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Quantitative methods for integrating climate adaptation strategies into spatial decision support models

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With the onset of rapid climate change and the legacy of past forest management and fire suppression policies, the capacity for forested landscapes to maintain core functionality and processes is being challenged. As such, managers are tasked with increasing the pace and scale of management to mitigate negative impacts of future large disturbances and improve resilience and climate adaptation of large landscapes. Such efforts require consensus building, with partners and stakeholders to determine where to allocate scarce resources. We present a methodology to identify strategic (where to go) and tactical (what to do) priorities across large landscapes to assist in project level planning. The model integrates a spatial assessment of current ecosystem resource conditions and spatial outputs from a landscape succession and disturbance simulation model (LANDIS-II) to assess the potential to achieve desired conditions under climate change with ongoing disturbances. Based on the expected trajectory of landscape conditions over time, the model applies fuzzy logic modeling to provide quantitative support for four management strategies (Monitor, Protect, Adapt, and Transform) across the landscape. We provide an example application of these methods targeting sustainable carbon loads across a 970,000 ha landscape in the central Sierras in California. By including future landscape conditions in the model, decisions made at the stand-level are inherently tied to and influenced by larger landscape-level processes that are likely to have the greatest impact on future landscape dynamics. The methods outlined here are able to incorporate multiple metrics to capture the many resources targeted by management. Model outputs could also be used as inputs into spatial optimization models to assess tradeoffs and synergies among treatment options and to aid in long-term planning.

KEYWORDS

climate change, decision support, landscape simulation model, socio-ecological resilience, restoration, ecosystem services, promote

1 Introduction

1.1 Landscape management planning under climate change

The magnitude and severity of disturbance in recent decades has led to concerted efforts among land managers and policymakers to increase the pace and scale of restorative and adaptive management across much of western North America (wNA) (Kelly et al., 2019; Hessburg et al., 2021; North et al., 2021; Prichard et al., 2021). Despite these efforts,

management substantially lags the levels needed to alter ecological trajectories and maintain ecosystem services in the long term (North et al., 2012, 2021). Identifying treatment priorities through a strategic planning process is generally not standard practice in affected regions but locally done to serve specific management needs. To address the extent of current and future impacts from natural disturbances, managers and policymakers are shifting to coordinated planning efforts that can collectively build resilient conditions across landscapes and jointly address multiple barriers to implementation (North et al., 2012; McIver and Becker, 2021; Manley et al., This issue). Scaling treatment needs to regional landscapes requires transparent, flexible, and repeatable methods that can identify potential treatment areas where uncertainty in attaining and maintaining resilient conditions is low and anticipated benefits from treatments are high.

While many models can be used to programmatically optimize treatment options over space and time (e.g., ForSys, EMDS), most do not directly incorporate future landscape dynamics under climate change (cf. Abelson et al., 2021 for an aspatial example). As a result, management is often directed towards (1) areas that are most departed from desired conditions under the assumption that management can make the most impact where conditions are currently poorest (Reynolds and Hessburg, 2005) and (2) areas proximal to infrastructure and other highly valued resources given their potential vulnerability to disturbance (Ager et al., 2021) under the assumption that proximal management can sufficiently reduce risk. Under this latter framework, management emphasizes resistant or defensive strategies targeting social and economic vulnerabilities without regard to ecological processes and interdependencies operating across landscapes. Certainly, treatments can lessen the negative effects of wildfire *in situ* (Lyons-Tinsley and Peterson, 2012; Povak et al., 2020; Prichard et al., 2020) and provide other ecological benefits (Stephens et al., 2021), especially when applied near the wildland urban interface (WUI, Johnson and Kennedy, 2019). However, as climate change continues to challenge the capacity for systems to retain characteristic patterns, processes, and functions, defensive strategies may wane in their effectiveness unless coupled with adaptation and resilience strategies implemented over large scales (Millar et al., 2007; Schuurman et al., 2022). The ability for treatments to sustain desired conditions over time will depend on neighborhood effects of surrounding environmental conditions, future climatic variability, and natural disturbance processes. Focusing solely on the most departed areas without consideration of future stressors may result in significant and sustained investments to maintain conditions over time, whereas future-informed management may be directed elsewhere on the landscape where conditions are more aligned with future projected climatic conditions and disturbances.

Incorporating climate change influences on species, disturbances, and environmental conditions is now essential at all levels of decision-making (MacDicken et al., 2015). For example, as biophysical conditions shift under climate change, many forest species may soon inhabit environments that are declining in suitability for establishment, growth, development, and reproduction (Decker et al., 2021; Hill and Field, 2021). In California, Thorne et al. (2017) estimated that climate stress will impact as much as 45–56% of the State's vegetated area by the end of the 21st-century.

However, planning efforts rarely include information about potential climate change impacts largely due to a lack of available methods (Prober et al., 2019). Several climate-informed management frameworks have been forwarded in recent years to anticipate ecological

impacts from climate change. Most emphasize a need to rethink past management paradigms that have focused on stability and resistance in favor of acceptance of change and uncertainty (Millar et al., 2007; Prober et al., 2019; Runyon et al., 2020; Peterson St-Laurent et al., 2021; Schuurman et al., 2022). For example, the RAD (Resist-Accept-Direct) framework provides managers with a decision space to allow change to unfold without interference (Accept), facilitate change to new desired system states (Direct), or resist (Resist) change to undesirable states through management intervention. Underlying this decision space is the notion that climate change will drive ecological transformations in which irreversible shifts in multiple ecosystem components will alter ecosystem functioning in the long term (Williams, 2022). However, the velocity and direction of change will vary across a region (Dobrowski et al., 2013; Morelli et al., 2016), and as such, the immediacy of management need will also vary spatially. Knowledge of where areas of relative stability are anticipated can help allocate management elsewhere on the landscape, and in turn, knowledge of where conditions will likely move towards more desirable conditions may indicate areas with high likelihood of near-term management success in facilitating the development of those conditions.

We developed a methodology to operationalize climate-informed management prioritizations (e.g., McWethy et al., 2019; Schuurman et al., 2022) using fuzzy logic to jointly evaluate current resource conditions and future resource stability under climate change. The model provides a series of spatial maps depicting the level of support for each of four management strategies: Monitor, Adapt, Protect, and Transform. The PROMOTE (Provisioning Resilience Outcomes for Management Optimization Tool) model integrates an assessment of current conditions to evaluate the current state of the system with an assessment of future landscape conditions under climate change to evaluate the potential for system components to achieve and maintain desired conditions over time. Model outputs express strategic (i.e., where to manage to invoke the largest impact) and tactical (i.e., what is the intended goal of treatments) priorities across a landscape within a single decision support model. Model outputs can be subsequently subjected to ranking, prioritization, or optimization to identify treatment locations, quantify tradeoffs among management options, spatially cluster proposed treatments, and develop landscape management plans (e.g., see Ager et al., 2017; Pascual et al., 2022).

Here, we introduce the PROMOTE model components and calculations, and apply it to a 1-million ha landscape located in the central Sierras, USA. PROMOTE can evaluate any number and type of data sources, and through the fuzzy logic analyses, these data can easily be combined at higher conceptual levels to evaluate multiple propositions regarding ecosystem conditions (e.g., forests are in a resilient condition; Manley et al., This issue). The model translates fundamental concepts of resilience and adaptive management into quantitative representations of the anticipated effectiveness of each management strategy in achieving targeted outcomes. Many definitions of resilience exist (Schmidt, 2021), and our modeling accommodates a broad interpretation of resilience concepts, which can be user-defined. Specifically, our model addresses the evaluation of resource conditions towards the goal of improving the long-term supply of ecosystems services under climate change. The model therefore assumes that improving the long-term condition of one or more resources (or processes) imparts a higher degree of resilience onto the landscape. Here, we provide an example application to a single ecosystem process: carbon sequestration.

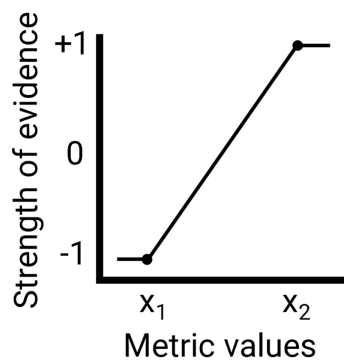


FIGURE 1

Example fuzzy logic ramp function for a given Metric. Value x_1 and x_2 represent target or desired conditions which are used to evaluate the metric and produce a strength of evidence score to determine the level of support for the proposition (e.g., that forest carbon levels for a given landscape unit exceed the 90th percentile for the landscape).

2 Methods and materials

Decision support systems (DSS) have a long history in forest management planning across the world (Reynolds et al., 2014; Marto et al., 2019). Relevant to our context, DSSs are knowledge-based systems that are commonly used to evaluate ecosystem conditions and facilitate prioritizing spatial management treatments (Reynolds and Hessburg, 2005; Reynolds and Hessburg, 2014; Povak et al., 2022). PROMOTE uses fuzzy logic to evaluate current ecosystem resource conditions across a landscape as well as the future potential and stability of these resources under climate change and natural disturbances. Fuzzy logic membership functions (*sensu*, Miller and Saunders, 2002) are mathematical transformations used to evaluate logical propositions (e.g., forest density is resilient to climate change). These functions translate raw data values (i.e., large trees per hectare) to values ranging from -1 (no support for the proposition) to $+1$ (full support, Figure 1). Numerical outputs from fuzzy ramp functions represent a strength of evidence (SOE) in support of the proposition. In Figure 1, this membership function shows that increases in metric values (e.g., large tree density increases) leads to concomitant increases in the strength of support for the proposition (e.g., large trees are abundant). Choices related to the directionality and “shape” of the membership function (e.g., positive or negative linear, two-tailed, asymptotic, exponential, etc.), and the selection of cutoff values (i.e., x_1 and x_2 in Figure 1) can be informed by the literature, expert opinion, or through inspection of the statistical distribution of the metric (e.g., 10th and 90th percentiles of the data distribution).

In the following section, we outline how we incorporated logic modeling conventions to integrate future landscape dynamics under climate change into the PROMOTE model.

2.1 PROMOTE management strategy scores

We first established a two-dimensional decision space represented as a Cartesian coordinate graph with both x - and y -axes ranging from -1 to $+1$. The x -axis represents the current state of the system, and the

y -axis represents the potential to achieve and maintain a given desired state. The trajectory of conditions for a given location and their uncertainty are then interpreted from the coordinates of a given location on the graph.

Conceptually, the plotting region can be partitioned into four quadrants (Figure 2) each representing a management strategy (Table 1). Within the plotting region, the proximity of a point on the graph to a plot corner determines the level of support (i.e., strength-of-evidence, SOE) for a given strategy (Figure 2). Accordingly, a set of four management strategy scores (i.e., Monitor, Protect, Adapt, and Transform) is calculated for a given landscape unit as the Euclidean distance from their coordinates to each of the four corners of the two-dimensional graph (Table 1).

Concretely, the possible distance from any point on the Cartesian graph to any corner of the graph (D_x) ranges from 0 (full support) to 2.8284 (no support; Figure 2). The subscript “ x ” applies to the Monitor, Protect, Adapt, or Transform (M, P, A, or T) strategy under consideration. Distances are then rescaled to -1 to $+1$ using a linear transformation [Eq. (1)]. On this scale, sites whose coordinates correspond to a given corner (i.e., $D_x = 0$) would receive a SOE score $S_x = +1$, which signifies full support for a given restoration strategy, while a site located on the opposite corner (i.e., $D_x = 2.8284$) would receive a $S_x = -1$ for no support. Thus, each location on the landscape can be evaluated based on the SOE for each of the four management strategies outlined in Table 1.

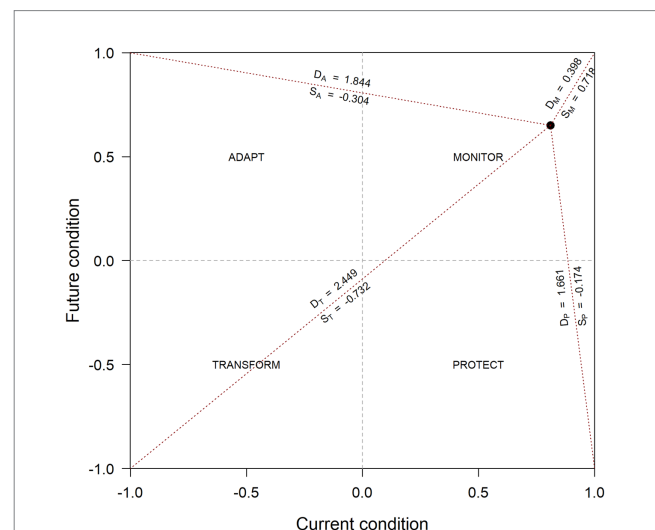


FIGURE 2

Cartesian graph representing the PROMOTE model scoring convention. The plotting region is segmented into four quadrant regions representing suggested management strategies based on the current and future conditions assessed for one or more sites within a landscape. The corners of the graph represent full support for each management strategy, and the distance from a given location in the plotting region to each corner is indicative of the level of support for a given management strategy. In this example, a site (black dot) scored 0.81 for current condition and 0.65 for future condition for a given Metric. The Euclidean distance (D_x) to each corner is determined and a linear transformation [Eq. (1)] is used to calculate a management score (S_x) for each restoration strategy where -1 represents no support for a given strategy and $+1$ indicates full support.

$$S_x = -1 * \left(-1 + \frac{2 * D_x}{2.8284} \right) \quad (1)$$

For example, if a given site within a landscape had a current condition score of 0.81 (x -axis) and future condition score of 0.65 (y -axis) it would have $D_M = 0.3982$, $D_P = 1.6609$, $D_A = 1.8435$, $D_T = 2.4492$. Accordingly, applying Eq. (1) to these values would yield $S_M = 0.718$, $S_P = -0.174$, $S_A = -0.304$, and $S_T = -0.732$ (Figure 2).

The Cartesian graph represents the level of support for each of the four management strategies (Figure 3). Scores can also be combined to emphasize different management objectives. For instance, managers may want to identify options for the protection of current resource conditions that are at risk of decline (e.g., Protect areas), as well as directing management to areas currently in poor condition but that exhibit the highest certainty of success (e.g., Adapt areas). A combined score representing where management opportunities are greatest for one or both strategies – hereafter referred to as the Management Opportunity (MO) score – would emphasize locations with strong support for either Protect (proximity to lower-right corner) or Adapt (proximity to upper-left corner) (Figure 3). As a technical detail, when emphasizing these two corners of the graph in an evaluation, the maximum distance from either the Adapt or Protect corners becomes 2 (the length of an axis) instead of 2.8284 (the distance between two opposing corners), and as a result, the range of possible management opportunity scores is restricted to -0.4142 to $+1$ (Figure 4A). These scores are rescaled to span the full -1 to $+1$ scale using Eq. (2) (Figure 4B),

$$MO_{\text{rescale}} = (1.4142 * MO) - 0.4142 \quad (2)$$

where MO is the original management opportunity score.

2.2 Example application of the PROMOTE model to identify stable carbon

The 907,000 ha Tahoe-Central Sierra Initiative (TCSI) landscape (Figure 5) is a diverse, multi-ownership landscape in the central Sierra Nevada in California and Nevada that is the current focus of a collaborative effort among state, federal, nonprofit, and private partners. The goal of TCSI is to increase the pace and scale of management to improve forest health and resilience across the region. The landscape serves as an excellent case example for the PROMOTE model, given that it is a regional-scale planning landscape that encompasses a diverse array of socio-ecological environments – ranging from urban areas and major interstate highways to vast areas of National Forest, multiple wilderness areas, and Lake Tahoe, a major destination for outdoor recreation. In addition, it is inclusive of an entire west to east swath across the central Sierra Nevada, spanning a steep elevational gradient from the foothills to the crest (~ 900 m to over 3,300 m), along which responses to climate change are expected to be pronounced.

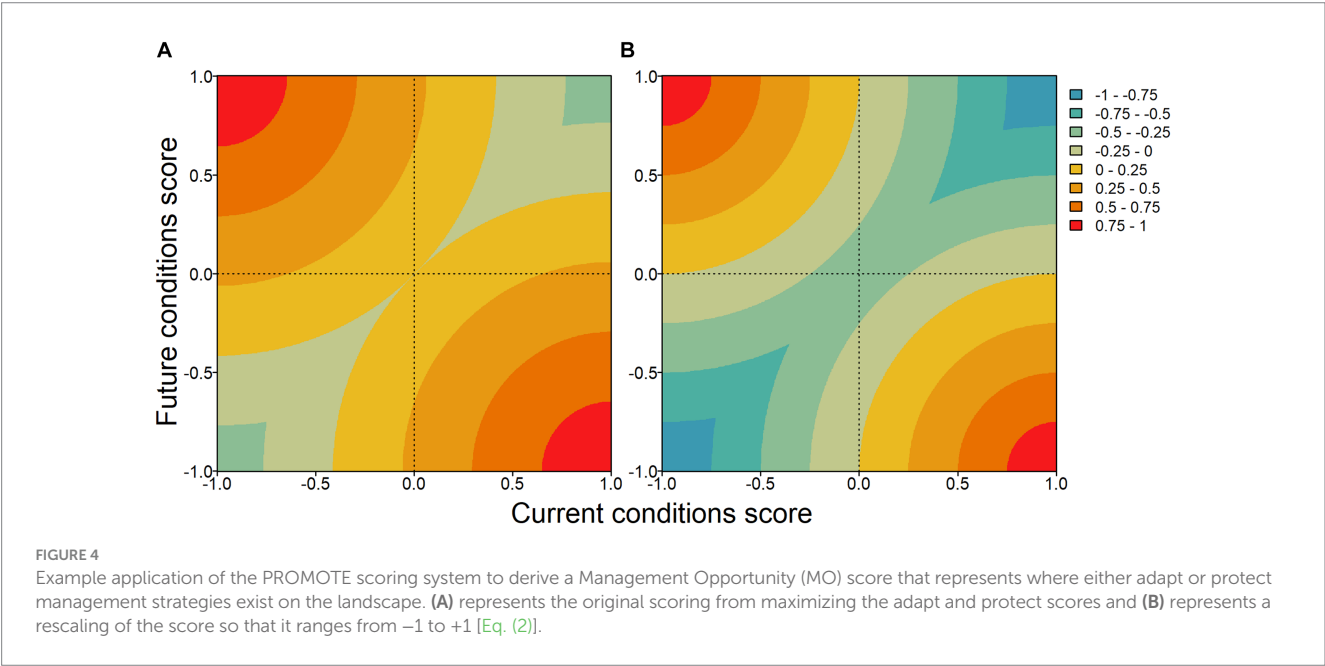
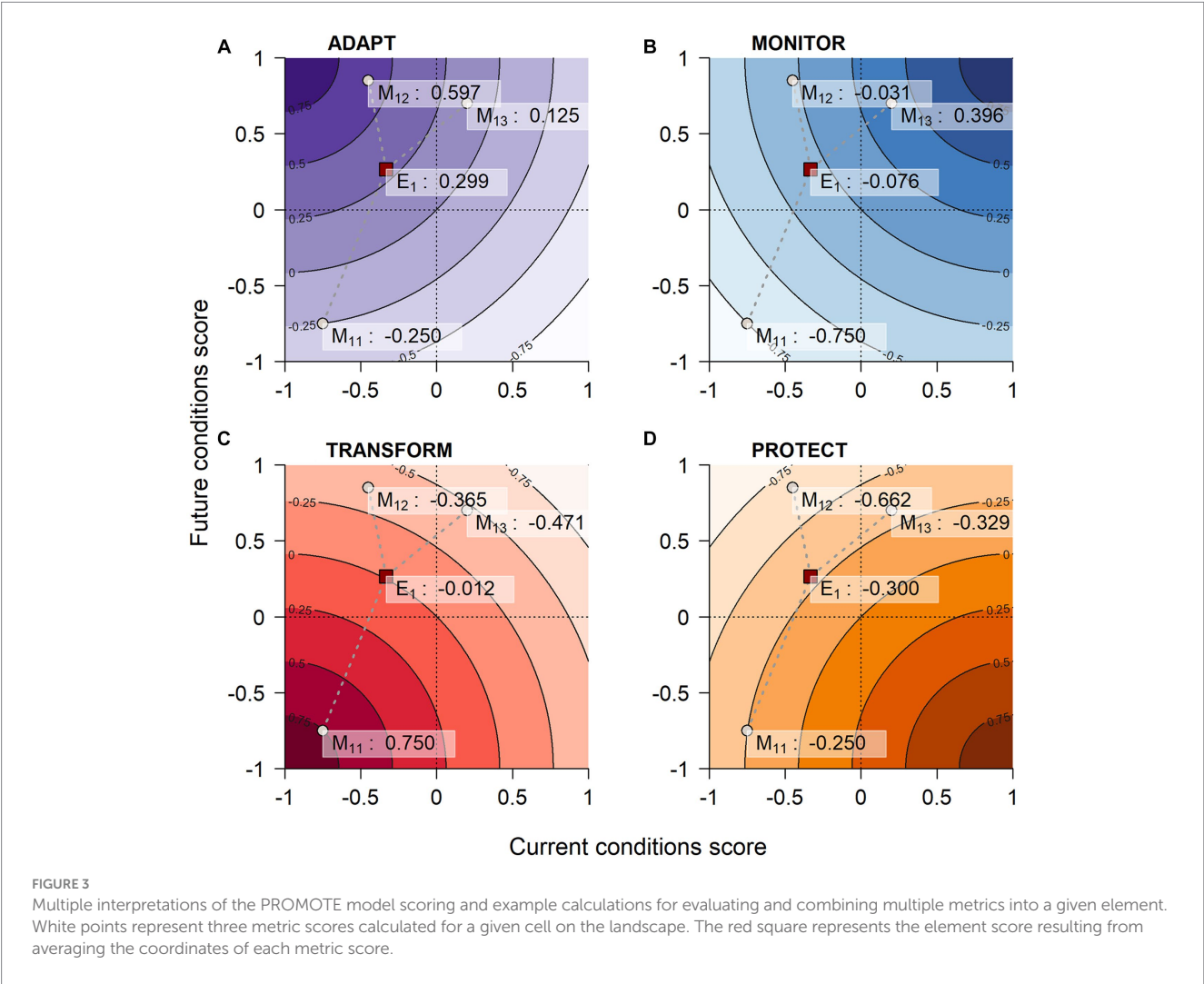
The PROMOTE model was developed in collaboration with several local area experts representing state environmental collaboratives, US Forest Service scientists and managers, and non-profit agencies. Through a series of work sessions, participants contributed expert knowledge on the ecology and restoration needs in the landscape to help inform the development of these models, which included the selection of metrics, spatial data, fuzzy ramp target values, and the interpretation of the results.

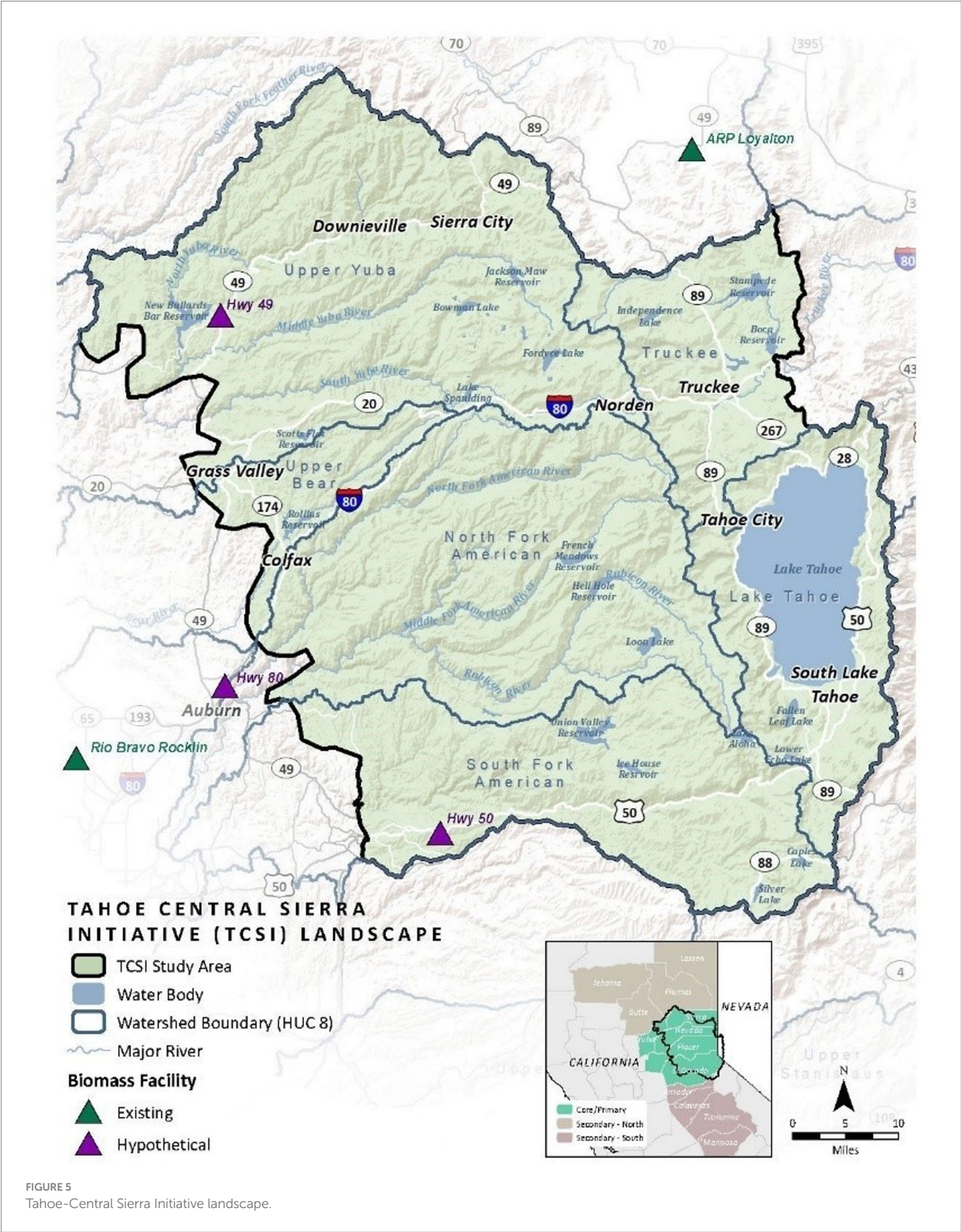
To illustrate the model's functionality, we provide an evaluation of aboveground live carbon levels across the TCSI. The proposition being evaluated is that resilient forested landscapes exhibit enhanced carbon sequestration capacity that is stable and sustainable in the long-term. The capacity to store carbon (C) over the long-term is a critical ecosystem service provided by natural

TABLE 1 Description of the quantitative assessment of current and future conditions within the PROMOTE model.

Management strategy	Cartesian graph quadrant membership	Coordinates on Cartesian graph for full support	Description
Monitor	Top right	$[X = +1, Y = +1]$	Conditions are favorable now and in the future. These areas may require minimal near-term management to maintain resilient conditions
Protect	Bottom right	$[X = +1, Y = -1]$	Conditions are currently favorable but decay in the future under climate change and natural disturbance processes. To prevent the loss of key ecosystem benefits, treatments can be scheduled in and around these areas to maintain their functionality over time
Adapt	Top left	$[X = -1, Y = +1]$	Conditions are currently unfavorable but improve over time under climate change and natural disturbances. Given these areas are currently in need of restoration treatments and have a demonstrable ability to reach desired conditions, management could be prioritized for these areas to attain and maintain resilient conditions over time
Transform	Bottom left	$[X = -1, Y = -1]$	Conditions are currently unfavorable and continue to be so in the future. These areas have high management need but have less support for prioritizing management given they have not demonstrated an ability to achieve and maintain desired conditions over time

Descriptions of management strategies correspond to the four quadrants established within the PROMOTE decision space shown in Figures 2, 3.





areas. By regulating greenhouse gases, including human-derived emissions, these areas play a crucial role in regulating global atmospheric processes (Sierra et al., 2021). There is currently growing interest in C accounting in forests to value their contributions as C sinks towards offsetting greenhouse gas to achieve emissions reduction targets (Badgley et al., 2022).

Sequestration incentives, therefore, are contingent upon forestlands sustaining a net C sink status in the long-term.

2.3 Current and future carbon modeling with LANDIS-II

As climate continues to change and natural disturbances from wildfire, insects, and drought continue to impact forest growth and mortality, the capacity for forests to maintain their status as net C sinks is greatly compromised (Anderegg et al., 2020). Integrating landscape simulation modeling into C accounting can reveal where current C hotspots are sustainable, and where future C sinks can mature over time.

Data used to characterize the carbon Metrics were derived from the LANDIS-II landscape simulation model (Scheller et al., 2007). In the current application, we apply the LANDIS-II model developed by Maxwell et al. (2022) for the TCSI landscape. The model incorporated the NECN (Net Ecosystem Carbon and Nitrogen; Scheller et al., 2011) successional dynamics, the SCRPPLE (Social-Climate Related Pyrogenic Processes and their Landscape Effects; Scheller et al., 2019), the base biological disturbance agents (BDA; Sturtevant et al., 2004), and biomass harvest (Gustafson et al., 2000) extensions. The model was run under the MIROC 8.5 climate change scenario over a 40 years period (2020–2060). The MIROC climate model was one of five recommended by California's Fourth Climate Change Assessment (Pierce et al., 2018) and, after extensive testing, was the only one to adequately represent recent exceptional droughts (2003–2004, 2012–2015) (Maxwell et al., 2022). Climate projections were downscaled using the MACA methodology (Abatzoglou and Brown, 2012) and are available through the USGS Geo Data Portal.¹

A four-decade simulation period was selected given the project focus of informing near-term forest management planning (1–2 decades). Longer simulation periods would incorporate a higher level of uncertainty and would be less well connected to current vegetation conditions and outcomes associated with vegetation transitions and climate interactions over typical planning periods. A total of five model replicates were run to capture stochastic variation among replicates.

LANDIS-II was run under a minimal harvest scenario, wherein management was restricted to private lands and within a wildland urban interface (WUI) 2 km buffer around built environments. We chose this scenario to best understand the evolution of vegetation conditions under climate- and vegetation-driven changes in wildfire disturbances without management interventions in the associated wildlands.

A 2019 vegetation base map developed by NCX (formerly SilviaTerra) was derived using statistical imputation methods to distribute geographically relevant FIA tree lists to individual 15 m cells. The NCX modeling workflow (1) processed remotely-sensed imagery from 30 m Landsat 8 and Sentinel-1, 30 m tree cover data from the National Landcover Dataset (Dewitz, 2019), and a 10 m digital elevation model from the National Elevation Dataset (U.S. Geological Survey, 2019), (2) reduced data dimensions using

principal components analysis, (3) summarized FIA plot data and grew it forward to a common year, (4) algorithmically predicted FIA plot locations, (5) trained a set of imputation models, and (6) generated predictions of forest density, basal area, tree summaries for 2.5 cm diameter classes, and species importance. These data were then resampled to 180 m for model processing.

LANDIS-II-modeled above-ground dry weight biomass was converted to carbon equivalents by multiplying biomass (g m^{-2}) by 0.47 (IPCC, 2006; Manickam et al., 2014). Dead biomass (i.e., soil, coarse woody debris, and snags) was not included as it was determined by consensus that such sources do not represent stable carbon, the focus of the evaluation.

2.4 Logic model development

Logic models were developed to evaluate current (Figure 6) and future (Figure 7) aboveground C stocks across the TCSI landscape. Evaluations occurred from individual pixels up to HUC-10 watershed scales (Hydrologic Unit Code, HUC-10 watersheds, range 16,000 to 100,000 ha, USGS 2013). Hydrologic units are often used to stratify the landscape in forest management applications (Keane et al., 2010).

2.5 Current carbon condition evaluation

Current C levels were evaluated using a pair of fuzzy logic membership functions that were combined using a UNION operator, which gave the results equal weighting (Figure 6). In the first evaluation, we developed a membership function to relativize the mean C levels for each HUC-12 subwatershed (4,000 to 16,000 ha).

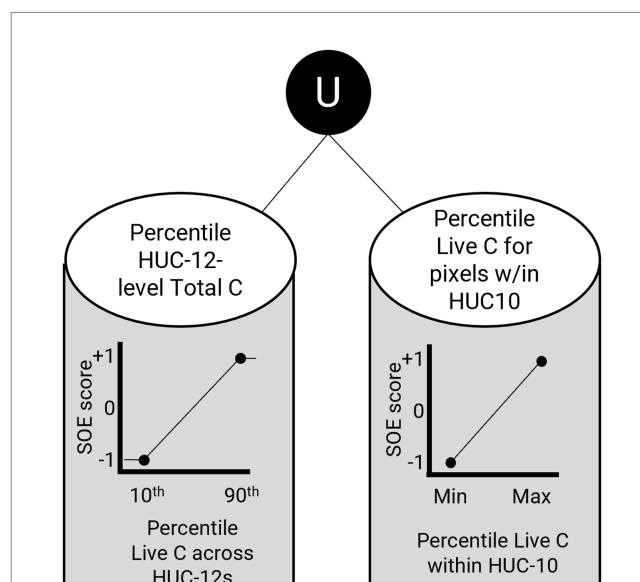


FIGURE 6

Fuzzy logic structure evaluating the current carbon conditions of cells. Fuzzy logic ramps were used to quantify the strength of evidence of a given metric. SOE scores range from -1 (no support) and +1 (full support). The union (U) operator was used to calculate the average of the two SOE scores to represent the overall current condition for Carbon. HUC stands for hydrologic unit code.

¹ <https://cida.usgs.gov/gdp/>

HUC-12 subwatersheds were identified in the planning process as a management-relevant landscape scale, where finer-scaled treatment patches could be delineated and prioritized within these hydrologically based land units. The use of the HUC-12-level was to differentiate total live C levels at a broader scale such that larger planning areas could be rank ordered based on their ability to store carbon over time. We used the 10th and 90th percentile conditions summarized across all HUC-12s within the TCSI landscape to assign low (−1) to high (+1) SOE scores, respectively.

A second evaluation quantified the amount of C within 81 ha (~200 ac) focal windows around each cell and compared those levels to the minimum and maximum levels within their respective HUC-10 watershed. Summing C levels within a focal neighborhood allowed for identifying “patches” of high producing carbon areas rather than depending on estimates at the cell-level, which may vary considerably over space and time.

2.6 Future carbon condition evaluation

For future conditions, a pair of metrics were evaluated (Figure 7) and combined using the AND operator, which results in a condition representation being based on the most limiting condition (i.e., minimum level of support).

The metrics (top, Figure 7) evaluated the (1) maximum and (2) standard deviation of C levels for each cell across the simulation periods. Like the current conditions assessment, total live C was summarized to 81 ha moving windows around each cell. The 10th and

90th percentiles of each Metric were then calculated at the HUC-10 scale, and these percentiles were used to assign the SOE scores for each cell. Cells with large maximum C levels and with low variability across model replicates received high SOE scores.

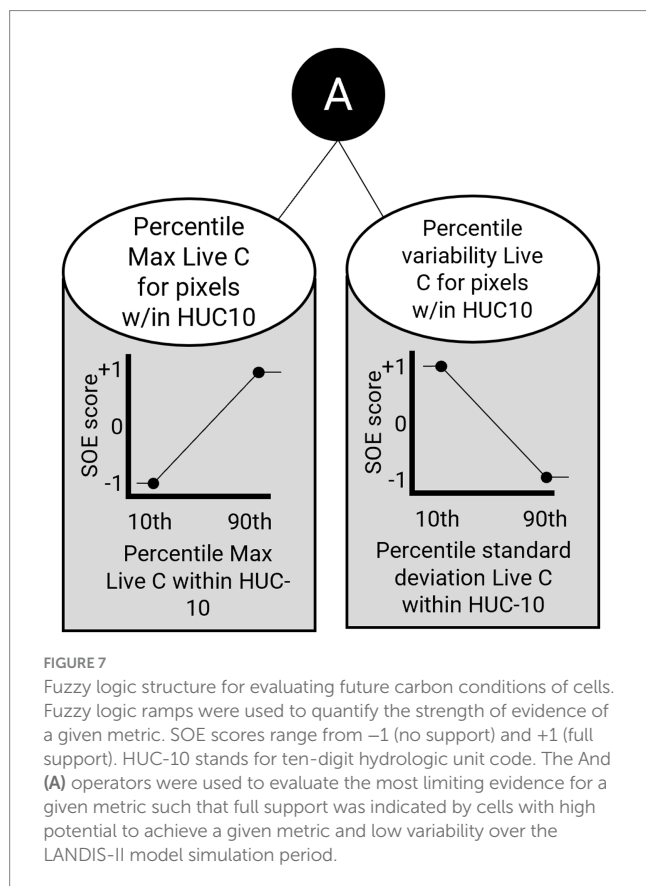
3 Results

For current conditions, the landscape supported a broad distribution of carbon values across the landscape, but with more limited occurrence of very high and very low carbon values (Figure 8A). The distribution of areas with low C storage (warm colors, Figure 8A) was highly clustered and occurring at low elevations (western edge), within high elevation wilderness areas (southwest of Lake Tahoe), and within recent fire footprints (center, 2013 American Fire and southern, 2014 King Fire). Based on current conditions alone, there were broad areas available for C conservation, with the majority of high C storage occurring in the mid elevational ranges, and much of the Lake Tahoe basin.

The potential future condition presented a very different outcome (Figure 8B). The landscape transitioned from a broad array of C storage conditions to an intermix of juxtaposed high and low C storage, with intermediate values primarily occurring as transitions between high and low C storage areas (Figure 9). Carbon storage stability was more patchily distributed with isolated pockets of stable C stores (cooler colors, Figure 8B). High and low elevations did not exhibit much improvement or stability in C levels over the LANDIS-II simulations. Carbon levels over much of the 2013 American Fire and 2014 King Fire footprint remained low over the course of the simulation period. Some stable C pockets were identified in the northern portion of the landscape and around the Lake Tahoe basin. Future conditions greatly narrowed the extent and fragmented the distribution of areas that could be strong candidates for C storage and indicated that the combination of protecting current and fostering potential future C stores would provide the most robust foundation for management investments toward C conservation.

From the current and future assessments, we used the methods outlined above to calculate the management strategy scores for the Carbon pillar (Figures 9, 10). The resulting interpretation clearly identifies areas where (1) stable C is high and expected to remain high without management investment (Monitor), (2) risk reduction efforts can increase the likelihood of sustaining stable C over the next few decades (Protect), (3) stable C can likely be improved through management investments (Adapt), and (4) management is unlikely to yield C dividends (Transform).

In sum, the extent of areas with strong support (strategy score > 0.50) for any given management strategy was generally low across strategies: Monitor (12.1% of the forested landscape), Transform (10.7%), Protect (7.6%), and Adapt (0.6%) (Figures 9, 10). Strong support for any given strategy was found across 31% of the landscape, but only 8.2% of the landscape was of high management priority (i.e., Adapt or Protect strategies). Areas with the opportunity for increasing carbon storage (Adapt) were the most limited (<1% of the landscape). When weaker strategy scores were also considered (SOE > 0.25), 81.8% of the landscape showed support for one of the four strategies and 29.2% of the landscape had support for either Adapt (4.7%) or Protect (24.5%) strategies.



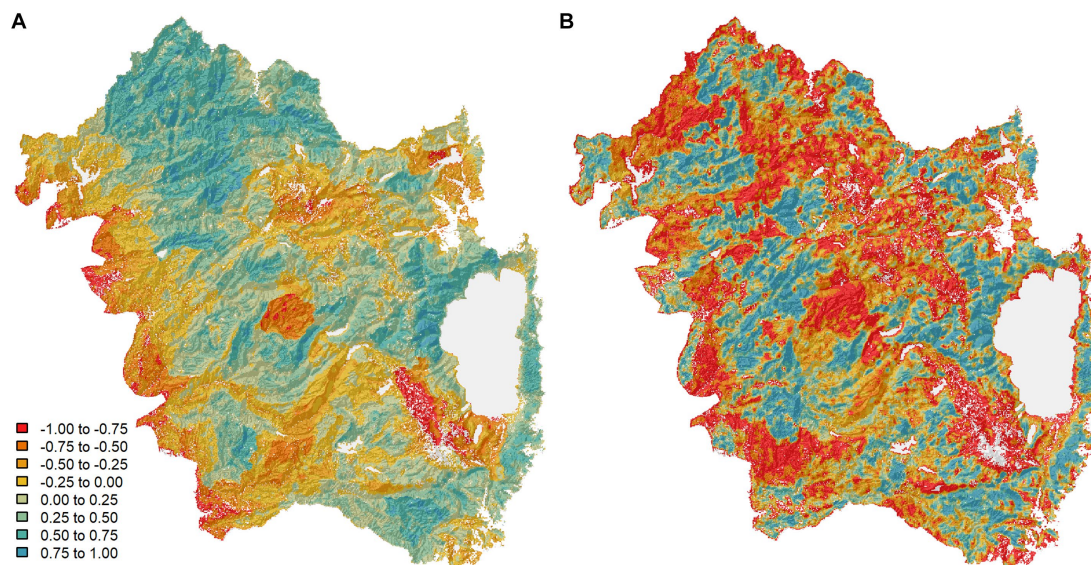


FIGURE 8
Spatial raster depicting strength of evidence scores for (A) current and (B) future (mid-21st century) carbon conditions. Cool colors indicate higher values for amount and/or stability of carbon while warm colors indicate lower values for amount and/or stability.

4 Discussion

We present the PROMOTE decision support model, which provides a methodology to inform strategic (where to go) and tactical (what to do) management decisions towards the goal of improving social-ecological resilience at landscape and regional levels while considering potential impacts from climate change. This effort expands upon central tenets from previous climate-informed management frameworks [e.g., Resist-Accept-Direct (Schuurman et al., 2022) and Resistance-Resilience-Transformation (Peterson St-Laurent et al., 2021)] by providing a quantitative evaluation of current and future resource conditions within a flexible fuzzy logic model. Landscape simulation modeling with climate change and natural disturbances was used to spatially represent the potential for achieving desired resource conditions over time. PROMOTE model outputs provide spatial maps representing quantitative support for each of four management strategies that cover the full range of potential management responses, from Monitor (intact conditions with low vulnerability over time) to Transform (poor conditions that remain unsuitable into the future). The model allows for an accounting of each management strategy across a landscape and facilitates the development of strategic management plans across ownerships within the analysis domain. These methods can be adapted to include multiple metrics in the evaluation and at multiple scales relevant to landscape and regional planning (Manley et al., This issue). Furthermore, the PROMOTE model is amenable to alternative representations of future conditions where landscape modeling is not available or feasible to implement. For example, Povak et al. (2024) provide an assessment of future ecosystem resource stability using climate analog modeling at 1 km resolution for the state of California. Other approaches (e.g., Thorne et al., 2017; Triepke et al., 2019) can be readily applied across large spatial extents and require less model calibration and processing time compared to simulation modeling.

4.1 Scaling management to landscapes

Climate change and natural disturbances will continue to be the main determinants of system-level dynamics (North et al., 2021; Larson et al., 2022). While treatments are effective at local scales, strategic planning is required to effectively allocate scarce resources (i.e., crews, equipment, funding, time) at scales large enough to positively impact landscape-scale dynamics and secure ecosystem services. Landscape resilience, therefore, is not a property that can be evaluated or conferred at the patch- or stand-scale, because the dominant pattern-process interactions impacting resilience occur across multiple spatial and temporal scales (Hessburg et al., 2019). Management for resilience is not a stand-level proposition. Without a broader perspective on how disturbances and other broad-scale processes (e.g., seed dispersal and climate adaptation) impact future fine-scale processes (i.e., successional development, carbon sequestration), and how fine-scale patterns (i.e., old forest structural complexity) provide the template for broader scale processes (i.e., high severity fire spread), evaluations of management priorities may fall short in meeting resilience goals (Vose et al., 2021). Specifically, addressing future wildfire disturbances requires a more holistic approach that includes traditional resource-focused management balanced with decision making that integrates future landscape dynamics under climate change. Identifying where resistance will likely not be a successful strategy in the future (Clifford et al., 2022) and working with the dominant natural disturbance processes will be essential to achieve resilience goals at landscape scales.

4.2 Implications of individual management strategies

The PROMOTE model generates a quantitative, continuous value representation of the strength of affiliation with each management

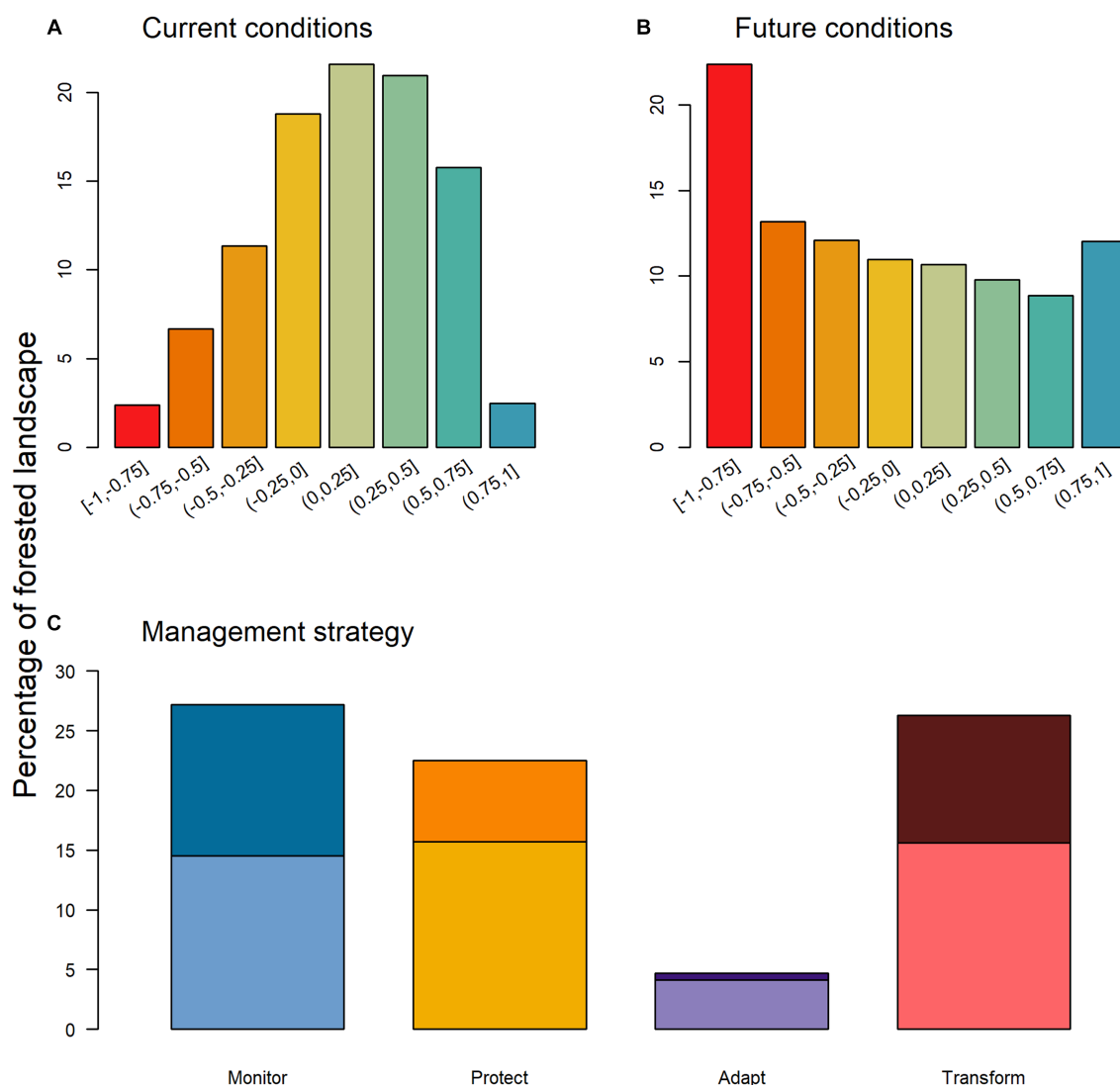


FIGURE 9

Histograms depicting the distribution of (A) current conditions scores, (B) future conditions scores for carbon across the TCSI landscape, and (C) the percentage of the landscape represented by strong (>0.50, dark shaded bars) and weak (0.25–0.50, light shaded bars) management strategies scores. The colors in panel (C) correspond to the spatial distribution of these scores in Figure 10.

strategy. Although the four management strategies represent portions of a gradient along a continuum, the implications of membership in each strategy provides the foundation for effective tactical approaches. Importantly, these four strategies are interpretations of the decision space constructed through the joint assessment of current and future conditions (Figures 2–4), and the four strategies presented here are rooted in the literature and were supported through collaboration. However, inferences made from these evaluations are ultimately left to the users who may have uniquely place-based interpretations of how best to respond to the conditions assessments based on their management priorities. Below, we present interpretations of each management strategy we used to characterize the PROMOTE decision space.

Monitor – This strategy is unique relative to other climate-informed management frameworks in that it identifies areas that do not currently need management input to retain resilient conditions into the future. In our application, strong Monitor areas accounted for approximately 12% of the forested landscape with some higher

concentrations in the northernmost reaches of the landscape (Figure 9). Such areas may represent stable climatic and/or disturbance refugia where changes in vegetation and disturbances are less likely or somewhat more remote in time (Carroll et al., 2017; Meddens et al., 2018), and where no management investments are currently warranted. This strategy has two important implications: it (1) identifies areas that are most likely to support a stronghold of favorable conditions that management might want to build on in terms of expanding their size and extent by investing in adjacent areas and (2) enhances efficient and effective management investments by directing them away from Monitor areas and toward those that are more likely to yield short- and long-term benefits.

Protect – The Protect management strategy implies that management can enhance the future prospects of conditions that are otherwise likely to decline with changing climate. In our application, management would most effectively be directed towards vulnerable C hotspots that currently play a valuable role as C sinks and are vulnerable to future climate change. In our study, about 25% of the

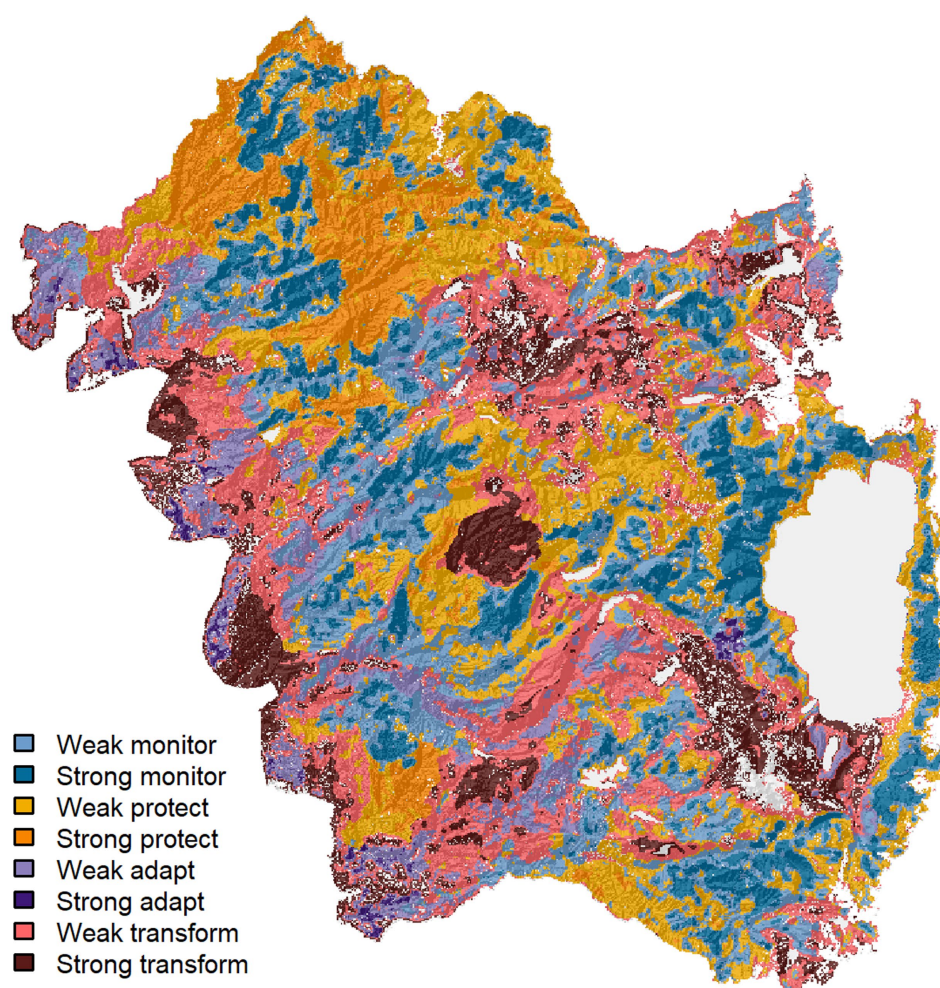


FIGURE 10

Spatial raster depicting strength of evidence scores for management strategy scores for the carbon pillar across the TCSI landscape. (A) Adapt, (B) Monitor, (C) Transform, and (D) Protect. Scores ranged from -1 (no support for a given management strategy) and $+1$ (full support). Strong scores were those >0.50 and weak scores were between 0.25 and 0.5 .

forested landscape had some support for the Protect strategy indicating much of the C storage capacity on the landscape is vulnerable to disturbances and climate change. This is not unique to the central Sierras; evidence suggests that future drought-induced mortality and large severe disturbance events will likely compromise the capacity of forests to retain their status as carbon sinks (Kurze et al., 2008; Fargione et al., 2018; Albrich et al., 2022). Some studies suggest that Sierran forests are currently overstocked with C and that historical C levels were much lower under an active fire regime (Krofcheck et al., 2017; Liang et al., 2017; Knight et al., 2020; Bernal et al., 2022). Our results suggest that C can be maintained, although at reduced levels, in frequently disturbed forests in the future, likely with strategic management investments.

Adapt – Areas affiliated with the adapt strategy identify areas currently in poor condition but have the demonstrable ability to improve over time under climate change and natural disturbances. The role of management would be to facilitate the attainment of those conditions in the near term with the expectation that they will be stable over time. The PROMOTE model enables managers to differentiate adapt from transform areas that, in contrast, are unlikely to improve in the face of future climate (see below). Management investments can

then be made where they have the greatest opportunity to retain high functioning conditions on the landscape while facilitating changes where conditions can likely be sustained. Concomitant with a substantial opportunity for improvement, adapt areas are also most likely to benefit from a wider range of management investments, although some will undoubtedly be more effective than others. Management investments are driven and constrained by a wide array of factors, so adapt areas offer opportunity for progress regardless of the type or character of treatment options that might be available to managers. In our evaluation, we found that areas with currently low C storage account for 63% of the landscape. Within that subset, the adapt strategy accounted for $<1\%$ of the area and transform accounted for the balance (62%), suggesting that active restoration likely has a limited capacity to increase C amounts in the future where C is currently deficient. However, in contrast, McCauley et al. (2019) found landscape treatments increased C 9–18% over no-harvest scenarios in the US Southwest, suggesting that strategic treatment implementations may have landscape-level C benefits over time by reducing losses to wildfire broadly and increasing forest productivity locally.

Transform – Areas identified as strong transforms can be interpreted in two ways. Firstly, these areas may provide

opportunities to manage for alternative stable states (e.g., non-forest types, early seral stages, dominant species composition) that provide alternative or additional functionality. In western North America, early seral and non-forest types were historically an integral component of the landscape when fires and other disturbances played a more active role in shaping vegetation patterns (Swanson, 2012; Hessburg et al., 2016, 2019, 2021; Hagmann et al., 2021). Such areas can serve important ecological functions such as providing key foraging habitat for certain wildlife species and mitigate the spread and severity of wildfires. Secondly, management may opt to apply treatments in Transform areas but with the knowledge that these conditions may require additional longer-term investments to achieve and maintain management objectives. As such, the model facilitates a shift in management focus on improving areas in the worst condition towards those areas with the highest likelihood of near- and long-term success. Deferring such investments to areas with a higher likelihood of success (e.g., adapt areas) may improve return on investments as these areas have a demonstrated ability to achieve desired conditions.

5 Conclusion

The scale and scope of land management problems requires a flexible and multifaceted approach that includes both engineered solutions aimed at reducing near-term risks to resources from disturbances and ecological solutions aimed at improving long-term social-ecological resilience (Millar et al., 2007; Seddon et al., 2020a,b). Such an approach necessitates access to tools to ensure that investments made at the stand-scale can impact landscape resilience properties while procuring ecosystem service benefits. By modeling landscape dynamics over time under climate change, the PROMOTE model captures the relevant dynamics at the scale necessary to capture top-down drivers from climate and contagious disturbances processes (i.e., meso-scale, Moritz et al., 2011). Doing so provides the broader context with which to evaluate possible future trajectories and outcomes from management, thereby enabling managers to account for the complexity of interacting ecological and social factors acting within landscapes. Furthermore, PROMOTE model outputs can be used within a multi-criteria decision (Marques et al., 2021) or optimization (Ager et al., 2017) modeling framework to assess tradeoffs and synergies among strategic planning options. Such models help resolve complex decision-making problems where there are multiple resources of interest and varying priorities among interest groups to consider. These models also allow for the inclusion of other factors that may influence decisions including treatment costs and revenues, social/political/cultural factors, and other potential limitations on treatment activities.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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Author contributions

NP: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Investigation. PM: Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – original draft. KW: Conceptualization, Funding acquisition, Investigation, Project administration, Writing – original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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