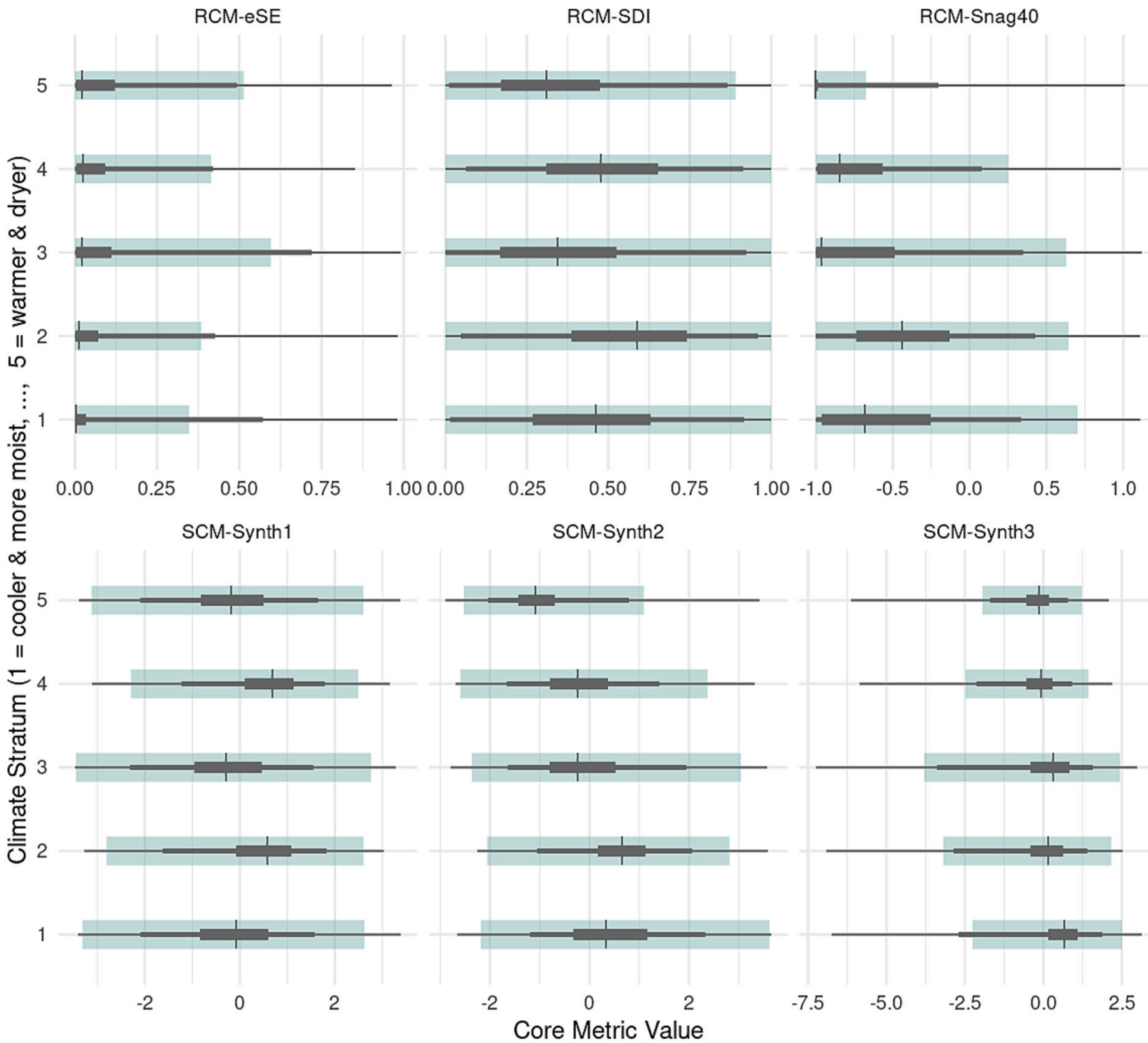

Fig. 9. Boxplots showing the statistical distribution of the real core metrics (RCM) and synthetic core metrics SCM) representing forest resilience across the Sierra Nevada, California. The statistics are summarized for each climate stratum mapped across the landscape. The shaded region in each boxplot represents the range within the endpoint values selected through outlier detection.

more normally distributed than the real core metrics metrics (Fig. 9). Synth1 (Density/Simplicity) and Synth2 (Late-Successional) exhibited skewness and kurtosis values closer to a normal distribution across most climate strata (Table S4). However, Synth3 (Post-Disturbance Recovery) retained a consistent negative skew (approx. -1.2 to -1.8) and high kurtosis (> 5.9), indicating a non-normal distribution (Table S4). Synth2 also showed some non-normality in the hot-dry-low Stratum 5 (Skew $=$ 1.1, Kurtosis $= 5.48$; Table S4). Despite the general reduction in outlier-driven skewness via factor analysis, the endpoint values derived from our outlier approach still varied considerably across climate strata for all three synthetic metrics. For example, the upper endpoint for Synth2 ranged from a high of 3.62 in Stratum 1 to a low of 1.09 in Stratum 5 (Table S4). Similarly, the lower endpoint for Synth1 ranged from -3.45 in Stratum 3 to -2.29 in Stratum 4 (Table S4).

These results highlighted the efficacy and dual function of our chosen normalization strategy. While the issue of extreme, influential outliers was less pronounced with synthetic metrics, the methodology remained useful for systematically capturing the biophysical context. The variation in endpoints suggested that the typical range for each ecological dimension was different depending on the local climate. The outlier-detection method therefore served as a robust and reproducible technique for identifying these stratum-specific endpoint ranges. Summary statistics of the synthetic core metrics and their endpoint values selected through the outlier-detection approach are presented in Table S4. Boxplots with quantile marks and the region within the endpoint values for the synthetic core metrics are shown in Fig. 9.

3.3. Weight optimization

The initial “naive” equal weighting of real core metrics revealed a substantial imbalance in the contribution of each real core metric, as measured by the proportion of variance explained in the composite indicator (Table 2). For instance, in Climate Stratum 4, the highly skewed eSE metric initially explained 47.1% of the composite indicator variance, while the more normally distributed SDI explained only 16.5%. This demonstrated that without intervention, the composite score would be disproportionately sensitive to changes in eSE. The application of our optimization algorithm successfully corrected this imbalance.

Our optimization procedure systematically adjusted the weights, reducing the weight for real core metrics with high initial influence and increasing it for those with low influence, until a balanced solution was achieved (Table 2). The result was a near-perfect equalization of influence in every climate stratum, with each of the three real core metrics contributing approximately 33.3% of the variance to the final,

Table 2
Composite variance explained by each of three real core metrics of forest resilience for each of five climate strata across the Sierra Nevada, California, before and after weight optimization, including the final (optimized) weights.

Metric	Stratum	Initial Explained Variance	Optimized Weight	Optimized Explained Variance
SDI	1	0.162	0.375	0.334
SDI	2	0.303	0.340	0.334
SDI	3	0.286	0.348	0.334
SDI	4	0.165	0.420	0.334
SDI	5	0.269	0.390	0.334
eSE	1	0.447	0.306	0.334
eSE	2	0.245	0.357	0.334
eSE	3	0.345	0.330	0.334
eSE	4	0.471	0.260	0.333
eSE	5	0.440	0.304	0.334
Snag40	1	0.391	0.319	0.332
Snag40	2	0.451	0.303	0.332
Snag40	3	0.369	0.323	0.332
Snag40	4	0.363	0.320	0.333
Snag40	5	0.469	0.306	0.333

optimized composite indicator. For example, in Stratum 4, the algorithm reduced the weight of eSE to 0.26 while increasing the weight of SDI to 0.42 to achieve this equilibrium.

A deeper analysis revealed that the initial imbalance resulting from the "naive" analysis was not primarily driven by inter-metric correlations (Becker et al., 2017; Suraci et al., 2023), which were generally low to moderate, but rather by the inherent statistical distribution of the metrics themselves (Table S3). We found a consistent relationship where metrics with highly skewed, non-normal distributions had a much larger initial influence on the composite. The eSE, which exhibited extreme positive skewness (e.g., > 3.3) and kurtosis (e.g., > 14.8) across all strata, consistently exerted the strongest initial influence in most cases. Such distributional properties are a notable feature of ecological data. Conversely, SDI, which was the most normally distributed, often had the weakest initial influence. This suggests that the presence of extreme values and long tails in a metric's distribution can cause it to statistically dominate a composite indicator if left unsupervised.

In the case of the synthetic core metrics, their initial (suboptimal) influence on the composite indicator was already well-balanced (Table 3). For example, in Climate Stratum 1, the initial variance explained by the three core synthetic metrics was 33.2%, 32.5%, and 34.3%, respectively, which was very close to the ideal 33.3% target of equalized influence. While some strata exhibited a moderate initial imbalance, the deviation was substantially smaller than that observed

Table 3
Composite variance explained by each of three synthetic core metrics of forest resilience for each of five climate strata across the Sierra Nevada, California, before and after weight optimization, including the final (optimized) weights.

Metric	Stratum	Initial Explained Variance	Optimized Weight	Optimized Explained Variance
SynthMet1	1	0.332	0.334	0.334
SynthMet1	2	0.366	0.315	0.334
SynthMet1	3	0.414	0.295	0.334
SynthMet1	4	0.310	0.342	0.334
SynthMet1	5	0.407	0.235	0.333
SynthMet2	1	0.325	0.338	0.334
SynthMet2	2	0.331	0.339	0.334
SynthMet2	3	0.293	0.355	0.334
SynthMet2	4	0.268	0.361	0.334
SynthMet2	5	0.345	0.354	0.334
SynthMet3	1	0.343	0.329	0.333
SynthMet3	2	0.303	0.347	0.333
SynthMet3	3	0.293	0.350	0.333
SynthMet3	4	0.422	0.296	0.333
SynthMet3	5	0.248	0.411	0.333

with the real core metrics. This result was an expected but desirable outcome of using principal factors as input metrics: their statistical construction promotes orthogonality and symmetric distributions, which in turn prevents single dimensions from dominating the composite indicator. Although the initial composite was already well-balanced for the synthetic core metrics, we still applied the optimization algorithm as a final "fine-tuning" step to achieve a near-perfect influence equalization. After this final calibration, the influence of each synthetic core metric on the composite was equalized to approximately 33.3% across all strata (Table 3).

3.4. Metric aggregation for the forest resilience composite indicator

The distributional properties of the final indicators, both across the landscape and within climate strata, reveal that the methodological choices made during their construction were not trivial, but rather had noticeable impacts on the final assessment of the forest resilience scores. The following subsections describe the differences in the outcomes given the overall pathway (Theoretical versus climate-stratified RCM and SCM), aggregation method (compensatory versus non-compensatory) and the information retention by type of metrics (real core versus synthetic core).

3.4.1. Composite indicator derivation

At the full landscape scale, we compared the Theoretical pathway (TPOR framework: no climate stratification, no optimized weighting, compensatory aggregation) to the two optimized pathways. The Theoretical pathway produced a composite indicator with a highly compressed distribution. Its total range of values (0.55 out of a maximum of 1.00) was only 55% of the RCM's range (1.00) and 58% of the SCM's range (0.95), and its interquartile range (IQR) of 0.09 showed that the central 50% of its values were packed into a narrower band than for the RCM (IQR = 0.14) or SCM (IQR = 0.13) pathways (Fig. 10). This compression was a direct consequence of the Theoretical pathway's landscape-wide min-max normalization, which flattened diverse ecological conditions into a narrow, centralized scale, masking the true extent of variability. While the resulting landscape-wide distribution was deceptively symmetric (Skewness = 0.07), this was likely an artifact of averaging many metrics, which obscured detail instead of revealing true central tendency. In contrast, the RCM and SCM pathways produced composites with much greater dispersion. This dispersion trend between the Theoretical pathway and the RCM and SCM pathways remained consistent across the five climate strata (Fig. 10). For instance, the RCM and SCM pathways revealed that the warmest and driest strata (4 and 5) exhibited the greatest internal variability in resilience scores (e.g., RCM IQR of 0.17 in Stratum 5 vs. 0.12 in Stratum 3), an important nuance missed by the Theoretical pathway whose IQR remained consistently low (0.07–0.09) across all strata. Summary statistics of the Theoretical, RCM, and SCM composite indicators by climate strata and across the landscape are presented in Table S5.

The comparison of the RCM and SCM pathways within and among climate strata revealed important differences (Fig. 10, Table S5). First, the median score and the max values for the RCM indicator were consistently higher than the SCM indicator. Second, the SCM pathway consistently yielded a more symmetric distribution compared to the RCM pathway. For instance, in Stratum 1, the SCM skewness was −0.02 (nearly zero), while the RCM skewness was a more pronounced −0.53 and appeared to be driven by the higher max values. This pattern held constant across most strata and was a direct result of the SCM's statistically well-distributed synthetic inputs, making it an arguably more elegant approach. The RCM pathway inherited a faint signature of its sometimes-skewed real-metric inputs, which may be a desirable trait for managers who prefer indicators tied to directly measurable, tangible variables.

The analysis of the median scores for the RCM pathway indicated that four of the five climate strata (Strata 1, 2, 3, and 5) consistently

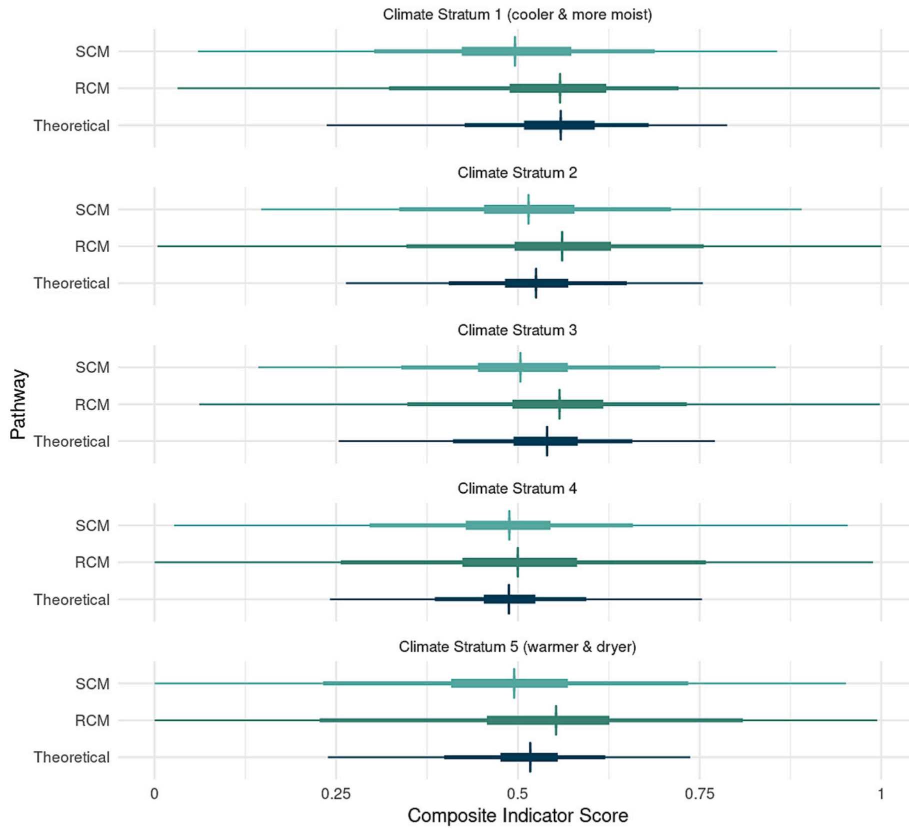

Fig. 10. Boxplots showing the statistical distribution of the composite indicator of forest resilience across the Sierra Nevada, California, for each methodological pathway: Theoretical, real core metrics (RCM), and synthetic core metrics (SCM). The statistical distribution is presented for each climate stratum mapped across the landscape.

performed slightly above the midpoint of the score's range (0 to 1), achieving 55–56% of their respective forest resilience scores (Fig. 10, Table S5). Stratum 4 (one of the hottest and driest) stood out as a somewhat notable exception, with a lower median score of 0.50, indicating that its overall condition was less favorable compared to the rest of the landscape. The SCM pathway offered a slightly different, but equally insightful, narrative (Fig. 10, Table S5). Its results showed a significant consistency across the entire landscape, with the median scores of all five strata hovering very tightly around the midpoint of the score's range, between 0.49 and 0.51. This suggested that when viewed through the lens of the synthetic factors, the varied climatic zones were all performing at a nearly identical level, that is, approximately 50% of their intrinsic potential. The subtle difference between the core metric pathways, with the RCM identifying Stratum 4 as a lower-performing outlier and the SCM depicting broad-scale uniformity in relative performance, was a direct result of their different core metrics (real vs. synthetic) and highlighted how even rigorous, well-constructed indicators can lead to different nuances in interpretation.

3.4.2. Compensatory and non-compensatory aggregation

We compared the RCM and SCM pathways using both a compensatory (weighted arithmetic mean) and a non-compensatory (weighted geometric mean) approach. It is important to note that the non-compensatory approach was conducted on the original "naive" normalized metric values (no optimized weighting), as applying the influence-balancing weight optimization would defy the purpose of the non-compensatory aggregation by artificially masking the very imbalances it is designed to penalize. Thus, the comparison of compensatory and non-compensatory aggregations serves to reveal the impact of one or more unfavorable metric values that would otherwise be masked in a compensatory approach.

The effect of applying a non-compensatory aggregation to the RCM pathway was not merely a shift, but resulted in a substantial reduction of the indicator values, exposing the severe imbalance in optimized weights among the underlying real core metrics (i.e., normalized metrics with disparate co-located values; Fig. 11). For example, the median composite score in Climate Stratum 1 dropped from near mid-point at 0.565 in the compensatory model to a near-zero 0.053 in the non-compensatory model (Table S6). This indicated that the average location, while appearing satisfactory under a compensatory lens, was in fact deeply imbalanced, with critically low performance in one metric being masked by high performance in another. This pattern held constant across all climate strata (Fig. 11). Furthermore, the shape of the distribution was radically transformed. The modest negative skew of most compensatory indicators (e.g., −0.65 in Stratum 1) was inverted into an extreme positive skew (1.42), coupled with very high kurtosis (5.50) (Table S6). This was the signature of a non-compensatory function applied to highly imbalanced data: the vast majority of scores are clustered near zero.

The SCM pathway also revealed the penalizing effect of non-compensation, but the impact was significantly less severe, confirming the more inherently balanced nature of the synthetic inputs (Fig. 11). For example, in Stratum 1, the median score dropped from 0.497 (compensatory) to 0.105 (non-compensatory) (Table S6). While this was a substantial reduction, the resulting median value was nearly double that of the RCM pathway's non-compensatory score. This demonstrated that while the synthetic profiles also exhibited imbalances that were masked by simple averaging, they were far less extreme than those of the real core metrics. Similarly, the SCM indicator's distribution shifted from being nearly perfectly symmetric (skewness of −0.03) to being moderately positively skewed (0.87), but to a much lesser degree than the RCM indicator (Table S6). Stratum-wise and across-landscape summary

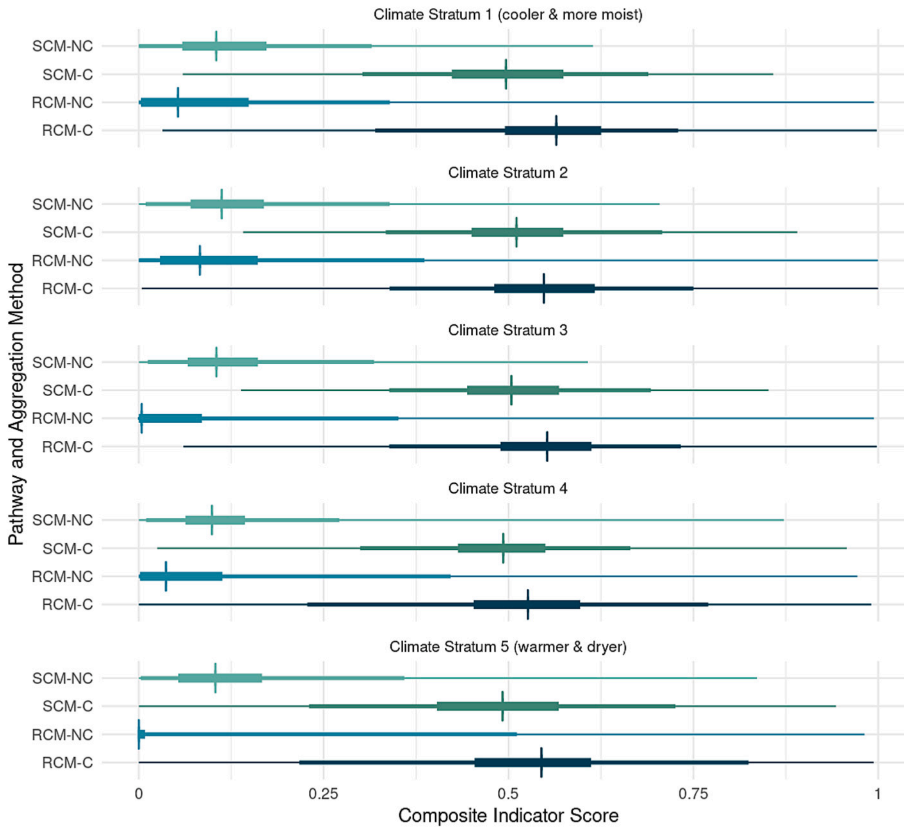

Fig. 11. Boxplots showing the statistical distribution of the composite indicator of forest resilience across the Sierra Nevada, California, for the proposed methodological pathways: real core metrics (RCM) and synthetic core metrics (SCM), and based on the aggregation method: compensatory (C) and non-compensatory (NC). The statistical distribution is presented for each climate stratum mapped across the landscape.

statistics of the RCM and SCM composite indicators based on compensatory and non-compensatory aggregation are presented in Table S6.

Wide-ranging and imbalanced values are to be expected, and therefore of consequence, in composite indicators for a suite of ecological metrics that represent a given facet of forest ecosystems. In application, the selection of compensatory and/or non-compensatory aggregation will depend on management objectives (positive outcomes) and the degree to which ecological vulnerabilities (low scoring metrics) pose a threat to those objectives. In our example, a direct comparison of the two non-compensatory indicators revealed two different portraits of the landscape's condition when balance is required. The RCM non-compensatory indicator described a landscape where balanced, high-performing conditions were exceptionally rare. Its median scores were consistently and dramatically low (e.g., as low as 0.004 in Stratum 3), and its extreme positive skew indicated that a few of the metrics were high scoring, and the composite result reflected a state of severe metric imbalance (Table S6). In contrast, the SCM non-compensatory indicator, with higher median scores (e.g., 0.105 in Stratum 1) and less extreme skewness (Table S6), portrayed a landscape where imbalance existed but was not as acute. The comparison of RCM and SCM scores highlighted an interpretive choice> The RCM non-compensatory indicator based on a small number of metrics suggests that resilient conditions exist on the landscape, but they are a rare, outlier in a landscape dominated by unfavorable conditions In contrast, the SCM non-compensatory indicator based on a much larger number of metrics portrayed a more smoothed representation of the landscape, with a more moderated distribution of conditions.

3.5. *Composite indicator performance and sensitivity evaluation*

3.5.1. *Information retention index*

A central challenge in creating a composite indicator is the inevitable loss of information when a large, complex pool of metrics is reduced to a smaller, more manageable set. To quantify this loss, we developed and applied a novel, spatially-explicit, Information Retention Index (IRI), which measures the percentage of variance-weighted information from the initial ten metrics that is preserved by the selected core metrics across space. A higher IRI indicates a more effective and representative selection process. This analysis revealed a clear and consistent difference in the statistical efficiency of the RCM and SCM pathways.

The SCM pathway consistently demonstrated superior performance in retaining metric information compared to the RCM pathway, both at the landscape scale and by climate strata (Fig. 12, Table S7). The median IRI for the SCM pathway across all strata was 40.1%, indicating that its three synthetic factors successfully captured over 40% of the variance-weighted information from the original ten metrics. In contrast, the RCM pathway had a median IRI of 36.6%. While still substantial, this suggested that the selection of just three tangible metrics came at a quantifiable cost of information relative to the SCM approach. This result was expected given the RCM method cannot fully account for the information lost in the metrics that were discarded.

The pattern of SCM superior performance was also expressed across all climate strata (Fig. 12, Table S7). In all five zones, the SCM pathway yielded a higher median IRI than the RCM pathway. This performance gap was particularly pronounced in the driest, most stressed environments; in Climate Stratum 5, the SCM pathway retained 41.1% of the information, while the RCM pathway captured only 31.5%. The consistent outperformance of the SCM pathway across diverse ecological settings underscored the robustness and statistical power of using factor

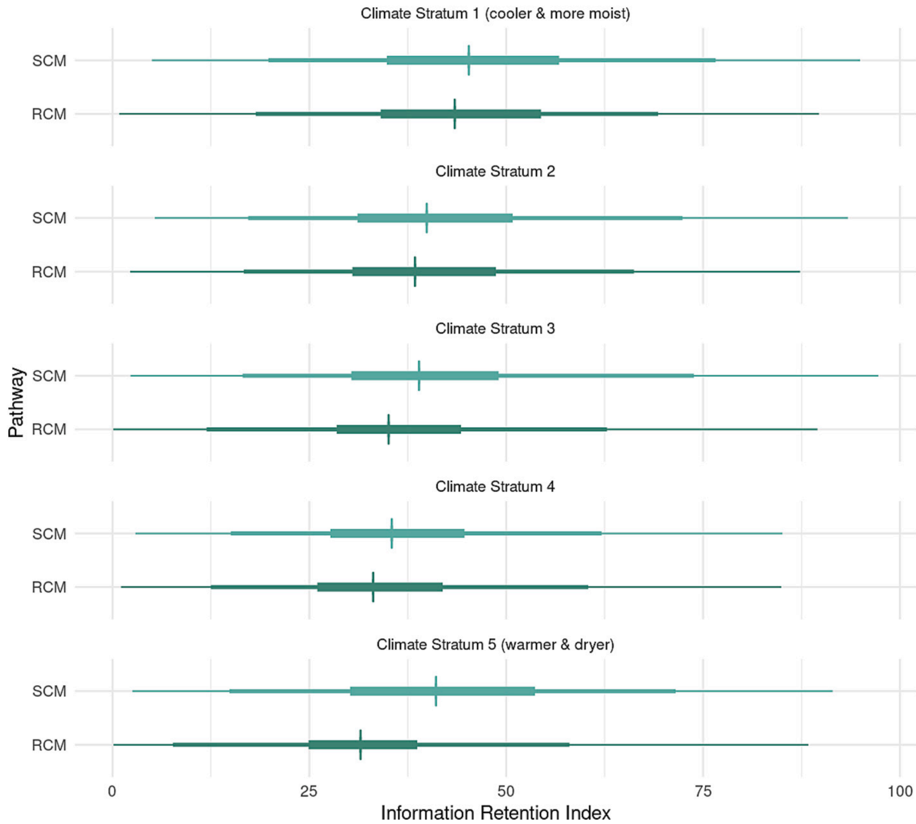

Fig. 12. Boxplots showing the statistical distribution of the information retention index (IRI) across the Sierra Nevada, California, for the proposed methodological pathways: real core metrics (RCM), and synthetic core metrics (SCM). The statistical distribution is presented for each climate stratum mapped across the landscape.

analysis for metric reduction.

3.5.2. *Sensitivity analysis*

To assess the robustness of our findings, we conducted a comprehensive sensitivity analysis to quantify how three key methodological criteria, namely (1) normalization endpoints, (2) metric weights, and (3) aggregation method, influenced the final composite scores from the RCM and SCM pathways. We found that the two pathways exhibited fundamentally different sensitivity profiles, highlighting where the most critical methodological leverage exists in each approach (Fig. 13, Table S8). For the RCM pathway, the choice of aggregation method was the most influential criterion driving the final composite score, yielding a mean sensitivity index of 0.286 (potential range of 0 to 1). The wide confidence interval for the aggregation index (0.126–0.434) further indicated that the magnitude of its influence was not only large but also highly variable, reinforcing its status as the most critical and uncertain methodological criterion for this pathway (Fig. 13). Metric weighting was the second most sensitive parameter (0.217), followed by the choice of normalization endpoints (0.114). The high sensitivity to aggregation confirmed our earlier finding: the RCM's inputs (SDI, eSE, Snag40) were significantly imbalanced. Accordingly, the decision to allow or not allow compensation (i.e., choosing between a weighted arithmetic or geometric mean) was the single most impactful criterion. This decision significantly changed the indicator's final scores. The moderate sensitivity to endpoints reflected the skewed nature of the real metrics (especially eSE): because the distributions had long tails, the decision of where to define the metric's effective range had a non-trivial impact on the results. RCMs relative lack of sensitivity to weights was logical in this context: since the effect of aggregation was dominating, adjustments to the weights had a comparatively smaller influence on the outcome.

The SCM pathway was more sensitive to the choice of metric weights, which registered an exceptionally high mean sensitivity index of 0.682 (Fig. 13, Table S8). This parameter also exhibited the widest confidence interval (0.448–0.906), denoting a high degree of uncertainty in its effect. The aggregation method (0.215) and endpoint selection (a negligible 0.012) were significantly less influential. This seemingly counterintuitive result validated the unique nature of the SCM approach. The synthetic metrics were, by design, statistically balanced and orthogonal. Their "naive" state was one of equal influence on the composite indicator. The SCM pathway's extreme sensitivity to weights resulted because of this inherent balance. Any deviation from equal weighting was a significant disruption to this influence equilibrium and thus had a very large impact on the final composite score. Conversely, the SCM pathway showed almost no sensitivity to endpoint selection most likely because the synthetic factors were symmetrically distributed, and because the extreme outliers that make endpoints an issue for the RCM pathway were absent. This pathway was also less sensitive to the aggregation method since its inputs were already balanced, meaning the penalty applied by the non-compensatory geometric mean was much less severe. Statistics summarizing the sampled endpoint and weight values for the sensitivity analysis are presented in Table S9.

3.6. *Pillar aggregation for ecosystem resilience representation across the Sierra Nevada*

While our analysis focused on a single-level aggregation for clarity, the quantitative architecture we developed is inherently modular and ideally suited for constructing more complex, multi-level hierarchical composite indicators. The core methodological steps, namely core metric selection (RCM or SCM), climate-based stratification, robust normalization, and weight optimization, can be applied iteratively at each level of our hierarchical theoretical framework. For instance, we had an initial pool of metrics that were aggregated into each of the 10

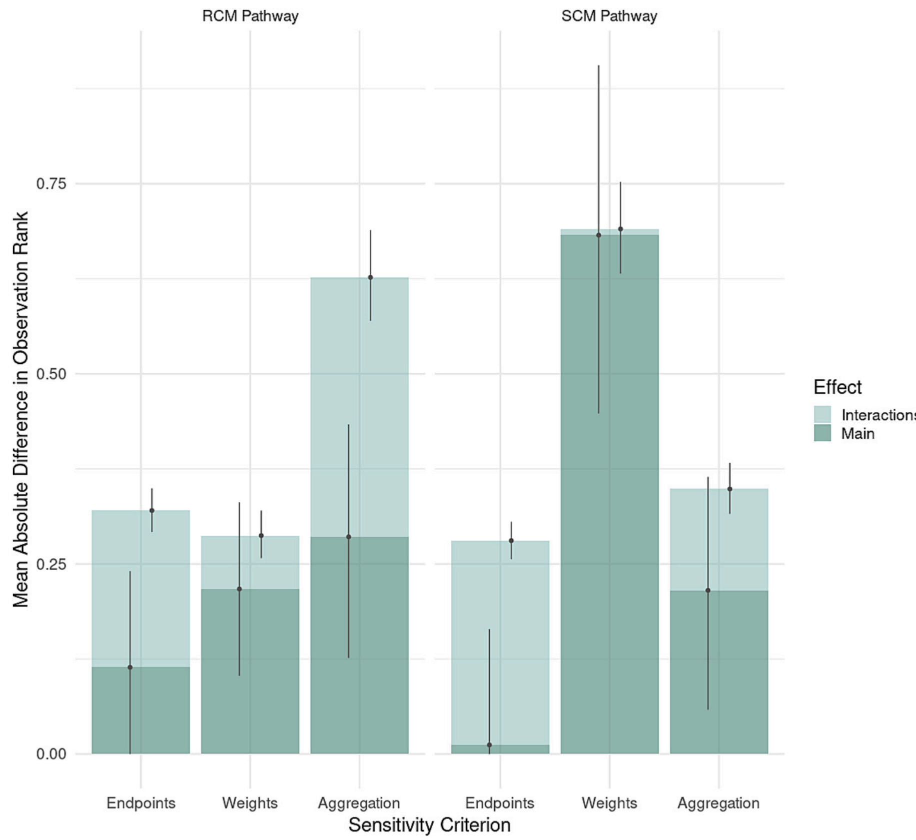

Fig. 13. Barplots showing the composite indicator sensitivity index, expressed as the mean absolute difference in data point (i.e., observation, raster cell) rank by sensitivity criterion (endpoint values, weights, and aggregation method), across the Sierra Nevada, California. Error bars indicate the 5th, 50th, and 95th percentiles. The observations receive a composite indicator score and they are ranked based on this value. As the values of a sensitivity criterion change, the composite indicator score changes and so does the rank. The sensitivity analysis randomly selects different values for each criterion via Monte Carlo simulation. The effect of the sensitivity criterion is assessed as the main effect and as a confounding (i.e., interaction) effect.

pillars (e.g., fire dynamics, forest resilience, biodiversity conservation, economic diversity etc). These dimensions can be treated as new inputs for a second level of aggregation to represent the ecosystem overall, in our case to make inferences about overall socio-ecological resilience, by again applying the same rigorous normalization and weighting procedures. As an example of the multi-level applicability of our proposed framework, we followed the RCM and SCM pathways, including stratified normalization with endpoint selection and aggregation with optimized weights, for the 10 pillars defined by the TPOR Framework (Table S10). We then aggregated the resulting pillar scores to obtain the final Socio-Ecological Resilience score (Fig. 14). This nested application provided a consistent, data-driven engine for each aggregation step, removing the subjectivity often present in hierarchical models that rely on expert-assigned metrics and weights at different levels.

4. Discussion

The pathways for composite indicators presented in this study directly address the growing and urgent international call for robust, multi-dimensional, and spatially explicit assessments of forest resilience. The methodological challenges of constructing such assessments are no longer abstract academic concerns; they are now central to the implementation of landmark environmental policies, laws, and initiatives. In the United States, legislation such as the pending Fix Our Forests Act mandates the identification of high-risk landscapes and the prioritization of treatments to increase resilience, a task that inherently requires a spatially explicit, multi-faceted assessment of ecological condition and risk of degradation or loss. Our work provides a feasible, generalized, and data-driven system that meets the specific needs articulated by these efforts, particularly regarding the demand for multi-dimensional indicators, the necessity of methodological simplification for practical application, and the requirement for advanced statistics to ensure transparency and rigor. Our theoretical framework and composite indicator pathways directly answer this call. By grounding our assessment in the Ten Pillars of Resilience (TPOR) and offering complementary pathways for composite indicator derivation for pillars and ecosystems, we provide the multi-dimensional structure required by these initiatives. The final output is not a single, abstract number but a high-resolution map that allows managers to visualize and prioritize conservation and restoration needs across heterogeneous landscapes, directly enabling the kind of strategic planning envisioned by efforts in the US and around the globe. Furthermore, the comprehensive breadth of pillars in the TPOR framework enable it to serve a translational role, serving as a common language for evaluating change and progress across multiple initiatives with varied individual metrics but shared pillars. Accordingly, the TPOR framework is currently being adopted in interactive decision support models such as Planscape (planscape.org) to provide an information architecture for organizing, disseminating, and analyzing regional and national datasets for the use in project planning. Future adoptions and their impact will bring to light the ultimate utility of the framework.

The construction of composite indicators to measure complex phenomena like socio-ecological resilience comes with methodological challenges that can lead to subjective, irreproducible, or ecologically ambiguous outcomes. Global frameworks like the Kunming-Montreal Global Biodiversity Framework and the EU's forest monitoring system implicitly require that their indicators be robust, repeatable, and transparent to be credible for tracking progress and ensuring accountability (Burgess et al., 2024; Resco de Dios and Boer, 2025). This study

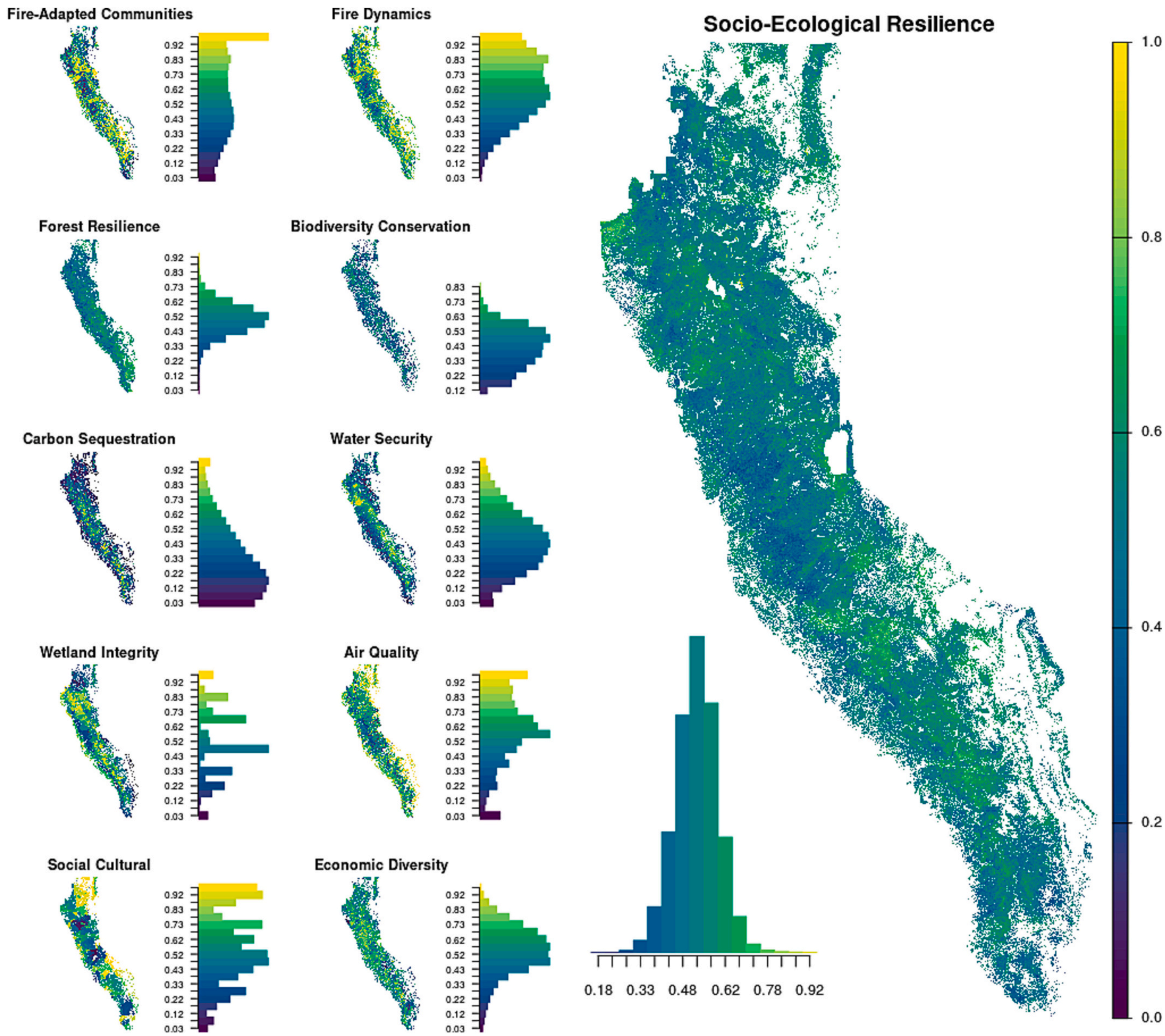

Fig. 14. Maps of composite indicator scores for each of the 10 pillars and the overall socio-ecological resilience score across the Sierra Nevada, California.

confronted these challenges directly by developing and testing a quantitative, transparent, and adaptable quantitative methodology. Our composite indicator pathways were explicitly designed to meet these challenges with a suite of advanced statistical solutions. Our results demonstrate that the specific choices made during the indicator construction process, from metric selection and normalization to weighting and aggregation, are not merely technical details but are fundamental drivers of the final assessment, profoundly shaping its meaning, robustness, and ultimate utility for management. Major components of the composite indicator system presented here are as follows.

Climate-Based Stratification: By first partitioning the landscape into distinct biophysical regions, we ensure that all subsequent analyses, particularly metric normalization, are ecologically context-dependent. This aligns with the IPCC's emphasis on regional and ecosystem-specific adaptation (*IPCC*, 2023) and avoids the statistical artifacts of a "one-size-fits-all" approach.

Data-Driven Weight Optimization: Instead of relying on subjective or equal weighting, our use of a stratum-constrained mathematical optimization algorithm systematically adjusts weights to ensure a balanced contribution from each core metric. This fully quantitative and reproducible process directly addresses the critique of arbitrary weighting and ensures the final composite is not unintentionally biased.

The Real Core Metrics (RCM) Pathway: A metric selection technique that provides a scientifically defensible method for producing a subset of representative metrics that adequately represent key components of socio-ecological systems while emphasizing model parsimony and interpretability.

The Synthetic Core Metrics (SCM) Pathway: For applications where statistical rigor is crucial, this factor analysis-based SCM pathway offers a powerful alternative. By creating statistically independent, synthetic metrics, it reduces multicollinearity and maximizes the representation of the data variance, resulting in an exceptionally robust and efficient indicator. Furthermore, it offers a quantitatively robust and sensitive measure of change that reflects the values of individual metrics and their relationships with one another.

Information Retention Index (IRI): A rigorous statistical approach to quantify the information retained in a composite indicator compared to the full set of metrics. It provides a transparent measure of the trade-off between interpretation and statistical power, a critical step in building trust and credibility in the assessment process.

Sensitivity analysis: A Monte-Carlo simulation was used to quantify the influence of endpoint selection, weighting scheme, and aggregation techniques to evaluate the uncertainty associated with each decision point in the composite indicator development. Such information can be important to quantify uncertainty in the analysis steps, to determine the impact of these decisions, and to communicate these outcomes to the end-user to justify the approach taken.

By replacing subjective decisions with these data-driven procedures, our methods provide a blueprint for constructing ecosystem resilience indicators that are transparent, adaptable, and defensible. It demonstrates that the process of building an indicator is as important as the final result, aligning with the need for credible and reliable tools to guide the monumental task of managing for socio-ecological resilience in an era of global change.

4.1. *Theoretical framework and stratification*

A core principle highlighted in the literature is that a composite indicator must be grounded in a strong theoretical framework to be meaningful (Booysen, 2002; Burgass et al., 2017; Greco et al., 2019; Nardo et al., 2008). Our findings provide validation for this principle. The successful identification of the same three ecological dimensions of the forest resilience pillar, namely Structure, Composition, and Disturbance, through two independent statistical methods (ICLUST for the RCM pathway and factor analysis for the SCM pathway) confirms that our core metrics contained a coherent underlying structure aligned with our TPOR framework. Furthermore, our results underscore the inadequacy of a "one-size-fits-all" approach under the model of biophysical context for intrinsic ecological productivity (Jeronimo et al., 2019). The climate-based stratification successfully partitioned the study area into five statistically distinct ecological regions, each with a unique profile of productivity and water stress. The stratification step proved significant, as the subsequent normalization revealed that the existing and favorable range for a given metric often varied significantly among these strata. This variation aligns well with our assumption that what constitutes "favorable" or "unfavorable" values to promote resilience as part of the core metric normalization process should be context-dependent to account for intrinsic ecological gradients.

4.2. *Counteracting statistical artifacts*

The analysis of the core metrics revealed significant skewness and the presence of extreme outliers, particularly for the RCM pathway. These statistical properties are oftentimes undesirable during normalization as they can lead to statistical artifacts on the resulting composite indicator, such as tightly compressed values within a small band around the mean (Tarasewicz and Jönsson, 2021). The application of our stratified, outlier-aware normalization method was therefore crucial for creating a stable indicator that was robust to extreme values. Similarly, our stratum-constrained mathematical optimization of weights proved effective in balancing the contribution of each core metric on the final composite indicator. Studies have suggested using mathematical optimization techniques to balance the influence of metrics on the composite indicators (Becker et al., 2017; Paruolo et al., 2012; Suraci et al., 2023). The ideal outcome of the optimization process is a set of (unequal) weights, one for each metric that, when used in the aggregation process, results in the composite indicator being almost equally correlated to all the metrics. Our approach applied these optimization-based solutions in both pathways (RCM and SCM), and it demonstrated that a "naive" equal-weighting scheme would have allowed skewed metrics to dominate the final score. The optimization algorithm corrected this imbalance by systematically adjusting weights to ensure each core metric had equal influence on the resultant composite indicator. Interestingly, this step was less critical for the SCM pathway, whose statistically balanced inputs were already in a state of near-equal influence. This highlights a key insight: the necessity of a given methodological step is contingent on the nature of the inputs, and a robust analytical system should be able to account for this.

4.3. *The trade-off between interpretability and representativeness*

A primary challenge in large-scale monitoring is the tension between scientific completeness and practical feasibility. While a vast number of metrics can characterize an ecosystem, data availability is often inconsistent, and interpretation can become overwhelmingly complex for decision-makers. This is recognized in the Kunming-Montreal GBF, which proposes a limited number of "headline indicators" for high-level tracking and communication, supported by a broader suite of component and complementary indicators (Burgess et al., 2024). This GBF framework acknowledges the need for simplified, yet powerful, metrics that can be consistently applied. The RCM pathway developed in our study is a direct, quantitative solution to this challenge, and likely a more robust approach to selecting a limited set of indicators on which to base accomplishment, accountability, and policy. Composite indicators derived from measurable metrics can be directly used to define and prioritize management actions across a landscape (Suraci et al., 2023; Tarasewicz and Jönsson, 2021). The RCM pathway provides a scientifically defensible method for selecting a few representative "headline indicators" that global frameworks require, but that also remain anchored in the ecosystem facets they represent and affiliated with the other related metrics from which they were selected.

However, a central finding of this study is the characterization of the trade-off between the RCM and SCM pathways. The Information Retention Index (IRI) revealed that this direct interpretability and usability came at a quantifiable cost: the RCM pathway retained less of the total information from the initial dataset than its synthetic counterpart. Conversely, the SCM pathway, by design, consistently achieved a higher IRI across the landscape and within every climate stratum. Outputs from FA (e.g., scores) can be used directly as synthetic metrics or as (sub-) indicators (Nicoletti et al., 2000) that efficiently represent the statistical dimensions of the data (Fusco, 2015). However, the cost of this statistical efficiency is the use of abstract metrics that are one step removed from direct physical measurement. Furthermore, in tracking change over time, the metric representations in each SCM are likely to change, putting emphasis on the fate of the elements represented by the SCMs (e.g., structure, composition, disturbance) as opposed to the metrics themselves. Consequently, composite indicators based on techniques such as FA may present a challenge in informing specific management options to improve ecological conditions (Hermans et al., 2008; Saisana and Tarantola, 2002). Future research should help develop ways to map FA scores back to the individual metrics to help understand the relative influence of each metric on the final composite score to aid in its interpretation.

The IRI was not used to declare a single "best" pathway. Rather it provided a measure of strength of representation, highlighting the trade-off between direct interpretability and statistical representativeness. For RCM, the IRI provided a quantitative and repeatable measure of the RCM cost of selecting one core metric to represent a set of metrics. As such, it quantified the cost of the RCM pathway's primary benefit: the use of a single, directly measurable metric for each cluster. Similarly, for SCM the IRI reflected its primary benefit: its superior statistical efficiency and information retention. Overall, the explicit trade-off between the RCM and SCM pathways was reflected in the final composite indicators, where the RCM pathway identified Stratum 4 as a low-performing outlier while the SCM pathway depicted a landscape of more uniform relative performance, illustrating how these methodological choices can lead to different interpretation.

While RCM methods excel at interpretability, the results here highlight the influence of the skewed nature of the data distribution of the raw and interpreted metrics – a common feature in ecological data – on the composite scores. The SCM method ameliorated this given their higher degree of symmetry. As mentioned, this was evident in the high sensitivity of the RCM to the aggregation method and thus indicating another cost of interpretability in the composite indicator development.

4.4. Aggregation, sensitivity, and the meaning of an indicator

The choice of aggregation method is a profound statement about the assumed nature of the system being measured, and the comparison among compensatory and non-compensatory aggregation methods illustrated this point. For the RCM pathway, switching to a non-compensatory geometric mean caused the indicator scores to collapse, revealing that the seemingly acceptable scores from the compensatory method were masking low scoring conditions across most of the landscape and the associated underlying imbalances among the core metrics. This effect was far less severe for the more inherently balanced SCM pathway. This finding has critical management implications, suggesting that if the conditions of all metrics have bearing on resilience, the true state of the system will be better represented by a non-compensatory aggregation of metrics, and may be in greater peril than a simple averaging of metrics would suggest.

Our sensitivity analysis provided a “user's guide” to assess the robustness of each composite metric derivation pathway. This confirmed that the RCM indicator is most sensitive to the choice of aggregation method, while the SCM indicator is generally more sensitive to the choice of weights, given its already balanced initial state (i.e., quantitatively derived multivariate axes). This pinpoints the largest sources of uncertainty in each quantitative approach, allowing for a more honest and responsible application of these tools. An interesting outcome of the sensitivity analysis was the finding that endpoint selection (e.g., how to determine metric values to represent full support and no support for the proposition that a given metric is in a resilient state) was never the most influential component of the composite indicator calculation. Much of the process in developing these indices is gaining consensus among end-users on what values to choose to represent full support (or no support) for a metric being in a resilient condition (e.g., what is the optimal tree density for a given forest). The sensitivity analysis suggests that there is some leeway in the assignment of these values without impacting the outcome; a finding that may help facilitate this process in collaborative settings.

4.5. Monitoring and assessment implications

Monitoring and assessment are integral to land management planning as part of adaptive management (assessment, planning, implementation, monitoring, adaptation; Bormann et al., 2007). Assessments serve to identify where work is needed (prospective), and monitoring serves to quantify where and how much progress toward desired outcomes is being achieved (retrospective), as well as supporting future assessments. Although individual metrics are relevant to monitoring and assessment (e.g., timber volume, stand density index), forest policies and regulations particularly on public lands, mandates that management actions foster and maintain overall forest health, sustainability, and resilience. Forest management activities, such as large-scale land management or fire suppression, can either enhance or degrade resilience (Falk et al., 2022; Manley et al., 2025). Thus, information systems are needed to inform where, when, and how management can be effective, and to determine the degree to which health and resilience are being accomplished as reflected in individual and composite metrics.

Monitoring and assessment can support a variety of outcomes depending on management goals and objectives, such as reducing risks to resources and infrastructure, protecting habitat values, enhancing landscape connectivity improving overall resilience (e.g., Manley et al., 2025; Povak et al., 2024; Zeller et al., 2023). Most data collection systems for monitoring and assessment rely on publicly available data sources, and even as data are becoming more available and reliable, interpreting them to inform forest management remains in the hands of individual users, most of whom are not data scientists. Data analysis systems offering metrics that directly support monitoring and assessment are highly valuable to managers.

We observed a strong concurrence between the performance of the RCM and SCM pathways and the objectives of monitoring and assessment as key components of adaptive management, suggesting that this system of analysis and synthesis for individual and across multiple metrics could fill this important analysis and interpretation gap.

For example, the RCM and SCM pathways generated maps displaying different spatial patterns, providing users with unique, complementary interpretations of the landscape. RCM, which identifies a sparse set of key metrics, is a user friendly option for deriving “headline” metrics that are readily understandable to broad audiences. Monitoring change in RCM scores provide a reliable and relatable measure of the degree to which a landscape is becoming more resilient (increasing scores), less resilient (decreasing scores), and conserving resilient conditions (high scores persist). However, the RCM values are not directly actionable except in cases where the metric itself is of interest. Rather, they are intended to be representative of overall conditions resulting from past management and disturbance. In contrast, SCM scores are information rich and retain a larger proportion of information from the full range of metrics representing resilience. As such, SCM metrics can provide a robust and comprehensive foundation for RCM headline metrics, as well as providing additional insights in where and how to foster overall forest health and resilience.

Compensatory and non-compensatory aggregation measures are also complementary and together can serve to meet the objectives of monitoring and assessment. Compensatory aggregation provides a representation of average conditions across a landscape, and over time it provides a steady measure of progress toward management objectives of retaining, improving, or restoring resilience. Although average values change more slowly over time, they also provide a non-volatile measure of change that can better track management investments, as well as the effects of unplanned events, such as large-scale disturbances. Stable measures also lend themselves to providing reliable measures of turnover in conditions across landscapes: the amount, location, and distribution of change in condition (no change, improvement, or degradation). Alternatively, non-compensatory aggregation provides a representation of the preponderance of unfavorable conditions (low scoring areas) in a landscape, and mapped renditions of these areas can indicate where work to improve conditions is most needed. They may also provide a measure of vulnerability and potential risk to the overall ecosystem in circumstances where unfavorable conditions are vulnerable to disturbance and a potential liability to neighboring assets and resources.

The statistical distribution of non-compensatory conditions can change more rapidly, making them less stable but more reactive, and therefore a more sensitive measure of progress compared to compensatory representations.

Optimized weighting is central to both RCM and SCM pathways to provide a representation of conditions that are equivalently influenced by their composite metrics. While fairly intuitive and not computationally intensive, it is not standard practice in ecosystem management and assessment contexts. By taking into account the correlation structure of the metrics, optimized weighting ensures each metric is equally influential in the composite scores, an assumption that some users may have about unweighted averages. In some circumstances, users may want to bypass optimized weights in favor of intentional weighting, such as when one metric or set of metrics is known to have greater influence on the ecosystem (e.g., keystone species or processes) or has undue importance to managers (e.g., high societal value). Even under these circumstances, optimized weights can be used to compare user-defined weightings to those objectively defined to equalize metric contributions. Making an informed choice to use or not use optimized weighting will require a more mainstream understanding of its utility and value by managers.

Finally, as climate conditions continue to stress ecosystems, it is essential to consider the impacts and constraints that future climate is projected to have on landscape conditions (e.g., Povak and Manley, 2024) and to inform effective investments in both near-term and long-term outcomes of importance (e.g., Bastiaansen et al., 2020; Cumming, 2011; Povak and Manley, 2024). The RCM and SCM pathways offer multiple options for managers to portray and assess conditions, compare and plan activities to achieve desired outcomes in light of changing climate and its impacts, and evaluate progress through monitoring over time. In addition, these methods provide insights into ecosystem-level change and the potential near- and longer-term implications for sustainability and resilience. Specifically, in each successive condition evaluation, the values of the individual metrics will change, as will their quantitative relationship with one another. In SCM, for instance, the entire suite of metrics will change to some degree, reflecting changes in the range and distribution of values for individual metrics and changes in the strength and directional relationship metrics have with one another. These shifts in metric values and relationships across landscapes, combined with shifts in how SMC scores are distributed across landscapes, provide scientists and managers with invaluable clues as to the drivers of change, implications for ecosystem services and stability, and management and conservation options that are most likely to be effective in protecting and improving resilience.

5. Conclusions

There is a clear global consensus that assessing and monitoring ecosystem resilience is fundamental to climate change adaptation, and that forests are an essential component of ecosystem resilience. Increasing wildfire severity, drought-induced mortality, and the potential for large-scale vegetation type-conversions press for robust, spatially explicit methods to quantify forest resilience in a way that can effectively guide management and conservation investments to help secure forest sustainability into the future (Keane et al., 2018; Forzieri et al., 2022). The pathways we developed to derive and evaluate composite indicators of forest resilience address three of the most commonly identified barriers in regional, national and global conservation and monitoring programs: 1) effectively identifying metrics that are tangible and actionable to build consensus for core metrics across multiple entities (agencies, states, countries); 2) reliably determining status and tracking change across the diverse and sometimes divergent components of socio-ecological systems (e.g., water, carbon, biodiversity, economics); and 3) sufficiently meeting both of these needs to credibly attribute benefits to policy and finance investments. These pathways are not only reproducible and transparent but also highly flexible and transferable. They are agnostic to the number of input metrics or hierarchical levels or spatial scales, making them scalable to different ecosystems and applications. The combination of the two pathways (RCM and SCM) offers a robust representation of conditions that can be used to meet the needs of diverse applications (e.g., regional, national and global initiatives). The ability to validate indicator values with the IRI and the post-hoc sensitivity analyses further enhances the ability for composite indicators to be transparent. Ultimately, the dual-pathway approach combined with information retention and sensitivity analyses provides a robust and adaptable system for building multi-level forest ecosystem indicators to inform the significant, large-scale, high-stakes investments required to mitigate forest degradation and loss.

CRediT authorship contribution statement

Bryan A. Fuentes: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Patricia N. Manley:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Nicholas A. Povak:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, 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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2026.114814.

Data availability

Data will be made available on request.

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