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An ecosystem model based composite indicator, representing sustainability aspects for comparison of forest management strategies

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ABSTRACT

Forests provide a wide range of ecosystem services, and ecosystem models can be applied to assess the contribution of different forest management strategies to climate mitigation and adaptation. Complex model output and trade-offs between environmental, economic, and social sustainability dimensions are difficult to convey. To facilitate stakeholder communication, we developed composite indicators based on ten ecosystem service indicators obtained from ecosystem model simulations representing 19 forestry management strategies across three ecoregions and climate scenario projections in Sweden. Eight alternative composites were generated around a central framework addressing sustainability aspects in terms of wood production, preservation of biodiversity, climate change mitigation and adaptation (risk management). A combination of principal component analysis, exploratory factor analysis, Cronbach's coefficient alpha, and hierarchical cluster analysis was applied to account for the statistical relationships between indicators. Z-score normalization was superior to min-max normalization in capturing differences among management strategies. Two weighting schemes were applied, based on policy prioritizations between sub-components that reflected 1) current policy with an equal emphasis on production and biodiversity, and 2) a stronger focus on nature protection. Equal emphasis generated a larger range of scores (76.0 ± 21.2) than the focus on nature protection (32.0 ± 5.8), as the latter would provide less production benefits and thereby fewer trade-offs between production and other aspects. The final scores of the 19 management strategies fell within a variance boundary of each other, showing their contribution to different policy targets and the usefulness of combining strategies at the landscape level. The composites displayed agreement across regions and scenarios. They indicated that a shift from even-aged conifer monocultures towards a combination of continuous cover, broadleaf-mixture, and unmanaged would work well for balancing goals under changing climate conditions.

1. Introduction

Forestry comprises a significant portion of Sweden's economy, contributing 10% of the tree products traded globally (Keskitalo et al., 2016). Forest ecosystems cover 28 million hectares, which is 69% of the country's total land area. Over 90% of that land is currently classified as productive stands (Lindahl et al., 2017). Standing volume for Swedish forests is comprised of Norway spruce (Picea abies) (42%) and Scots pine (Pinus sylvestris) (39%), motivated by the intersection of silvicultural preferences, economic pressures, and tradition (Lindahl et al., 2017). Sweden's biodiversity has declined over time in tandem with the transition from extensive farmland to intensive forestry (Felton et al., 2016; Angelstam et al., 2020). Dwindling biodiversity in managed and unmanaged landscapes threatens ecosystem function and magnifies biosphere vulnerability to disturbance events, pests, pathogens, and climate change (Hooper et al., 2012). The Swedish Forestry Act regulates profit and sustainability goals, equally emphasizing wood production and environmental conservation (Lindahl et al., 2017). Owners adhere to management requirements, but fear of profit losses has slowed the implementation of more sustainable practices (Lidskog et al., 2013; Lindner et al., 2014). A significant portion of this inaction is attributed to a deficiency in the knowledge and comprehension needed to make decisions (Klapwijk et al., 2018).

Sweden's climate is projected to warm by 2 to 7 °C by the end of the century, altering precipitation and increasing extreme weather events (Kjellström et al., 2014; IPCC, 2021). Warmer winters will lengthen the growing season and affect ecosystem composition, species range, and damage from pests and pathogens (Jönsson et al., 2009; Seidl et al.,

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2011). These factors combine to put forestry-related ecosystem services at-risk (Felton et al., 2016). In response, the Intergovernmental Panel on Climate Change (UNG, 1988), the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (Díaz et al., 2015), and the Swedish Forestry Agency (Pettersson et al., 2017) stress the importance of changing forest management strategies to 1) incorporate ecosystem service (ES) benefits beyond biomass production, 2) meet Sweden's environmental objectives (EO), and 3) adhere to the United Nation's Sustainable Development Goals (SDGs) for holistic social and environmental improvement. Despite synergies, these three initiatives distribute focus between ecological and social priorities differently, adding confusion to stakeholders' decisions and resulting in Sweden not being on track to meet any of them (Angelstam et al., 2020).

Humans exist within the natural world's boundaries and depend on its biodiversity, ecosystem functions, and services (Naeem et al., 2012; Folke et al., 2016). Recent population growth and economic expansion demand more energy and materials from the environment than it can provide (Díaz et al., 2015). In forested ecosystems, the focus has been on increasing yields and maximizing profits, leading to a quantifiable degradation of biodiversity and ecosystem function (Triviño et al., 2015; Díaz et al., 2019). Sustainable development is defined as "meeting the needs of present generations without compromising the ability of future generations to meet their own needs," also described as human well-being (HWB) (WCED, 1987). This can be separated into the underlying dimensions of environment, society, and economy. There is a clear connection between sustainable forest management and reducing CO_2 emissions driving climate change (Rehman et al., 2021). Synergies and trade-offs within multi-use forestry include tensions between production, climate change mitigation, risk management, and biodiversity. Together these groups capture different key aspects of ecosystem-human well-being (EHWB).

Lagergren and Jönsson (2017) used a dynamic ecosystem model to determine the effect of different combinations of management practices for multiple regions throughout Sweden while balancing economic, environmental, and social values in a climate change context. While the results are valuable, their format poses a challenge to the non-scientific community to interpret (Angelstam et al., 2020). Composite indicators (CIs) help represent complex phenomena, mathematically simplifying multidimensional concepts into a single value (Sarra and Nissi, 2020). CIs are widely used and help inform decisions to meet policy targets for sustainability (Singh et al., 2009). To handle potential subjectivity during construction (OECD, 2008), one must understand the context in which the CI is intended and evaluate different methodologies to select the best approach for a specified purpose (Alam et al., 2016).

This study aims to construct a CI for the modeled results from Lagergren and Jönsson (2017) to capture the complexity of ecosystem dynamics while conveying recommendations to balance environmental, economic, and social sustainability. The scope encompasses three ecological regions throughout Sweden for future climate projections to the end of the century, at the landscape scale, by addressing the following questions: 1) Which CI methodology best represents modeled differences between management strategies at the landscape scale? 2) Using the developed CIs, which forest management strategies for production stands are recommended across regions in Sweden to fulfill a range of sustainability goals? Do these recommendations change over time under different climate scenario projections?

2. Materials and methods

Sweden ranges between 55°N and 69°N and 10°E to 24°E, and historic alternating glaciation-deglaciation periods have generated moraine till soils throughout the country (Rytter et al., 2016). This study is based on three ecoregions in northern, central, and southern Sweden, reflecting northern boreal, southern boreal, and boreo-nemoral conditions, respectively (Ahti et al., 1968).

2.1. Model-based ecosystem indicators

Ecosystem modeling allows for evaluating forest management strategies through time at varying spatial scales, putting different synergies and trade-offs into perspective. Model output can be designed to focus on specific proxies and measures for ecosystem components (Wood et al., 2018). The Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) (Smith et al., 2001; Smith et al., 2014) is a dynamic global vegetation model (DVM) that can account for biogeochemical ecosystem processes with differing management schemes. LPJ-GUESS dynamically captures forest vegetation structure at landscape, regional, and global scales as its bottom-up design links ecosystem processes. Required input includes temperature, precipitation, incoming solar radiation, soil properties, and atmospheric CO_2 concentrations (Smith et al., 2001). Vegetation represented by plant functional types (PFTs) captures the high variability of plant species through groupings of shared life-strategy, bioclimatic niche, structural type, and biogeochemical characteristics (Ahlström et al., 2012). Structural dynamics are organized into stands representing the overall modeled area for a grid cell separated into a specified number of patches with a 0.1 ha extent. Patches have a random sampling of vegetation cohorts, consisting of several PFTs that can survive in the area based on environmental conditions. Vegetation composition is defined from resource competition, such as canopy properties' effect on incoming shortwave radiation (Smith et al., 2001). The model's suitability to capture climate and vegetation trends across Sweden has been evaluated and validated by numerous studies (e.g., Morales et al., 2005; Ahlström et al., 2012; Lagergren et al., 2012).

Lagergren and Jönsson (2017) ran LPJ-GUESS for a total of 19 forest management schema. Sixteen varieties of even-aged forestry (EAF), two continuous cover forestry (CCF), and unmanaged (Fig. 1) were simulated with 50 patches each to capture different stand ages. EAF involves repeated planting of seedlings followed by clear-cutting after a set period of growth, varying by four species compositions accounting for the majority of trees used in Swedish forestry: 1) Picea abies (Norway spruce), 2) Pinus sylvestris (Scots pine), 3) a boreal-broadleaf mix of Betula pendula, Betula pubescens, Popolus tremula, and Alnus incana (birch, aspen, and grey alder), and 4) a nemoral broad-leaf mix of Quercus robur, Fagus sylvatica, and Fraxinus excelsior (oak, beech, and ash). The density of planted seedlings and rotation period length depended on soil quality and were represented to allow natural regeneration and composition changes based on environmental conditions. Two rotation periods, "normal" and "short," were explored. An additional parameter is pre-commercial thinning (PCT) intensity, which removes naturally established trees from stands, with "high" and "low" tolerances to natural regeneration implemented. Two CCF schemes varied based on regularly occurring interval harvesting strategies: 1) selective thinning throughout the stand and 2) targeted cutting above a maximum diameter threshold. Both CCFs had a minimum diameter preventing any trees from being cut, and an upper limit beyond which trees were universally cut. The CCF simulations were dominated by shade-tolerant species, predominantly Picea abies in boreal conditions and Fagus sylvatica in nemoral conditions (Lagergren and Jönsson, 2017). Simulations representative of unmanaged forests were only influenced by environmental constraints on PFTs and naturally occurring disturbance events.

A bias-corrected representative sub-ensemble of regional climate models (RCMs) from EURO-CORDEX (Kotlarski et al., 2014) provided daily input climate data for RCP8.5 (1951–2099) at a 50 km spatial resolution for nine grid cells per ecoregion. A spin-up period with natural establishment and stochastic disturbance events was run before management implementation. This ensured stable conditions for the scenario model runs, for which three periods of time (P1, P2, and P3 for 2000–2019, 2040–2059, and 2080–2099, respectively) offered a way to capture inter-annual variations in climate conditions. A benefit of using RCP8.5 with this temporal depiction scheme is that each period also represents end-of-century conditions under different climate scenarios.

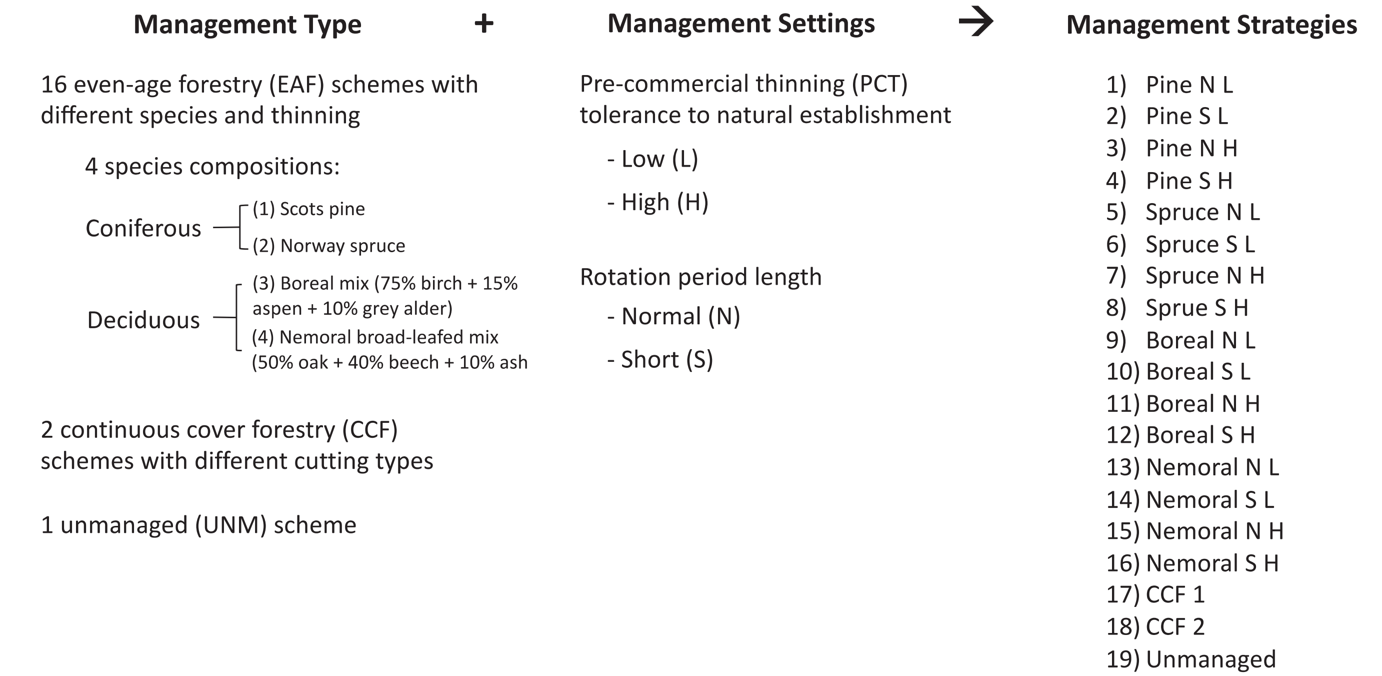

Fig. 1. The 19 forest management strategies (Lagergren and Jönsson, 2017) included even-aged forestry with four species compositions subjected to two thinning intensities and two rotation period lengths. Continuous cover forests are cut in 15-to-30-year intervals, with CCF1 having a higher harvest strength (40%) than CCF2 (20%). Unmanaged was subject to natural establishment and disturbances.

RCP2.6 at the year 2100 is analogous to P1 under RCP8.5, with mid-century RCP8.5 (P2) comparable to end-century RCP4.5 and RCP6.0 (Moss et al., 2010; IPCC, 2014). Variation in forest soil fertility, which affects production yield, was represented with three site quality classes (SQCs): low, medium, and high fertility. SQCs were incorporated into the model by scaling a proxy parameter (radiation-use efficiency). Sub-modules to incorporate forest management, economy, risk of storm damage, and biological indicator values were applied (Lagergren et al., 2012, Jönsson et al., 2015).

Ten ES indicators were generated as output from LPJ-GUESS runs from each of the four sub-ensemble RCMs. 1) Harvested biomass for both timber and pulp from the stem pool. 2) Net income calculated from established market values averaged over ten years for set dimensions and size of cut timber at harvest stage per ha. 3) Storm damage resistance derived from a sensitivity index based on tree proportions, PFT sensitives, neighboring stands, and root system damage from soil freeze.

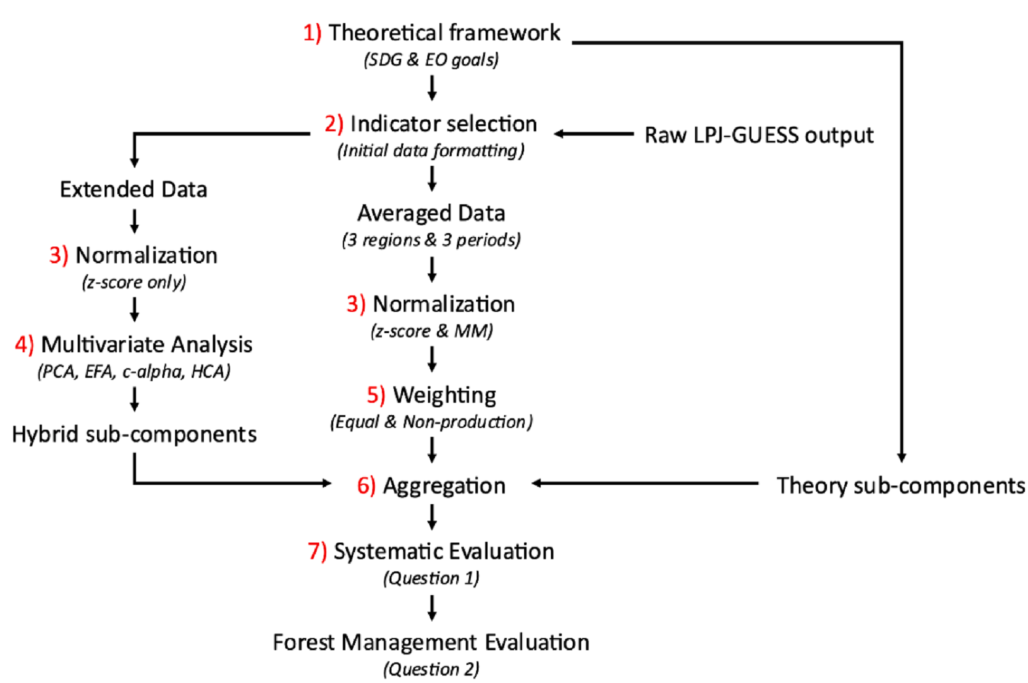

Fig. 2. Stepwise process for CI development. Extended indicator values (Fig. 4) were used in multivariate analysis (2.2.2.). The following CI structures were based on averaged values that had been normalized (2.2.3.), weighed (2.2.4.), and aggregated (2.2.5.). The final CI structure was selected through systematic evaluation (2.2.6.) and used to evaluate management practices for regions and periods (3.4.).

LPJ-GUESS already outputs several variables with information on carbon pool state, which generated 4) total carbon stored in biomass, 5) annual carbon sequestration in biomass, and 6) annual carbon sequestration in soil. Finally, a sub-module for forest biodiversity produced 7) the fraction of broad-leafed trees in a stand, 8) the number of old trees above a regionally dependent age threshold, 9) the number of old broad-leafed trees, and 10) the amount of stem (woody) litter. Old trees, old broad-leafed trees, fraction of broad-leafed forest, and stem litter acted as proxy measures for biodiversity as specified by Sweden's EOs. Details on sub-ensemble cluster development, SQCs, management scheme implementation, and ES indicators used can be found in Lagergren and Jönsson (2017).

2.2. Development of composite indicators

Individual indicators can be combined into a single value representing the multidimensional phenomenon as a composite indicator (CI) (OECD, 2008; Singh et al., 2009). CIs are widely applied in policy-making, e.g., to facilitate adaptive change (Booysen, 2002; Zhou et al., 2012; El Gibari et al., 2019). This study followed the guidelines of OECD (2008) (Fig. 2): 1) Develop a theoretical framework of the CI. 2) Select indicators to address different CI dimensions and perform initial data formatting. 3) Normalize individual indicators so different units do not conflict. 4) Perform multivariate analysis to evaluate combinations of indicators. 5) Weight sub-components based on two policies. 6) Aggregate sub-components into final CI scores based either on the theoretical framework or a combination of the multivariate analyses. 7) Evaluate final CIs.

2.2.1. Framework and theoretical sub-components

A theoretical framework was generated to link ES indicators to EOs and SDGs (Fig. 3). Goals from EOs and SDGs related to each type of ES. When combined in the CI, they captured ecosystem-human well-being (EHWB).

A quality assessment and summary table of descriptive statistics (mean, minimum, maximum, and standard deviation) for each indicator was generated for each of the ecoregions and periods concerned, in addition to an overall average for combined regions and periods (see Appendix A).

2.2.2. Selection of indicators and data formatting

In this study, the raw output from LPJ-GUESS included ten ES indicators and 19 management strategies for each of three site quality classes (SQCs) for three regions, covering nine grid cells each. Data for three separate 20-year time intervals across four model runs driven by four different climate data sets were used. The data, stored in a $10 \times 19 \times 3 \times 3 \times 9 \times 3 \times 20 \times 4$ array, was imported into MATLAB (R2020a, The Math Works Inc., 2020). SQCs for the grid cells in the same period and region were combined into a single representative value using the weighted mean based on area-specific average SQC level (Table 2 in Lagergren & Jönsson, 2017). Averaged SQCs reduced the number of data dimensions and represented a reasonable simplification by having uniform production potentials within each region (Gan et al., 2017). For the CI development, an array of 10x19x3x3x9x4 (ES indicator, management strategy, region, period, grid cell, RCM) was used to address uncertainties between the RCMs ($n = 61560$ data points). For the final CI construction, a data set averaged across regional grid cells and RCMs set was formed as an array of 10x19x3x3 (ES indicator, management strategy, region, period), separated into nine output files, corresponding to three regions and three periods (n = 1710 data points, Fig. 4). The modeled data did not include any missing values or erroneous outliers, as all data points conveyed relevant information concerning the given period and region's associated management strategies.

2.2.3. Normalization

Normalization adjusts variables with different units to a common scale (OECD, 2008; Singh et al., 2009), enabling the equal contribution of indicators at all stages of CI construction (Ebert and Welsch, 2004). While all ten indicator variables have carbon at the core of their measures, their units and distributions differ, which necessitate normalization prior to comparative statistical analysis (2.2.4.) and aggregation of the final CIs (2.2.5.). It was important to keep statistical outliers and preserve distributions for each indicator as representative values for their affiliated management strategies.

Two different normalization types, Z-score and min–max normalization, were applied to the data to determine which better represented modeled ecological processes for constructing CIs (OECD, 2008). Z-score standardization shifts the mean of each indicator to zero and the standard deviation to one. Values were represented as distances from the mean in units of standard deviation (Eq. (1)):

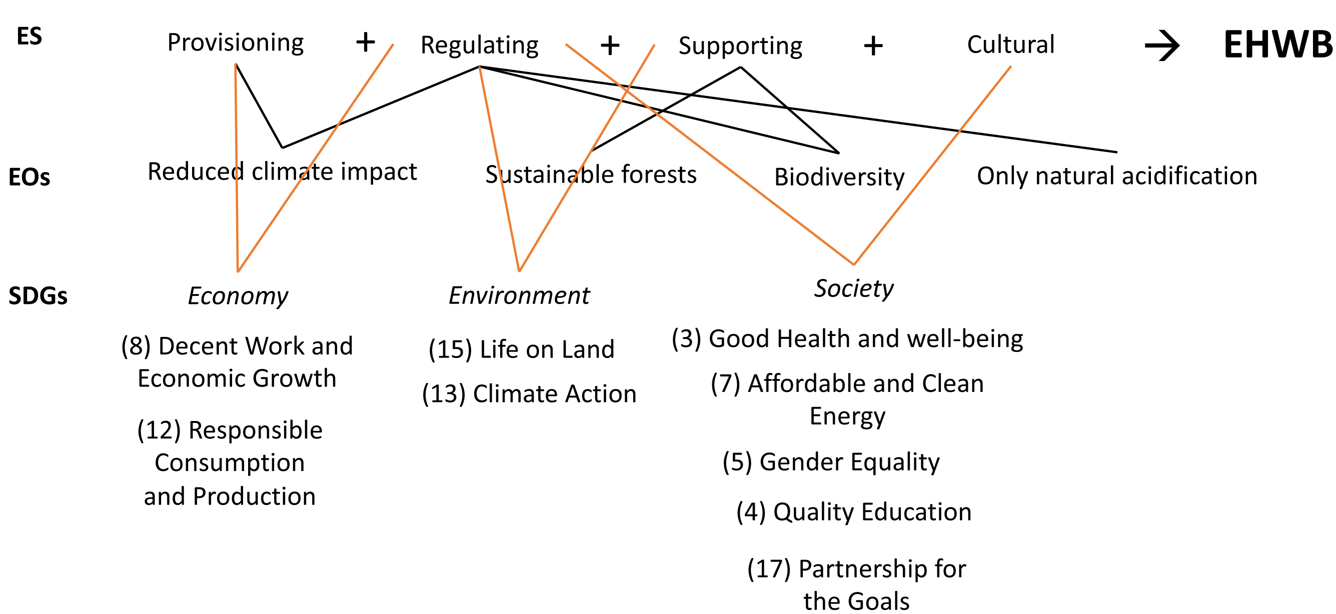

Fig. 3. Overview of links between forest ecosystem services (ES), environmental objectives (EOs, Swedish EPA, 2012), and sustainable development goals (SDGs), contributing to ecosystem-human well-being (EHWB).

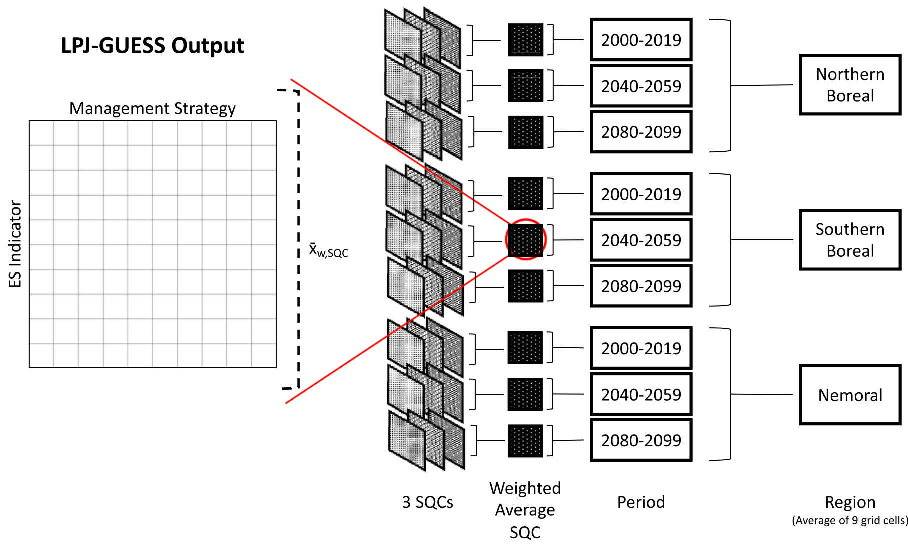

Fig. 4. Data management, output from LPJ-GUESS were averaged to produce indicator values for three regions and time periods. An extended data set used in multivariate analysis was produced by combining the site quality class (SQC) values (low, medium, and high) ($n = 61560$), while the averaged data set used for forest management evaluation included additional averaging of the nine grid cells per region, and four RCM runs ($n = 1710$).

$$Z = \frac{x_m - \overline{x}}{s} \quad (1)$$

where x_m is the raw value for the m-th management strategy, $\overline{x}$ is the mean of all indicator values, and s is the standard deviation.

Min-max normalization (MM) shifts the range of all indicator values to between zero and one. MM preserves the shape of each indicator's distribution and is especially good for variables with raw values on a small scale (Brunet, 2002). Values are calculated by finding the distance each management value is from the smallest value and dividing by the range (Eq. (2)):

$$MM = \frac{x_m - \min(x)}{\max(x) - \min(x)} \quad (2)$$

where x_m is the raw value for the m-th management strategy, min is the minimum value for the i-th indicator, and max is the maximum value. A consequence of being based on each indicator's range is the possible distortion caused by outliers as they are drawn closer to the mean. Other normalization approaches were considered (Student's t-statistic, Studentized residual, Standardized moment, and Coefficient of variation) but were not suitable for this modeled data as they would require regression estimations or use of hypothesized population averages, which would introduce unnecessary complexity (Alam et al., 2016; Greco et al., 2019).

2.2.4. Hybrid sub-components

The theoretical framework was compared with a hybrid framework, generated through multivariate analysis, as the multidimensional nature of the indicators benefited from mathematical insights of nested components (Brunet, 2002; Hair et al., 2006). The ten ES indicators of extended LPJ-GUESS output (3.2.) were sorted based on mathematically derived sub-components following Booysen (2002) and El Gibari et al. (2019). This step also served as validation that the ten indicators were proven to be meaningful and not just arbitrarily selected (Greco et al., 2019).

Principal component analysis (PCA), exploratory factor analysis (EFA), Cronbach's coefficient alpha (C-alpha), and hierarchical cluster analysis (HCA) were used, as the application of several multivariate techniques provide greater understanding regarding data structure (Gan et al., 2017). Both PCA and HCA are types of linear non-parametric unsupervised machine learning, meaning the dataset's structure is being analyzed, not predicted. PCA is solely based on statistical variance, while HCA considers variable similarity. EFA expands upon PCA by finding inferred and unobserved latent variables not directly measured by the ten modeled indicators. At the same time, C-alpha represents how well all indicators measured the same phenomena judging by how their behavior changes if each variable were excluded. All multivariate analyses were done with z-score normalized data, as the wide-ranging variance and different units of indicators would otherwise introduce bias.

2.2.4.1. Principal components analysis. PCA interprets the variation between variables by forming principal components (PCs) that are based on correlation while preserving the total variation (Dunteman, 1989). The greatest amount of variance is retained within the first PC, followed by the second, and so forth in descending order. Three rules were applied to distinguish between significant and random variability: the proportion of variance test (PoVT), Cattell's scree test (CST), and Kaiser criterion (KC). The modeled nature of the dataset supported the use of multiple stopping rules to determine the appropriate number of PCs (Alam et al., 2016; Greco et al., 2019). PoVT identified significant PCs based on a cumulative variance being captured, ranging from 70 to 80%. CST is similar but used scree plot visualization to identify the PCs to retain, those that fell before the "elbow" of the variance proportion curve (Martin and Maes, 1979; OECD, 2008). KC discarded all PCs with squared eigenvalues < 1.0 (as PCs should at minimum explain the variance of one individual indicator) (Yong et al., 2013). A low correlation between PCs signified that the component suitably captured the statistical dimensions of the original indicators and were mathematically valid groupings as CI sub-components (Hair et al., 2006). PCA was run five times: once for all extended data and four additional times for the regions and periods with the most contrast (Nemoral vs. N. Boreal and 2000–2019 vs. 2080–2099).

2.2.4.2. Exploratory factor analysis. EFA uses a specific rotation model to explain the association between indicators with the fewest latent components (Harman, 1976). It creates underlying components that could not be captured in the original data or directly observed by maximizing variance on a fixed number of reduced loadings (Yong et al., 2013). Univariate and multivariate normality, and a linear relationship between factors and variable covariance, were checked before performing the EFA. Confirmation of satisfactory conditions was achieved with Bartlett's Test of Sphericity (BTS, $p \leq 0.05$), which checks for an identity matrix, and Kaiser-Meyer-Olkin (KMO ≥ 0.5) measure of sampling adequacy between variables through the strength of their partial correlations. PCA was used to extract factor loadings, equivalent to the PCs determined by PoVT, CST, and KC stopping rules. Factors were then rotated to maximize variance and identify how loadings differentiate from original indicators (Yong et al., 2013). Varimax rotation was used (Kaiser, 1958). It is the most commonly used orthogonal rotation that minimizes the number of indicators with high loadings per factor while assuming that factors are uncorrelated (Rummel, 1988; DeCoster, 1998). Final factor loadings captured the strength of correlation between the original indicators and factor components to inform sub-component assignment (Yong et al., 2013). EFA was run the same number of times as PCA.

2.2.4.3. Cronbach's coefficient alpha. C-alpha was included as it measures the internal consistency of all ten indicator variables (Cronbach, 1951). As a form of reliability analysis, it evaluated the relation among indicators by comparing their independent variability and their correlations. C-alpha does not assume unidimensionality, but it measures how related a group of variables are by checking for separate latent clusters (Hair et al., 2006; OECD, 2008). The cut-off point for an acceptable C-alpha is debated, but Nunnally's (1979) of 0.7 is considered adequate (OECD, 2008). It represents a suitable balance between being too lenient or strict when applied to indicator values sourced from an ecosystem model (El Gibari et al., 2019). The range of correlation values allowed up to three indicator groupings to be determined, matching the number of theoretical sub-components. High correlation (C-alpha = 1) is associated with capturing the same latent object well, so sub-component groupings were identified by dividing between highly correlated, moderately correlated, and uncorrelated (C-alpha = 0) indicator pairings (OECD, 2008; Singh et al., 2009).

2.2.4.4. Hierarchical cluster analysis. HCA, also known as tree clustering, created hybrid sub-component groups based on a mathematical hierarchy of increasingly nested classes (OECD, 2008; Kaufman and Rousseeuw, 2009). Unique groups with homogeneous members were delineated with distances, which equated to degrees of similarity or dissimilarity between variables (Späth, 1980). Indicator values clustered together were most akin to one another within the grouping while most different from other groupings. The clustering algorithm regulated how space between clusters was measured, known as the linkage criteria (Szekely and Rizzo, 2005). Ward's method (Ward, 1963), which determines links based on minimum variance (sum of squared deviations from cluster mean), opposed to distance or weight-based algorithms, was the criterion used. Values with the least variance between each other were considered most similar. It yielded the strongest agglomerative (bottom-up) coefficient for average group linkage than other criteria, best capturing the clustering structure for the modeled indicators (Kaufman and Rousseeuw, 2009). Results were visualized as a dendrogram to represent the distance (height) between cluster groups. Groupings of clusters into sub-components were determined based on minimum height relative to the three components desired (i.e., Production, Biodiversity, Climate Change Mitigation and Risk Managment (CCMRM)). As with PCA and EFA, five runs were made on all extended values and subsets with contrasting spatial and temporal conditions. An additional five clusters were done for averages of each normalization approach, totaling ten between z-score and MM for averages and subsets. Another 18 runs were performed on averaged values for both z-score and MM normalizations on all region-period combinations. HCA is the only multivariate approach where MM normalization was suitable to include. Averaged indicator values for individual regions and periods were also clustered for each normalization approach.

2.2.5. Weighting

Weights can be applied to individual indicators, sub-components, or both (Gan et al., 2017). However, explicitly weighing individual indicators is only recommended when each captures a distinct phenomenon (Alam et al., 2016). The second method was selected as the individual indicators displayed some correlation, and as the three sub-components informed differences in goals and ES. Mathematical approaches to account for and offset connections (El Gibari et al., 2019) were not used, as the sub-components' construction acted as implicit weighting and satisfied the correlation concern (Attardi et al., 2018).

A theoretical nature protection (NP) weight was employed and compared with equal (E) weights. The Swedish Forestry Act specifies that production and conservation efforts are given equal priority, so weighing each sub-component the same would satisfy these policy conditions (Lindahl et al., 2017). Critique from non-government organizations and other reports argue the merits of transitioning to valuing ecosystem biodiversity conservation and climate change mitigation over harvestable forest products (Tollefson, 2018; Díaz et al., 2019; Angelstam et al., 2020). NP weighing consisted of multiplying sub-components by a percentage to offset Production ES. Biodiversity and CCMRM were each multiplied by 0.40 while Production was by 0.20. The NP scheme was skewed to give greater weight to sub-components representing nature protection ES, allowing the exploration of a scenario where policy is altered.

2.2.6. Aggregation

The three weighted sub-components were averaged together to yield CI scores (Alam et al., 2016). Due to multi-dimensional correlation between sub-components, multiplication was selected instead of summing (OECD, 2008; Gan et al., 2017). Linear aggregation - additive or multiplicative - is recommended for modeled ES values (Singh et al., 2009; Alam et al., 2016). Linear is ideal when raw units are the same, and while the units vary, the core of each indicator is carbon. As LPJ-GUESS output was averaged, and every value is representationally significant, linear techniques account for each value without worry that they will skew or produce misleading CI scores (Greco et al., 2019).

A total of 1368 CI scores were produced: 152 values for 19 management strategies across eight CI structures—each with two normalization schemes [z-score and MM], two sub-component groupings [theory and hybrid], and two weighting schemes [E and NP] (2x2x2)—done over three regions and three periods (19x8x3x3) (Fig. 5).

2.2.7. Systematic evaluation

Evaluation of construction decisions is recommended (OECD, 2008; Singh et al., 2009; Alam et al., 2016). The process addresses the first research question by selecting a CI structure. CI scores for each aspect of the development process (normalization, sub-component grouping, and weighting) were averaged and compared through visualization and unpaired samples t-testing (OECD, 2008). Evaluating aspects with individual statistical tests increased comprehension, useful for structural decisions as each aspect was only compared to itself instead of simultaneously against all other aspects as would occur with ANOVA (Burgass et al., 2017). Averaged values were used for each comparison because the ideal CI would be representative across all regions and periods. CI aspects were selected based on the statistical tests, and nature protection and equal weighting schemes were purposefully retained to explore both management priorities.

The final CI structure was examined using averages with E and NP weights for regions and periods. The nine combinations of the three regions and three periods were averaged into a single score for each of the 19 forest management practices, with standard deviation indicating spatial and temporal variation. Color was used to visualize the contribution of each sub-component to a management strategy's CI value. The fractional proportion of a sub-component relative to the CI value was calculated and then min–max normalized (Eq (2)), so each sub-component had a value between zero and one. When plotted together

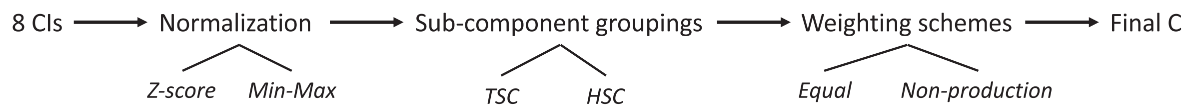

Fig. 5. Eight CI structures based on data for 19 management strategies over three regions and three periods were developed to evaluate the effect of normalization methods, sub-component groupings (determined with theoretical background [TSC] or a hybrid with multivariate analysis [HSC]), and weighting (reflecting an equal balance between production and protection, or enhanced nature protection).

in an RGB color space, this generated a color, denoting the trade-offs each management approach has concerning the ES goals represented by the respective sub-components. Management scores were sorted in descending order for all regions and periods for E and NP weight schemes. Regional and period averages of both E and NP weighting provided four additional sets of sorted CI scores. Averaging and sorting CI scores of forestry management strategies between regions, periods, and combined regions and periods answered the second research question by identifying management choices for forest owners based on policy priority and climate conditions.

3. Results

The results cover the development and evaluation of CIs and their use in the evaluation of management options.

3.1. Development of composite indicators

The theoretical sub-components were created by grouping the ten ES indicators into three sub-components that factored into provisioning, regulating, and supporting services (Table 1). A total of 39 multivariate analyses were carried, and the number of times each indicator was allocated to a specific sub-grouping was counted (Table 1). Final hybrid sub-components were determined by the indicators assigned to each grouping the most. Compared to theoretical ES-groupings, biomass sequestration shifted from CCMRM to Production. Carbon storage moved to Biodiversity.

Normalized indicators were visualized using heatmaps, and axes were paired with HCA dendrograms to elucidate clustering changes over regions and periods (Fig. 6). Z-scores presented a mean of 0 and standard deviation of 1 for all regions and periods averaged together, with a range of 3.8 from −1.7 to 2.1. Within regions or periods, the range only varied by 0.1, while a difference of 1.8 between the region range and period range existed. MM had a range of 1 from 0 to 1(M = 0.4, SD = 0.3). The mean and standard deviation did not vary across or within regions and periods.

For all PCA runs, PoVT, CST, and KC supported three significant PC loadings equivalent to Production, CCMRM, and Biodiversity groupings. Three PCs captured 70.7% of the cumulative variance while having squared eigenvalues > 1.0 (Fig. 7a). Production (PC1) was assigned harvested biomass, net income, and biomass sequestration from having significant eigenvalues $\geq \pm 0.5$. Storm resistance and carbon storage were grouped as CCMRM (PC2), while soil carbon sequestration, fraction of broad-leafed forest, old trees, old broad-leafed trees, and storm litter were allocated to Biodiversity (PC3). The criteria for performing EFA were met (BTS = 2.22e-16, KMO = 0.59). Factor loadings were derived from significant PCs; varimax rotation for all extended data assigned harvested biomass, biomass sequestration, and net income to Production (MR1) (Fig. 7b). Biodiversity (MR2) was given carbon storage, storm litter, and old trees, while CCMRM (MR3) had fraction of broad-leafed forest, old broad-leafed trees, storm resistance, and soil carbon sequestration.

The internal consistency was moderately robust (C-alpha = 0.71), indicating covariance between individual indicator values. Separation into three sub-components based on high, moderate, and low correlation with total was done (Fig. 7c). Harvested biomass, net income, carbon sequestration in living biomass, and fraction of broad-leafed trees showed the highest correlation and were designated as Production. Old trees, old broad-leafed trees, and the amount of stem litter had a moderate correlation and were assigned to Biodiversity. Soil carbon sequestration, carbon storage, and storm resistance presented a low correlation with the total and represented CCMRM. The analysis per region and period provided insignificant results (C-alpha $\leq$ 0.68).

Indicator similarity was determined by HCA cluster groupings. In total, 28 clusters were analyzed, delegating harvested biomass, biomass sequestration, and net income as Production. Carbon storage, storm litter, and old trees were assigned to Biodiversity. ES indicators for storm resistance, fraction of broad-leafed forest, old broad-leafed trees, and soil carbon sequestration were CCMRM. The same sub-components were identified with the extended values (Fig. 7d) and the averaged values, combined across all regions and periods, using z-score normalization (Fig. 6b). Averaged MM normalization was similar but sorted old broad-

Table 1
Ten modeled ecosystem service (ES) indicators were sorted into three sub-component groupings: The theoretical groupings Provisioning, Regulating, and Supporting were based on ES classification, Environmental Objectives (EOs), and dimensions of sustainability (SDGs). Hybrid groupings of indicators Production, Climate Change Mitigation and Risk Management (CCMRM), and Biodiversity emerged through multivariate analysis of extended data with principal component analysis ($n = 5$), exploratory factor analysis ($n = 5$), Cronbach's alpha for internal consistency ($n = 1$), and hierarchical cluster analysis ($n = 28$). Final hybrid groupings were based on how many times each indicator was assigned to a sub-component (max 39).

	Background theory assignment			Multivariate hybrid assignment			Final groupings	
ES Indicators	ES	EO	SDG	Production	CCMRM	Biodiversity	Theoretical	Hybrid
harvest_bm	Provisioning	Reduced climate impact	Economy	39	0	0	Production	Production
net_income				37	1	1	Production	Production
storm_sens	Regulating	Reduced climate impact + Biodiversity	Environment + Economy	5	32	2	CCMRM	CCMRM
c_storage				2	6	31	CCMRM	Biodiversity
bm_seq				39	0	0	CCMRM	Production
soil_seq				5	25	9	CCMRM	CCMRM
cmass_leaf	Supporting	Sustainable forests + Biodiversity + Acidification	Environment	3	33	3	Biodiversity	CCMRM
old_forest				3	5	31	Biodiversity	Biodiversity
old_decfor				1	10	28	Biodiversity	Biodiversity
stem_litter				4	3	32	Biodiversity	Biodiversity

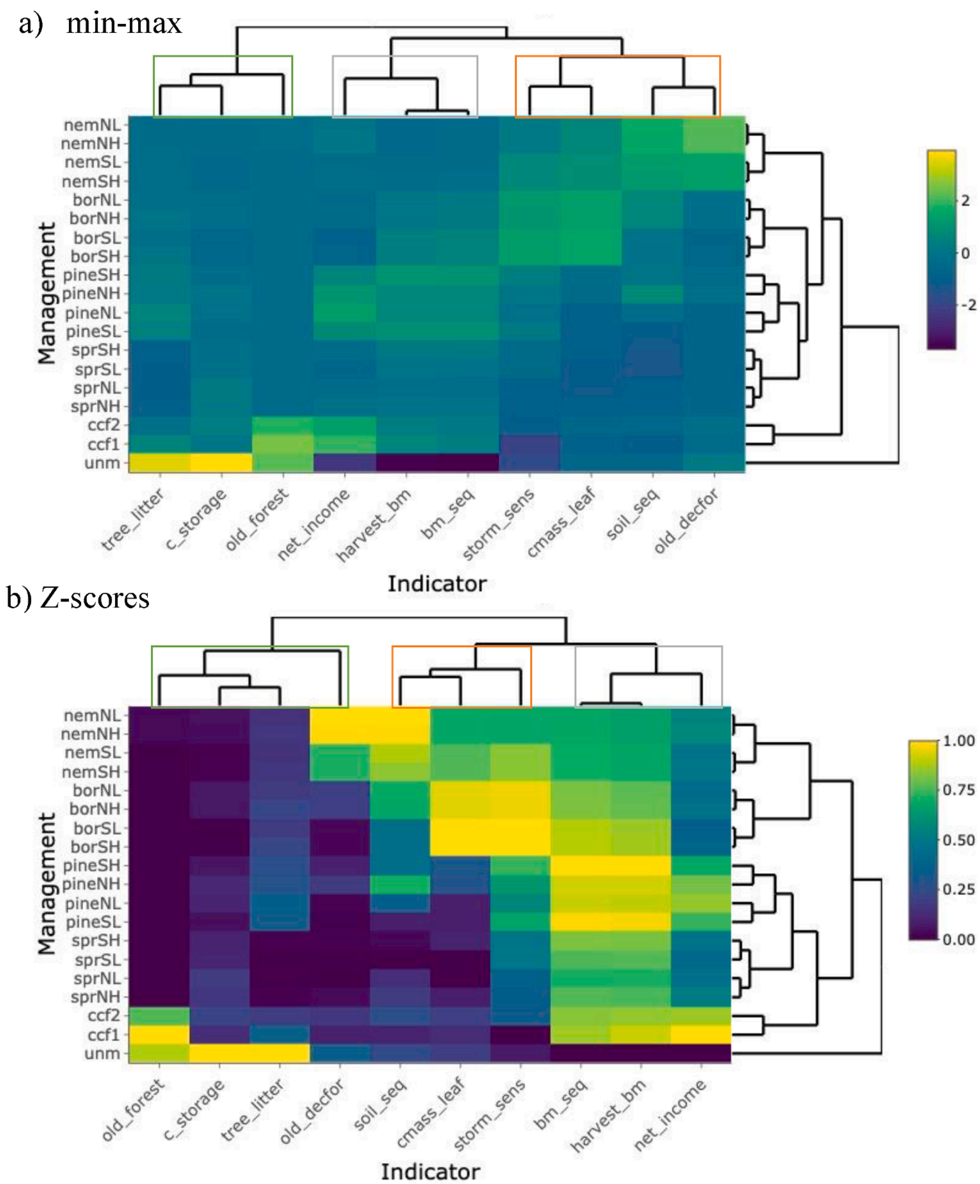

Fig. 6. Density heatmap for indicators normalized with (a) min–max and (b) z-scores, averaged across RCMs, regions, and periods. Production, CCMRM, and Biodiversity aspects are indicated by HCA cluster dendrograms.

leafed trees as Biodiversity (Fig. 6a).

3.2. Systematic evaluation of composite indicators

Normalized values with theoretical and hybrid sub-component groupings, E and NP weighting, generated eight CIs for each of the 19 forest management strategies (Fig. 8). All CIs based on z-scores had means centered at zero and presented a greater overall range than MM. The range difference was evident in the contrast displayed between normal and short rotation periods in EAF managements, low-scoring spruce EAF values, and unmanaged scores for E weighting.

The z-score CIs and MM CIs differed significantly ($p = 1.3e\text{-}07$), and the Z-score CIs showed greater variability between management strategies than MM (Fig. 9a). The two Z-score sub-component groupings, theoretical and hybrid, did not differ significantly (Fig. 9b). The main divergence was the score for unmanaged EHWB, with theoretical being much lower than hybrid. There was no significant statistical difference between the E and NP weighting, with the lower amplitude of the NP indicating the inherently reduced tradeoff between production and other aspects. Both schemes were suitable for evaluating management strategies and provided good contrast between relevant priorities (Fig. 9c). Z-score normalization of hybrid sub-component groupings for both E and NP weighing schemes were selected for further analysis, as these CIs depicted policy-relevant differences between management strategies.

3.3. Management evaluation

It was possible to average EHWB scores into a single set of management values, one each for E and NP weighting (Fig. 10), as only minor differences were found between the management scores for the nine combinations of each region and period. E-weighting had a larger range of scores (76.0 ± 21.2) compared to NP (32.0 ± 5.8). For E, most managements fell within a variance boundary of each other and supported different policy targets. They would be beneficial when implemented in tandem, depending on the local conditions. CCF1 was the management strategy providing most Biodiversity and Production ecosystem benefits for E (28.9 ± 13.8), closely followed by CCF2 (22.0

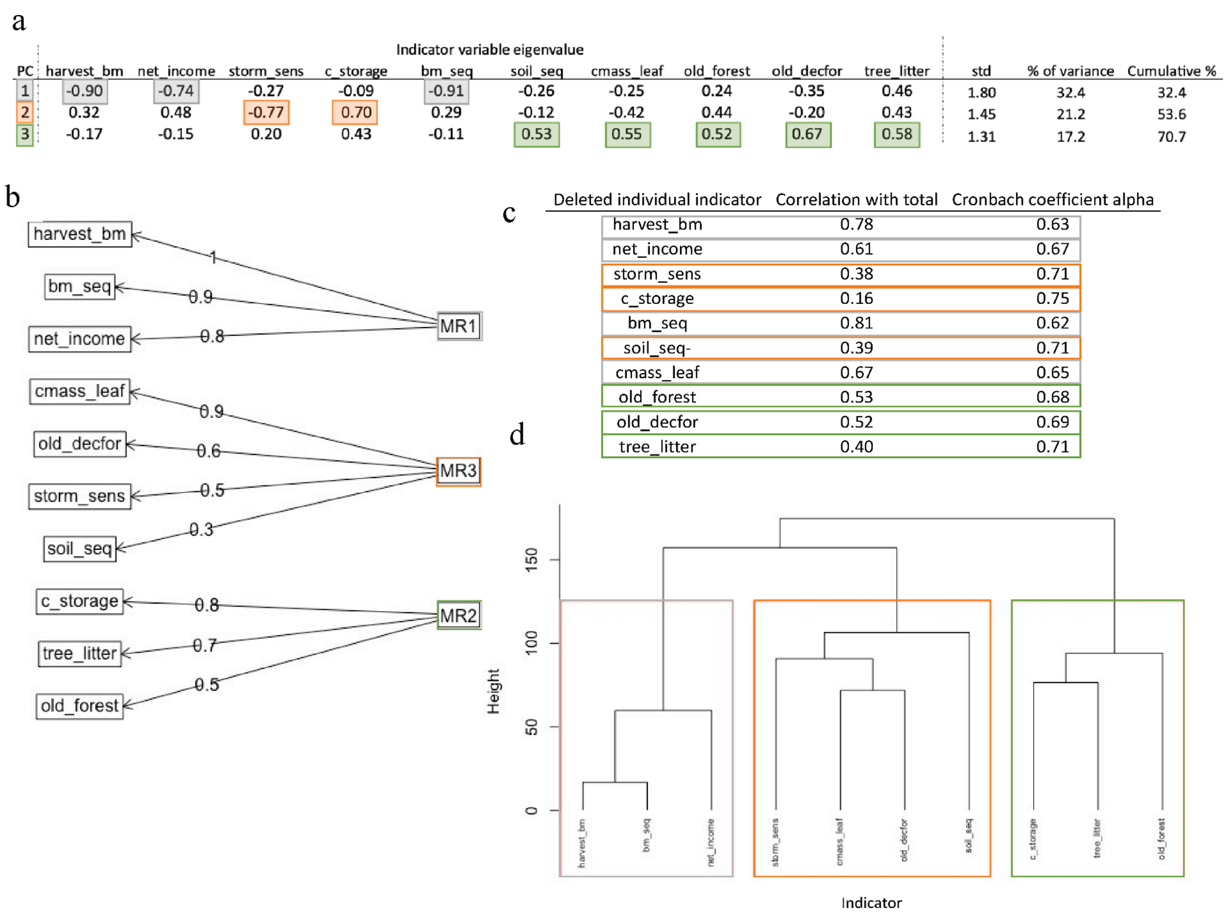

Fig. 7. Multivariate sub-component groupings (Production, CCMRM, and Biodiversity) of extended individual indicators for (a) PCA eigenvalues, (b) EFA loadings with varimax rotation, (c) C-alpha correlations (removed from total variance and sorted based on total correlation), and (d) HCA dendrogram with a height threshold of three.

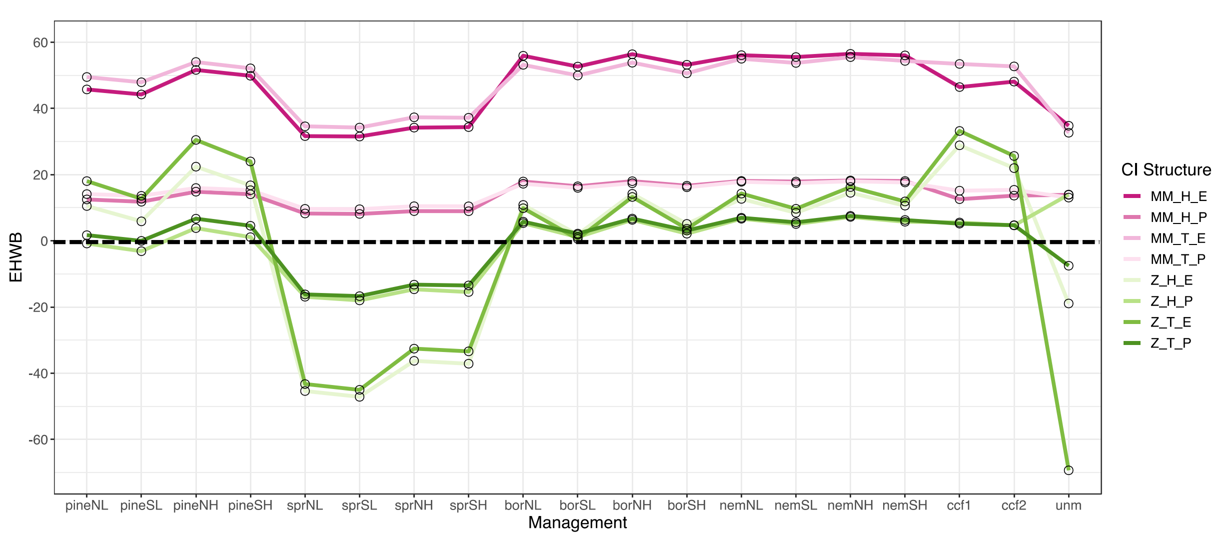

Fig. 8. The eight CI structures for ecosystem-human well-being (EHWB) were constructed from min-max (MM) and z-score (Z) normalizations, theory (T) and hybrid (H) sub-component groupings, and equal (E) or nature protection (NP) weighting schemes. Scores averaged across three regions and periods. Lines between dots display the contrast between CIs in relation to the different management strategies.

± 19.2), both with a wide variation between regions and periods. EAF pine with normal rotation and high PCT tolerance had a slightly higher average but lower spatial and temporal variability (22.3 ± 8.1), primarily supporting Production. Additional well-scoring strategies favoring CCMRM within a similar SD range included normal rotation length nemoral-broadleaf mixtures (12.7 ± 12.7 for low, and 14.5 ± 11.8 for high PCT), boreal-broadleaf mix with normal rotation and high PCT (14.2 ± 11.3), and short rotation high PCT pine (16.8 ± 8.0). For NP, unmanaged forestry had the largest contribution to EHWB (14.0 ± 3.1), followed by normal rotation nemoral-broadleaf mix (6.7 ± 6.1 for low

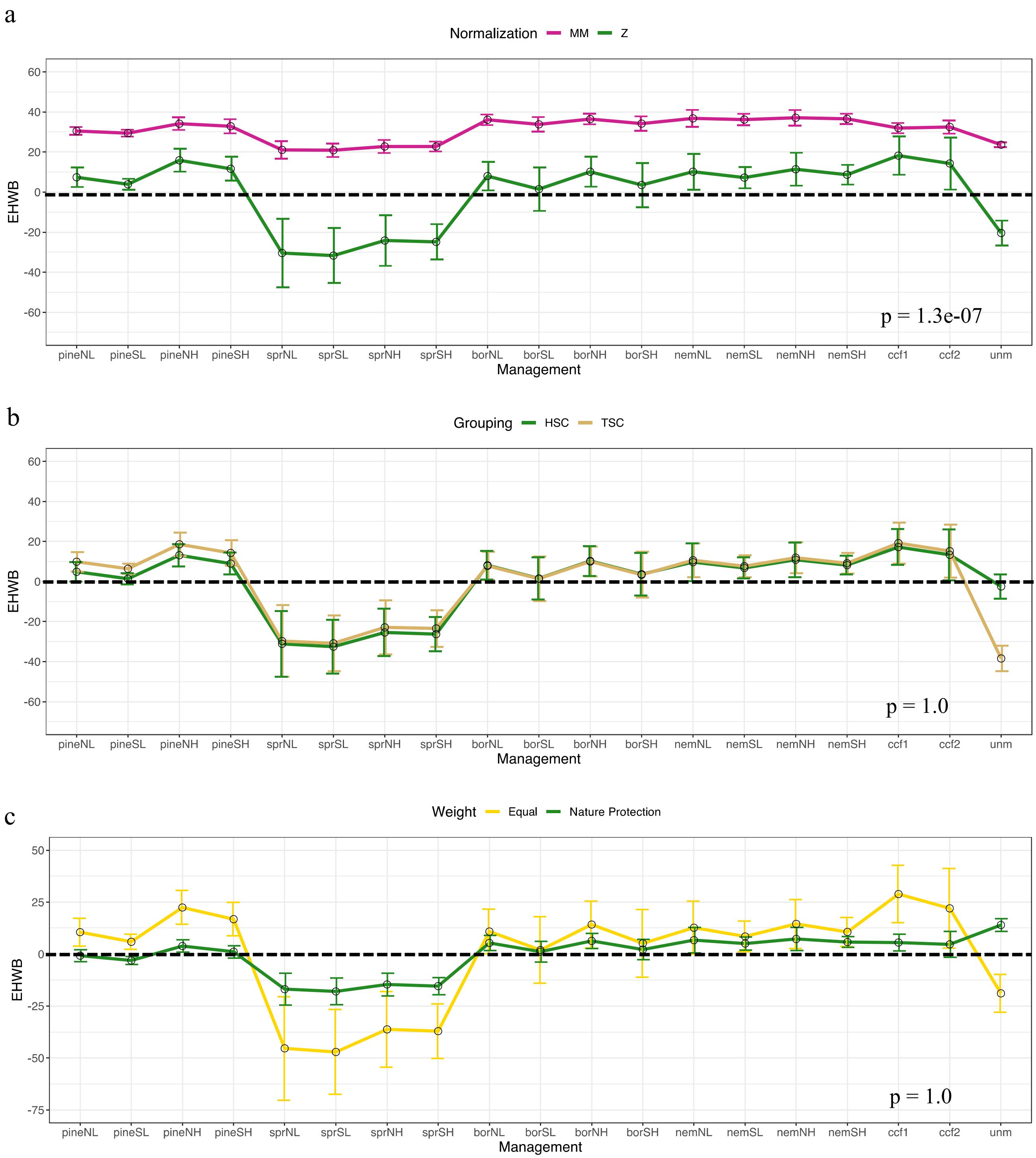

Fig. 9. Systematic evaluation of CIs based on unpaired t-tests (a) min–max (MM) vs. z-score (Z) normalization, (b) theoretical (TSC) vs. hybrid (HSC) sub-components, and (c) two weighting schemes.

and 7.2 ± 5.5 for high PCT), CCF1 (5.5 ± 4.0), boreal-broadleaf mix with normal rotation period and high PCT tolerance (6.3 ± 3.6), and CCF2 (4.7 ± 6.3). EHWB values indicated these five approaches as most beneficial if implemented together as they combine Biodiversity and CCMRM targets. All four EAF spruce strategies scored negatively (i.e., below average) in all regions and period combinations for both E and NP. Besides spruce, negative averages were present in unmanaged (-18.9 ± 9.0) and low PCT pine for E and NP, respectively. While negative z-scores alone indicate poor large-scale feasibility, the addition of understanding what ES benefits they provide means they can be complementary when combined at smaller scales to other approaches.

The highest EHWB scores for E weighting showed agreement between regions and periods (Fig. 11), indicating a consensus regarding best-practice while considering climate change. Among the best performing strategies were different varieties of CCF and high PCT EAF pine. Nemoral and boreal mixed stands with normal rotation periods also performed well and primarily supported CCMRM, covering all policy targets when incorporated with the other strategies. For the N.

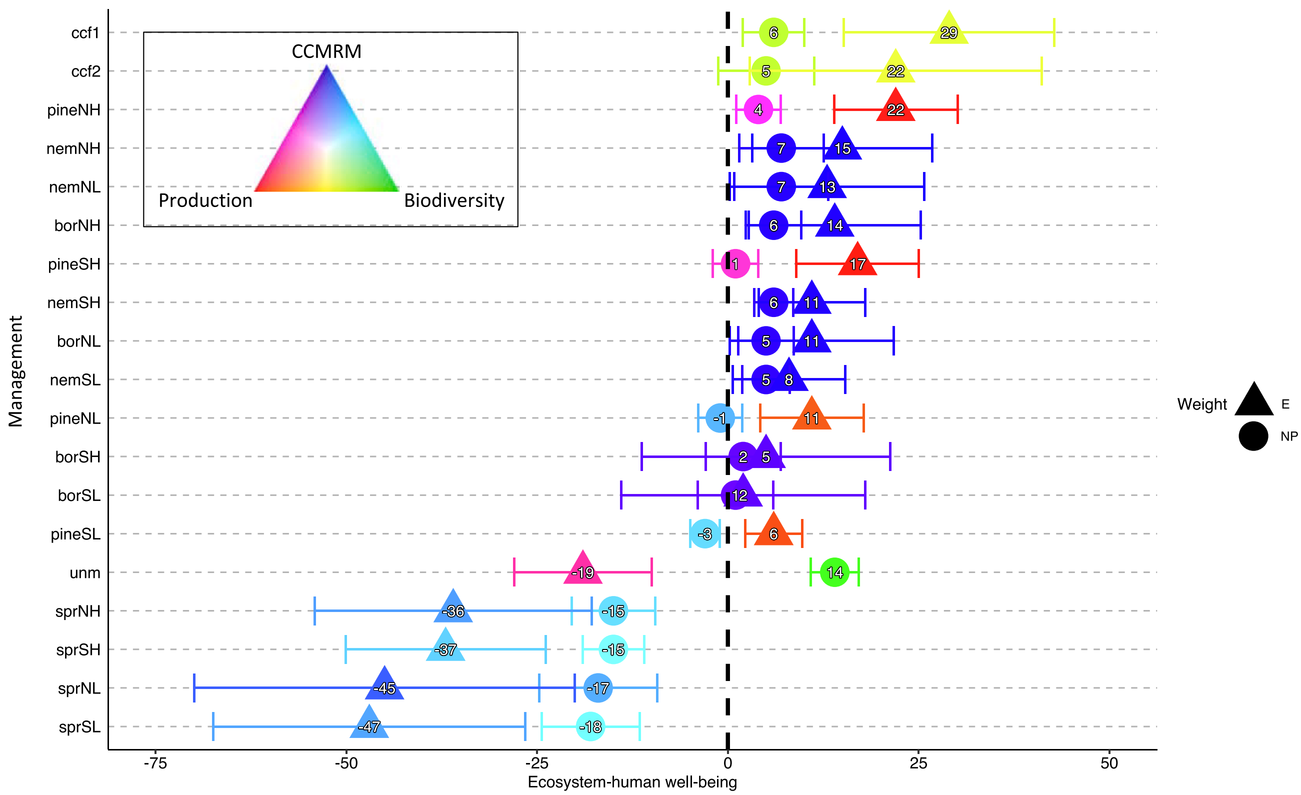

Fig. 10. Composite indicators of managed forest contribution to ecosystem-human well-being for equal (E) and nature protection (NP) weighting schemes, Symbol coloring is proportional to the contribution of CCMRM, Production, and Biodiversity (upper-left triangle). Whiskers display standard deviation of spatial and temporal variations. The values, based on z-scores and hybrid sub-components, were sorted in descending order.

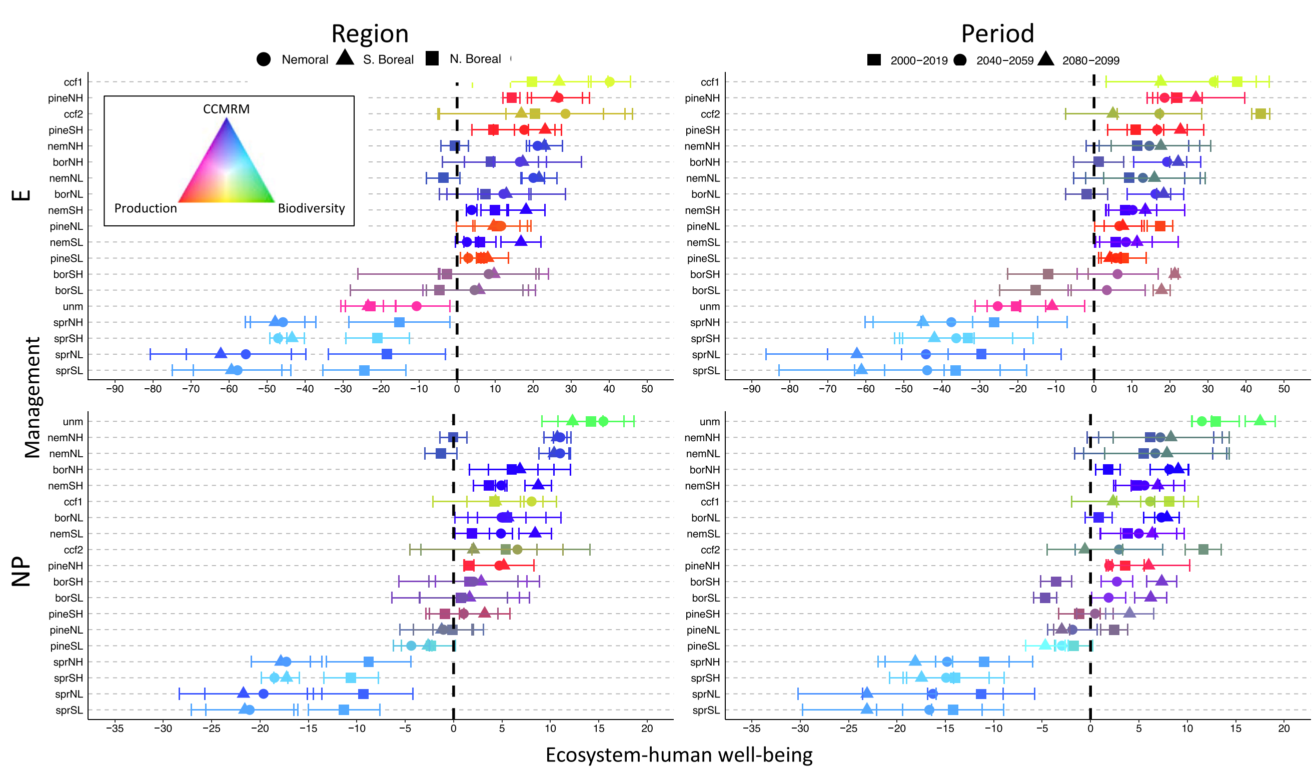

Fig. 11. Managed forest contribution to ecosystem-human well-being (EHWB) for regions (left) and periods (right) based on equal (upper) and nature protection (lower) weighting schemes. Same outline as Fig. 10.

Boreal, high variability was found for boreal-broadleaf mix management with short rotation periods (-4.7 ± 23.4 and −2.7 ± 23.4, for low and high PCT, respectively), indicating sub-optimal ES provisioning over time. Normal rotation high PCT pine appeared most stable for N. Boreal with a lower mean EHWB than CCFs but with less variation over time (14.3 ± 2.2). CCF1 contributed positively towards Biodiversity and Production policy targets over time (19.6 ± 15.6), but CCF2 risked a negative impact (20.5 ± 25.5). For S. Boreal, suitable strategies include CCF1 (26.8 ± 12.8), CCF2 (16.9 ± 21.6), high PCT tolerance pine (26.3 ± 6.7 for normal and 23.2 ± 4.3 for short rotations), and nemoral mixtures with normal rotation periods (21.6 ± 4.8 for low and 23.0 ± 4.7 for high PCT tolerance). Multiuse forestry aims were satisfied best in the Nemoral region by continuous cover practices (CCF1 = 40 ± 5. 5 and CCF2 = 28.5 ± 15.6) in addition to pine stands with high PCT tolerance (for normal 26.7 ± 8.1 and short 17.7 ± 8.1 rotation times) as together those strategies balance Production, Biodiversity, and CCMRM targets. Nemoral and boreal mixed stands with normal rotation periods also performed well for incorporation with the other strategies, offering the greatest amount of terrestrial carbon sequestration and risk reduction.

All strategies except spruce EAF and CCF showed a small rise in EHWB over time (Fig. 11 upper right). However, an overall decrease was observed when comparing all approaches and their regional variation: maximum EWHB diminished from 43.8 ± 21.0 in P1 to 31.5 ± 25.9 in P2, and 26.8 ± 23.9 in P3. CCF strategies were highest for all regions until P3, by which point pine or boreal bread-leaf mix and nemoral broad-leaf mix with high PCT tolerance presented higher EWHB for N. and S. Boreal regions. Only the Nemoral region persisted with a high score for CCF1 into P3. Over P1, CCF2 performed best (43.8 ± 2.3) along with CCF1 (37.6 ± 5.1) and EAF pine with normal rotation and high PCT tolerance (21.9 ± 6.5), pointing to these strategies being ideal following RCP2.6 for Production and Biodiversity. The same three strategies performed well across all regions for P2 and the same boreal and nemoral mixtures ideal for S. Boreal and Nemoral regions, widening the different practices providing CCMRM ES under RCP4.5. Pine with high PCT tolerance performed best in P3 (comparable to conditions for RCP8.5) alongside boreal mix for both rotation lengths and high PCT, nemoral mix with normal rotation and high PCT, and CCF1. Unmanaged, spruce, and nemoral broad-leaf mixtures with normal rotation lengths scored negatively (i.e., below average) across regions and periods.

The different ES priorities represented by NP weighting shifted the combination of multifunctional forestry approaches recommended by the CI compared to E weighting (Fig. 11 lower left). There was complete agreement between the highest overall EHWB scores when considering spatial and temporal variability as seen with E weighting. Unmanaged, mixed nemoral-broadleaf stands with normal rotation periods, and boreal- and nemoral-broadleaf mixtures with high PCT tolerance were the most suitable strategies for satisfying Biodiversity and CCMRM NP forestry goals. CCF2 exhibited a high temporal variability within N. and S. Boreal regions (5.4 ± 8.8 and 2.0 ± 6.0, respectively), indicating sensitivity to changing climate conditions. Despite lower mean EHWB scores, the same sensitivity is observed for boreal-broadleaf mix with short rotation times (0.7 ± 7.1 for low and 1.6 ± 7.3 for high PCT tolerance), suggesting their efficacy in higher latitudes could be optimized depending on the climate conditions. Unmanaged had the highest ES utility for all regions, but S. Boreal and Nemoral regions substantially benefitted from nemoral mixtures with normal rotation period length. In addition to the already mentioned strategies, short rotation nemoral mix (8.4 ± 1.7 for low and 8.7 ± 1.4 for high PCT tolerance) performed well in S. Boreal. Like CCF2 in E weighting managements, CCF1 scored moderately in lower Nemoral (8.1 ± 1.2) and S. Boreal (4.3 ± 2.0) latitudes but risked a negative goal target impact depending on temporal and climate variability in the N. Boreal (4.2 ± 6.4).

After unmanaged, EHWB in all regions under changing climate conditions benefited the most from normal rotation length nemoral mix strategies (Fig. 11 lower right). Both high (6.2 ± 6.6 for P1, 7.2 ± 6.4 for P2, and 8.3 ± 6.0 for P3) and low (5.5 ± 7.1 for P1, 6.7 ± 7.4 for P2, and 7.9 ± 6.4 for P3) PCT tolerances were effective. Nemoral mix with short rotation and high PCT was moderately beneficial to CCMRM EHWB for all periods, increasing from P1 to P3, and would perform better across all latitudes with warmer conditions. Similarly, P1 displayed a low mean score for boreal mix with normal rotation and high PCT (1.8 ± 1.3) but improved greatly under P2 and P3 (8.1 ± 2.0 for P2 and 9.1 ± 1.1 for P3). Boreal-broadleaf managements scored poorly for all regions in the near future but were universally enhanced under warmer scenarios. All periods scored moderately high with CCF1, but CCF2 only performed well in P1 (11.6 ± 1.9) and not the more severe scenarios (2.9 ± 4.5 and −0.6 ± 3.9 for P2 and P3, respectively). This elucidates a sensitivity to climate conditions from CCF when subjected to the cutting scheme of CCF1. CCF1 was highest in P1 and P2, especially for the Nemoral region, but had low EHWB for P3, suggesting the approach is only suitable under RCP2.6 or RCP4.5. Besides CCF, all EAF and unmanaged strategies increased in average EHWB over time, indicating better multifunctional performance in a warmer climate (not including EAF spruce). CCF showed the opposite trend with a decrease in average EHWB with warmer conditions. As with E weighting, EAF spruce managements contributed negatively to ES and goal targets across all regions and periods, as did pine and short rotation boreal strategies.

4. Discussion

Forest ecosystems provide a diverse range of services (Reyers et al., 2013; Wood et al., 2018). Every form of management alters the ecosystem's capacity to generate ES and presents different trade-offs and synergies (Nelson et al., 2007; Costanza et al., 2017; Rehman et al., 2021). This study synthesized ecosystem model output for ten ES indicators into one representative composite, detailing how different management practices contribute to EHWB at the landscape level. Policy to equally prioritize production and conservation could be better supported by further implementing continuous cover and broadleaf-mixture strategies. The CIs indicated the benefit of high tolerance PCT in EAF strategies over intensive clearing, permitting more naturally regenerated deciduous tree species to grow within coniferous plantations. Normal rotation lengths showed higher multifunctional value compared to shorter rotations. Under changing climate conditions, recommendations remain the same for all ecoregions.

4.1. Composite development

CIs are not an end-all-be-all representation of scientific results but a tool that can aid incentive programs, monitoring, and policy enforcement, as CIs excel at communicating complex information to decision-makers (c.f. OECD, 2008; Alam et al., 2016; Attardi et al., 2018; Eyvindson et al., 2018). This study contributed to new methodological insights as few CIs consider all three sustainability dimensions (Singh et al., 2009), and developing a CI based on ecosystem model output instead of observed values is less common (El Gibari et al., 2019; Greco et al., 2019). Multiple sources of uncertainty exist throughout a CI development process (Böhringer and Jochem, 2007; OECD, 2008). Comparison against real-world observations to validate and optimize CI structures, specifically sub-components and aggregation, would improve confidence in the EHWB values. The modeled nature of input data prevented such analytical techniques, representing a weakness in this composite. However, LPJ-GUESS's structure and parameters have been extensively evaluated and are considered sufficient in a forestry context (Lagergren and Jönsson, 2017). Under these circumstances, using systematic evaluation to select the final CI structure would be satisfactory and supported by previous studies (Burgass et al., 2017; El Gibari et al., 2019; Greco et al., 2019). This included the comparison of averaged scores for each contrasting stage of development, and t-tests to determine whether a decision between two structures was based solely on expert judgment or due to mathematical significance. An analysis of the CI design is recommended for environmental-based CIs (Böhringer and Jochem, 2007; Klapwijk et al., 2018). The normalized z-scores preserved outliers and were significantly different from MM, while the sub-components and weighting schemes were not statistically different because their structures were very similar in EHWB values. Hybrid groupings better accounted for the underlying correlation between indicators, owing to the large variety of multivariate techniques employed, and that HCA was applied for each normalized grouping. Both weighting schemes were retained to add more depth to management recommendations.

The procedure outlined by Alam et al., (2016) and OECD (2008) was applied in this study to balance complexity with comprehension, a necessity when aiming to inform management practices (Greco et al., 2019). CIs can be useful, but it is crucial to consider the subjectivity under which they are developed (Lehtonen et al., 2016). The formation of theoretical sub-components influenced the subsequent developmental stages. EOs and SDGs were categorized by which of the three sustainability dimensions each goal resonated with, but all goals are interlinked, and debate exists about how they can be structurally arranged (Griggs et al., 2014). ES types were similarly separated between theoretical sub-components to capture the feedbacks related to policy goals, each corresponding to the related dimension of sustainability (Table A1). In the real world, these indicators are linked to each other in ways not easily separated (Labuschagne et al., 2005). Sorting these complex concepts is nearly impossible because of the endless ways humans can interact with ES (Wood et al., 2018). However, the final CI represents biosphere wellness, which adjacently builds the foundation for net HWB across dimensions and goals.

The shift of three ES indicators between theoretical and hybrid sub-components demonstrates the highly interconnected nature of ES. Modeled carbon storage was based on ecosystem carbon balance, not retention time, which is more relevant to climate change mitigation and makes sense placed under Biodiversity (Harrison et al., 2014). The fraction of broad-leafed trees going from Biodiversity to CCMRM is also supported by literature, since Norway spruce trees are highly vulnerable to storm damage, and replacing them with less sensitive broad-leafed species has a substantial statistical impact on risk reduction (Canham et al., 2001; Lagergren et al., 2012). Biomass sequestration was highly correlated to harvested biomass in Production as, over time, it will transform into harvested biomass (or soil carbon if left unmanaged). This transformation occurs over hundreds of years, so the extracted moments in time are considered still-standing or recently-harvested forest (Sitch et al., 2003; Lagergren and Jönsson, 2017). Complete agreement across the four multivariate approaches did not exist, indicating how other shifts could be justified. However, the application of several multivariate techniques made the hybrid groupings robust (El Gibari et al., 2019), and conducting these techniques on extended data with four RCM runs from different climate model ensembles reduced uncertainties (Burgass et al., 2017).

Cultural ESs are challenging to quantify, especially with models, as societal SDGs are only implicitly captured by combining all service types, not capturing specific trade-offs (Wood et al., 2018). The risk management portion of CCMRM was only captured in the context of storm sensitivity. This does not directly consider forest fires or pest damage. However, a strong correlation exists between storm damage and the amount of windthrown trees that both serve as brood material for bark beetles and heighten the likelihood of forest fires due to the presence of dry, flammable wood (Jactel et al., 2009; Kärvemo et al., 2014). Such risks further relate to the indicators of carbon storage and old trees. Additional statistical analysis would be required to assess if bark beetle and forest fire indicators would contribute significant new information.

4.2. Multifunctional forestry management

While Sweden has been practicing clear-cut rotation monoculture forestry since the early 19th century (Lundmark et al., 2014), the 1993 Swedish Forestry Act was an essential shift to including conservation goals equally with production efforts. As private forest owners freely implement these parallel priorities at their discretion, the economic tradition of prioritizing high-yield management persists across all institutional levels in Sweden (Angelstam et al., 2020). Shifting attitudes about forests' roles in supplying more than economic value is essential to meeting Sweden's sustainability goals (Lindahl et al., 2017). The environment is the common factor in meeting SDGs; some goals explicitly concern ecosystem function while others are indirectly linked (Folke et al., 2016; Wood et al., 2018). All goals benefit from the restoration, protection, and sustainable use of the biosphere (Perkins et al., 2015; Rehman et al., 2021).

Exploring the prioritization of nature protection on services saw a shift to unmanaged forestry well beyond any other strategy, and forest areas should be set aside as unmanaged as their impact on biodiversity is unquestionably valuable (Felton et al., 2016; Angelstam et al., 2020). However, while unmanaged forests show the highest potential for biodiversity and climate mitigation, they score poorly under E weighting as they do not contribute to production benefits. For managed forest, the CIs based on both weighting schemes agrees that combinations of continuous cover and broadleaf-mixture managements are optimal to balancing production, biodiversity conservation, and climate change mitigation priorities. Such recommendations are, to some extent, already in place in the forest certification standards (PEFC, 2017; FSC, 2020). To promote sustainability, both FSC and PEFC stipulate that broadleaf trees should dominate at least 5% of areal cover, and 10% of the stems in a coniferous stand should be broad-leaved. FSC also states that part of the forest should be managed with adapted methods such as CCF to promote natural and social values. Stronger actions, including restricted clear-cutting, have recently been suggested in relation to the new EU forest strategy for 2030 (EU, 2021).

Biodiversity goals and climate change mitigation overlap with risk management strategies, as species more resistant to storm damage grow longer and sequester more carbon (Canham et al., 2001; Kärvemo et al., 2014). Higher scores for broadleaf mixtures compared to CCF for P3 capture this. By the century's end, RCP8.5 conditions for mid and lower-latitude ecoregions would be more tolerant to CCF as biodiversity indicators are complemented by increased storm resistance by broadleaves (Keskitalo et al., 2016; Lagergren and Jönsson, 2017). Triviño et al., (2015) modeled alternative management strategies across the boreal forests of Finland and found that "business-as-usual" approaches prioritizing production output are incapable of improving carbon sequestration and biodiversity. Despite a temporary reduction in yields while new CCF regimes are implemented as trees are only removed during the final cut, they would be a cost-effective long-term approach to mitigating climate change and securing ecosystem function (Felton et al., 2016; Angelstam et al., 2020).

The relationship depicted by the CIs is highly dependent on scale, meaning that the recommendations carried out for entire regions and 20-year periods do not directly equate to what would be best for each owner for smaller parts of land (Rioux et al., 2019). Furthermore, while the main CI accounts for the variation across time periods following RCP8.5, the period-specific CIs reflect a narrower range of climate conditions. No single management strategy exists that can simultaneously promote production, biodiversity, and climate mitigation goals. However, a diversified combination of regimes at the landscape level would satisfy their trade-offs (Triviño et al., 2015; Keskitalo et al., 2016; Angelstam et al., 2020), and real-world implementation of alternatives would be done gradually between mixtures and environmental conditions (Felton et al., 2016). The large variation in averaged EHWB scores with E weighting supports the use of multiple strategies best optimized for specific regions, with different strategy combinations at the landscape level fulfilling different overarching goals (Lagergren and Jönsson, 2017). A combination of CCF, normal rotation nemoral mixtures, and high PCT tolerance pine strategies were suited for Nemoral and S. Boreal ecoregions, while N. Boreal leaned more towards CCF.

EHWB decreased in CCF over time under RCP8.5, as CCF strategies represent one of the lowest scoring strategies for storm resistance, and the root anchorage capacity during winter storms will decrease in a warmer climate as an effect of fewer days with frozen soil (Lagergren et al., 2012).

More study is needed to optimize parameterization within LPJ-GUESS and specify which species and strategies are suited for specific forestry plots at finer spatial extents (Lagergren and Jönsson, 2017). While the spruce-dominated CCFs had high CI values in boreal regions, EAF spruce for all PCT tolerances and rotation lengths had low CI values throughout all regions, periods, and averages. Normalized indicators before aggregation show low values for deadwood, old deciduous forest, and biomass sequestration. Spruce species grow in higher densities, produce less naturally-thinned litter, and have higher harvest frequencies, so less old forest is generated (Lagergren and Jönsson, 2017). However, spruce and pine should yield similar growth and biomass values (Jönsson et al., 2015), and the low biomass sequestration for spruce suggests the need to improve parameters relating to spruce management. This study averaged cohort SQC together, but tree species respond differently to soil conditions, influencing growth rates, root structure, and the strength of generated ESs (Jandl et al., 2007; Jungqvist et al., 2014). As soil characteristics are not uniform across Sweden, weighted averaging accounts for this variability, but findings are still not representative of local conditions and are only applicable at regional landscape scales. Preserving SQC variation over ecoregions and different climate conditions minimizes this shortcoming. Recommendations should not be applied for specific nutrient-poor or rich areas but used to inform based on general regional soil conditions.

4.3. Outlook

Warmer temperatures in Sweden will lead to longer growing seasons, accelerating nutrient turnover, and increasing CO_2 concentrations, leading to a higher forest production capacity (Reyer et al., 2014). While this could be considered a positive regarding harvestable wood products and expanding the amount of carbon stored in standing biomass, exacerbated EWE frequency and severity puts pressure on ecosystems and heightens risks from drought, fire, storm damage, and pest outbreaks (Jactel and Brockerhoff, 2007; Sturrock et al., 2011; Jönsson and Lagergren, 2018). ES benefits vary and are hard to quantifiably represent with their sometimes-indirect effects or complex nature (Harrison et al., 2014). The theoretical framework employed here combined various indicators to ensure cultural ES benefits are indirectly addressed, but more study into the social nature of forest management is recommended, especially at local spatial extents (Balvanera et al., 2014; Harrison et al., 2014).

Sweden's EO system tracks national climate and biodiversity policy targets while aligning with agreements from international bodies, including the SDGs. Drawing on reports from the IPCC, IPBES, and other UN environmental policies, priority is given to recovering ecosystems, protecting biodiversity, mitigating climate change, and changing human-use and consumption habits of the natural world to be more sustainable (Tollefson, 2018; Díaz et al., 2019). The overarching aim behind the EOs outlines how significant, meaningful changes must be made at every level of society and done within one generation for progress to be fulfilled (Larsson and Hanberger, 2016). Our results incorporated this intent and considered multiple policy levels, highlighting how combining management strategies in a multifunctional approach will best resolve the synergies and trade-offs. One strategy will not be sufficient for large areas; instead, adaptation based on local conditions must occur. Variation in approaches to explore at smaller scales include further understanding the climate risks, species selection, rotation lengths, and thinning regimes. It is essential to evolve a more holistic forested land-use approach to ensure sustainability across environmental, economic, and social dimensions (Díaz et al., 2015; Tollefson, 2018). Applying this perspective at the core of future CI development will ensure that research and recommendations contribute to these aims.

5. Conclusion

We developed CIs based on modeled ES indicators to aid communication about the impact of different forest management strategies in relation to sustainable development goals. The theoretical ES categorizations were evaluated to account for the statistical similarity between indicators. Resulting hybrid sub-components with z-score normalization and two weighting schemes for different policy prioritizations were combined into CIs. The weights with equal emphasis generated a larger range of scores (76.0 $\pm$ 21.2) than weights with a stronger focus on nature protection (32.0 $\pm$ 5.8), as the latter inherently included less trade-offs between production and other aspects. The final scores of the 19 management strategies fell within a variance boundary of each other, showing their contribution to different policy targets and the usefulness of combining strategies at the landscape level. The composites displayed agreement across regions and scenarios, indicating that a shift from even-aged conifer monocultures towards a combination of continuous cover, broadleaf-mixture, and unmanaged would work well for balancing goals under changing climate conditions. Areas of improvement include continued development of the ecosystem model to represent managed forests better, incorporating more ES indicators, and further development of the CI framework to represent combined strategies at the landscape level.

Author contributions

This study was carried out as part of a master thesis project by Nicolas Tarasewicz in Physical Geography and Ecosystem Science at the Department of Physical Geography and Ecosystem Science, Lund University. The project, supervised by AM Jönsson, contributed to the Forest Vision project, FORMAS grant number 2019-01968.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2021.108456.

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