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Blueprint for Resilience: The Tahoe-Central Sierra Initiative

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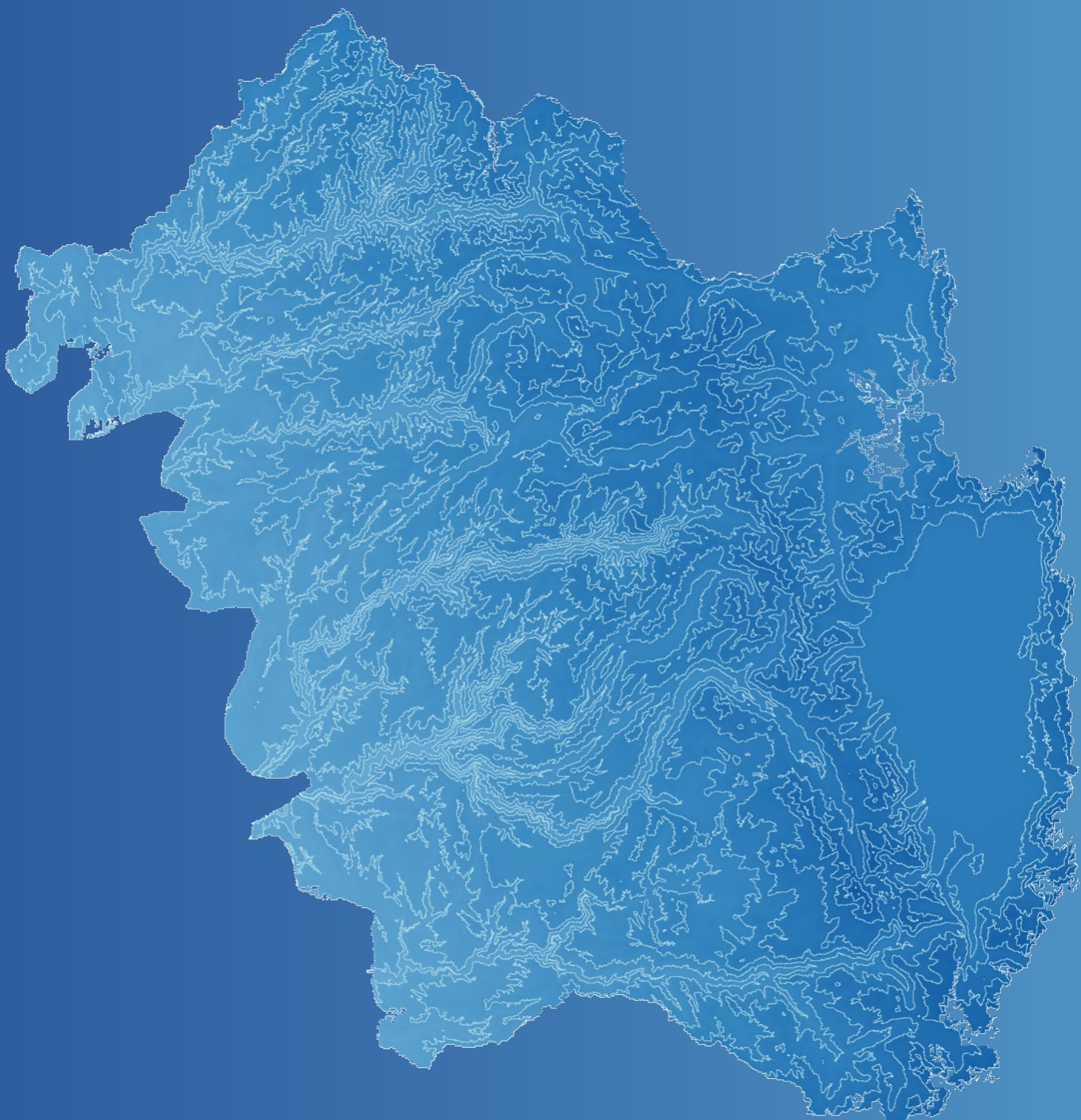

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Cover: GIS (geographic information system) image of the Tahoe-Central Sierra Initiative area in northeastern California and northwestern Nevada. Elevation contour lines are shown with Lake Tahoe in the lower right of the image. Map by Nicholas A. Povak.

Abstract

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The Tahoe-Central Sierra Initiative (TCSI) Blueprint for Resilience (hereafter TCSI Blueprint) is a set of strategy maps that identify opportunities for forest protection and adaptation across a 978 381-ha (2.4 million-ac) region of the central Sierra Nevada. The TCSI partners, along with scientists and forest managers versed in the concept of resilience, defined resilience based on 10 ecological and social pillars. The TCSI Blueprint includes evaluations of 30 unique metrics, such as large tree density and probability of high-severity fire, that describe conditions across five of the pillars of resilience: forest resilience, fire-adapted communities, fire dynamics, biodiversity conservation, and carbon sequestration. The TCSI Blueprint uses a novel application of the Ecosystem Management Decision Support tool and fuzzy logic modeling to evaluate the degree to which current conditions are indicative of resilient landscapes. The TCSI Blueprint integrates assessments of both current (2019) and future (2020–2060) conditions under climate change (based on dynamic forest modeling) to reflect where management can likely make the most impact toward achieving functions on the landscape now and into the future. The model outputs spatial maps of condition scores ranging from -1 (out of target conditions) to +1 (within target conditions) for current and future conditions separately. These metric scores are then mapped onto a two-dimensional space, with current conditions on the x-axis and the potential to achieve target conditions in the future on the y-axis. Within that space, scores for each of four climate-informed management strategies are calculated and mapped: monitor, protect, adapt, and transform. The full suite of data used to generate the TCSI Blueprint offers a robust foundation for large landscape management and project planning, from strategic to tactical to operational.

Keywords: Resilience, socioecological, decision support, fuzzy logic, Sierra Nevada, Tahoe-Central Sierra Initiative.

Summary

The Tahoe-Central Sierra Initiative (TCSI) Blueprint for Resilience (hereafter TCSI Blueprint) is a set of strategy maps that identify opportunities for forest protection and adaptation across a 978 381-ha (2.4 million-ac) region of the central Sierra Nevada. It is the culmination of an effort to improve resilience to anticipated climate change and wildfire as well as beetle- and drought-caused tree mortality. The TCSI group, along with scientists and forest managers versed in the concept of resilience, defined resilience based on 10 ecological and social pillars. The TCSI Blueprint includes evaluations of 30 unique metrics, such as large tree density and probability of high-severity fire, that describe conditions across five of the pillars of resilience: forest resilience, fire-adapted communities, fire dynamics, biodiversity conservation, and carbon sequestration.

The TCSI Blueprint uses a novel application of the Ecosystem Management Decision Support tool to evaluate spatial data layers against target conditions that are indicative of resilient landscapes. The TCSI Blueprint integrates assessments of both current (2019) and future (2020–2060) conditions under climate change to reflect where management can likely make the most impact toward achieving functions on the landscape now and into the future. The model outputs spatial maps of condition scores ranging from -1 (out of target conditions) to +1 (within target conditions) for current and future conditions separately. These metric scores were then mapped onto a two-dimensional space, with current conditions on the *x*-axis and the potential to achieve target conditions in the future on the *y*-axis. Within that space, four restoration strategies were identified: monitor, protect, adapt, and transform (fig. S.1).

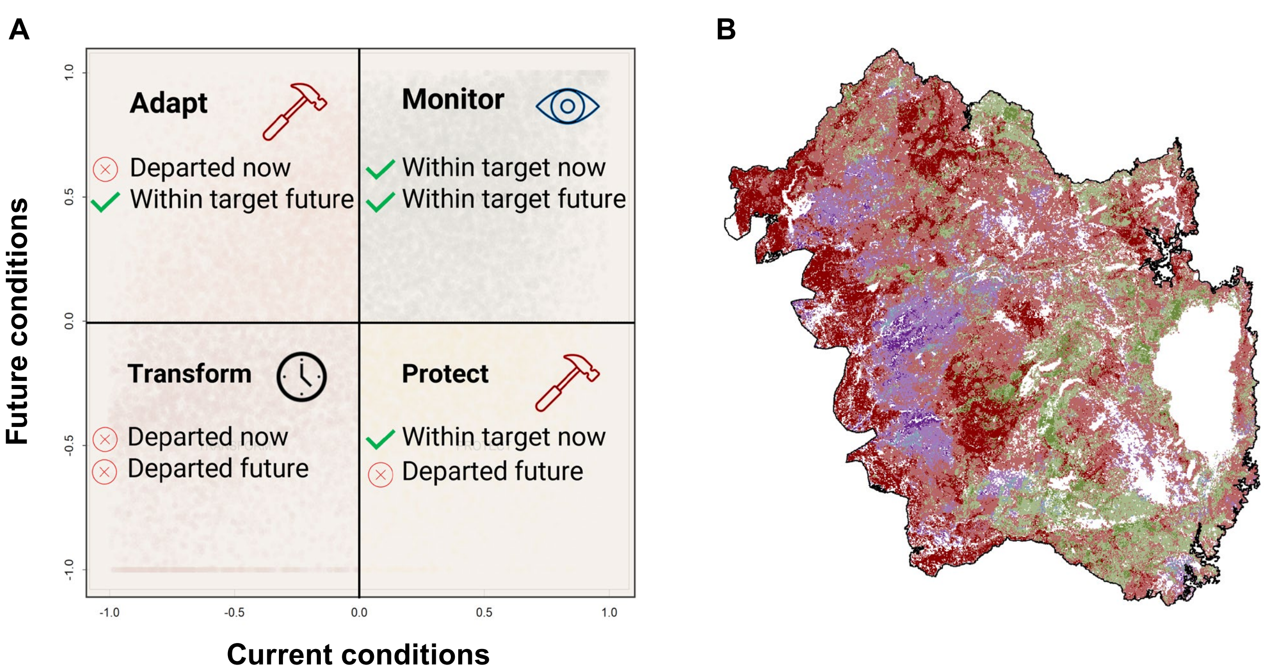


Figure S.1—Management strategy score (A) derivation and (B) representation of each strategy across the Tahoe-Central Sierra Initiative (TCSI) landscape. Areas within the TCSI boundary but without a strategy assignment are nonforest (e.g., water, developed land, rocks, grasslands, shrubs, or meadows).

To reach the goal of improved resilience, the TCSI prioritized maintaining areas that are within target conditions currently and increasing the area in target conditions where those conditions are likely to be retained in the future. Areas identified as “monitor” and “protect” are currently within target conditions; monitor areas stay within target in the future and do not appear to need management, while protect areas move outside of target conditions without management intervention. Because of their inherent stability, monitor areas may have value as anchors in the landscape to expand from and connect to desired conditions. Areas identified as “adapt” and “transform” are currently outside of target conditions; adapt areas move into target conditions in the future, and management can speed up that transition, while transform areas are less likely to reach target conditions in the future and are a lower priority (fig. S.2). Management strategy and management impact maps were developed for each metric, element, and pillar and were further summarized in a final ecosystem-level map that combined scores across all five pillars.

The forest restoration strategies defined in the TCSI Blueprint allow managers to tailor actions to be strategic, forward-looking, and responsive to projections of climate change impacts. The TCSI Blueprint can help managers determine where restoration treatments are likely to improve conditions over time and, conversely, where they are not needed, or where their impacts are less certain in the future. The TCSI Blueprint maps presented below and available online are best used as a guide for land managers and other stakeholders to prioritize targeted forest restoration strategies. These strategies can enhance the resilience of current forest conditions where climate change is unlikely to compromise restoration investments.

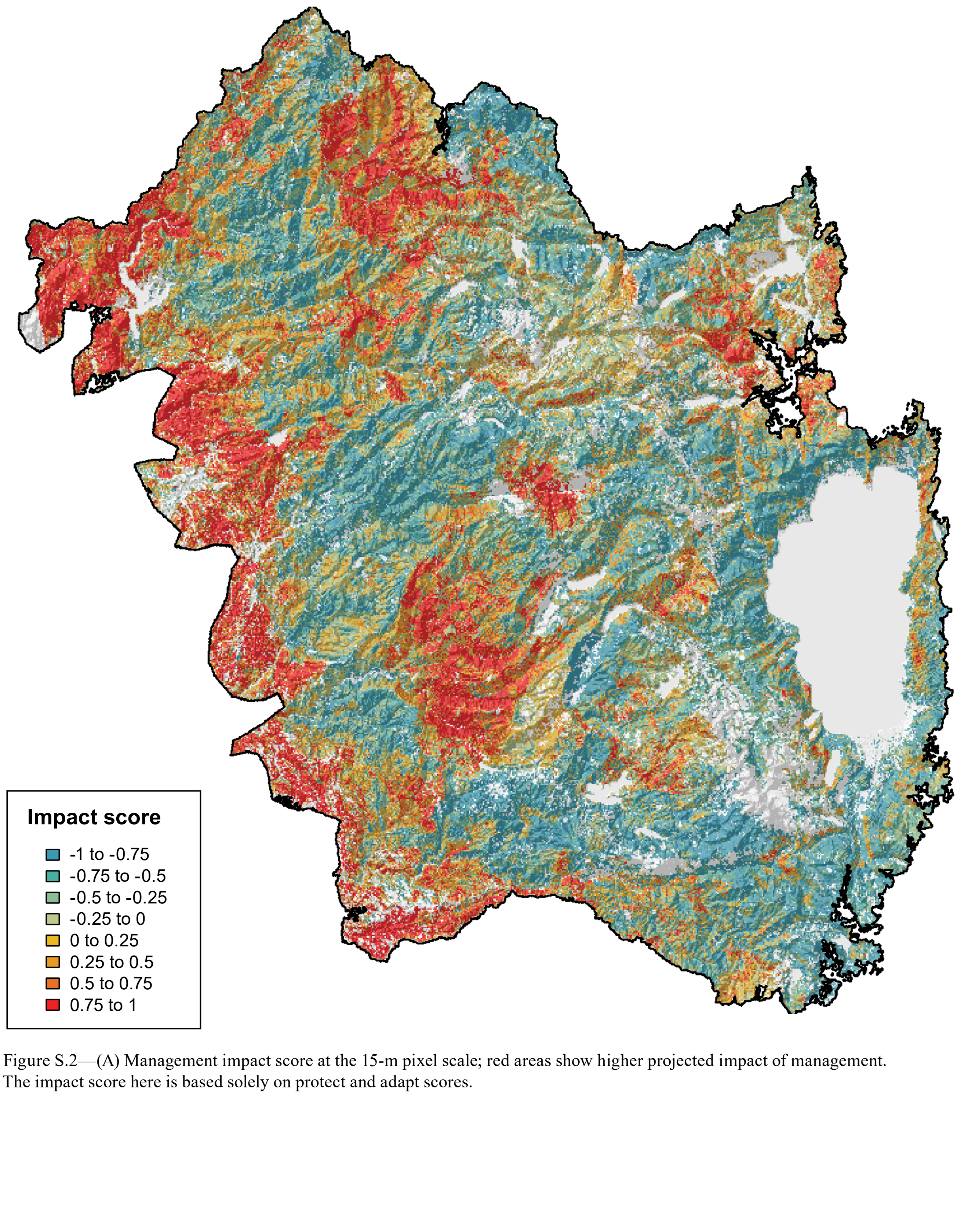


Figure S.2—(A) Management impact score at the 15-m pixel scale; red areas show higher projected impact of management. The impact score here is based solely on protect and adapt scores.

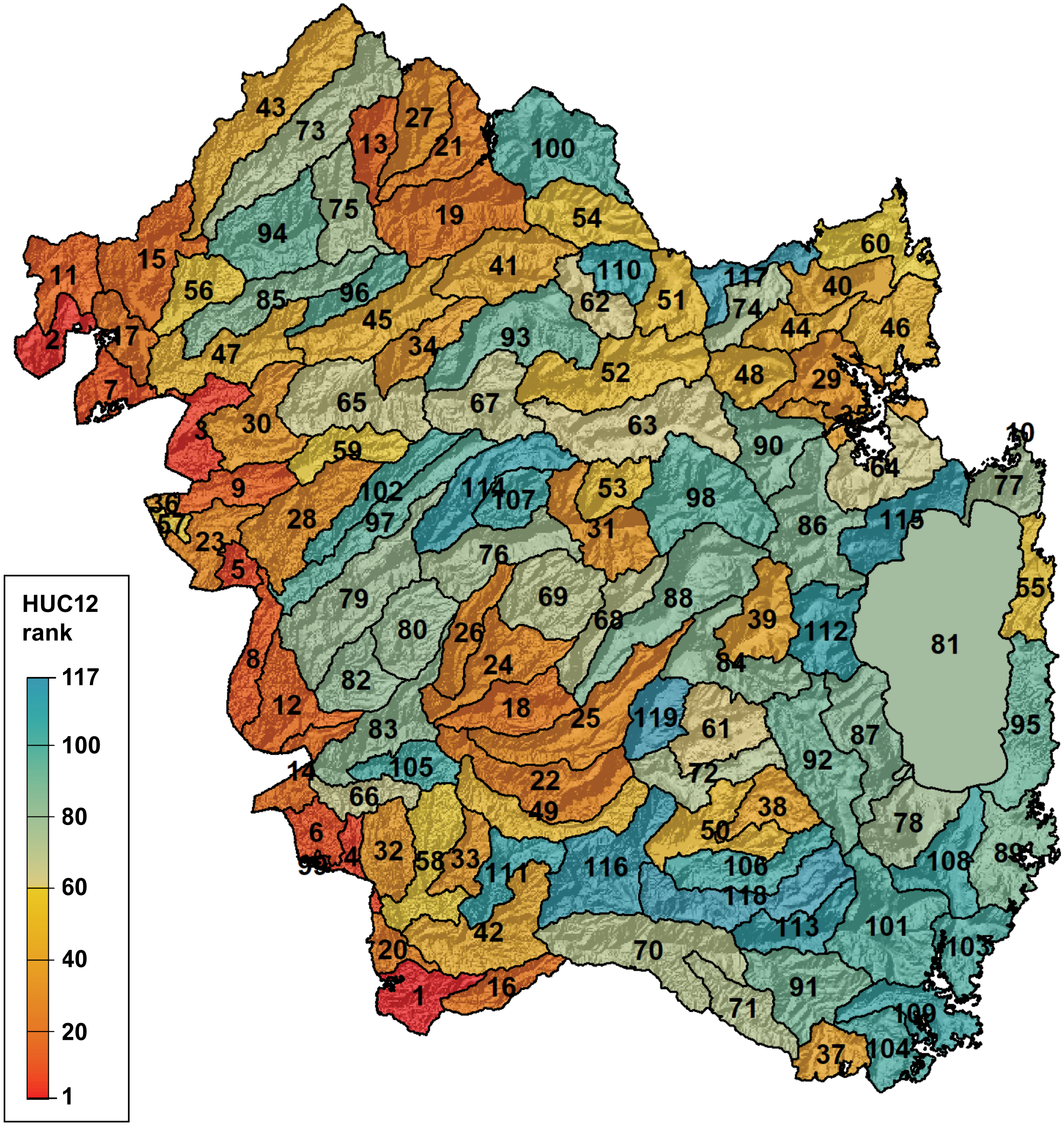


Figure S.2—(B) Final ranking of HUC12 subwatersheds within the TCSI landscape based on their mean Ecosystem Adapt-Protect score. Lower numbers and warmer colors indicate HUC12s with greater management need than those HUC12s with higher numbers and cooler colors.

Contents

Introduction

Landscape Restoration Planning in a Changing Climate

Climate change, high-severity wildfire, and drought threaten the resilience of forests and communities in the Sierra Nevada. The area burned by high-severity wildfires annually is increasing, and prolonged droughts coupled with beetle outbreaks have the potential to result in massive tree mortality, leaving extremely large areas of dead trees. These factors, along with fire suppression and unsustainable logging practices, shaped the forests we know today, which are less resilient to wildfire and drought than pre-European-settlement forests. Despite significant efforts since the early 1990s to improve forest health and resilience using restoration thinning and prescribed fire, the current pace and scale of proactive forest management is not enough to reverse the increasing trend of large fires and widespread beetle-caused tree mortality tied to drought. There is a need to better understand how much and what kind of forest management is needed and where and what co-benefits can be expected.

Tahoe-Central Sierra Initiative

The Tahoe-Central Sierra Initiative (TCSI) is a partnership of state and federal agencies, nongovernmental organizations, the timber industry, and researchers that was established to improve forest and social resilience to climate change and other stressors across a 978 381-ha (2.4 million-ac) landscape (fig. 1). Increasing forest heterogeneity and decreasing fuel loads through ecologically based forest management will likely improve the forest and human communities' ability to adapt to future wildfires and drought under a changing climate. The TCSI established a four-part roadmap to resilience: (1) Framework for Resilience, (2) Assessment of Current Landscape Conditions, (3) Assessment of Future Landscape Conditions, and (4) Blueprint for Resilience.

The TCSI Framework for Resilience (TCSI 2020) (hereafter TCSI Framework) provides a structure for assessing landscape conditions, setting objectives, designing projects, and measuring progress toward socioecological resilience. The TCSI Framework offers a shared vision for landscape-scale resilience that recognizes the interdependent nature of social and ecological values. These values are described by 10 pillars that represent the desired outcomes of landscape resilience: forest resilience, carbon sequestration, fire dynamics, fire-adapted communities, economic diversity, social and cultural well-being, air quality, water security, wetland integrity, and biodiversity conservation (fig. 2). Elements, such as forest structure or focal species, represent the primary processes and functions that together make up a pillar. Each of the pillars' elements provide metrics for assessing landscape conditions and verifying that actions meet resilience objectives. Metrics describe the characteristics of elements in quantitative or qualitative terms. Users can use metrics to assess, plan for, measure, and monitor progress toward desired outcomes and greater resilience. Although pillars and elements are consistent across the Sierra Nevada, the metrics that a group uses may vary from region to region based on ecological and social differences (e.g., forest types, economy), available data, and user preferences.

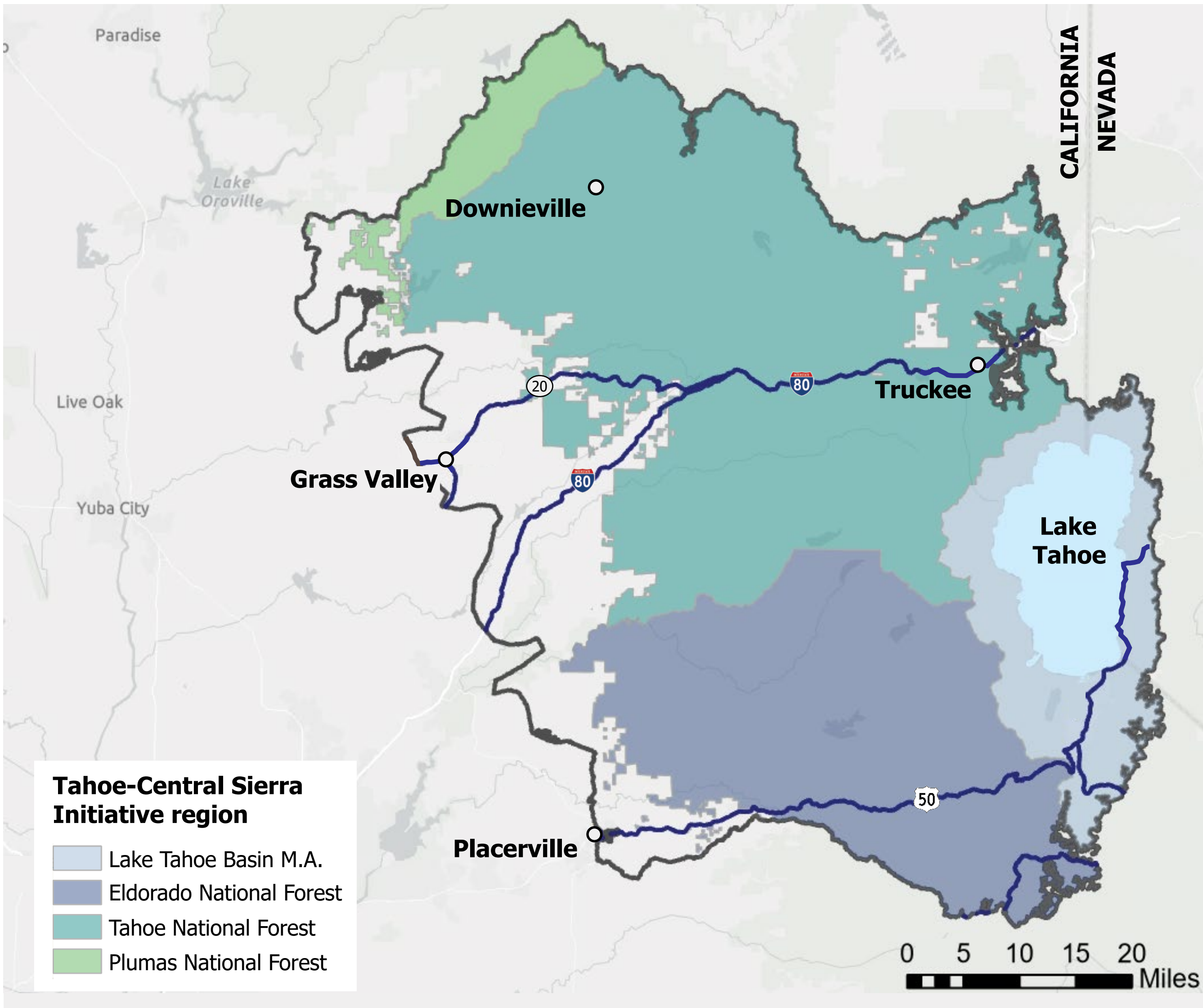


Figure 1—The Tahoe-Central Sierra Initiative is located in the central Sierra Nevada ecoregion. M.A. = Management Area.

The TCSI Framework is designed to help agencies, landowners, tribes, businesses, and other stakeholders plan and implement restoration projects that align with shared values at an accelerated pace and scale, and to clearly document progress toward local, regional, and statewide goals. Building on that, the TCSI Assessment of Current Landscape Conditions (Wilson and Manley 2021b) evaluates key features of the landscape in terms of resilience by assessing current (2018–2020) conditions across six of the ten pillars of resilience: forest resilience, fire dynamics, fire-adapted communities, biodiversity conservation, carbon sequestration, and economic diversity. The current conditions assessment along with the assessment of potential future conditions are essential steps in shaping desired outcomes and the degree to which management approaches can improve landscape conditions across the pillars of resilience in the face of future climate conditions.

The TCSI Blueprint for Resilience (hereafter TCSI Blueprint) process combines information from the current and future condition assessments with ecosystem management decision support systems to identify opportunities for restoration across the landscape. Ecosystem management decision support systems help identify opportunities to move toward desired target conditions across a wide array of metrics, resulting in the production of maps that identify where forest management could provide the greatest benefits based on a given set of priorities.

Figure 2—The 10 ecological and social pillars used to define resilience in the Tahoe-Central Sierra Initiative (TCSI) Framework for Resilience.

Blueprint Objectives

The TCSI Blueprint is a decision support tool to help managers and decisionmakers achieve multiple resource objectives across the TCSI landscape. The management objectives addressed by the TCSI Blueprint closely follow the 10 pillars of resilience (fig. 2) identified by the TCSI Framework (TCSI 2020). Each pillar describes landscape benefits provided by resilient socioecological systems, including resiliency to disturbance, the ability to sequester carbon, and the capacity to provide beneficial fire dynamics. The TCSI Blueprint incorporates spatially explicit data to represent current landscape conditions and future dynamics for 5 of the 10 pillars of resilience: forest resilience, fire dynamics, fire-adapted communities, biodiversity conservation, and carbon sequestration (fig. 3). These data are then evaluated against target conditions to determine the degree to which a specific given area currently provides a resource and the capacity for it to provide the resource into the future. Areas well within target conditions may sustain one or more benefits over time, while those not achieving target levels may be the focus of management to help achieve a desired resource benefit.

The role of the TCSI Blueprint is not to tell managers where and how to treat specific forested areas; rather, the intent is to identify opportunities across the TCSI landscape where management could procure the greatest number of resource benefits and contribute to landscape resilience. As such, the TCSI Blueprint provides a series of map-based representations of management benefits across

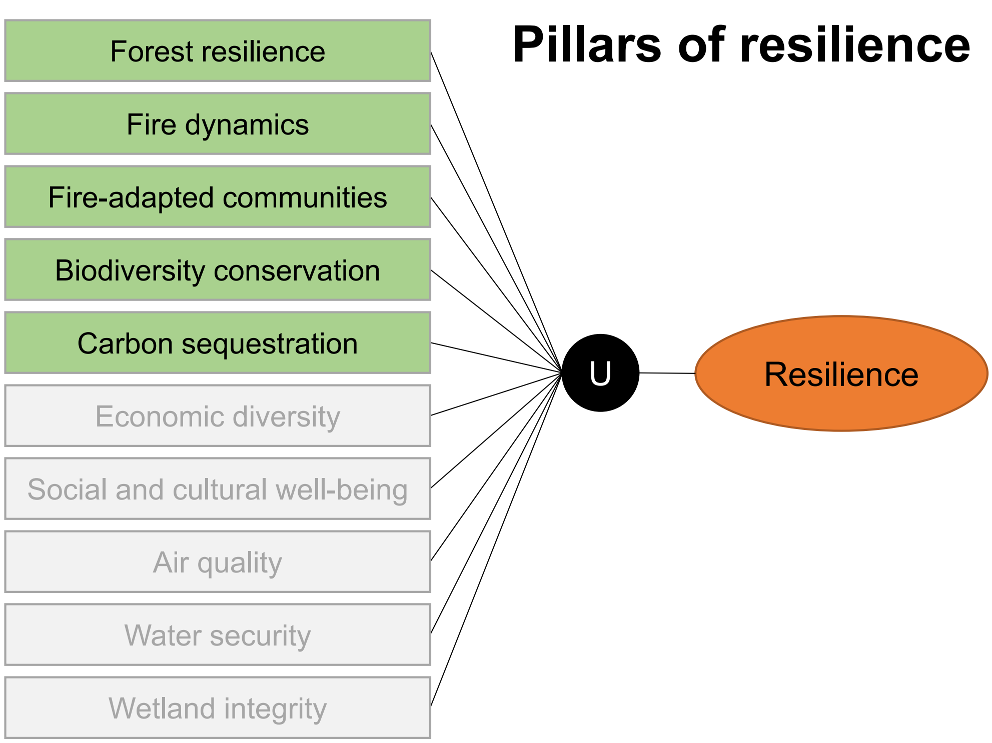


Figure 3—Five of the ten ecological and social pillars of resilience used in the Tahoe-Central Sierra Initiative Blueprint for Resilience. U = “UNION” logic model operator.

the TCSI landscape. Different pillars may be weighted to emphasize or prioritize objectives, thereby altering the spatial distribution of needs. Underlying every spatial data layer is a logic model based on target or desirable conditions that are expected to enhance resilience to disturbances and climate change.

Blueprint Building Blocks

Ecosystem Management Decision Support System

The principles of the Ecosystem Management Decision Support (EMDS) system were used to develop the TCSI Blueprint. The EMDS system is a general modeling framework used to develop and apply custom logic and decision models to aid in natural resource management decisionmaking (Reynolds and Hessburg 2014, Reynolds et al. 2014). The EMDS system allows users to address many kinds of questions related to landscape assessment and at whatever spatial scales are pertinent to address questions or issues.

The TCSI Blueprint is a spatially explicit model that uses fuzzy logic to evaluate the proposition that a given raster cell is within some target condition (e.g., a pixel provides high-quality spotted owl habitat now and into the future). Instead of a binary yes or no, fuzzy logic evaluates the strength of evidence (SOE) for a proposition. Logic model SOE output scores range between −1, representing no support for a proposition, and +1, representing full support for a proposition. Scores near 0 indicate an indeterminant assessment given the data. The fuzzy logic models rely on target values to set the mark for the evaluation. For example, a forested hectare with 500 trees may be overly dense for some forest types but not for others. By setting target tree densities for each forest type, we can evaluate forests against resilient forest conditions with similar environmental settings. The TCSI Blueprint's logic models are designed in R (R Core Team 2020) to evaluate the ecological status from the site scale up to the entire landscape.

Current, Future, and Target Conditions

The data used in the TCSI Blueprint come from a variety of sources (app. 1) depending on the pillar. Current (2019) vegetation conditions for forest composition and structure were created by NCX (formerly SilviaTerra; https://ncx.com) using Landsat satellite data and imputation based on USDA Forest Service Forest Inventory and Analysis (FIA) data. NCX assigned an FIA tree list to each 15-m pixel based on the similarities in environments and spectral characteristics of the FIA plot and candidate pixel. Imputed light detection and ranging (LiDAR) data from the California Forest Observatory was also used to assess canopy height and cover.

The Landscape Disturbance and Succession-II (LANDIS-II) landscape simulation model was used to represent future potential conditions for 2020–2060. We focused specifically on LANDIS-II model runs that used the Model for Interdisciplinary Research on Climate (MIROC) 8.5 climate scenario under a "business-as-usual" management scenario. The MIROC climate scenario was considered the "warm and dry scenario" and was found to best represent recent wildfire activity compared to other tested scenarios. The business-as-usual scenario represented potential conditions with minimal amounts of human intervention to determine where management could help direct natural forest dynamics toward more resilient conditions.

The TCSI Blueprint is aimed at providing strategic information for identifying management opportunities to achieve and sustain multiple resource objectives, but it does not inform management regarding the scheduling of specific treatment units, nor does it provide operational information regarding treatment implementation. Models such as ForSys (Ager et al. 2021a) and mixed-integer programming (Wei et al. 2019) specifically address treatment optimization and scheduling. Information from the TCSI Blueprint can be incorporated into these models to direct management operations at this scale.

The TCSI Blueprint is a living model that is intended to mature over time through interactions with and recommendations from its users. These inputs and suggestions are critical to the model's success and are encouraged.

Management Response: Monitor, Protect, Adapt, Transform

The TCSI Blueprint is a strategic model that assists in directing restoration work throughout the TCSI landscape to provide multiple benefits through restoration treatments and to move the landscape toward a more resilient condition in the face of ongoing climate change. This requires prioritizing and sequencing planning areas to achieve social and ecological benefits in the near and long term.

Assessing current conditions alone can help direct attention to departed conditions on the landscape that are not providing one or more benefits. However, it is also important to take into consideration the degree to which a site, patch, neighborhood, watershed, or landscape is reasonably capable of providing those benefits (i.e., potential to reach target conditions) or if restoration treatments can help facilitate the move toward target conditions. The future of ecosystem resilience will depend on the management intentions and inputs that position social and ecological systems to cope with and adapt to future climatic conditions and disturbances. All efforts to enhance adaptive capacity by necessity focus on managing change, but they have different rates of change and degrees of novelty (Moser and Ekstrom 2010, Stein et al. 2013).

Multiple climate adaptation strategies have been suggested over the past 15 years, going back to Millar et al.'s (2007) "resistance, resilience, and response" adaptation strategies. These represent a spectrum of management objectives that are informed by the degree to which desired target conditions can be met. Resistance strategies would entail management investments to maintain desired target conditions where they exist currently and are most appropriate where resource values are in good condition, or the potential to achieve and maintain them are high. Resilience strategies would entail management investments where they are most likely to be achievable and maintained. Response strategies would entail management investments to move current conditions into a less desirable state but one that is more achievable and will still yield valued ecosystem services. Since Millar et al. (2007), other adaptation frameworks have been proposed (Lynch et al. 2021), but they essentially reflect the same spectrum of outcomes that range from maintaining and protecting what is in good condition, implementing adaptive strategies in areas that can achieve target conditions with high certainty, and directing sites that have a low potential of achieving desired target conditions into a different state that will be more resilient to future climate and disturbance (Schuurman et al. 2022).

The combination of current, target, and potential future conditions provides a context for determining the most fruitful management investments to achieve multiple resource objectives. Climate change greatly diminishes certainty about the potential for sites to achieve and maintain target conditions. As a result, modeling provides a relative range of potential outcomes that can be used to guide management investments to areas that are most likely to achieve and maintain desired conditions across landscapes and over time. Specifically, outputs from future landscape simulation modeling provide our best estimate of the potential for a given area to achieve target conditions and maintain the stability of those conditions over time, based on a dynamic and uncertain climate future.

We categorized the range of management strategies to enhance the resilience and adaptive capacity to future climate conditions into four basic outcomes that represent a continuum of intended rates and degrees of change and novelty (sensu Millar et al. 2007). These four strategies are a function of where sites and landscapes fall in the bivariate space defined by current condition on the x-axis and the potential to achieve and appear to maintain desired target conditions 40 years into the future on the y-axis (fig. 4).

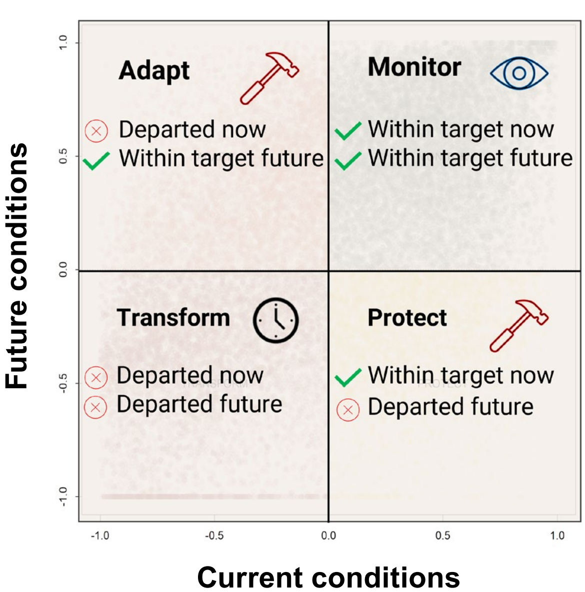


Figure 4—Current and potential future conditions over the next 40 years (with climate change) relative to desired target conditions. Departure values are standardized, ranging from +1, when conditions are consistent with desired target conditions, to −1, when conditions are far outside of desired target conditions.

1. **Monitor**—Target conditions are currently met and remain in the future without intervention.
2. **Protect**—Target conditions are currently met but are likely to degrade over time.
3. **Adapt**—Target conditions are not currently met but are observed to achieve target conditions over time.
4. **Transform**—Target conditions are not currently met and are not observed to be achieved over time.

This classification scheme can be used at every level of the TCSI Blueprint hierarchy from metric through pillar to assess one or more benefits. The management strategy affiliations can be used to inform and direct management at multiple stages and scales of project planning, so two applications for the management strategy characterizations of site conditions and potential were developed: (1) management impact score and (2) management strategy score.

Management impact score—

The "management impact score" is useful for ranking landscape units, such as watersheds or firesheds, for management investment over time. The score is driven by "adapt and protect" quadrant scores, as displayed in figure 5. Specifically, areas with a large proportion of adapt or protect conditions receive a high management impact score. For example, planning units with a high proportion of adapt and protect areas may be prioritized for management in the near term given they have the highest likelihood of success in achieving benefits from management. They have the greatest potential to contribute to the landscape into climate-ready, desired target conditions as soon as possible.

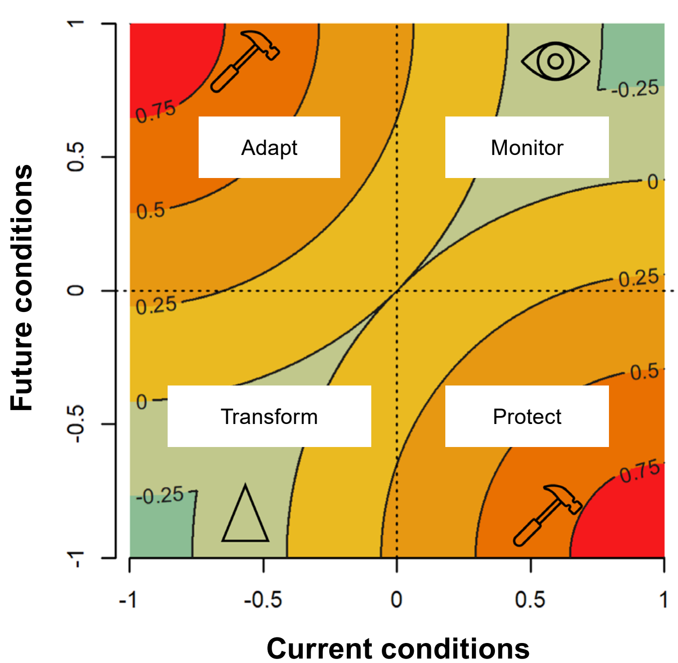


Figure 5—Management impact (MI) score values associated with the combination of current and potential future conditions relative to desired target conditions. MI scores are higher in areas more strongly associated with adapt and protect conditions (MI values closer to +1), where management value is greatest in the near term. Impact scores are lower in areas associated with monitor and transform conditions (MI values closer to −1), where management is either not needed or is less likely to be able to achieve or maintain desired target conditions.

Reducing risks to areas classified as "protect" serves the goal of keeping the benefits that already exist on the landscape and not losing them over time. An example would be patches of large and old trees that future modeling suggests have a high likelihood of loss over time owing to high-severity fire. Management targeting these units, or areas around these units, to reduce high-severity fire hazard would have a high management benefit in terms of retaining these valued resources.

Management investments in areas classified as "adapt" serve the goal of bringing areas into desired condition that are likely to retain desired conditions into the future. For example, a currently dense, young forest patch that is outside of desired condition may, over a 40-year simulation, attain desired mature forest structure, disturbances, and carbon sequestration that contribute to deficits in these conditions, making it a valuable investment for management. Management could intervene by thinning out shade-tolerant species to ensure desired characteristics are met in the shorter term. The future modeling results are used to identify locations where management investment is most likely to have lasting results. Prioritizing these areas for management can facilitate and accelerate the achievement of desired conditions.

Areas classified as "monitor" are those that are currently close to or within desired conditions. These areas may not need any management input in the short term, but threats to areas can change over time, so monitoring their condition and associated threats is the appropriate management input. As a result, locations that are dominated by monitor areas would not be as much of a priority as areas that need work or are at risk. Where these conditions occur, however, there are also opportunities for building onto these areas to increase the extent of resource conditions that may be limited at the watershed or basin scales. For example, some vegetation types and plant communities can be limited in their extent in some areas within their geographic range as a function of past disturbance or other impacts and barriers. Monitor areas that support such limited vegetation types (or other limited conditions) can serve as effective anchors to expand the extent of conditions for which there is a greater desired target extent.

Finally, areas classified as "transform" are not within desired target conditions, and based on future modeling, they have not demonstrated the ability to achieve desired conditions over the next 20 years in the absence of management. As such, they may or may not be able to achieve and maintain desired conditions and are considered as potential areas for transform management strategies. However, the intention is not to give up on these areas, rather they are merely of lower priority owing to the uncertainty in their ability to achieve and maintain desired conditions, which is particularly relevant in cases where the area that can be treated is less than the area that would benefit from management. As climate change and other anthropogenic stressors continue to catalyze change on the landscape, transforming conditions on the landscape to alternative vegetation types or lifeforms are more and more likely. Areas that are strongly in the transform category represent places on the landscape that have a high likelihood of transitioning to different, potentially less favorable, conditions (e.g., shrublands) providing a different, potentially diminished, set of benefits into the future. This could lessen the burden on management to achieve these goals elsewhere on the landscape.

Management strategy score—

The management strategy score is a second application of the juxtaposition of current and future potential conditions relative to desired target conditions; it reflects the management strategy most closely associated with current and future potential site conditions relative to desired target conditions (fig. 6). The management strategy score ranges from +1 (strong association) to −1 (weak association) within a given strategy. The score is intended to provide managers with site-specific information on the management strategies that are most indicated by current status and future indications for conditions. Management strategies that are most aligned with the future potential to achieve and maintain desired conditions will result in three important outcomes: (1) management effectiveness is improved; (2) the impact of management investments is enhanced; and (3) the pace of restoration is accelerated by maintaining areas in good condition, while bringing additional areas into desired condition.

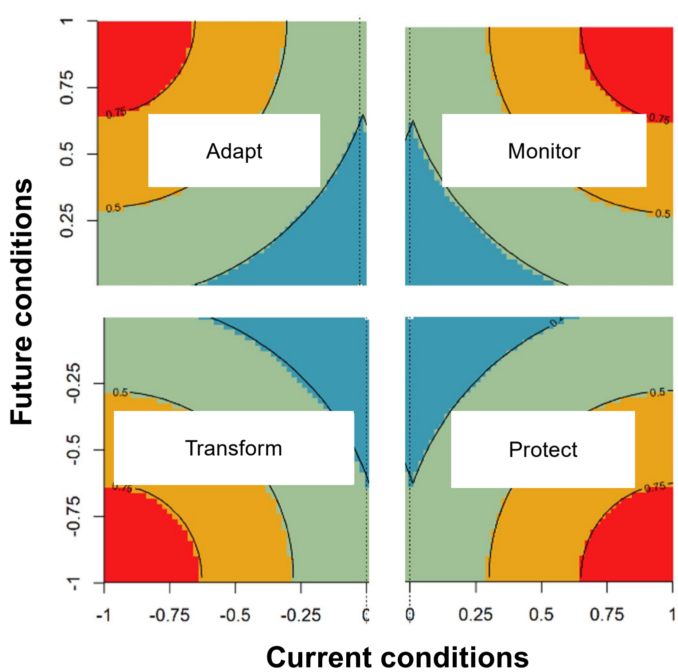


Figure 6—Management strategy (MS) score values reflect site-specific conditions and their strength of affiliation with a given strategy based on their current and potential future condition relative to desired target conditions. Each location on the landscape is affiliated with one strategy (quadrant) and assigned a management strategy score, which represents their strength of association with that strategy, with strong association scores (MS values closer to +1) at the most extreme current and future potential conditions, and weak association scores (MS values closer to –1) where conditions are not strongly distinguished among strategies.

Management zones—

We grouped the TCSI landscape into seven management zones that define forest management jurisdiction (fig. 7). National forest was separated into three categories based on administrative rules for timber harvest and wildfire management: general forest, roadless, and wilderness. Private land ownership was divided into private industrial and private nonindustrial timberlands using the California Department of Forestry and Fire Protection (CAL FIRE) timber harvest plan tracking system.

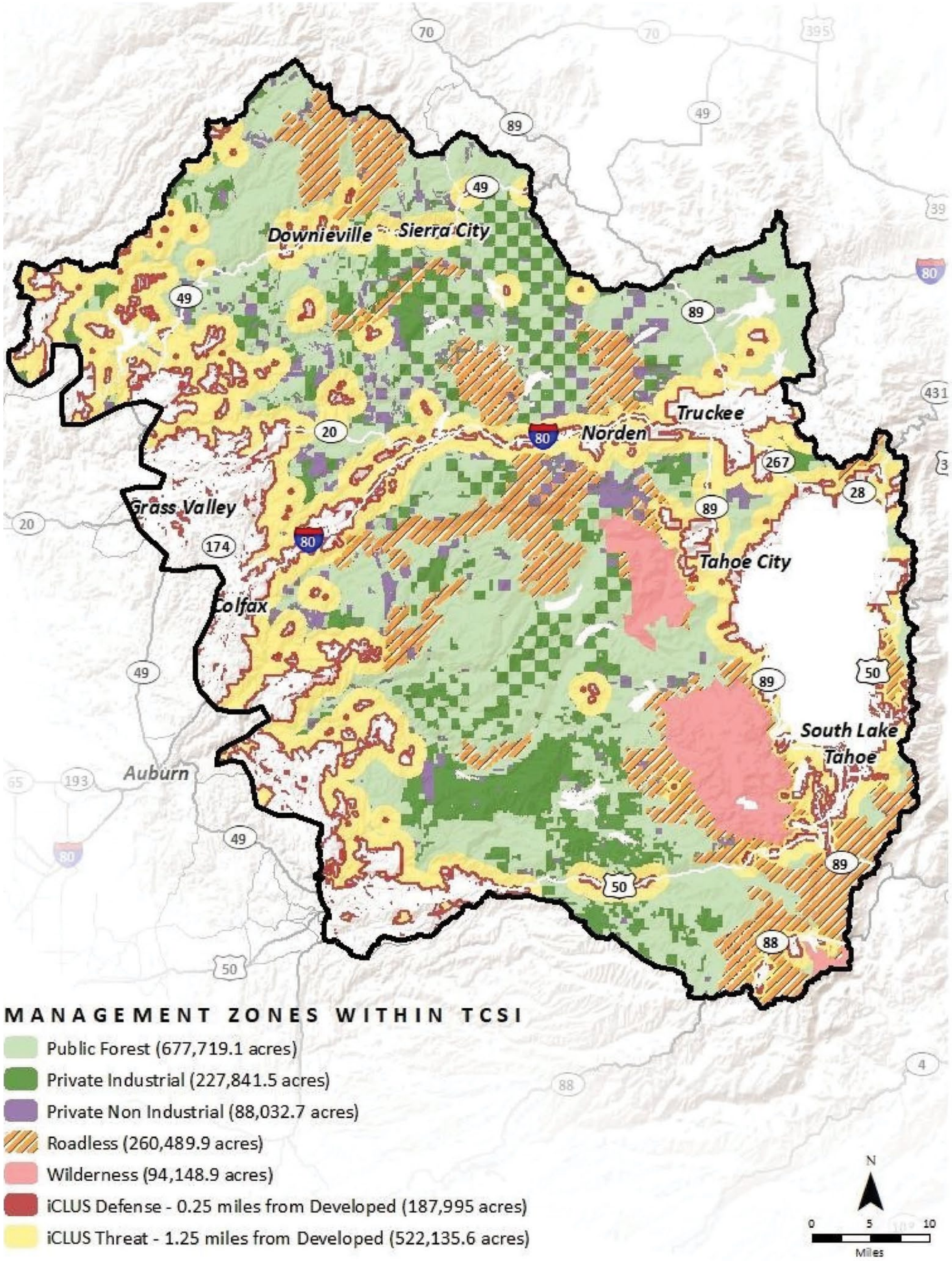


Figure 7—Management zones within the Tahoe-Central Sierra Initiative (TCSI) landscape by jurisdiction. ICLUS = Integrated Climate and Land Use Scenarios v2.1.

The CAL FIRE timber management dataset indicates only if a landowner enrolled their property into the timber production zone; it does not always mean the land is industrial or nonindustrial. This was the best dataset available to distinguish between the two. Defense and threat zones were based on buffered distances from developed areas, 0.25 and 1.25 mi, respectively. Developed areas were identified using the Integrated Climate and Land Use Scenarios (ICLUS) v2.1 Shared Socioeconomic Pathways (SSPs) 2 database (USEPA ORD 2017), and buffers away from developed areas were delineated as defense or threat zones.

The two largest management zones are public forest and ICLUS threat zones, which combined cover more than half of the TCSI forested landscape (fig. 7). Roadless and wilderness zones represent 13 and 5 percent, respectively, while private industrial and private nonindustrial zones represent 11 and 4 percent, respectively. Five national forests overlap the TCSI: Tahoe National Forest (44 percent of the TCSI), Eldorado National Forest (23 percent), Lake Tahoe Basin Management Unit (9 percent), Plumas National Forest (3 percent), and Humboldt-Toiyabe National Forest (<1 percent).

Logic Model Orientation

Logic model diagrams are included in each of the following pillar sections. EMDS system tools use a wide variety of mathematical and logic operators (table 1) for combining the standardized indicator scores. The most prevalent logic (i.e., fuzzy logic) operators used in the pillar models are the UNION and AND operators, which correspond to an average function and minimum/limiting function, respectively. A template of a basic logic model is displayed in figure 8. The choice between logic operators typically has significant consequences for model results.

Table 1—Logic model operators

Operator code	Operator	Description
A	AND	An AND node is true when all of its antecedents are true. It is false when any one of its antecedents is false. Functionally, it performs a weighted average of the values of its antecedents unless one of the antecedents is fully false. Compare this with the next definition of UNION.
U	UNION	A UNION node is true when all of its antecedents are true. It is false when all of its antecedents are false. As a practical distinction between AND and UNION nodes, antecedents to AND function like limiting factors, whereas antecedents to UNION function like compensating factors.
Q	QUADRANT	The point in the logic model where condition scores are translated to adapt-protect quadrant scores.

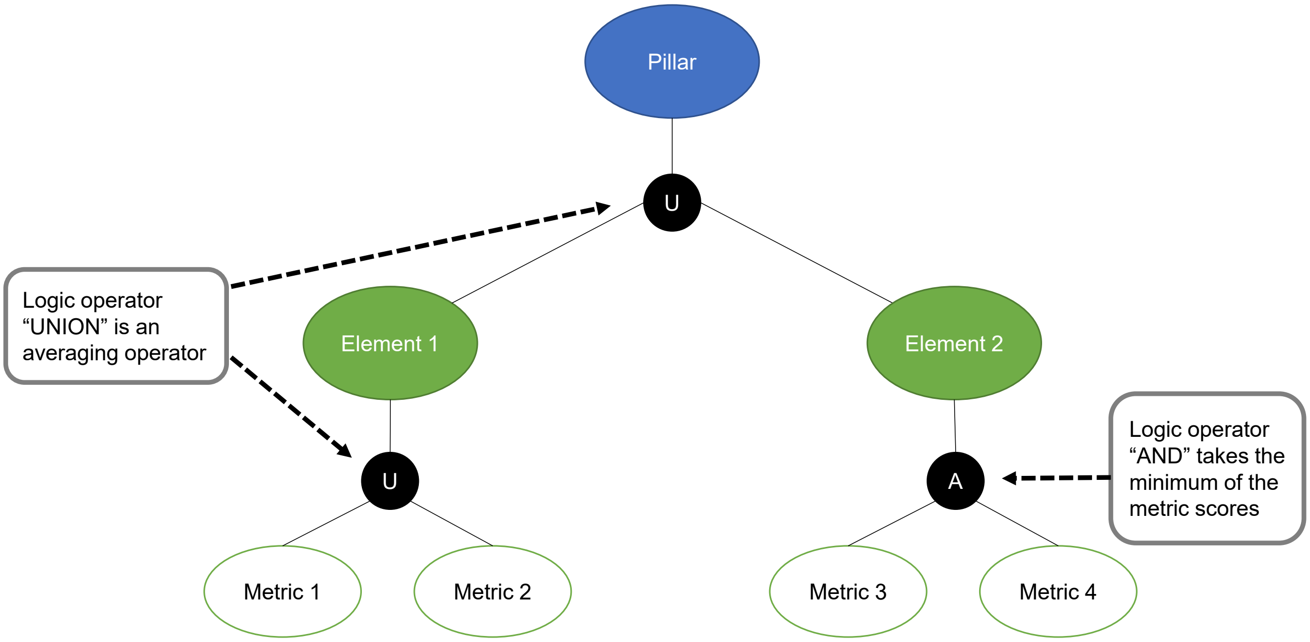


Figure 8—Diagram of a logic model demonstrating fuzzy/logical operators between pillars, elements, and metrics.

Forest Resilience Pillar

Overview

The forest resilience pillar evaluates forest vegetation composition and structure to determine their alignment with desired disturbance dynamics through time, within the tolerances of current and future biophysical conditions and considering changes due to climate change. There are three elements to this pillar: structure, composition, and disturbance, and each has specific metrics (figs. 9 and 10).

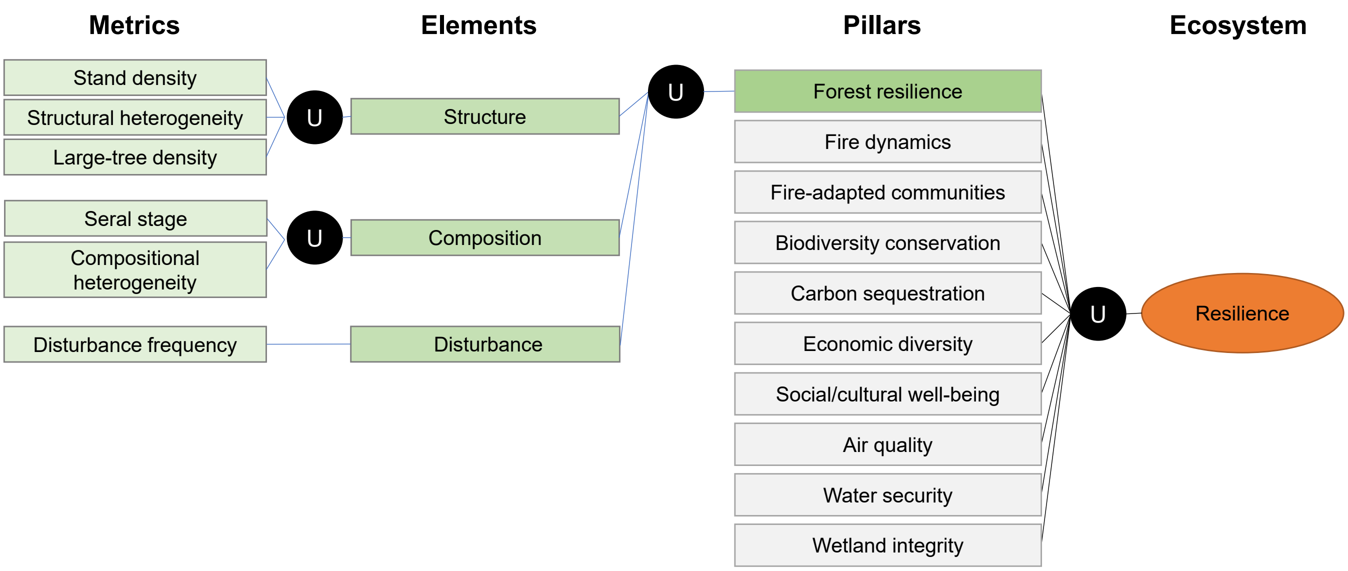


Figure 9—Metrics and elements representing the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. U = “UNION” logic model operator.

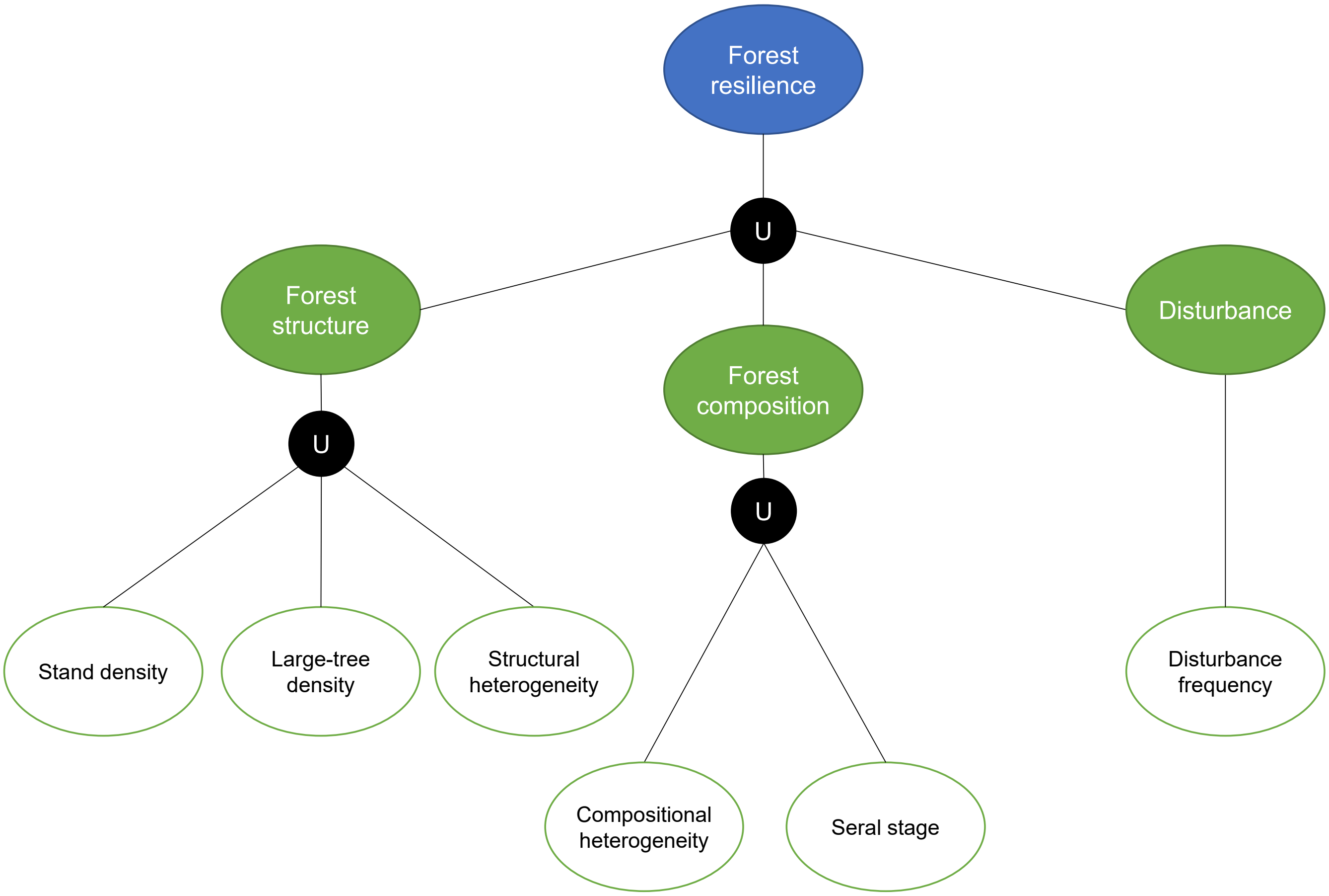


Figure 10—Forest resilience pillar logic model with associated elements and metrics in the Tahoe-Central Sierra Initiative Blueprint for Resilience. U = "UNION" logic model operator.

Vegetation Data and Modeling Methods

Current vegetation conditions were derived from multiple sources that were deemed appropriate for each metric. A primary source of current (2019) vegetation conditions was created by NCX using Landsat satellite data and imputation based on USDA Forest Service Forest Inventory and Analysis (FIA) data. NCX assigned an FIA tree list to each 15-m pixel based on the similarities in environments and spectral characteristics of the FIA plot and candidate pixel. This characterized tree density and basal area for each 1-ha pixel across the TCSI landscape and the contemporary reference sites based on 2019 NCX modeled vegetation. Through the California Forest Observatory system, imputed LiDAR data were used to assess canopy height and cover.

Future conditions were characterized at the 180-m (3.24-ha) scale across the TCSI landscape using modeling results from LANDIS-II that are based on 2019 NCX data. LANDIS-II model runs used the MIROC 8.5 climate scenario and a management scenario (management scenario 1) that modeled management on private commercial timber lands on an 80-year rotation and defense zone management (¼ mi around the built environment based on ICLUS [see "Fire-Adapted Communities Pillar"]). The MIROC climate scenario was considered the warm and dry scenario and was found to best represent recent wildfire activity compared to other tested scenarios. Management scenario 1 was a "business-as-usual" scenario and represented potential conditions with minimal amounts of human intervention to determine where management could help direct natural forest dynamics toward more resilient conditions. LANDIS-II landscape simulation model was used to represent future potential conditions for 2020–2060. The LANDIS-II model was run five times using the parameters for scenario 1, providing 5 replicates of each decadal interval, and 20 decade/replicate condition values to signify potential and variability of future conditions.

To establish target conditions for tree density and basal area, we used contemporary range of variability, which we define to reflect the stratification of reference site data based on climatic and topographic characteristics that enable extrapolation to conditions across the Sierra Nevada. Tree density and basal area target conditions represent conditions that are expected to be adaptable with future disturbance. By moving forested stands into their contemporary range of variability, it is expected that forests will continue to change over time in response to disturbance but maintain their characteristic species, functions, and benefits.

We stratified the TCSI landscape into management units based on their biophysical setting, similar to the methods of Jeronimo et al. (2019), which had described contemporary reference sites on federal lands across portions of the Sierra Nevada. The selected sites are areas where fires burned in proportions of severity similar to historical estimates and had no timber harvest. The contemporary reference areas covered about 21 000 ha across the Sierra Nevada, with a concentration in national parks in the southern end of the range. Jeronimo et al. (2019) stratified contemporary reference sites by climate classes and landscape management units. Climate classes are biophysical units based on several parameters, including climatic water deficit, January minimum temperature, actual evapotranspiration, and four topographic positions. Landscape management units (LMU) are topographic facets of the landscape: ridge, valley, and northeast- and southwest-facing slopes (Landscape Management Unit Tool v2) (North 2012). Climate class and landscape management unit classifications represent coarse- and fine-scale drivers, respectively, of forest structure that can inform restoration prescriptions to improve forest resilience (Jeronimo et al. 2019).

We developed a simplified four-class version of the landscape management unit layer that identified ridgetops, valley bottoms, northeast slopes, and southwest slopes. To make the sizes of the crossed units more realistic from a management perspective, we split landscape management units that were larger than 500 ha by watershed boundaries (hydrologic unit code 12 [HUC12] subwatersheds) and joined landscape management units smaller than 4 ha with neighboring landscape management units.

Each landscape management unit was then attributed to a majority climate class. Contemporary range of variability data did not exist for five of the fourteen climate classes within the TCSI landscape (135 856 ha, or 14 percent of the TCSI landscape). For these areas, we relied on adjacent climate class data. Northeast slopes and valleys in the **cold dry high montane** climate class and northeast slopes in the **foothill-low montane transition** climate class also lacked data. For these gaps, we used the maximum values from the other landscape management units for each respective climate class. The areas with extrapolated contemporary range of variability values are shown in table 2 and are included as an attribute in the spatial data.

Table 2—Contemporary range of variability in forest structure and thresholds used to define departure of current conditions

Climate class	Landscape management unit (LMU)	Tree density			Basal area			No reference,	inferred values
		Current	Target		Current	Target			
		Mean ± SD	10%	90%	Mean ± SD	10%	90%		
		- - - - Trees per hectare - - - -			*- - - - - - m^2 per hectare - - - - - -*				
Cold, dry, high montane	NE slope	220 ± 153	120	265	25 ± 18	18	45	Yes	Max of all LMUs
	Ridge	256 ± 174	120	265	29 ± 20	18	45	No	
	SW slope	190 ± 139	81	256	22 ± 16	16	36	No	
	Valley	264 ± 168	120	265	32 ± 22	18	45	Yes	Max of all LMUs
Cool, dry, high montane	NE slope	270 ± 171	63	247	32 ± 21	12	36	No	
	Ridge	298 ± 192	71	639	35 ± 24	16	84	No	
	SW slope	283 ± 173	68	325	32 ± 20	13	49	No	
	Valley	286 ± 166	61	246	34 ± 20	14	35	No	
Cool, dry, mid montane	NE slope	284 ± 181	100	255	32 ± 20	15	33	No	
	Ridge	322 ± 226	97	382	36 ± 26	15	44	No	
	SW slope	309 ± 192	92	383	35 ± 21	16	44	No	
	Valley	320 ± 197	106	413	35 ± 21	15	46	No	
Cool, mesic, high montane	NE slope	218 ± 148	49	261	26 ± 18	11	28	No	
	Ridge	243 ± 188	58	261	29 ± 24	13	27	No	
	SW slope	276 ± 180	60	254	32 ± 21	11	23	No	
	Valley	264 ± 168	45	179	30 ± 19	11	18	No	
Dry foothills, foothill valleys, hot, low montane, very hot, low montane	NE slope	418 ± 233*a*	87	411	37 ± 20[a]	12	54	Yes	Foothill-low Montane transition
	Ridge	526 ± 263[a]	87	411	48 ± 23[a]	12	54	Yes	
	SW slope	409 ± 219[a]	126	411	38 ± 20[a]	19	45	Yes	
	Valley	447 ± 215[a]	66	619	42 ± 20[a]	13	66	Yes	
Foothill-low montane transition	NE slope	443 ± 267	87	411	38 ± 24	12	54	Yes	Max of all LMUs
	Ridge	477 ± 276	87	411	42 ± 25	12	54	No	
	SW slope	362 ± 222	126	411	32 ± 20	19	45	No	
	Valley	441 ± 234	66	619	40 ± 21	13	66	No	
High Sierra	NE slope	159 ± 133	71	242	20 ± 17	13	37	No	
	Ridge	100 ± 95	117	710	15 ± 20	12	80	No	
	SW slope	200 ± 138	180	564	27 ± 19	29	79	No	
	Valley	150 ± 132	74	400	19 ± 17	13	51	No	
Warm, dry, low montane	NE slope	404 ± 240	81	439	40 ± 23	13	40	No	
	Ridge	454 ± 266	75	450	45 ± 25	13	49	No	
	SW slope	373 ± 225	76	598	37 ± 21	13	54	No	
	Valley	433 ± 229	104	588	43 ± 22	14	49	No	
Warm, mesic, low montane	NE slope	420 ± 246	65	323	43 ± 24	12	35	No	
	Ridge	476 ± 264	65	421	48 ± 26	13	45	No	
	SW slope	405 ± 249	74	381	42 ± 24	13	41	No	
	Valley	449 ± 257	67	383	46 ± 26	12	39	No	
Warm, mesic, mid montane	NE slope	311 ± 173	65	323	36 ± 20	12	35	Yes	Warm, mesic, low montane
	Ridge	348 ± 197	65	421	40 ± 22	13	45	Yes	
	SW slope	352 ± 192	74	381	39 ± 21	13	41	Yes	
	Valley	322 ± 166	67	383	36 ± 21	12	39	Yes	
Xeric, high montane	NE slope	261 ± 165	52	230	32 ± 20	13	39	No	
	Ridge	295 ± 167	62	325	35 ± 22	13	43	No	
	SW slope	264 ± 171	79	365	32 ± 21	15	45	No	
	Valley	276 ± 165	60	325	33 ± 22	15	43	No	

[a] = Only hot, low montane for current conditions; SD = standard deviation.

Forest Structure Element

Overview—

Prior to European settlement, forests in the Sierra Nevada were characterized by heterogeneous spatial patterns replete with individual large trees, gaps, and tree clumps of various sizes—patterns that were shaped by recurrent fire and other disturbances (North 2012, Taylor et al. 2014). After more than a century of fire exclusion, timber harvesting, and other land use practices, the predominant trend across Sierran forests is that they have become denser, with an ingrowth of small, shade-tolerant trees and less structural heterogeneity.

The forest structure element is represented by three metrics: stand density (M1), structural heterogeneity (M2), and large tree density (M3). Although snags are important structural components of forests, we were not able to get credible estimates of current or future standing dead trees so they are not included as a metric at this time in forest structure element.

M1: Stand density—

Importance and relevance—Quantitative estimates of forest tree density and basal area illustrate the degree to which current and future forest structural conditions are resilient or departed.

Description and derivation—In this metric, tree density and basal area are evaluated together as a single metric, stand density (aka structure departure from target), similar to the stand density index, which is often used to set density targets in restoration treatments of forested stands (North 2012). Here, a pixel with high basal area may be desirable if it is stocked with a few large-diameter trees but less desirable if it has a high density of small-diameter trees. Therefore, the combination of density and basal area allows for more meaningful comparisons to target forest structural conditions.

Forest structure comparisons were restricted to forests with quadratic mean diameter (QMD) >15.2-cm diameter at breast height (DBH) (stands with an average diameter of pole-size trees or larger), which excludes early-seral sites from this analysis. Given that contemporary reference sites used in the derivation of target conditions were chosen for their mature forest conditions, comparisons between them and early-seral (i.e., recovering from recent disturbance) pixels within the TCSI landscape would not be meaningful. Because the 15-m scale is too small to be useful for managers, the 15-m cell scores are summarized into 180-m (3.24-ha) patches and 720-m (51.84-ha) neighborhoods.

For current conditions, each mid- to late-seral, 15-m pixel is evaluated against target conditions for tree density and basal area individually, and then a composite structure score is calculated for each 15-m pixel scale. Target conditions (score = +1) for tree density were based on being below the 80th percentile of tree densities observed across corresponding LMU by climate class reference sites (Jeronimo et al. 2019). Condition scores drop from +1 to −1 between the 80th and 90th percentile densities.

Target conditions (score = +1) for basal area were based on being ≥20th percentile of basal areas observed across corresponding LMU by climate class reference sites (Jeronimo et al. 2019). Condition scores drop from +1 to −1 between the 20th and ≤10th percentile basal areas.

Tree density and basal area scores were then combined into a composite structure score that reflected the average of condition scores for the two metrics. At the 180-m patch and 720-m neighborhood scales, we calculated the proportion of 15-m pixels that were within target conditions (i.e., score = +1) (table 3, fig. 11).

Table 3—Tree density and basal area metric condition interpretation (logic model) in the forest structure element of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Current/future and scale	Data	Data source	Condition	Reference
Current tree density	15-m pixel	QMD >15.2 cm DBH; tree density for trees >15.2 cm DBH (LMU by CC reference)	NCX, contemporary reference areas, climate classes, landscape management units	Target: ≤80th percentile; fully departed: ≥90th percentile	Contemporary reference areas used as the source of target conditions
Current basal area	15-m pixel	QMD >15.2 cm DBH; basal area (LMU by CC reference)	NCX	Target: ≥20th percentile; fully departed: ≤10th percentile	Contemporary reference areas used as the source of target conditions
Current composite density	15-m pixel	Average of tree density score and basal area score assigned to cell	NCX	N/A	N/A
Current composite density	180-m patch	Proportion of 15-m pixels with condition score = +1 (2019)	NCX	Target: 100%; fully departed: 0%	N/A
Current composite density	720-m neighborhood	Proportion of 15-m pixel with condition score = +1 (2019)	NCX	Target: 100%; fully departed: 0%	N/A
Future composite density potential	180-m patch	Maximum decadal score 2020–2060	LANDIS-II scenario 1	20 chances to be in target	20 chances to be in target
Future composite density variability	180-m patch	Variability in decadal scores 2020–2060; 20 changes to be in target	LANDIS-II scenario 1	20 chances to be in target	20 chances to be in target
Future composite density potential	720-m neighborhood	Maximum decadal score 2020–2060	LANDIS-II scenario 1	20 × 16 chances to be in target	20 × 16 chances to be in target
Future composite density variability	720-m neighborhood	Variability in decadal score 2020–2060; 320 chances to be in target	LANDIS-II scenario 1	20 × 16 chances to be in target	20 × 16 chances to be in target

N/A = not applicable, QMD = quadratic mean diameter, DBH = diameter at breast height, LMU = landscape management unit, CC = climate class.

As such, the ramp from +1 to −1 for the individual metrics, or the composite structural metric, did not have any influence on patch and neighborhood scores (table 3, fig. 11).

For future conditions, each mid- to late-seral, 180-m patch was evaluated against target conditions at each decade of the 40-year simulation. This was repeated across the 5 replicates, for a total of 20 decade/replicate opportunities to achieve target conditions. We then calculated the proportion of cells within the 720-m neighborhood that were within target conditions for each of the 20 decade/replicate opportunities. The maximum score was selected to reflect the potential to reach target conditions under climate change. The standard deviation of the 20 scores was calculated for each cell to represent its variability over time (table 3, fig. 11).

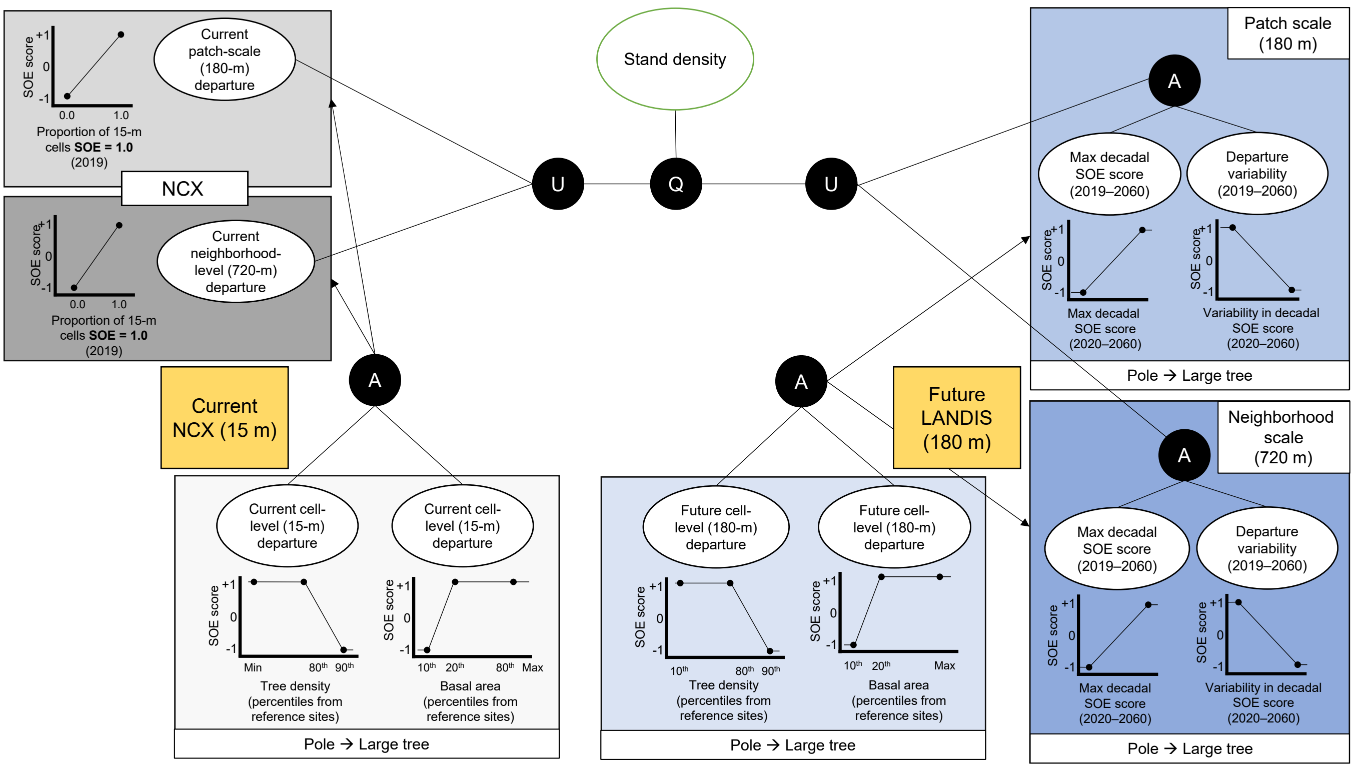
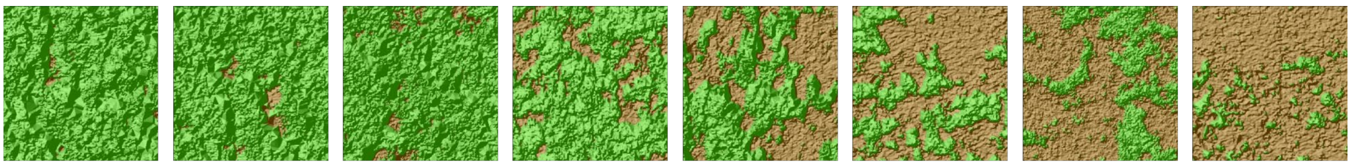


Figure 11—Tree density and basal area metric logic model of the forest resilience pillar shown as stand density (structure departure) in the Tahoe-Central Sierra Initiative Blueprint for Resilience. SOE = strength of evidence; logic model operators: A = AND; Q = QUADRANT; U = UNION.

M2: Structural heterogeneity—

Importance and relevance—Another key component to forest structure descriptions is the spatial heterogeneity (i.e., tree clumps and gaps), which influences vegetation growth, competition, succession, disturbance processes, and wildlife habitat. Developing spatial heterogeneity through mechanical and prescribed fire treatments is often a goal of restoration projects, and historical estimates of stand structure are often used to develop targets for the distribution of individual trees, clumps, and gaps.

Although many facets of heterogeneity can be measured and implemented during restoration projects, the two metrics that best characterized spatial heterogeneity based on 3-m resolution California Forest Observatory data are the percentage of area in gaps and the fractal dimension. The fractal dimension evaluates how fragmented the canopy is, with low values indicating closed canopy conditions and larger values indicating more clumps and gaps (fig. 12).



1.1 1.2 1.3 1.4 1.5 1.6 1.7 1.8

Figure 12—Fractal index values. Courtesy of Van Kane, University of Washington.

Description and derivation—In collaboration with the University of Washington, we used 3-m resolution California Forest Observatory canopy height data to develop a metric of heterogeneity for the TCSI landscape, representing 2020 conditions. This method compares the TCSI landscape to contemporary reference conditions, but instead of using percentiles to evaluate departure, "statistical distance" was used. That is, departure is evaluated using the number of standard deviations away from the average reference condition. The further away, the higher the departure (in either negative or positive direction). There is no way to develop a similar metric using LANDIS-II data owing to the coarse resolution of that model's outputs (i.e., 180-m by 180-m patches), so this metric was applied only to current conditions.

Target values were derived from contemporary reference conditions similar to other structure metrics described here (see "Vegetation Data and Modeling Methods" above), but instead of using percentiles to evaluate departure, departure from target conditions was evaluated using a measure of statistical distance. That is, departure is evaluated using z-scores, which are the number of standard deviations away from the average reference condition. The further away, the higher the departure in either negative or positive direction (table 4, fig. 13).

Table 4—Structural heterogeneity metric condition interpretation (logic model) in the forest structure element of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Current/future and scale	Data	Data source	Condition	Reference
Current percent gap	3-m cells characterized at 90-m scale	Statistical distance from contemporary reference (z-score)	California Forest Observatory 3-m data, contemporary reference areas	Target: 0 standard deviations away from the average reference condition Fully departed: +3 or −3 standard deviations away from the average reference condition	Jeronimo et al. (2019)
Current fractal dimension	3-m cells characterized at 90-m scale	Statistical distance from contemporary reference (z-score)	California Forest Observatory 3-m data, contemporary reference areas	Target: 0 standard deviations away from the average reference condition Fully departed: +3 or −3 standard deviations away from the average reference condition	Jeronimo et al. (2019)

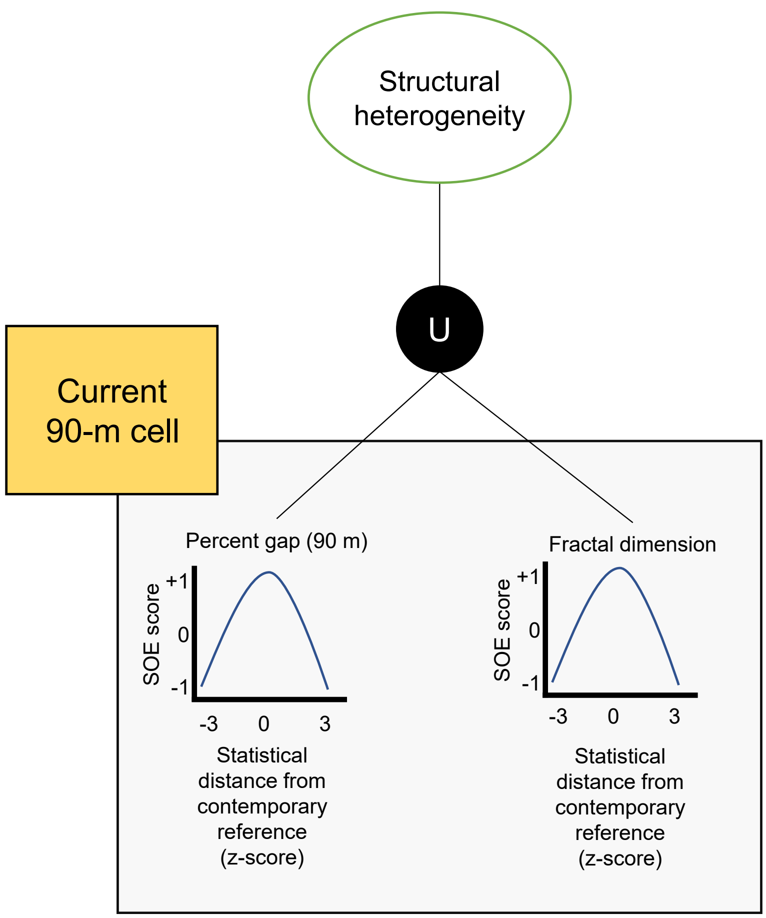


Figure 13—Structural heterogeneity metric logic model of forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. SOE = strength of evidence; U = "UNION" logic model operator.

M3: Large tree density—

Importance and relevance—Large old trees perform valuable functions in forest ecosystems, providing resources or other services, such as providing wildlife habitat. For example, California spotted owls are strongly associated with forest stands characterized by large-diameter or tall trees with dense canopy cover (North et al. 2017, Verner et al. 1992, Zielinski et al. 2004). Large trees contribute to critical processes, such as nutrient cycling, carbon storage, and hydrologic processes. In fire-prone systems, large trees have a greater likelihood of survival from fire than smaller diameter trees (Hood et al. 2007).

Forest structure across the Sierra Nevada is currently dominated by areas with small- and medium-size trees (Dolanc et al. 2014, McIntyre et al. 2015). The abundance of trees 10.2 to 30.5 cm DBH is estimated to have doubled in density in the Sierra Nevada between the 1930s and 2000s (McIntyre et al. 2015). The abundance of large trees in the Sierra Nevada is generally considered much lower today compared to pre-European settlement (Dolanc et al. 2014, McIntyre et al. 2015, North 2012), especially for trees >70.0 cm DBH (Dolanc et al. 2014). One study found large trees had declined by at least 50 percent between the 1930s and 2000s (McIntyre et al. 2015). However, variations in large tree density have been observed. For example, a study in the southern Sierras found trees 70.0 to 91.4 cm DBH were more common today than were found historically (Stephens et al. 2015). Although the precise size threshold above which larger trees are in deficit may vary between specific areas, a study across the central and northern Sierra Nevada (i.e., including the TCSI landscape) found a significant decline in the abundance of trees >91.4 cm DBH throughout the area (Dolanc et al. 2014). As such, protecting larger trees is often the focus of forest management along with fostering the development of future ones.

Description and derivation—Large trees were defined as ≥91.44 cm (36 inches) DBH. Large tree abundance target was based on contemporary reference sites (Jeronimo et al. 2019). These values were similar to estimates from Stephens et al. (2015), which found roughly 15 large trees per hectare for Sierran forests prior to European settlement.

The density of large trees was assessed using the contemporary reference sites for the evaluation of both the current and future conditions. Target densities were established separately for each climate class and LMU combination, similar to the forest structure metrics. Target values represented the 90th percentile for a given climate class and LMU setting, and values ranged from 4 to 33 large trees per hectare (median: 11 trees per hectare). Having zero large trees yields a condition score of −1. A pixel with a single large tree per hectare received a condition score of 0. This latter score was determined by a committee within a user group work session in which participants felt that the presence of even a single large tree should result in a neutral (i.e., non-negative) score. Current condition data for large tree density came directly from the NCX vegetation data layer. Future condition large tree densities were derived from LANDIS-II biomass outputs for the oldest size class (i.e., size class 5). A linear model was developed using FIA plot-level data to predict large tree density from biomass of trees >91.4 cm (adjusted $R^2 = 0.917$).

Patch-scale abundance was evaluated by taking the proportion of 15-m pixels within a 180-m window with condition scores greater than +1 (fig. 14). Patch-scale scores were evaluated on a linear scale from 0 to +1, where patches with 0 percent of pixels within target received a condition score of −1 and those with 100 percent of pixels within target received a score of +1. Neighborhood abundance was evaluated by taking the proportion of 15-m pixels within a 720-m window with condition scores greater than +1, and condition scores were calculated as described above.

For future potential conditions, the condition score reflected the degree to which target large tree abundance was reached (how many replicates of the 10-year time steps, 40 in total), and also how variable was large tree density over the replicates by time steps (fig. 14). The greater the abundance and lower the variability, the higher the SOE score that indicates the target condition could be met (table 5).

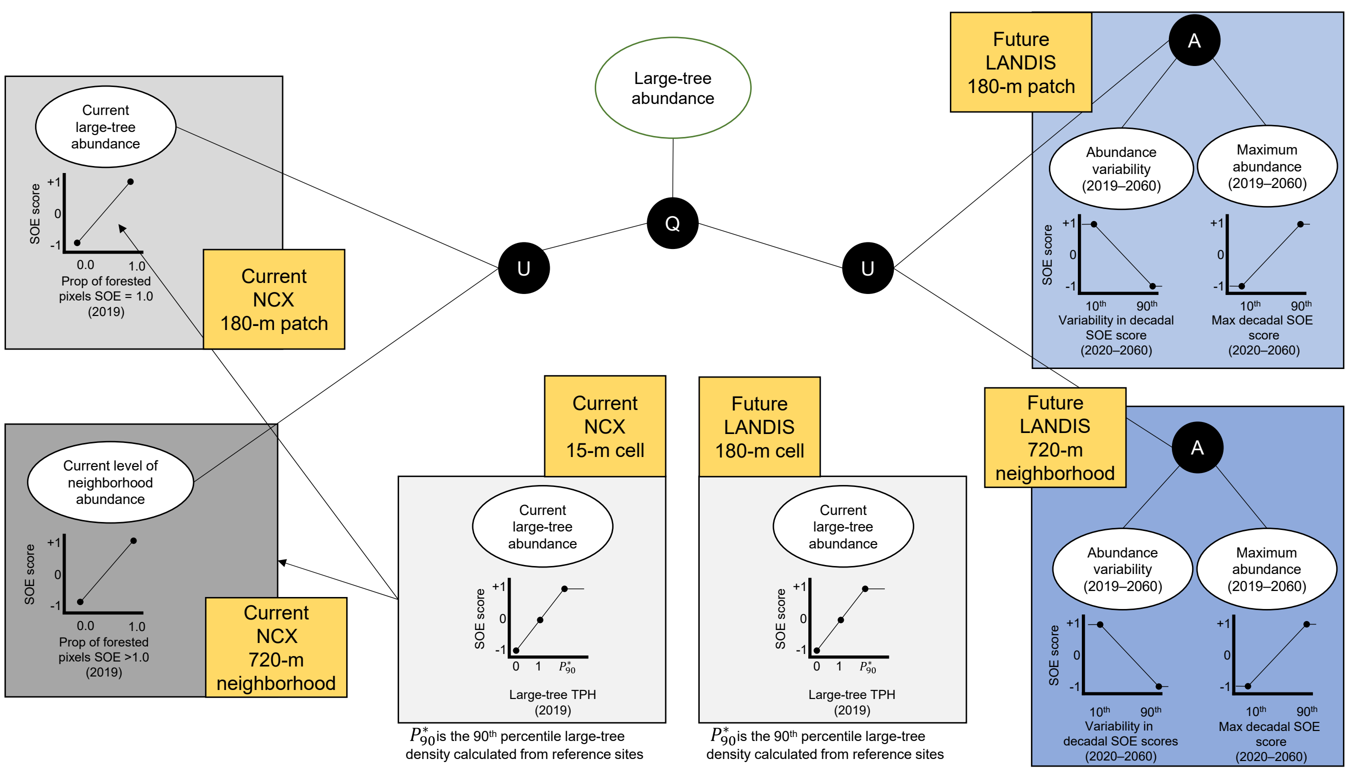


Figure 14—Large tree metric logic model as part of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. THP = trees per hectare, SOE = strength of evidence; logic model operators: A = AND; Q = QUADRANT; U = UNION.

Table 5—Large tree density metric condition interpretation in the forest structure element of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Scale	Data	Data source	Condition	Reference
Current large tree abundance	15-m pixel	TPH ≥91.4 cm DBH	NCX, contemporary reference conditions	Target: ≥90^{th} percentile of reference condition Marginal: 1 TPH Fully departed: 0 TPH	Jeronimo et al. (2019), Stephens et al. (2015)
Current large tree abundance	180-m patch	Proportion of 15-m pixels within target conditions	NCX, contemporary reference conditions	Target: 100% Fully departed: 0%	N/A
Current large tree abundance	720-m neighborhood	Proportion of 180-m patches within target conditions	NCX, contemporary reference conditions	Target: 100% Fully departed: 0%	N/A
Future large tree abundance variability	180-m patch	Variability in decadal scores (2020–2060)	LANDIS-II	Target: ≤10^{th} percentile Fully departed: ≥90^{th} percentile	N/A
Future large tree abundance potential	180-m patch	Maximum decadal condition score (2020–2060)	LANDIS-II	Target: ≥90^{th} percentile Fully departed: ≤10^{th} percentile	N/A
Future large tree abundance variability	720-m neighborhood	Variability in decadal scores (2020–2060)	LANDIS-II	Target: ≤10^{th} percentile Fully departed: ≥90^{th} percentile	N/A
Future large tree abundance potential	720-m neighborhood	Maximum decadal score (2020–2060)	LANDIS-II	Target: ≥90^{th} percentile Fully departed: ≤10^{th} percentile	N/A

DBH = diameter at breast height, TPH = trees per hectare, N/A = not applicable.

Forest Composition Element

Overview—

Tree species composition affects many aspects of forest dynamics and function. A diversity of tree and shrub species can confer greater resilience to climate change and beetle outbreaks. Tree species composition, of course, has substantial influence on other pillars, fire dynamics, water security, carbon sequestration, and economic diversity. Since European settlement and the adoption of fire suppression and logging, forests of the Sierra Nevada have shifted to increased dominance of shade-tolerant and fire-intolerant species, such as white fir (*Abies concolor* (Gord. & Glend.) Lindl. Ex Hildebr.), red fir (*Abies magnifica* A. Murray bis), incense cedar (*Calocedrus decurrens* (Torr.) Florin), Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco), and tanoak (*Notholithocarpus densiflorus* P.S. Manos, C.H. Cannon, & S.H. Oh) (Safford and Stevens 2017). Other species such as ponderosa pine (*Pinus ponderosa* Lawson & C. Lawson), Jeffrey pine (*Pinus jeffreyi* Balf.), sugar pine (*Pinus lambertiana* Douglas), and black oak (*Quercus kelloggii* Newberry), which are more shade-intolerant and fire-tolerant, declined in coverage (Safford and Stevens 2017). With increasingly larger and higher severity fire occurring, forest cover loss may be significant and shrub cover will increase.

The forest composition element has two main components: seral stage and compositional heterogeneity. Seral stage (M1) is a stand-alone metric. Compositional heterogeneity (M2) is divided into four submetrics: tree species diversity (M2a), tree species evenness (M2b), fire resistance (M2c), and risk of forest type conversion (M2d). In addition, beta diversity of tree species (within HUC12 subwatersheds) and beetle resistance are two metrics of interest that are being explored for a future version of the TCSI Blueprint.

M1: Seral stage—

Importance and relevance—The distribution of seral stages across landscapes was highly variable prior to major European settlement in the Western United States. These patterns were highly attuned to dominant disturbance regimes and the multiscaled variability in environmental conditions across topographic and climatic gradients. These patterns helped to reinforce fire regimes dominated by low- to moderate-severity fire across much of the region and provided for multiple habitat requirements for a wide variety of species.

Description and derivation—Seral stages were defined by average tree diameter, as per the California Wildlife Habitat Relationships (CWHR) database system (Mayer and Laudenslayer 1988) displayed in table 6. Because seral stage patterns can be highly variable at finer scales, it was evaluated here at the HUC10 watershed scale. There are 32 HUC10 watersheds on the TCSI landscape. The metric includes the percentage of a given landscape unit in early- and late-seral stages at the HUC10 and HUC12 scales.

Table 6—Seral stage classes and diameter at breast height (DBH) values from the California Wildlife Habitat Relationships database system (Mayer and Laudenslayer 1988)

Size class	Size (DBH)	Size (DBH)	Seral stage
	Inches	*Centimeters*	
1 seedling	<1	<2.5	Early
2 sapling	1–6	2.5–15.2	Early
3 pole	6–11	15.2–27.9	Mid
4 small	11–24	27.9–61.0	Mid
5 medium	24–36	61.0–91.4	Late
6 large	36–48	91.4–121.9	Late
7 extra large	>48	>121.9	Late

For target conditions, a different approach was used for early-seral compared to late-seral conditions. Target percentages for early-seral conditions (stand-replacing patches) primarily reflect the value of seral stage diversity, with less emphasis on the ecological value of early-seral conditions themselves. Target percentages for early-seral conditions were based on Collins and Stephens (2010). They found that stand-replacing patches made up 15 percent of the burned area between two mixed-severity fires in Yosemite. We increased this slightly up to 20 percent to allow leeway for some landscape units to provide a higher level of early-seral habitat and to also reflect feedback from the user group, which suggested that 20 percent of the area burned at high severity in large fires would be a positive outcome.

Target percentages for late-seral conditions reflect both the value of seral stage diversity and the value of late-seral conditions themselves, which contribute many valuable ecosystem services, such as to air and water quality. Target values for late-seral conditions are based on minimum percentages as opposed to a target range with maximums.

For current conditions, seral stage was determined based on NCX data input into LANDIS-II for modeling. Current conditions were evaluated based on starting conditions in LANDIS-II, with seral stage being derived from biomass by age class (back casting methods developed by NCX). Early-, mid-, or late-seral stage was assigned to each 180-m patch. The percentage of early- and late-seral condition in each HUC10 watershed was calculated and compared against the target condition values. HUC10 units within target conditions are assigned a score of +1. Early-seral condition scores declined from target conditions (score = +1) at 20 percent to fully departed from target conditions at 0 percent (table 7; fig. 15). Late-seral condition scores declined from target conditions (score = +1) at 25 percent to fully departed at 0 percent (table 7; fig. 15). The minimum (AND operator) was used to combine these scores to reflect the seral stage with the lowest level of support for obtaining desired conditions.

Table 7—Seral stage metric condition interpretation in the forest composition element of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Scale	Data	Data source	Condition	Reference
Current seral stage	180-m patch	Seral stage assignment: early, mid, late	LANDIS-II, NCX	N/A	N/A
Current-early-seral percentage	HUC10	Early-seral percentage (2019)		Target: ≥20 Fully departed: 0%	N/A
Current late-seral percentage	HUC10	Late-seral percentage (2019)		Target: ≥25% Fully departed: 0%	N/A
Current early-seral percentage	HUC12	Early-seral percentage (2019)		Target: ≥20% Fully departed: 0%	N/A
Current late-seral	HUC12	Late-seral percentage (2019)		Target: ≥25% Fully departed: 0%	N/A
Future seral stage	180-m patch	Seral stage assignment for each 20: early mid, late seral	LANDIS-II, NCX, 20 decade/replicate assignments	N/A	N/A
Future potential early-seral percentage	HUC10	Maximum condition score (2020–2060)		N/A	N/A
Future early-seral variability percentage	HUC10	Standard deviation in condition score (2020–2060)		Target: ≤10th percentile Fully departed: ≥90th percentile	N/A
Future late-seral potential percentage	HUC10	Maximum condition score (2020–2060)		N/A	N/A
Future late-seral variability percentage	HUC10	Standard deviation in condition score (2020–2060)		Target: ≤10th percentile Fully departed: ≥90th percentile	N/A
Future early-seral potential percentage	HUC12	Maximum condition score (2020–2060)		N/A	N/A
Future early-seral variability percentage	HUC12	Standard deviation in condition score (2020–2060)		Target: ≤10th percentile Fully departed: ≥90th percentile	N/A
Future late-seral potential percentage	HUC12	Maximum condition score (2020–2060)		N/A	N/A
Future late-seral variability percentage	HUC12	Standard deviation in condition score (2020–2060)		Target: ≤10th percentile Fully departed: ≥90th percentile	N/A

N/A = not applicable, HUC = hydrologic unit code.

Size	Diameter	Seral
Seedling	<1"	Early
Sapling	1–6"	Early
Pole	6–11"	Mid
Small tree	11–24"	Mid
Medium tree	24–36"	Late
Large tree	36–48"	Late
XL tree	>48"	Late

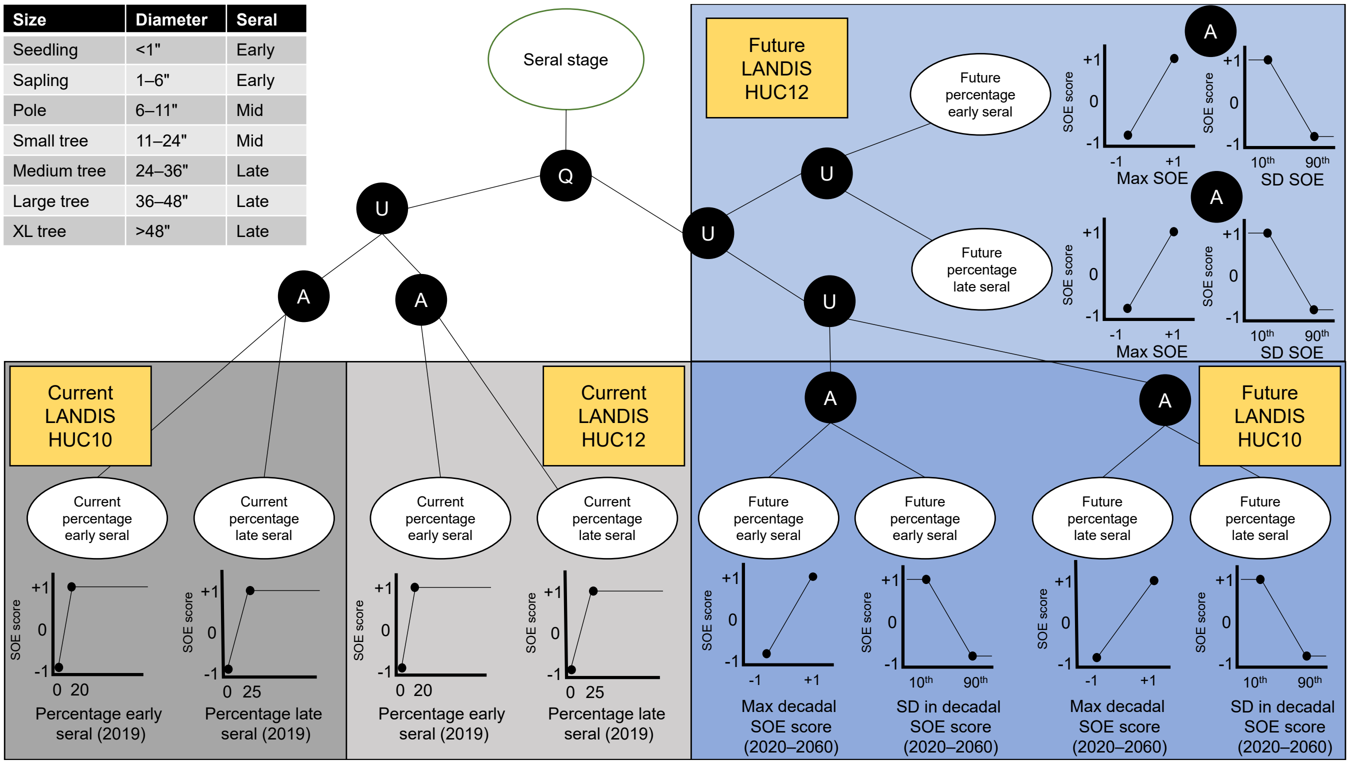


Figure 15—Seral stage metric logic model in the composition element of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. HUC = hydrologic unit code, SOE = strength of evidence; logic model operators: A = AND, Q = QUADRANT, U = UNION.

For future seral conditions, LANDIS-II modeling was used to evaluate every decade over the next 40 years and for each of the five replicates. Seral stage was assigned to each 180-m patch for each of the 20 decade/replicates. Condition scores were calculated to represent the potential (i.e., maximum condition value across all 180-m patches) and variability (i.e., standard deviation of the condition value across all 180-m patches) for early- and late-seral conditions across the 20 decade/replicates. Target conditions for variability is represented by standard deviation values across the 20 decade/replicates at the HUC10 scale in the $\leq 10^{th}$ percentile and fully departed variability is represented by values in the $\geq 90^{th}$ percentile (table 7; fig. 15). The minimum of the potential condition and variability scores are used to provide an overall representation of each seral stage (early and late); then early- and late-seral conditions are averaged to represent the condition of the seral-stage metric. Future condition scores at the HUC10 scale were then calculated based on the average score across 180-m patches (table 7; fig. 15).

M2: Compositional heterogeneity—

Compositional heterogeneity (M2) is divided into four submetrics: tree species diversity (M2a), tree species evenness (M2b), fire resistance (M2c), and risk of forest type conversion (M2d). These are individually explained in the following sections; all are based on the logic diagram in figure 16.

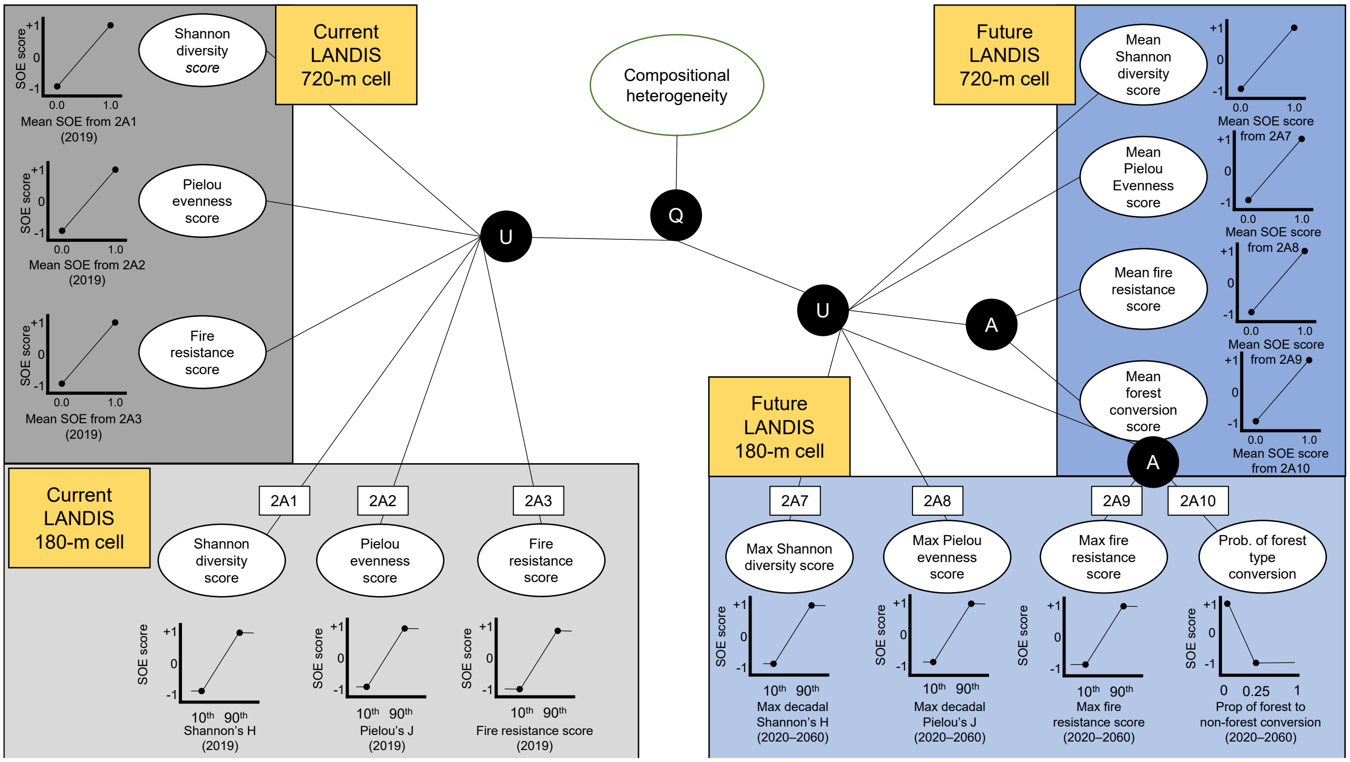


Figure 16—Compositional heterogeneity logic model and associated metrics in the composition element of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. Number-letter combinations in rectangles above graphs for current and future LANDIS-II 180-m cells denote calculations used for derivation of strength of evidence (SOE) scores for x-axis in LANDIS-II 720-m cell current and future LANDIS-II SOE score graphs. Logic model operators: A = AND, Q = QUADRANT, U = UNION.

M2a: tree species diversity—

Importance and relevance—Individualistic species-level responses to climate change will determine the degree to which forest composition will shift over time and the ability for certain species to remain in their current geographic range. Given the high level of uncertainty of species' responses to climate and future disturbances, areas with greater tree species diversity will likely be most responsive to the changing conditions as certain species may be better able to cope with the new environments moving forward. Where the dominant species is susceptible to disturbances, such as insect outbreaks or wildfire or other chronic conditions, such as high ozone levels or climatic water deficit, low species diversity may be poised for greater ecological change.

Description and derivation—LANDIS-II model outputs were used to characterize diversity at the 180-m patch scale by their tree species composition based on the amount of biomass represented by each species present across all age classes.

The Shannon diversity index (H) was calculated for each 180-m patch at time zero (i.e., 2019), for each decade of the 40-year simulation period, and across all five replicates for the future conditions (n = 20 decade/replicate values). The Shannon diversity index accounts for both abundance and evenness of the species present (Shannon 1948). The proportion of a given species (i) relative to the total number of species occurrences across all species (pi) is calculated then multiplied by the natural logarithm of this proportion (lnpi). The resulting product is summed across all species and multiplied by −1, as in the following formula:

$$H = -\sum_{i=1}^{S} pi \ln pi$$

High scores were assigned to patches with higher tree species diversity, and target condition scores were based on the distribution of H across decades.

Target conditions (score = +1) were assigned to cells with H above the 90th percentile condition across all model runs (table 8; fig. 16). Pixels with diversity indices in the ≤10th percentile were considered fully departed from target conditions and assigned a score of −1. The Shannon diversity index was only evaluated at the 180-m patch scale because larger areas (such as the 720-m neighborhood scale) are better aligned with measures of beta diversity.

Table 8—Tree species diversity and evenness metrics condition interpretations in the forest composition element of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Scale	Data	Data source	Condition	Reference
Current tree species diversity	180-m patch	Shannon diversity index based on the biomass of each tree species	NCX and LANDIS-II	Target: ≥90% Fully departed: ≤10%	Shannon (1948)
Current tree species diversity	720-m neighborhood	Mean 180-m patch SOE score	NCX and LANDIS-II	N/A	N/A
Current tree species evenness	180-m patch	Pielou evenness index based on the biomass of each tree species	NCX and LANDIS-II	Target: ≥90% Fully departed: ≤10%	Pielou (1966)
Current tree species evenness	720-m neighborhood	Mean 180-m patch SOE score	NCX and LANDIS-II	N/A	N/A
Future tree species diversity	180-m patch	Maximum Shannon diversity index based on the biomass of each tree species	NCX and LANDIS-II	Target: ≥90% Fully departed: ≤10%	N/A
Future tree species diversity	720-m neighborhood	Mean 180-m patch SOE score	NCX and LANDIS-II	N/A	N/A
Future tree species evenness	180-m patch	Maximum Pielou evenness index based on the biomass of each tree species	NCX and LANDIS-II	Target: ≥90% Fully departed: ≤10%	N/A
Future tree species evenness	720-m neighborhood	Mean 180-m patch SOE score	NCX and LANDIS-II	N/A	N/A

N/A = not applicable, SOE = strength of evidence.

M2b: tree species evenness—

Importance and relevance—Evenness is a measure of the degree to which species are present in the same abundance. It is ecologically relevant because with increased evenness among species, the more likely a given species will persist through disturbance events and adapt over time. This assumes that not all species are rare and that the existing suite of species includes a full complement of native species and a limited number of nonnative species. These assumptions currently hold true in the Sierra Nevada but could change in the coming decades, especially later in the century.

Most communities have a few common species and many less common species. Common species tend to be more generalists, whereas less common species tend to be more specialists. Evenness per se is not a realistic nor desirable goal, but strong representation of abundance across a diverse array of species likely represents a more resilient condition.

Description and derivation—The same data source and methods used to calculate the Shannon diversity index (see M2a above) were used to derive this evenness value. Evenness is calculated using the Pielou evenness metric (J), which varies between 0 and 1, and where values of 1 have complete evenness and values of 0 have not evenness (Pielou 1966). This metric was chosen in addition to the Shannon diversity metric to favor those areas with a more even distribution of species. The following formula is used:

$$J = H/Hmax$$

Where H is the number derived from the Shannon diversity index (see earlier section) and it is divided by $Hmax$, which is the maximum possible value of H (if every species were equally likely) calculated as:

$$Hmax = -\sum_{i=1}^{S} \frac{1}{S} \ln \frac{1}{S}$$

Where the number of species, S, is divided into 1, and multiplied by the natural logarithm of the same value, and then summed across all species. Target condition scores were assigned to values in the $\geq 90^{th}$ percentile and fully departed in the $\leq 10^{th}$ percentile condition across the LANDIS-II $_{model}$ runs (table 8; fig. 16).

M2c: fire resistance—

Importance and relevance—Forest composition can be quantified based on functional traits, such as the differential ability of species to tolerate disturbances such as fire. Given that fire is likely to be a primary driver of forest conditions in the Sierra Nevada, the ability of forests to persist will in part be a function of the ability of individual species to coexist with an active fire regime, including moderate- and high-severity fire.

Description and derivation—The fire resistance score is based on species-level traits, such as bark thickness, self-pruning, and flammability. Based on work done in the Sierra Nevada (Stevens et al. 2020), all major coniferous species were ranked from 0 (low fire tolerance) to 1 (high fire tolerance). Fire resistance was derived for current and future conditions based on interpretations of forest conditions from LANDIS-II modeling. For current condition, 180-m patches were scored based on the weighted average of the species scores, with weights being quantified by the amount of biomass represented by each species present. Targets and fully departed condition scores were assigned to the $\geq 90^{th}$ and $\leq 10^{th}$ percentile scores, respectively, across the LANDIS-II model runs (table 9).

For future conditions, fire resistance was calculated for each 180-m patch for each of the decadal time steps from 2020 to 2060 and for each of the five replicate runs of LANDIS-II for scenario 1 (20 decade/replicates). Future potential conditions were represented by the maximum diversity score observed over the 20 replicates. Targets and fully departed condition scores were based on the same 90th and 10th percentile scores, respectively, based on current conditions (table 9).

Table 9—Fire resistance metric condition interpretation in the forest composition element of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Current/future and scale	Data	Data source	Condition	Reference
Current fire resistance score	180-m patch	Weighted average of the species scores, with weights being quantified by the amount of biomass represented by each species present	LANDIS-II	Target: ≥90% Fully departed: ≤10%	Stevens et al. (2020)
Future fire resistance score	180-m patch	Maximum decadal score 2020–2060	LANDIS-II, scenario 1	Target: ≥90% Fully departed: ≤10%	Stevens et al. (2020)
Current fire resistance score	720-m neighborhood	Mean SOE from 180-m patch scale	LANDIS-II	N/A	Stevens et al. (2020)
Future fire resistance score	720-m neighborhood	Mean SOE from 180-m patch scale	LANDIS-II, scenario 1	N/A	Stevens et al. (2020)

SOE = strength of evidence, N/A = not applicable.

M2d: risk of forest type conversion—

Importance and relevance—A primary concern in managing for the future of forests in the Sierra Nevada is the potential for widespread loss of forests resulting from the inability to recover from significant disturbance, such as mortality from high-severity fire or bark beetle (Coleopterans of the family Curbulionidae, subfamily Scolytinae) infestations.

Description and derivation—The risk of forest type conversion to nonforest conditions pertains to future conditions only and is based on LANDIS-II modeling of scenario 1 over the first 40 years from 2020 to 2060 and across five replicates (20 decade/replicates). Risk of forest type conversion is represented as a probability and is based on the percentage of the 20 decade/replicates where forested conditions (at time zero) are converted to nonforest conditions (primarily shrub). Target conditions are displayed in table 10.

Table 10—Risk of forest type conversion metric condition interpretation in the forest composition element of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Current/future and scale	Data	Data source	Condition	Reference
Future risk of forest type conversion	180-m patch	Maximum decadal score 2020–2060	LANDIS-II, scenario 1	Target: 0% Fully departed: ≥25%	N/A
Future risk of forest type conversion	720-m neighborhood window	Mean SOE score from 180-m scale	LANDIS-II, scenario 1	Target: 0% Fully departed: ≥25%	N/A

SOE = strength of evidence, N/A = not applicable.

Disturbance Element

Overview—

Sierran forests evolved with a suite of frequent disturbances: wildfires, burning by indigenous people, bark beetle-caused mortality, drought-caused mortality, avalanches, landslides, and windthrow, all of which created forest heterogeneity across the landscape. This heterogeneity included variations in surface and ladder fuels that moderated fire behavior and spread and variations in stand density and forest opening that served as critical habitats. Forested areas are now more homogeneous owing to lack of disturbance. The lack of disturbance is evident in the forest structure.

Major disturbances not only influence ecological patterns, processes, and functions but create diversity and can influence management decisions about where to prioritize future treatments. Past disturbances can and regularly do contribute to forest restoration goals, or can affect objectives across a landscape. Management activities are also a form of disturbance, including woody extraction (i.e., harvesting of logs, other wood products, biomass), onsite processing (e.g., mastication), and prescribed and managed wildfire.

Disturbance is represented by combining two measures of disturbance: frequency and delinquency. Target frequencies and intensities for disturbance represent conditions that are expected to enable stands to adapt and flex with future disturbance. We expect that managing disturbance frequencies and intensities to a desired degree will result in forests continuing to change over time in response to disturbance, but they will maintain their characteristic species, functions, and benefits over time.

M1: Disturbance frequency—

Importance and relevance—Knowledge of the type and frequency of disturbance in relation to historical reference conditions can help land managers target areas most departed from their historical disturbance regime. Although disturbance types have different ecological influences, their main shared function is that they reduce tree density and biomass in various ways. Disturbances affecting forest structure and composition are generally due to a combination of disturbance types, so evaluations of time since disturbance and disturbance frequency should include a full array of disturbances.

Fire serves as an important feedback mechanism in disrupting succession and competition. The fire return interval (time between two successive fires) is a measure of the disturbance regime. The fire return interval departure (fire frequency pre-European settlement compared to recent fire history) is often used as an indication of the need to prioritize restoration thinning and prescribed fire treatments.

Impact levels of tree mortality attributed to bark beetle attacks range from small groups of trees to extensive landscapes, depending on the bark beetle species and numerous site conditions and other factors (Fettig et al. 2007). Bark beetle infestations are influenced by overall stand density, tree diameter, tree vigor, fire exclusion, and host species density (Fettig 2012, Hayes et al. 2009), and recent bark beetle outbreaks in parts of the Sierra Nevada are associated with warming temperatures (Millar and Stephenson 2015). Various measures of stand density, including stand density index or basal area, are positively correlated with levels of tree mortality from bark beetles (Fettig 2012, Hayes et al. 2009). Although it is difficult to predict future beetle mortality rates, with the extreme drought conditions that are now occurring, it is very plausible that beetles will be a primary driver on the TCSI landscape.

Forest management can be a primary disturbance agent in forests on the TCSI landscape. Where natural disturbance cycles have been suppressed, management can intervene to provide the ecological function of natural disturbances. Although altering forest conditions by removing material through thinning operations will not have exactly the same ecological effects as disturbance by fire (prescribed or wildfire), in combination with prescribed fire and managed wildfire, it can serve some of the important functions of natural disturbances.

We developed a composite measure of disturbance that combines the occurrence of fire, mechanical treatments (tree thinning and harvest), and insect-caused tree mortality to derive a disturbance return interval that is used to evaluate the degree of departure from historical disturbance regimes. While areas on the TCSI landscape have missed multiple fire events in recent decades because of fire suppression and other management activities, it may have been recently disturbed and therefore may not benefit from management intervention in the near term. As a result, we combined disturbance frequency and delinquency as a robust composite measure of disturbance that best represents the opportunity for management to improve conditions.

Description and derivation—A 50-year disturbance history for 30-m pixels was constructed across the TCSI landscape and compared to estimated historical fire return intervals. Fire occurrence data (1970–2019) were provided by the CAL FIRE

Fire and Resource Assessment Program (FRAP). For disturbance associated with bark beetle activity, mortality from bark beetle outbreaks is assessed annually through the USDA Forest Service, Pacific Southwest Region, Aerial Survey Program. Harvest and treatment data are based on the USDA Forest Service Activity Tracking System (FACTS) database (1970–2019), which pertains primarily to National Forest System (NFS) lands and the CAL FIRE nonindustrial timber management plans and timber harvest plans.

Additional forest harvest and mortality data due to road building or other sources were inferred from a database (Hansen et al. 2013) that assesses global forest extent and change using LANDSAT imagery (2000–2019) across all lands. The FRAP is in the process of developing a more comprehensive data source to track management treatments that will be a valuable source of these data when it becomes available.

For current conditions, disturbance data were at the 30-m-cell scale based on the source of the data. These data were evaluated at the HUC12-subwatershed scale to capture broader scale impacts neighboring disturbances may have had on individual cells as well as to account for some inaccuracies in the spatial disturbance datasets that may not adequately capture the spatial extent of disturbances (table 11).

Disturbance calculations include fire, mechanical thinning and harvest, mastication, and beetle-caused tree mortality. Datasets capturing each relevant disturbance agent were as follows:

- Fire using the FRAP and Monitoring Trends in Burn Severity multiagency program
- Management using the FACTS and CAL FIRE Management Activity Project Planning and Event Reporter (CalMAPPER)
- Bark beetle mortality using the Ecosystem Disturbance and Recovery Tracker (eDaRT) with LANDIS-II, aerial detection surveys, and data collected after recent mortality events in the Sierra Nevada (Fettig et al. 2019)
- Other disturbance using forest cover change detected with high-resolution global maps (Hansen et al. 2013)

Based on initial concerns about beetle modeling results across all the scenarios, the LANDIS-II extension was recalibrated using the eDaRT mortality magnitude index data for area affected and landscape-level mortality caused by beetles for scenario 1. The difference in area affected between eDaRT and the USDA Forest Service's annual aerial detection survey data was on the order of three to four times less.

The target disturbance frequency was based on the presettlement median fire return interval for the associated forest vegetation type (Safford and van de Water 2014). Condition scores for disturbance delinquency at the 30-m-pixel scale (i.e., disturbance delinquency) were assigned based on the percentage difference in time since last disturbance over the past 50 years (1970–2019) compared to the historical fire return interval for the associated vegetation type. Pixels that had disturbance delinquency of >20 percent of their fire return interval are considered within target conditions and get a score of +1 (table 11). Pixels that were overdue for disturbance by >20 percent of their fire return interval received a declining condition score to fully departed (score = −1) at 66 percent past their fire return interval. Disturbance delinquency was given a narrow window to quickly identify areas that were ready for treatment. Pixels with no disturbance in past 50 years were assigned a condition score of −1 (fig. 17).

Table 11—Forest disturbance element condition interpretation (logic model) of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Scale	Data	Data source	Condition	Reference
Current disturbance frequency	30-m pixel	Average number of years between disturbances relative to FRI	Multiple state sources and literature	N/A	N/A
Current disturbance frequency	HUC12	Average disturbance frequency across 30-m pixels	Multiple state sources and literature	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A
Current disturbance delinquency	30-m pixel	Number of years since the last disturbance relative to the FRI	Multiple state sources and literature	N/A	N/A
Current disturbance delinquency	HUC12	Average disturbance frequency across 30-m pixels	Multiple state sources and literature	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A
Current composite disturbance	HUC12	Average of the disturbance frequency and delinquency scores at each scale (four values)	N/A	N/A	N/A
Future disturbance frequency	180-m patch	Frequency of disturbance over the 20 decade/ replicates	LANDIS-II eDaRT	N/A	N/A
Future disturbance frequency	HUC12	Average frequency across 180-m patches	LANDIS-II eDaRT	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A
Future disturbance delinquency	180-m patch	Delinquency of disturbance over the 20 decade/ replicates	LANDIS-II eDaRT	N/A	N/A
Future disturbance delinquency	HUC12	Average delinquency across 180-m patches	LANDIS-II eDaRT	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A
Future composite disturbance	HUC12	Average of future frequency and delinquency scores	N/A	N/A	N/A

Note: target conditions are based on the fire return interval (FRI) for the associated forest type.

N/A = not applicable, HUC = hydrologic unit code.

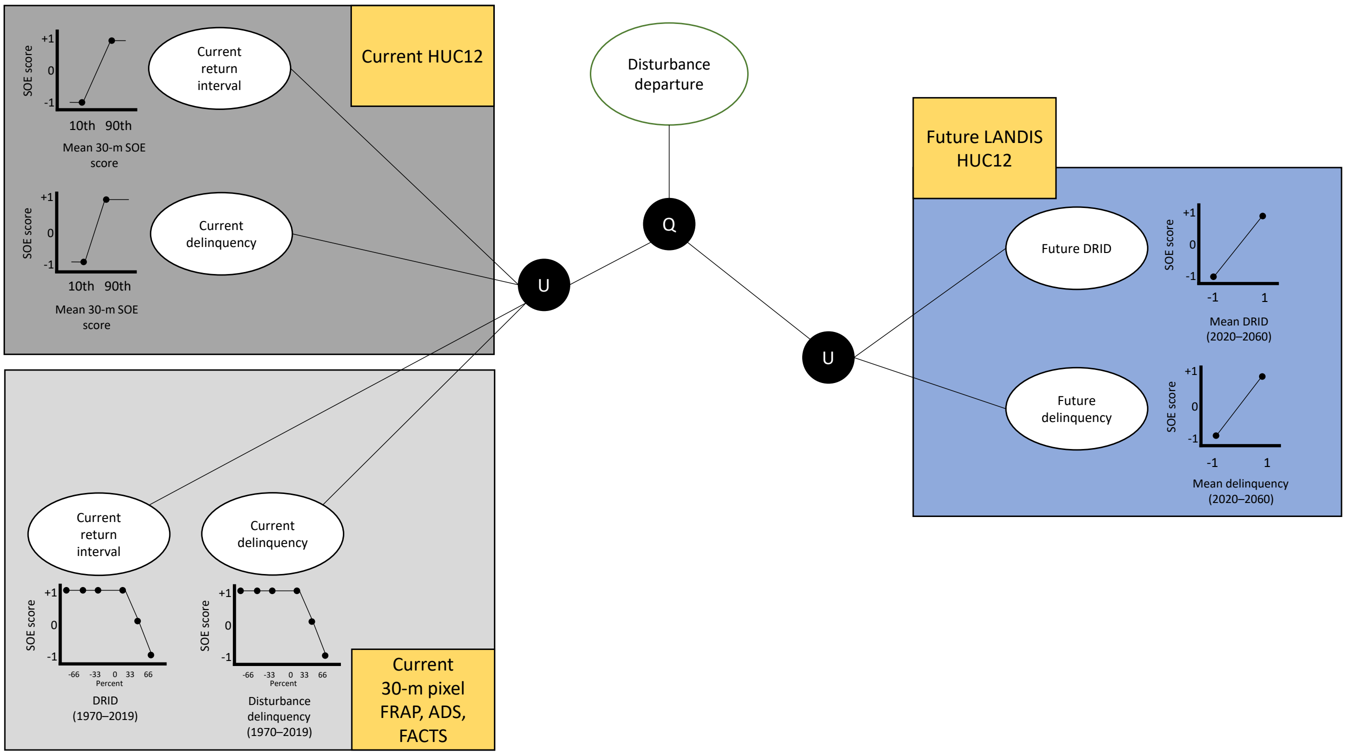


Figure 17—Disturbance element logic model and associated metrics of the forest resilience pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. ADS = aerial detection surveys, FACTS = (USDA) Forest Service Activity Tracking System, FRAP = (California) Fire and Resource Assessment Program, DRID = disturbance return interval departure, SOE = strength of evidence; logic model operators: A = AND, Q = QUADRANT, U = UNION.

Condition scores for disturbance frequency (i.e., disturbance return interval departure) at the 30-m-pixel scale were assigned based on historical fire return interval. If a disturbance frequency (i.e., number of disturbances between 1970 and 2019) was equal to or greater than its fire return interval, it was considered within target condition and received a score of 1. Condition scores declined for longer intervals between disturbances down to fully departed at greater than twice the fire return interval (100 percent less than fire return interval) (fig. 17).

At the HUC12-subwatershed scale, condition scores for disturbance frequency and delinquency were considered within target (score = +1) when they were in the $\geq 90^{th}$ percentile of all HUC12 scale scores and declined to fully departed (score = −1) in the $\leq 10^{th}$ percentile. Finally, a composite of current disturbance condition score was derived by averaging the two patch-scale and the two watershed-scale scores (fig. 17).

For future conditions, disturbance frequency was based on observed frequency of disturbance over the next 40 years based on the five replicate model runs at the 180-m patch scale. The condition score for frequency was derived at the HUC12-subwatershed scale by calculating disturbance frequency at year 40 for each of the five LANDIS-II model replicates, then calculating the percentile breaks as per the "current conditions" score above, and then average values across the HUC12 for each model replicate, and then average across all model replicates.

Disturbance delinquency was based on the observed last disturbance at year 40 across the five replicate model runs at the 180-m patch scale. Condition score for delinquency was then derived at the HUC12-subwatershed scale, with target conditions in the ≥90th percentile and declining to fully departed in the ≤10th percentile (table 11; fig. 17).

Finally, a composite future disturbance score was derived by averaging the delinquency and frequency scores at the HUC12-subwatershed scale.

Fire Dynamics Pillar

Overview

Sierra Nevada forest ecosystems are evolutionarily adapted to fire, a fundamental ecosystem process that was largely suppressed through much of the 20th century. Before the advent of fire suppression, fire was more widespread and less intense (Stephens et al. 2007, van Wagtendonk and Fites-Kaufman 2006). Fire suppression, in addition to past management practices and climate change, have led to high tree density, mortality, and the accumulation of hazardous forest fuels. Fires have become larger and more frequent across the Western United States (Calkin et al. 2005, Westerling and Bryant 2006). In the Sierra Nevada, the area burned annually in federally managed forests was found to have increased by more than 10 000 ha per decade between 1970 and 2015 (Westerling et al. 2015). Fire size has also changed, especially in recent years where many extremely large fires have burned, compared to the historical record, including the 2021 Dixie and Caldor Fires, and the 2014 King Fire. In fact, 9 of the 10 largest recorded fires in California history have occurred since 2012 (CAL FIRE 2022). The history of fire suppression combined with rising temperatures and prolonged drought make Sierra Nevada forest ecosystems vulnerable to more large-scale, high-intensity wildfires and other uncharacteristic disturbances. Large, high-severity fires are a concern given that they pose a significant threat to life, property, and forest persistence.

Fire dynamics pertains to the range of characteristics of fire, whether it occurs unintentionally (accidental fire starts) or intentionally through prescribed fire, Indigenous burning, wildfires that are allowed to burn, or arson. Fire dynamics reflect fire as an ecological process and the functions that it performs. Fire dynamics vary depending on multiple factors, including the vegetation type and location on the landscape. Based on historical fire dynamics, low- and moderate-severity fire was a dominant process in Sierra Nevada, with greater fire frequencies in yellow pine (5–40 years) and dry, mixed-conifer forests (5–50 years) on average, compared to moist, mixed-conifer forests (5–80 years) (Safford and Stevens 2017). High-severity fire was limited to small areas that were generally less than 100 ha in size.

Although fire dynamics pertain to the entire landscape, the ecological role of fire is most relevant to landscapes outside of the wildland-urban interface (WUI).

Within the WUI, protection of life and property take priority over the role of fire as a process. As a result, the fire dynamics pillar pertains to areas outside of the WUI. The complementary fire-adapted communities pillar pertains to areas inside the WUI. Designation of the WUI was based on the ICLUS dataset (see "Fire-Adapted Communities Pillar" below).

The fire dynamics pillar evaluates whether fire burns in an ecologically beneficial way to perpetuate heterogeneity. High-severity fire has a limited role, while low- and moderate-severity fire is considered functional and is a dominant process. The fire dynamics pillar is composed of two elements: fire severity and functional fire (fig. 18). These elements relate to the character, location, and frequency of fire across the landscape. In the management impact evaluation, the fire severity and functional fire elements carry equal weight (fig. 19), and the management impact score reflects the lesser of the fire-severity and functional fire scores.

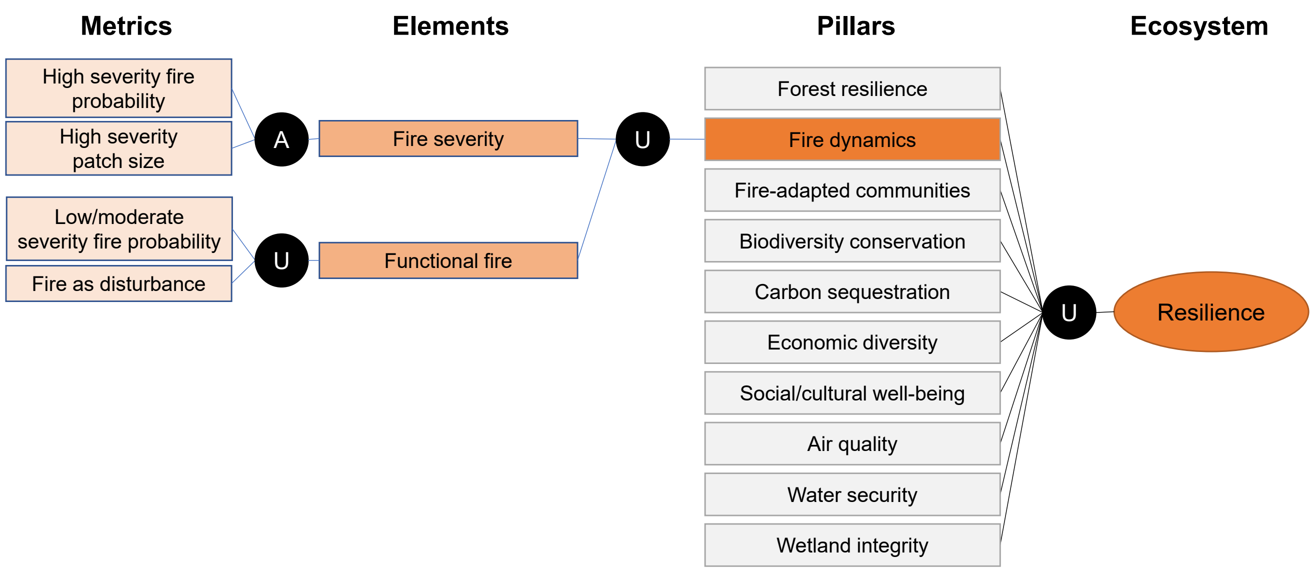


Figure 18—Elements and metrics representing the fire dynamics pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. Logic model operators: A = AND, U = UNION.

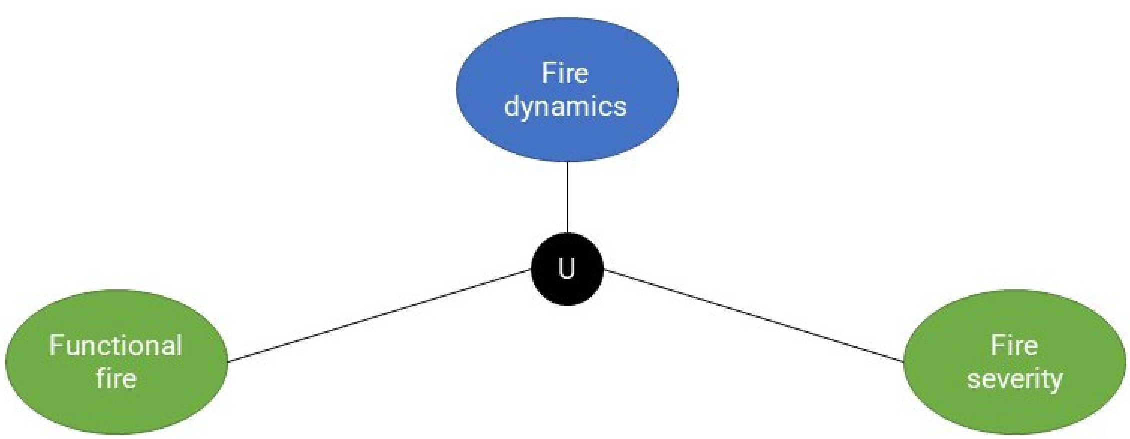


Figure 19—Fire dynamics pillar logic model with associated elements in the Tahoe-Central Sierra Initiative Blueprint for Resilience. U = "UNION" logic model operator.

Fire Dynamics Modeling Methods

Fire simulation modeling was used to quantify fire hazard across the TCSI landscape. Here, we define "hazard" as the product of the calculated probability of a wildfire, derived through Monte Carlo simulation, and the potential intensity of fire, which is based on local weather and fuels and interpreted as flame length (e.g., 4-ft flame lengths) (Scott et al. 2013). A variant of the FSim large-fire simulator (Short and Finney, n.d.) was used to quantify wildfire hazard across the TCSI landscape at a pixel size of 90 m. The FSim is a comprehensive fire occurrence, growth, behavior, and suppression simulation system. It uses locally relevant fuel, weather, topography, and historical fire occurrence information to make a spatially resolved estimate of the contemporary likelihood and intensity of wildfire across the landscape. FLEP-Gen is a deterministic model that refines the FSim modeling by (1) incorporating fire intensity in nonheading spread directions and (2) developing weather scenarios that better represent conditions represented by their relative area burned in combination with their temporal relative frequency.

All data and interpretations representing the current time period are consistent with the TCSI Current Conditions Assessment (Wilson and Manley 2021b). The vegetation dataset was derived from LANDFIRE 2014 with modification to reflect fuel disturbances between 2015 and 2018. Fuel disturbances were incorporated based on the two wildfire datasets: Monitoring Trends in Burn Severity, Rapid Assessment of Vegetation Conditions after Wildfire, and Geospatial Multi-Agency Coordination fire perimeter data. Additional disturbances from forest harvest were based on the FACTS data and tree-mortality data from the eDaRT. The fuelscape was created using the LANDFIRE Total Fuel Change Tool.

High-severity fire was evaluated using FLEP-Gen to evaluate current probability of fire, the probability of high-severity fire, and the potential high-severity patches. LANDIS-II landscape simulation model was used to represent future potential conditions for 2020–2060.

We classified flame lengths >8 ft as high-intensity fire, similar to what would result in high-severity fire effects on vegetation, which is measured postburn. While >8-ft flames are considered high-intensity fires, 4 to 6-ft flame lengths are moderate intensity, and <4-ft flame lengths are low intensity. The >8-ft flame lengths indicate fire that would be challenging to suppress even with air defense and in places where the fire would likely cause >75 percent tree mortality. To prioritize places in the TCSI landscape with the highest risk of high-intensity fire, we isolated >8-ft flame lengths with >43 percent burn probability (upper quartile of the data) and delineated continuous areas based on the four-neighbor rule for areas greater than 100 ha in size. These are not fire patches but continuous cells with high probability of high-intensity fire.

Fire Severity Element

Overview—

The fire severity element identifies areas most susceptible to high-severity fires now and into the future. Areas receive a high management impact score where high-severity fire is currently of low concern and the probability increases in the future and, conversely, where high-severity fires is currently a concern but future modeling suggests it has the potential to shift into a low- to moderate-severity-dominated regime in the future.

The fire severity element has two metrics: probability of high-severity fire (M1) and high-severity fire patch size (M2).

M1: Probability of high-severity fire—

Importance and relevance—While high-severity fires have historically been a part of fire regimes throughout the Western United States, forests are currently experiencing unprecedented levels of high-severity fire over much of the region. Resilience is diminished as the probability of high-severity fire increases.

Description and derivation—Probability of high-severity fire was quantified for both current and future conditions. It reflects probability of fire severity based on the condition of the land, not the proportion of any given fire to burn in a certain way. For current conditions, probability of high-severity fire was evaluated using FSim modeling, which replicates thousands of fire seasons based on recent ignition patterns, weather streams, topography, fuels distributions, and fire suppression.

We took a conservative view of high-severity fire risk where high scores (+1) were given to those areas with 0 percent chance of high-severity fire and low scores (−1) where high-severity probabilities were 1.0 based on the FSim/FLEP-Gen modeling. For future conditions, probability of high-severity fire was calculated for each 180-m patch for each of the 20 decade/replicates for scenario 1 LANDIS-II model runs (table 12; fig. 20). Future conditions are based on the LANDIS-II model (SCRPPLE fire extension), which uses similar data to the FSim model, but the LANDIS-II and extension models fires into the future under climate change and uses empirical models to inform fire spread rather than the physics-based equations of the FSim model. Climate change generally increases the severity of fire dynamics, particularly in dry forest ecosystems.

Table 12—Fire severity element condition interpretation (logic model) of the fire dynamics pillar in the Tahoe-Central Sierra Initiative (TCSI) Blueprint for Resilience

Data description	Scale	Data	Data source	Condition	Reference
Current probability of high-severity fire	30-m pixel	Probability of high-severity fire (2019)	FLEP-Gen (30 m)	Target: 0 Fully departed: +1	Based on thresholds from TCSI assessment (Wilson and Manley 2021b) of current conditions
Current high-severity fire patches	30-m pixel	High-severity fire patch size (ha) (2019)	FLEP-Gen (30 m)	Target: ≤0.09 ha Fully departed: ≥100 ha	Based on thresholds from TCSI assessment of current conditions
Future probability of high-severity fire	180-m patch	Number of model iterations where a high-severity fire occurred out of a total of 5 LANDIS-II iterations of 40 years each	LANDIS-II (180 m)	Target: 0 out of 5 model iterations Fully departed: 5 out of 5 model iterations with high-severity fire	N/A
Future proportion of cells in high-severity fire	720-m neighborhood window	Proportion of cells that experienced a high-severity fire	LANDIS-II	Target: 0% of cells Fully departed: 100% of cells	N/A

Note: high-severity fire is defined as cells with >0.6 probability of >8-ft flame length.

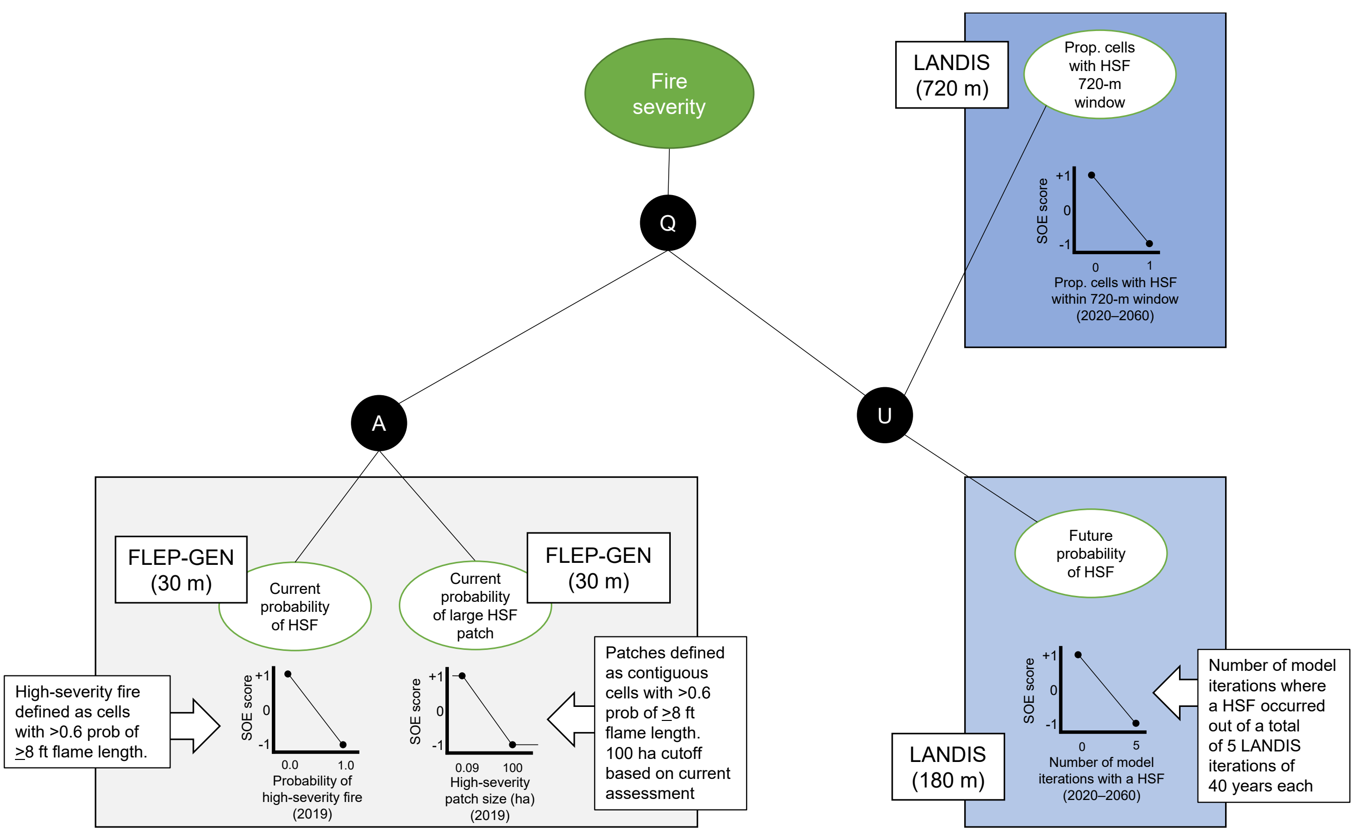


Figure 20—Fire severity element logic model of the fire dynamics pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. HFS = high-severity fire; logic model operators: A = AND, Q = QUADRANT, U = UNION.

M2: High-severity patch size—

Importance and relevance—Ecosystem resilience is diminished as the size of contiguous areas of high-severity fire increase beyond the ability of the landscape to regenerate naturally.

Description and derivation—Collins and Stephens (2010) found that stand-replacing patches composed 15 percent of the burned area in two mixed-severity fires that occurred in upper elevation mixed-conifer forests in Yosemite, and they recommended 15 percent high-severity fire as a general management target. Membership in large, high-severity fire patches is based on contiguous areas of cells with a high probability of high-severity fire, not on an estimate of fire behavior. These are not fire patches but continuous cells with high probability of high-intensity fire. Based on historical fire data, average sizes of high-severity fire in the Sierra Nevada were about 40 ha, but ranged widely (Kelsey 2019, Safford and Stevens 2017). We used a 100-ha maximum patch size to better reflect a range of patch sizes and still have a high probability of natural regeneration based on proximity to seed sources.

Current conditions were assessed at the 30-m scale, based on the scale of the input data for the current fire risk modeling using the FLEP-Gen (Wilson and Manley 2021b). Delineated continuous areas reflect areas with four or more adjacent 30-m cells (the four-neighbor rule) with a contiguous area of >100 ha (table 12; fig. 20).

Future conditions are based on LANDIS-II scenario 1 modeling as discussed in the above “Forest Resilience Pillar” section. The probability of high-severity fire is assessed at the 180-m patch size. The probability of future high-severity fire was based on the number of times high-severity fire occurred in any given location out of the five model replicates (table 12).

Functional Fire Element

Overview—

Increasing the pace and scale of restoration on the landscape will require using a variety of tools to accomplish restoration targets. Prescribed fire and managed wildfires, where appropriate, can contribute to the restoration need. This is particularly true where fires burn primarily at low and moderate severity with stand-scale patches of high severity dispersed throughout the burned area, which we refer to from here on as “functional fire.” Functional fire is when fire burns in an ecologically beneficial and socially acceptable way, perpetuating landscape heterogeneity and rarely threatening human safety or infrastructure.

This element evaluates the role fire has played in the recent past, the likelihood that fires would burn with low and moderate severities under current fuel and weather conditions, and the potential for fires to play a restorative role in the future under climate change.

The functional fire element has two metrics: probability of low- and moderate-severity fire (M1), and frequency of fire as a disturbance process (M2). The two metrics carry equal weight, and their values are averaged to derive the management impact score value for the functional fire element (fig. 21).

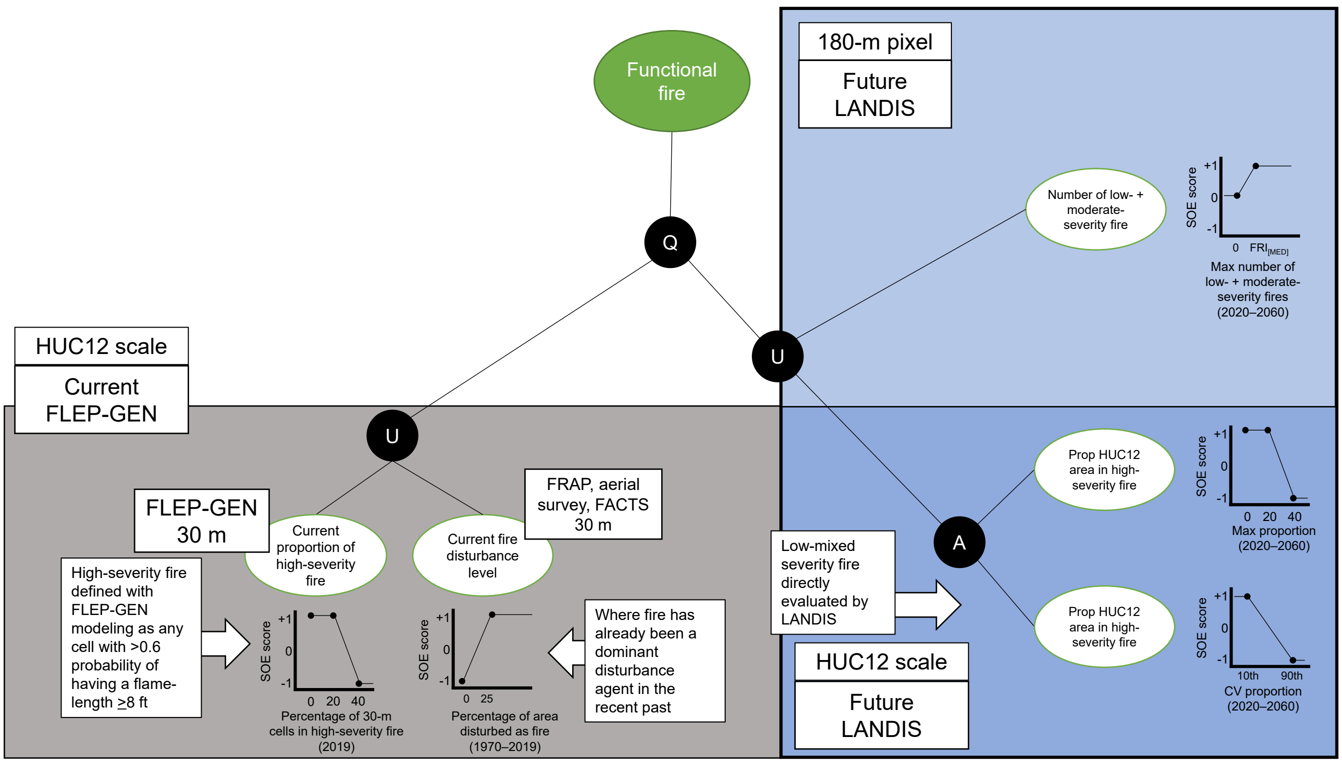


Figure 21—Functional fire element logic model of the fire dynamics pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. CV = coefficient of variation, FACTS = (USDA) Forest Service Activity Tracking System, FRAP = (California) Fire and Resource Assessment Program, HUC = hydrologic unit code, SOE = strength of evidence; logic model operators: A = AND, Q = QUADRANT, U = UNION.

M1: Influence of low- and moderate-severity fire—

Importance and relevance—The probability of low- and moderate-severity fire metric reflects how a location might burn. Based on historical fire dynamics, low- and moderate-severity fire was a dominant process in the Sierra Nevada, with greater fire frequencies in yellow pine (5–40 years) and dry, mixed-conifer forests (5–50 years) on average, compared to moist, mixed-conifer forests (5–80 years) (Safford and Stevens 2017). High-severity fire was limited to small areas that generally were less than 100 ha.

Description and derivation—Although the focus of this element was to evaluate low- and moderate-severity fire patterns, it was easier to interpret most evaluations in terms of high-severity fire. Therefore, most fuzzy logic ramps were evaluated against high-severity fire levels with higher scores given to areas with lower high-severity fire expectancies and lower scores where high-severity fire was more prevalent.

We relied on values from the literature where available. Targets for high-severity fire percentages were derived from Collins and Stephens (2010), who found that for two mixed-severity fires in Yosemite, stand-replacing patches composed 15 percent of the total burned area. Similarly, Miller et al. (2012) found that high-severity fire accounted for 7 to 15 percent of fire in Yosemite (1984–2010), depending on forest type, and this was mostly consistent with LANDFIRE Biophysical Settings early-seral estimates (i.e., estimates of the vegetation that may have been present prior to Euro-American settlement). Other sources serve as points of reference for historical fire return interval, such as the target number of low- and moderate-severity fires for a given pixel was based on published historical fire return intervals (Stephens et al. 2007, van de Water and Safford 2011) and measured using the LANDIS-II modeling output.

Current conditions were assessed at the HUC12-subwatershed scale. FLEP-Gen was used to model current levels of high-severity fire (>8-ft flame lengths). High scores for the current condition existed where FLEP-Gen modeling suggested <20 percent of the area in a given HUC12 subwatershed was in high-severity fire conditions (i.e., probability >0.6 for 0- to 8-ft flame lengths).

Target values are consistent with the target values for the early-seral stage metric, described in the above "Forest Composition Element" section, where stand-replacing patches compose less than 15 percent of the total burned area (Collins and Stephens 2010).

For future conditions, the proportion of the landscape burned over multiple decades was assessed at the HUC12-subwatershed and 180-m-pixel scales. Future condition scores were used to evaluate the potential to achieve functional fire targets and the variability in the role of functional fire over time.

At the 180-m-pixel scale, high scores were identified for pixels that experienced low- and moderate-severity fires that approximated their respective median historical fire return interval (van de Water and Safford 2011), and where there was low variability in the number of low- and moderate-severity fires across model iterations (i.e., in the $\leq 10^{th}$ percentile).

The future condition score evaluated at the HUC12-subwatershed scale is similar to the current condition; the score is high where high-severity fires represent ≤20 percent of a given HUC12 subwatershed and there is low variability across model iterations.

M2: Frequency of fire as a disturbance process—
Importance and relevance—Disturbance creates diversity, and fire has served as an important feedback mechanism in disrupting succession and competition. Fire frequency is based on studies of historical fire return intervals in the Sierra Nevada and reflects how often a location has burned over time.

Description and derivation—For current conditions, the frequency of fire as a disturbance-process metric was evaluated as percentage of area disturbed by fire (fig. 21). The desired condition for percentage of disturbances that consist of fire, which contribute to disturbance dynamics, is >25 percent, and fully departed is ≤25 percent, of fire disturbances (table 13; fig. 21); the time period is the same as that used for the fire return interval metric. High scores occur where fires represented >25 percent of the disturbances that occur over time within a given HUC12 subwatershed. Fire-occurrence data (1970–2019) were provided by the FRAP.

Table 13—Fire dynamics pillar condition interpretation (logic model) in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Scale	Data	Data source	Desired condition	Reference
Current proportion of high-severity fire	HUC12	Percentage of 15-m forested cells in low- and moderate-severity fire (2019)	FLEP-Gen (30 m)	Target: ≤20% of HUC12 Fully departed: >40% of HUC12	Collins and Stephens (2010), Miller et al. (2012)
Current percent of fire as disturbance	HUC12	Percentage of the disturbances that are fire (1990–2019)	FRAP, aerial surveys, FACTS (30 m)	Target: ≥25% of disturbances Fully departed: 0% of disturbances	N/A
Future number of low- and moderate-severity fires	180 m	Maximum number of low- and moderate-severity fires (2020–2060)	LANDIS-II	Target: median fire return interval Fully departed: 0 fires	van de Water and Safford (2011)
Future proportion of HUC12 in high-severity fire	HUC12	Future high-severity fire area (2020–2060)	LANDIS-II	Target: ≤20% of HUC12 Fully departed: ≥40% of HUC12 area	N/A
Variability in HUC12 area in high-severity fire	HUC12	Future high-severity fire area (2020–2060)	LANDIS-II	Target: ≤10th percentile Fully departed: ≥90th percentile	N/A

HUC = hydrologic unit code.

Fire-Adapted Communities Pillar

Overview

As discussed in the above "Fire Dynamics Pillar" section, wildfires are a keystone disturbance process in TCSI area forests, and this includes areas that have become part of the wildland-urban interface (WUI). Rather than focus solely on the restoration of natural disturbance processes on the landscape, in the WUI, we recognize the capacity for humans to coexist with wildfire and the need for restoration strategies to protect life and property.

The fire-adapted communities pillar evaluates the degree to which communities are living safely with fire and are accepting of management and natural ecological dynamics. This pillar also evaluates the capacity for communities to manage desired, beneficial fire and suppress unwanted fire. For these reasons, the fire-adapted communities pillar differentiates acceptable tolerances of fire from those identified in the fire dynamics pillar. In the fire-adapted communities pillar, the bar is set lower for unacceptable fire severity (moderate + high severity), and targets are based on risk reduction rather than historical fire regime properties.

The fire-adapted communities pillar comprises two elements: fire hazard and fire preparedness (fig. 22). The fire hazard and fire preparedness elements carry equal weight (fig. 23).

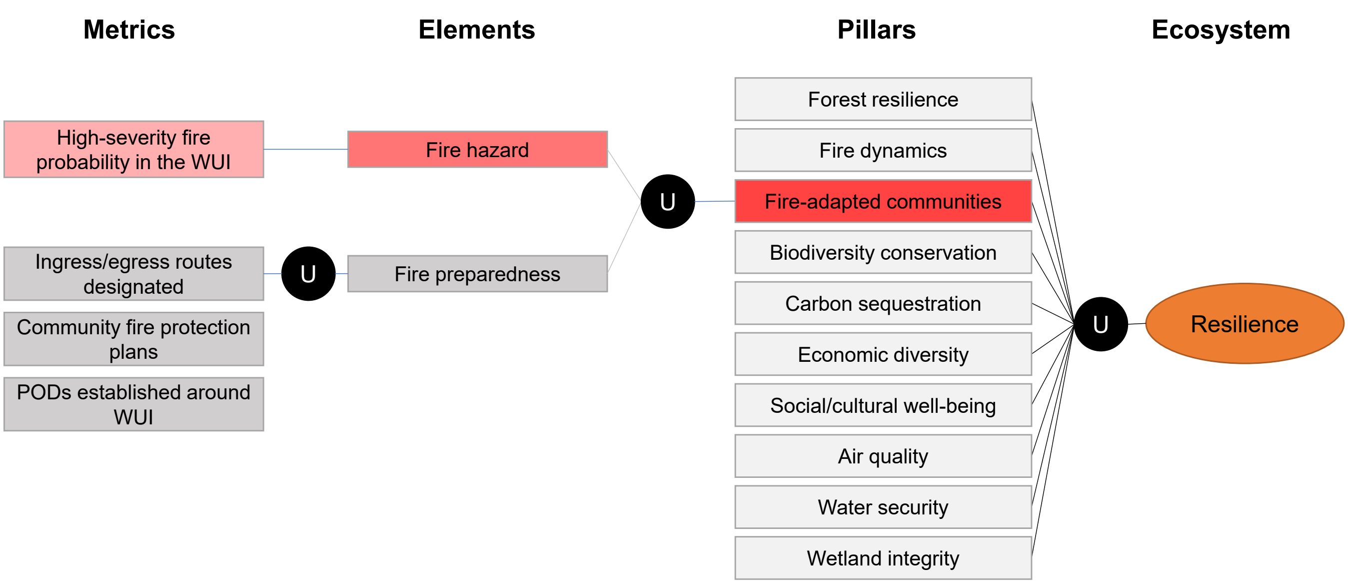


Figure 22—Elements and metrics representing the fire-adapted communities pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. PODs = potential operational delineations, U = "UNION" logic model operator, WUI = wildland-urban interface.

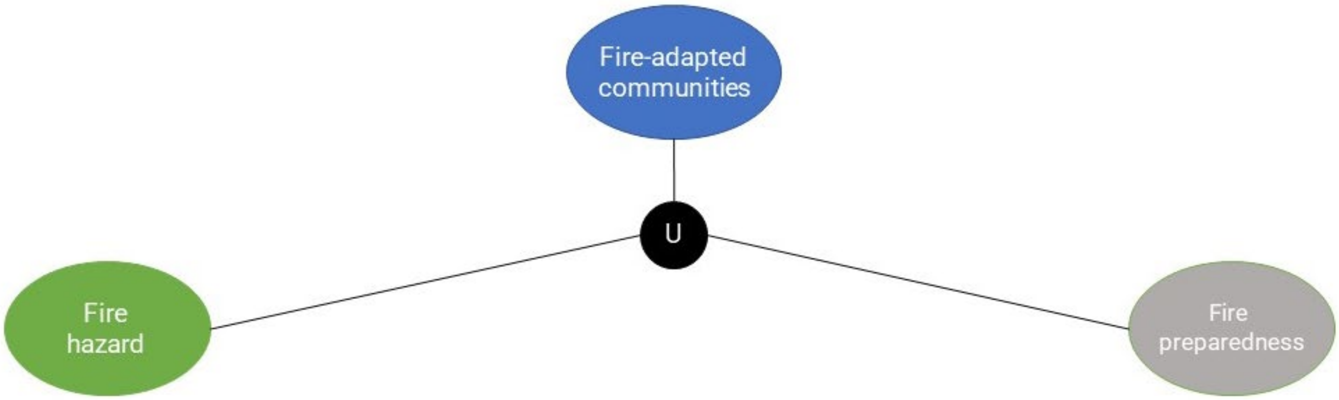


Figure 23—Fire-adapted communities pillar logic model with associated elements in the Tahoe-Central Sierra Initiative Blueprint for Resilience. Fire preparedness oval represents measures and metrics that are not represented in the TCSI Blueprint. U = UNION.

Fire-Adapted Communities Modeling Methods

The WUI areas are identified consistently across the TCSI landscape using the ICLUS v2.1 database for the Fourth National Climate Assessment, SSP2 (USEPA ORD 2017). ICLUS is a raster-based (1-km cell) growth model based on social, economic, and technological trends that are named "shared socioeconomic pathways" (SSPs). The categories of development included urban, exurban, and suburban with a density ranging from 2 dwelling units per 40 ha to 10 dwelling units per 0.4 ha, along with commercial, industrial, institutional, transportation, and golf courses/parks.

Because the definitions of defense and threat zones differ between the USDA Forest Service and CAL FIRE, we identified the defense and threat zones as defined by the Healthy Forests Restoration Act (HFRA) of 2003 (16 U.S.C. §§108–148). This allows for consistency of the WUI definition across the TCSI landscape. The Healthy Forests Restoration Act defines the WUI as follows:

> …(i) an area extending ½ mi [0.8 km] from the boundary of an at-risk community; (ii) an area within 1½ mi [2.4 km] of the boundary of an at-risk community, including any land that (I) has a sustained steep slope that creates the potential for wildfire behavior endangering the at-risk community, (II) has a geographic feature that aids in creating an effective fire break, such as a road or ridge top, or (III) is in condition class 3, as documented by the Secretary in the project-specific environmental analysis; (iii) an area that is adjacent to an evacuation route for an at-risk community that the Secretary determines, in cooperation with the at-risk community, requires hazardous fuels reduction to provide safer evacuation from the at-risk community.

The fire-adapted communities pillar has two elements: fire hazard and fire preparedness. The fire hazard element is active in the TCSI Blueprint. The fire preparedness element was not active in the TCSI Blueprint at the time of this report, primarily as a result of not having consistent data layers available for relevant metrics across the TCSI landscape. The fire preparedness element is intended to be an assessment of community safety through a variety of measures, such as identifying and maintaining ingress/egress routes, protection of critical infrastructure, and community awareness.

Fire Hazard Element

Overview—

The fire hazard element characterizes the fire risk in the WUI defense and threat zones. This element currently has one metric, risk of moderate- and high-severity fire in the WUI (M1 below; fig. 24). Because there is only one metric in this element for this TCSI Blueprint, the management impact evaluation for the fire hazard element is the same as the evaluation of the M1 metric.

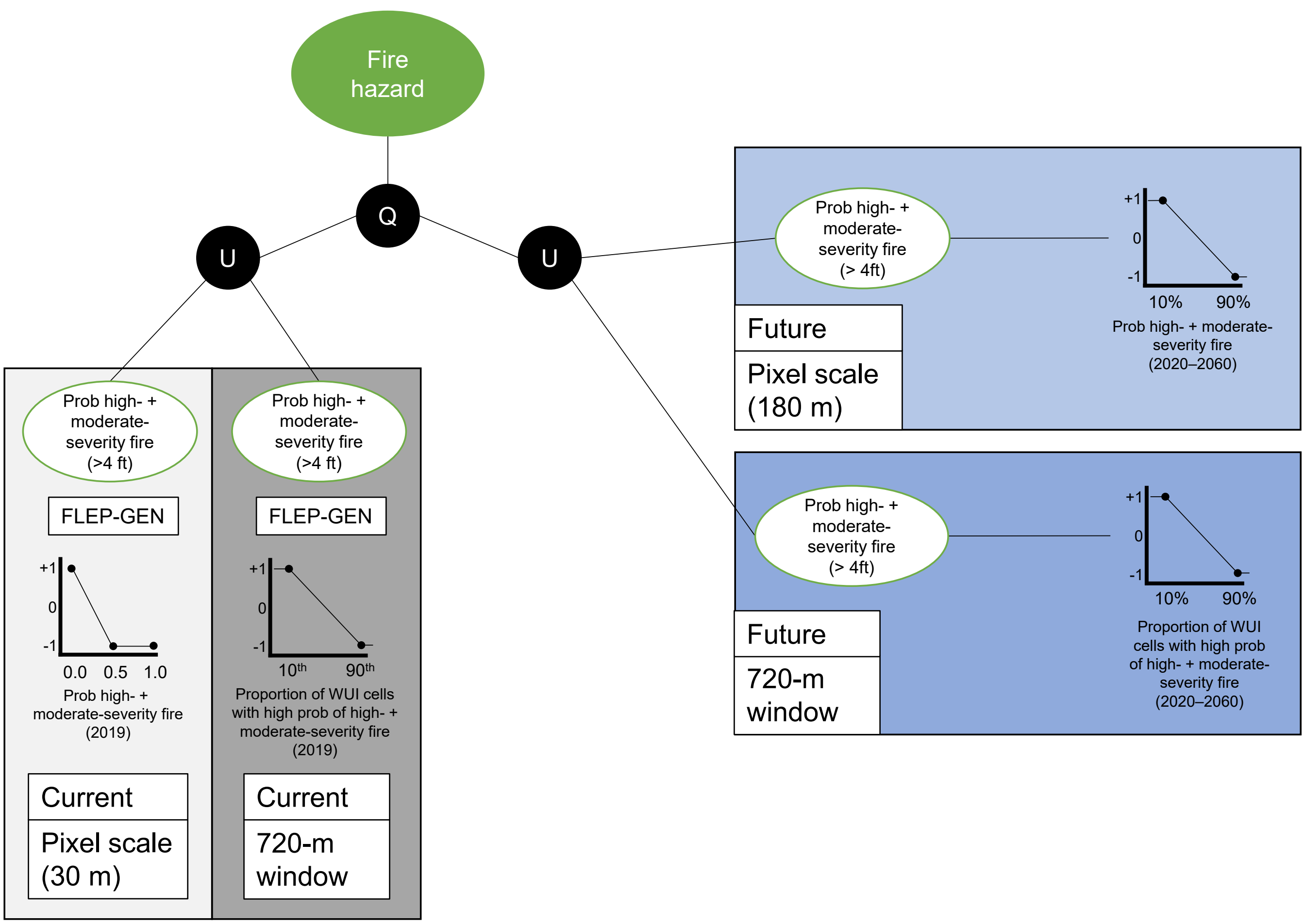


Figure 24—Fire hazard element logic model and metrics of the fire-adapted communities pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. Logic model operators: Q = QUADRANT; U = UNION.

M1: Risk of moderate- and high-severity fire in the wildland-urban interface—
Importance and relevance—The WUI is the area where homes and wildland vegetation meet or intermingle, and where wildfire problems have become most pronounced. The density of houses and other private structures in California's WUI have grown substantially in the past few decades (Safford et al. 2009). Development in the WUI has led to increasing fire ignitions, increasing losses of property and life, greater risks to firefighter safety, and escalating costs of wildfire management (Gude et al. 2013). The increased development in the WUI has exacerbated the increasingly high-severity wildfire behavior that is associated with the buildup of fuels resulting from fire suppression and associated with warming temperatures and drought conditions (Safford et al. 2009). Although wildfire behavior is driven by fuels, weather, and topography, fuels is the primary factor that can be manipulated to reduce the risk of moderate- and high-severity fire in the WUI.

Description and derivation—This metric specifically evaluates the relative risk of undesired fire effects near infrastructure and population centers. Literature values were not relied upon to identify specific targets or thresholds. Rather, the targets were either set to be conservative in their acceptance of moderate- and high-severity fire, or were relativized to the TCSI landscape. Risk to given pixels was ranked across the TCSI landscape, so areas with higher risk were scored lower (i.e., −1), and areas with limited risk were scored higher (i.e., +1).

There is a low tolerance for fire severity inside the WUI compared to outside of the WUI, as reflected in the fire dynamics pillar. Within the WUI, anything derived from FLEP-Gen that is low severity (<4-ft flame lengths) is considered desirable, and in contrast, both moderate- and high-severity fire are considered undesirable. Details on how low-, moderate-, and high-severity fire probabilities are modeled and interpreted are documented in the above "Fire Dynamics Pillar" section.

For current conditions, the risk of moderate- or high-severity fire is assessed at two scales (30-m pixel and 720-m window). The target condition at the 30-m pixel scale (the scale of the fire modeling) is a zero probability of risk of moderate- or high-severity fire based on FLEP-Gen modeling results. Any location with a probability of moderate- or high-severity fire exceeding 50 percent is considered fully departed. The final evaluation of condition is at the 720-m scale (52 ha), where the target proportion of cells that are fully departed is in the $\leq 10^{th}$ percentile, and fully departed is in the $\geq 90^{th}$ percentile (table 14; fig. 24).

For future conditions, the risk of moderate- or high-severity fire is assessed at two scales (180-m pixel and 720-m window) based on LANDIS-II modeling results. Future conditions were represented by five replicates of 40 years into the future. Similar to current conditions, the target condition at the 180-m pixel scale (the scale of the LANDIS-II modeling) is a zero probability of risk of moderate- or high-severity fire. Any location with a probability of moderate- or high-severity fire exceeding 50 percent is considered fully departed. The final evaluation of condition is at the 720-m scale (52 ha), where the target proportion of cells that are fully departed is in the ≤10th percentile, and fully departed is in the ≥90th percentile (table 14; fig. 24).

Table 14—Fire-adapted communities pillar condition interpretation (logic model) in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Description	Scale	Data	Data source	Condition	References
Current probability of moderate and high fire severity	30-m pixel	Probability of ≥4-ft flame length	FLEP-Gen	Target: 0% Fully departed: ≥60% probability of moderate and high-severity fire	Based on the current condition assessment
Current probability of moderate and high fire severity	720-m neighborhood	Proportion of WUI cells with high probability of ≥4-ft flame length, i.e., moderate-severity fire + high-severity of fire (2019)	FLEP-Gen	Target: ≤10th percentile Fully departed: ≥90th percentile	N/A
Future probability of moderate and high fire severity	180-m patch	Probability of moderate-severity fire and high-severity fire (2020–2060)	LANDIS-II	Target: ≤10% Fully departed: ≥90% probability of moderate and high-severity fire	N/A
Future probability of moderate and high fire severity	720-m neighborhood	Proportion of WUI cells with high probability of moderate and high-severity fire (2020–2060)	LANDIS-II	Target: ≤10th percentile Fully departed: ≥90th percentile	N/A

WUI = wildland-urban interface, N/A = not applicable.

Fire Preparedness Element

Overview—

The fire preparedness element is an important part of the fire-adapted communities pillar. It can be represented by a variety of metrics that are tailored to the type and complexity of the landscapes being assessed. This TCSI Blueprint was limited by the availability of consistent community protection data layers across all of the TCSI landscape. Community-based measures that represent preparedness and protection for wildfire events include ingress and egress routes, defensible space around structures, critical infrastructure protection, home hardening, fire-safe councils, and community wildfire protection plans. This element may be developed later as part of ongoing investments in community awareness and protection efforts.

Biodiversity Conservation Pillar

Overview

Biodiversity is essential to forest resilience in many ways, including reforestation, postburn recovery, and essential services of ecosystems to ecology and society, such as seed dispersal and pollination, recreational activities (consumptive and nonconsumptive), and adaptation to change over time. Elements of biodiversity range from genetic diversity and population persistence of individual species of interest or concern to suites of species that perform critical ecosystem functions, to community interactions and interdependencies that support the persistence of individual species.

Biodiversity conservation pertains to how we manage for biological diversity for all animals, plants, and micro-organisms, and for all the ecosystems in which these species occur. Biodiversity provides the essential foundation for the many goods and services a healthy environment provides, including those that are fundamental to our health, such as clean air, fresh water, food products, and timber and fiber. Biodiversity also provides other important services such as recreational, cultural, and spiritual nourishment that maintain our personal and social well-being. California has ambitious biodiversity conservation goals, as reflected in the 2017 Biodiversity Initiative and subsequent Executive Order B-54-18, the 2017 Safeguard California Plan, and the 2015 State Wildlife Action Plan.

The biodiversity conservation pillar has three elements: focal species, species diversity, and community integrity (fig. 25). Elements were given equal weight in the logic model for the biodiversity conservation pillar (fig. 26).

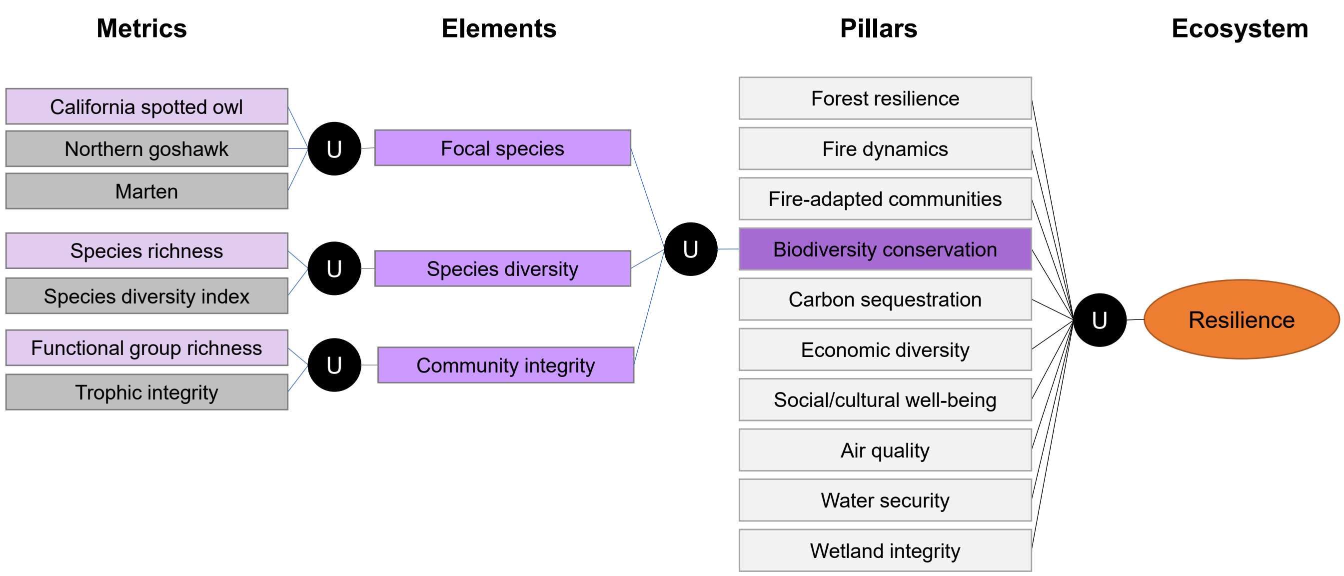


Figure 25—Elements and metrics of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. U = “UNION” logic model operator.

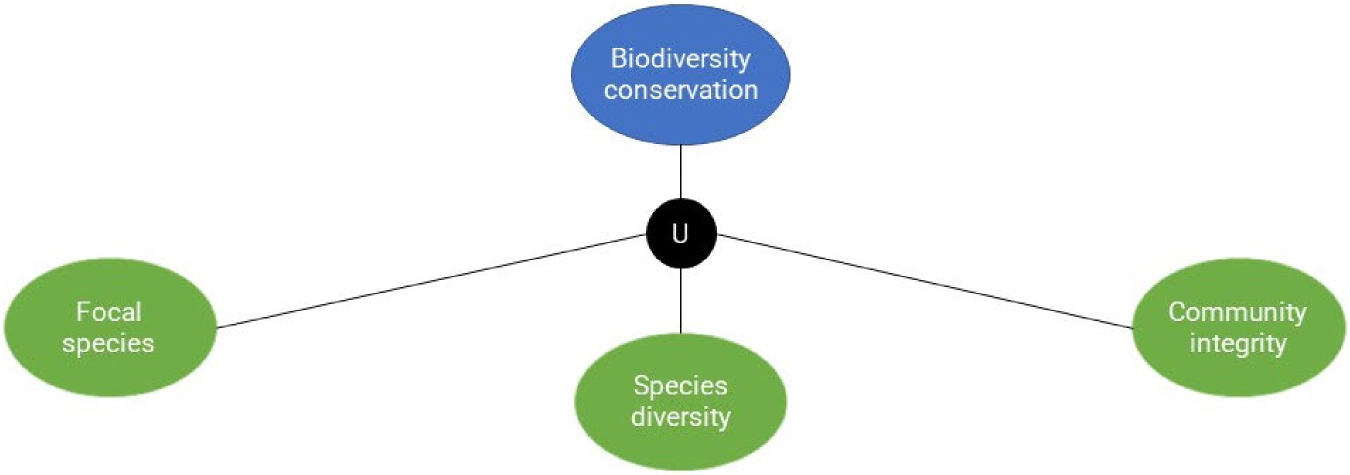


Figure 26—Biodiversity conservation pillar logic model with associated elements in the Tahoe-Central Sierra Initiative Blueprint for Resilience. U = "UNION" logic model operator.

Biodiversity Modeling Methods

Species included—

The CWHR database (CDFW CIWTG 2014) was used to identify species to be included in the analysis. For the habitat analysis, we queried CWHR software (version 9.0) to select species that (1) were native; (2) overlapped with Alpine, Amador, Butte, El Dorado, Nevada, Placer, Plumas, Sierra, or Yuba Counties; and (3) had year-long presences in one or more of those counties. We subsequently filtered out species that did not have reproductive habitat in any of the 16 cover types simulated by the LANDIS-II model (described previously) or were primarily associated with aquatic environments. This resulted in identifying 202 species for the habitat modeling: 95 birds, 81 mammals, and 26 reptiles (app. 2).

We filtered the species list further for the connectivity modeling. We assumed it would only be informative if the range of a species from the CWHR database covered at least 20 percent of the TCSI landscape and removed any species whose range composed less than 20 percent of the study area. Next, we filtered by estimated dispersal distance. Given the relatively large pixel size of the LANDIS-II outputs and the relatively small dispersal distance of many of the species identified for the habitat analysis, we only used species for the connectivity analysis that had dispersal distance of at least 1200 m. If documented and available, dispersal distances were obtained from the CWHR database. When dispersal distances were not available, they were estimated by either home range size, or if home range size was not available, they were estimated by body size. For mammals, when home range sizes were available, the formula from Bowman et al. (2002) for calculating dispersal distance was used. The formula from Paradis et al. (1998) for birds, and the formula from Pough (1980) for reptiles was used when only body size was available. This filtering process resulted in 81 species for the connectivity analysis: 59 birds and 22 mammals (app. 2).

Suitable habitat—

The LANDIS-II raster outputs were crosswalked to land cover classes and seral stages used in the CWHR database. We then applied the CWHR values for each species to the crosswalked rasters. The CWHR database applies values of 0, 0.11, 0.22, or 0.33 to species, seral stage, and canopy cover for each of three habitat categories: reproductive habitat, feeding habitat, and cover habitat. For estimating habitat suitability across the study area, we were only interested in the quality of reproductive habitat. We assumed that reproductive habitat was the best proxy for population status. Therefore, for the habitat analysis, the reproductive values were applied to the outputs for the current time step and each subsequent 5-year time step to the year 2060 and rescaled from 0 to 1. For connectivity, we were interested in all three habitat categories and summed the CWHR values for reproductive, feeding, and cover habitats to get an overall habitat score.

Modeling connectivity—

We modeled connectivity using cumulative resistant kernels (Compton et al. 2007), which calculate cost and distance from source points distributed across the study area and then sums the kernels to get a synoptic connectivity surface that represents the density of movers in each pixel. Cumulative resistant kernels require source points and a resistance surface. For the source points, we first calculated the percentage of the TCSI study area covered by the range of each species and sampled source points relative to the percentage of coverage. The maximum number of source points on the landscape was set at 2,084, and that would be the number of source points used if the species range covered 100 percent of the TCSI landscape. For the 2019 time step, we sampled the source points according to the habitat suitability surface so that more source points were placed in higher quality habitat than other habitat. Because we modeled dynamic connectivity through time, the source points for the future time steps were sampled on the connectivity surface generated in the previous time step. The connectivity surface for time step t_i was rescaled from 0 to 1, and source points for time step t_{i+1} were sampled on this surface.

For the resistance surfaces, we applied the summed values across all three CWHR categories for each pixel, which resulted in surfaces with values from 0 to 0.99. We then rescaled the surfaces to 1 to 100 for each species and took the inverse to get resistance. We created cumulative resistant kernels for each species and time step with UNICOR v. 2.0 software (Landguth et al. 2012). Because we are calculating connectivity at 10-year time steps, we used 10 times the dispersal distances estimated for each species as the “edge distance” value in UNICOR. The edge distance serves as a threshold in the spread of each kernel when the cumulative cost distance reaches this value.

Multispecies habitat, connectivity, and change—
We produced binary maps from the reproductive habitat outputs by classifying <0.3 as zero and >0.3 as 1. For each time step, we used the binary habitat maps in the R package landscape metrics (Hesselbarth et al. 2019) to calculate the following: (1) overall species richness; (2) species richness for each functional group of predators, cavity excavators/nesters, soil aerators, herbivores, seed/spore dispersers, and insectivores (app. 2); and (3) habitat connectivity metrics for each species (aggregation index, largest patch index, mean core area, mean nearest neighbor distance, number of patches, and percentage of the landscape).

Focal Species Element

Overview—
Fourteen focal species were identified in the TCSI Assessment of Current Landscape Conditions (Wilson and Manley 2021b) based on their sensitivity to impacts from restoration thinning, prescribed fire, and wildfire. The California spotted owl, northern goshawk, American marten, and 11 other focal species were identified as relevant in multiple planning and permitting documents, most notably from species identified in the USDA Forest Service, Pacific Southwest Region "Regional Forester's 2013 Sensitive Animal Species List" (USDA FS 2013), which includes U.S. Department of the Interior (USDI), Fish and Wildlife Service listed, proposed, and candidate species. Some category 3 "management indicator species" (USDA FS 2007) are also included in the list of focal species (i.e., mule deer, mountain quail, and sooty grouse).

The only focal species included in the TCSI Blueprint is California spotted owl, which commonly holds substantial importance for forest management. The USDA Forest Service California Spotted Owl Conservation Strategy in the Sierra Nevada (USDA FS 2019) was recently developed to provide scientific information and applicable adaptive management recommendations. The California spotted owl metric represents territory density based on areas that exceed a required threshold of suitable habitat as defined in the California Spotted Owl Conservation Strategy. CWHR-based habitat models could be included as desired for additional focal species in future iterations of the TCSI Blueprint and then given equal weight, or some species could be weighted more than others based on some set of criteria (fig. 27).

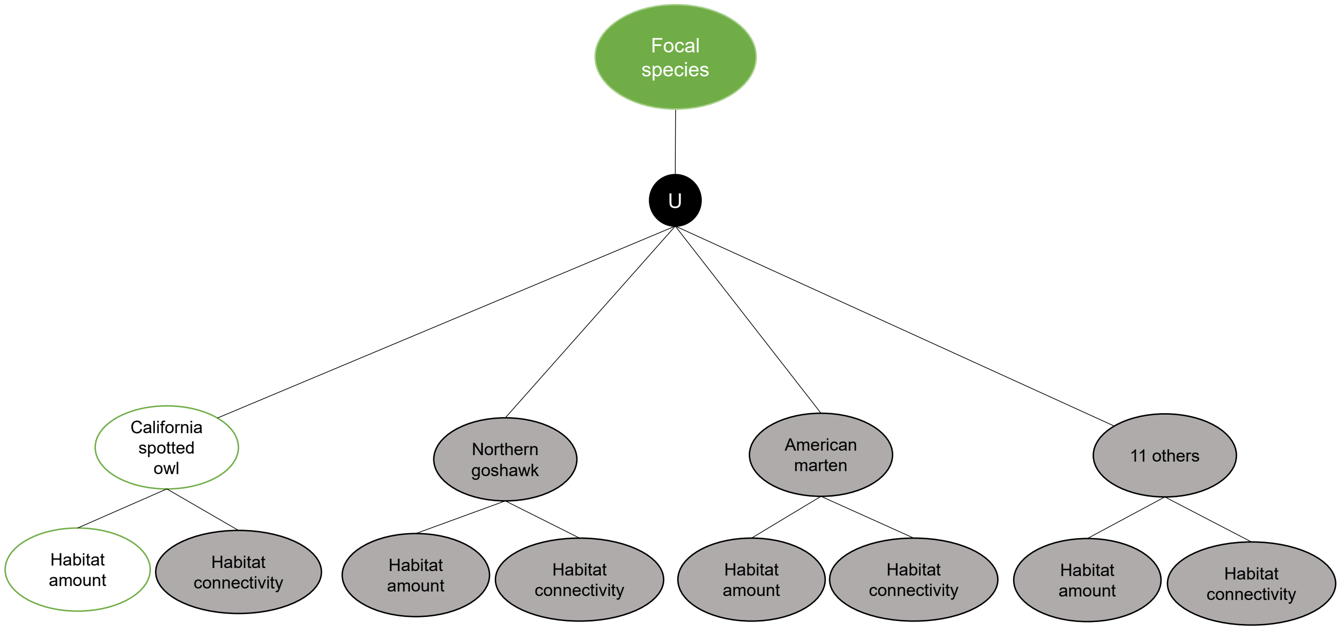


Figure 27—Focal species element logic model with associated focal species metrics of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative (TCSI) Blueprint for Resilience. Shaded ovals represent measures and metrics that are not represented in the TCSI Blueprint. U = "UNION" logic model operator.

M1: California spotted owl habitat—

Importance and relevance—Although the California spotted owl is continuously distributed on the western slope of the Sierra Nevada and inhabits elevations ranging from 1,000 to more than 7,000 ft, it is a USDA Forest Service, Pacific Southwest Region "sensitive species" (USDA FS 2013) and management indicator species (representing late-seral, closed-canopy coniferous forest). In November 2019, the U.S. Fish and Wildlife Service issued a 12-month finding on a petition to list the California spotted owl under the U.S. Endangered Species Act (1973) and determined that it was not warranted at the time (USDI FWS 2019). Although the California spotted owl is declining throughout much of its range and faces continued threats because of wildfire, habitat loss, and competition from barred owls, the U.S. Fish and Wildlife Service determined that existing regulatory mechanisms were sufficient (USDI FWS 2019). The California spotted owl is recognized by the state of California as a "species of special concern" and a "species of greatest conservation need" (CDFW 2008, 2015).

Dozens of scientific papers have been published over the past 20 years pertaining to the owl's population status, habitat associations, and vulnerabilities to habitat loss and disturbance (Blakesley et al. 2010; Gutiérrez et al. 2017; Jones et al. 2016, 2020; North et al. 2017). Population trends from four demographic study areas in the Sierra Nevada suggest that the populations are declining on NFS lands on the Eldorado, Lassen, and Sierra National Forests, and are stable or increasing in the Sequoia Kings Canyon study area (Conner et al. 2013, 2016; Gutiérrez et al. 2017; Keane 2014; Tempel 2014; Tempel and Gutiérrez 2013). The 1993 through 2013 data from these demography study areas indicate that California spotted owl populations declined on the three national forests: the Eldorado (by 50 percent), Lassen (by 44 percent) and Sierra (by 31 percent) National Forests (Conner et al. 2016, Tempel 2014). Recent research indicates that observed population declines of the California spotted owl on NFS lands in the Sierra Nevada may in part be the result of a lag effect from prior removal of large trees (Jones et al. 2018).

A conservation assessment for the California spotted owl was conducted in 2017 (Gutiérrez et al. 2017). This was followed by the development of a conservation strategy to guide habitat management on NFS lands (USDA FS 2019). The conservation strategy for the California spotted owls in the Sierra Nevada aims to balance the need to conserve essential habitat elements around sites occupied by the California spotted owls, while simultaneously restoring resilient forest conditions at the landscape scale (USDA FS 2019).

Habitat management for the California spotted owl on NFS lands is guided by forest plan direction for managing known nest sites, associated activity centers, and surrounding habitat within 2.4 km of activity centers. The conservation strategy for the California spotted owl is being incorporated into future planned projects. The forest plan direction has a significant effect on the extent, location, and types of treatments that are conducted. The USDA Forest Service designates a 121.5-ha (300-ac) protected activity center around each known nesting area or activity center. The protected activity center is a USDA Forest Service land allocation designed to protect and maintain high-quality California spotted owl nesting and roosting habitat around active sites. Territorial owls typically defend a geographic area consistently used for nesting, roosting, and foraging, containing essential habitat for survival and reproduction. The USDA Forest Service calls for an area of 405 ha (1,000 ac) in the central Sierra Nevada around core use areas, including the associated protected activity center.

Description and derivation—The California spotted owl habitat metric evaluates the 1,000 ac around each 15-m pixel to determine if it meets minimum habitat requirements to support a territory. The nesting habitat requirement is 121.5 ha within a 405-ha circular area, and is represented by CWHR habitat types 4M, 4D, 5M, 5D, and 6 (table 15; fig. 28). The foraging habitat requirement was an additional 121.5 ha (243 ha total) within the 405-ha circular area and was represented by CWHR habitat types 3M and 3D as well as nesting habitat types.

Table 15— Focal species element, California spotted owl habitat metric condition interpretation (logic model) of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Scale	Data	Data source	Condition	Reference
Current habitat type	180-m patch	Suitable habitat type (4M, 4D, 5M, 5D, 6)	LANDIS-II	N/A	N/A
Current amount of suitable nesting habitat	405-ha area	Contiguous area of suitable nesting habitat (5M, 5D, 6)	LANDIS-II	Target: >121.5 ha Fully departed: <121.5 ha	N/A
Current amount of suitable foraging habitat	405-ha area	Area of suitable foraging habitat (nesting habitat plus 4M, 4D)	LANDIS-II	Target: >243 ha Fully departed: <162 ha	N/A
Future habitat type	180-m patch	Suitable habitat type	LANDIS-II	N/A	N/A
Future amount of suitable nesting habitat	405-ha area	Maximum area of suitable nesting habitat	LANDIS-II	Target: >121.5 ha Fully departed: <121.5 ha	N/A
Future amount of suitable foraging habitat	405-ha area	Maximum area of suitable foraging habitat	LANDIS-II	Target: >243 ha Fully departed: <162 ha	N/A

N/A = not applicable.

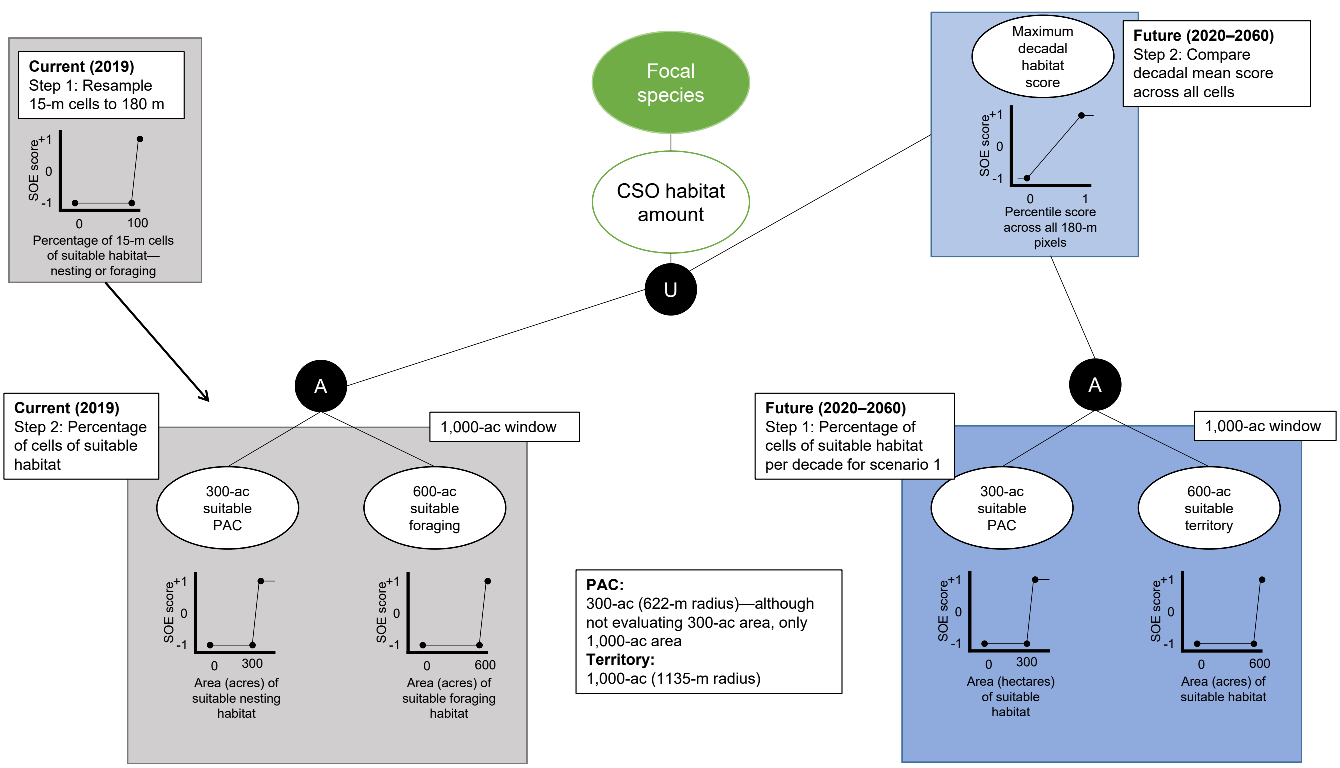


Figure 28—California spotted owl (CSO) metric logic model in the focal species element of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. PAC = protected activity center; SOE = strength of evidence; logic model operators: A = AND, U = UNION.

Species Diversity Element

Overview—

Species diversity is a function of both the number of different species in the community and their relative abundances. Larger numbers of species and more even abundances of species lead to higher species diversity. Species diversity can be calculated in a variety of ways to represent the type and magnitude of differences among species, their number, and their abundances. In the TCSI Blueprint, we have just one metric of species diversity, species richness (M1), which is represented as a combination of two measures: a simple count of native vertebrate species for whom the habitat conditions are suitable to support reproduction (richness) and the connectivity of species-rich locations (fig. 29). A habitat connectivity metric was also evaluated to complement each species diversity metric to indicate the greater or lesser value of the location based on its connectivity. High connectivity indicates a lower potential for species loss and a greater contribution for spatial adaptation to changing climates. The CWHR database (CDFW CIWTG 2014) was used to represent the probability that a location in the landscape could support reproduction based on habitat conditions that were highly suitable for reproduction. The species list per 15-m pixel can then be evaluated in a variety of

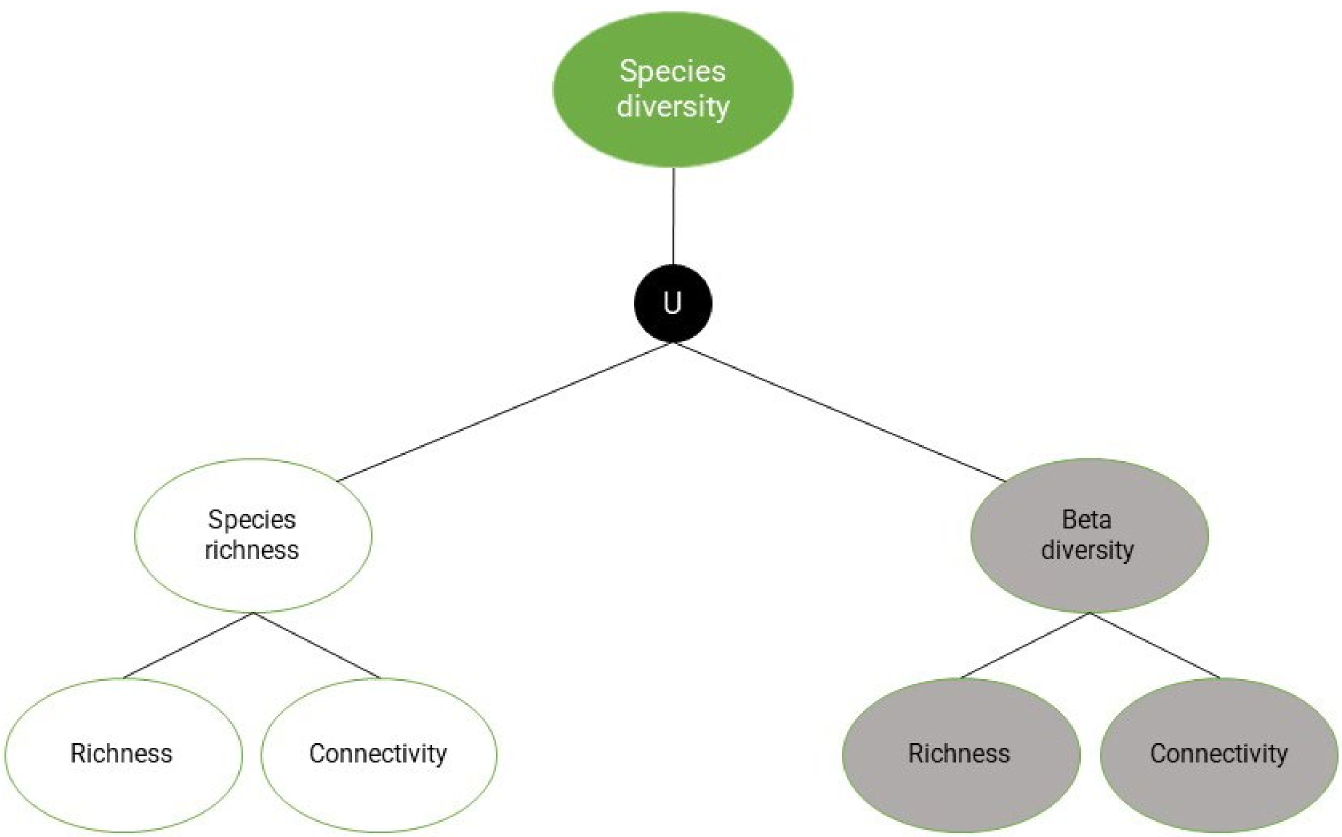


Figure 29—Species diversity element logic model with associated focal species (metrics) of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative (TCSI) Blueprint for Resilience. Shaded ovals represent measures and metrics that are not represented in the TCSI Blueprint. U = “UNION” logic model operator.

ways and at various scales to make inferences about species diversity. It would be valuable to include an additional metric of species diversity, beta diversity, such that vertebrate species richness and beta diversity are both included in representations of species diversity (fig. 29).

M1: Species richness and connectivity—
Importance and relevance—Species richness is a measure of the number of species present in a community, which indicates the ability of a site to support many species. In general, sites with high native species richness serve to support a greater number of individuals across the landscape and support greater resilience to impacts from disturbance than sites with lower species richness.

Description and derivation—Estimates of species richness are based on whether habitat that supports high-quality reproductive habitat for a given species exists. This metric represents species for which a 180-m patch had high reproductive CWHR habitat value, based on LANDIS-II habitat conditions at time zero (2019).

We calculated the 10^{th} and 90^{th} percentile of species richness across all 180-m patches on the TCSI landscape, current and future (to 2060, scenario 1 MIROC8.5_5), to derive a measure of potential richness. We considered values in the $\leq 10^{th}$ percentile to be in departed condition (−1) and values in the $\geq 90^{th}$ percentile are considered in target condition (1) (table 16; figs. 30 and 31).

For future conditions, species richness condition was evaluated based on the observed potential range of richness values observed over 40 years into the future. Future conditions were based on scenario 1 for five iterations, where only private timberlands and the defense zone are managed. We also calculated variability of future conditions based on the standard deviation of richness values observed over 40 years into the future (table 16; figs. 30 and 31). High future richness is good, but high variability is not good. The minimum condition score of future richness and variability was used to represent potential.

Table 16—Species diversity element, species richness and connectivity metric condition interpretations (logic model) of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Scale	Data	Data source	Condition	Reference
Current species richness/ connectivity	180-m patch	Species count/landscape connectedness	LANDIS-II, CWHR	Target: ≥90th percentile Fully departed: ≤10th percentile of full range of species richness observed current and future	N/A
Current species richness/ connectivity	720-m neighborhood	Mean condition score across all the 180-m areas		N/A	N/A
Future species richness/ connectivity	180-m patch	Maximum species richness over next 40 years (2020–2060)	LANDIS-II	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A
Future species richness/ connectivity	720-m neighborhood	Mean condition score across all the 180-m areas over 40 years	LANDIS-II	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A
Future variation species richness/ connectivity	720-m neighborhood	Standard deviation in mean condition scores over 40 years	LANDIS-II	Target: ≤10th percentile Fully departed: ≥90th percentile	N/A

Note: richness was evaluated as the number of species, while connectivity was evaluated as the connectedness of the landscape for all species. Each richness and connectivity metric was evaluated similarly across each metric and condensed here for simplicity.

CWHR = California Wildlife Habitat Relationships; N/A = not applicable.

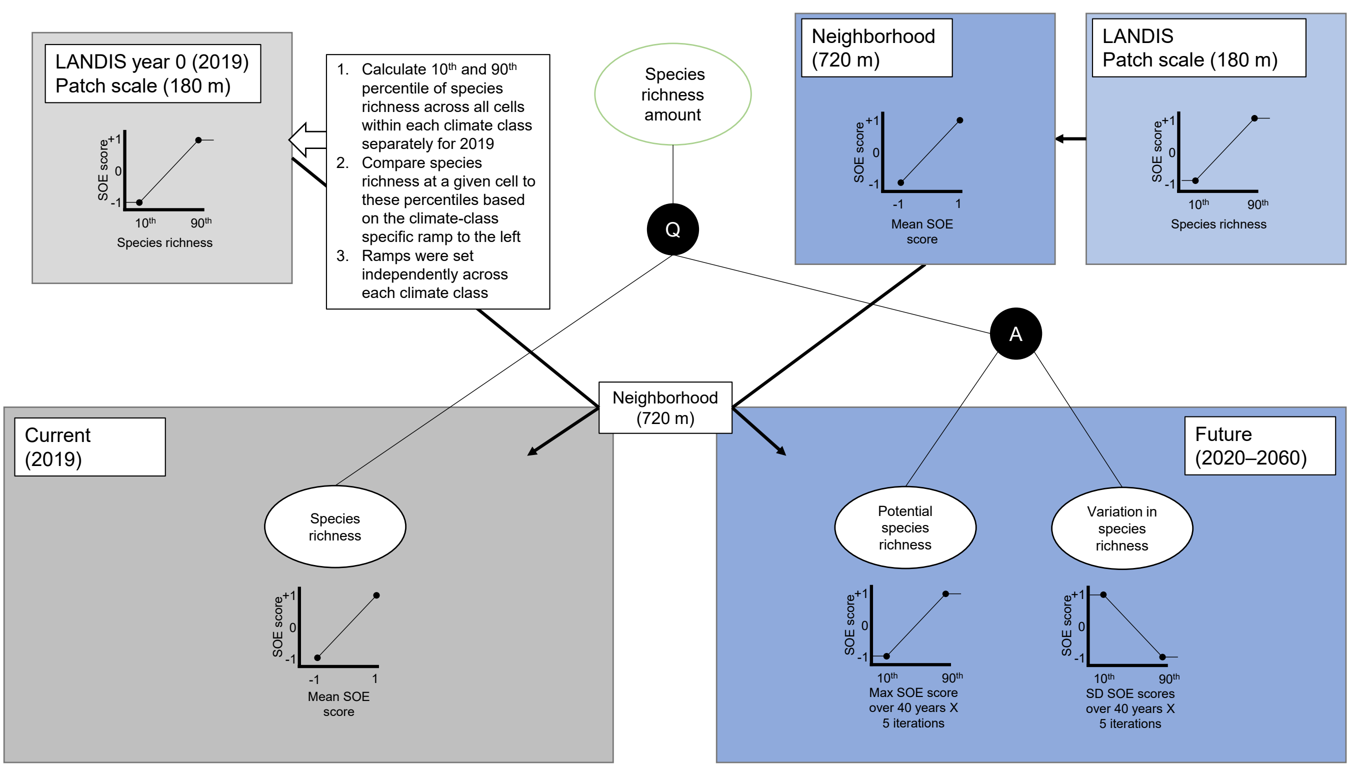


Figure 30—Species richness metric logic model in the species diversity element of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. Logic model operators: A = AND, Q = QUADRANT; SOE = strength of evidence.

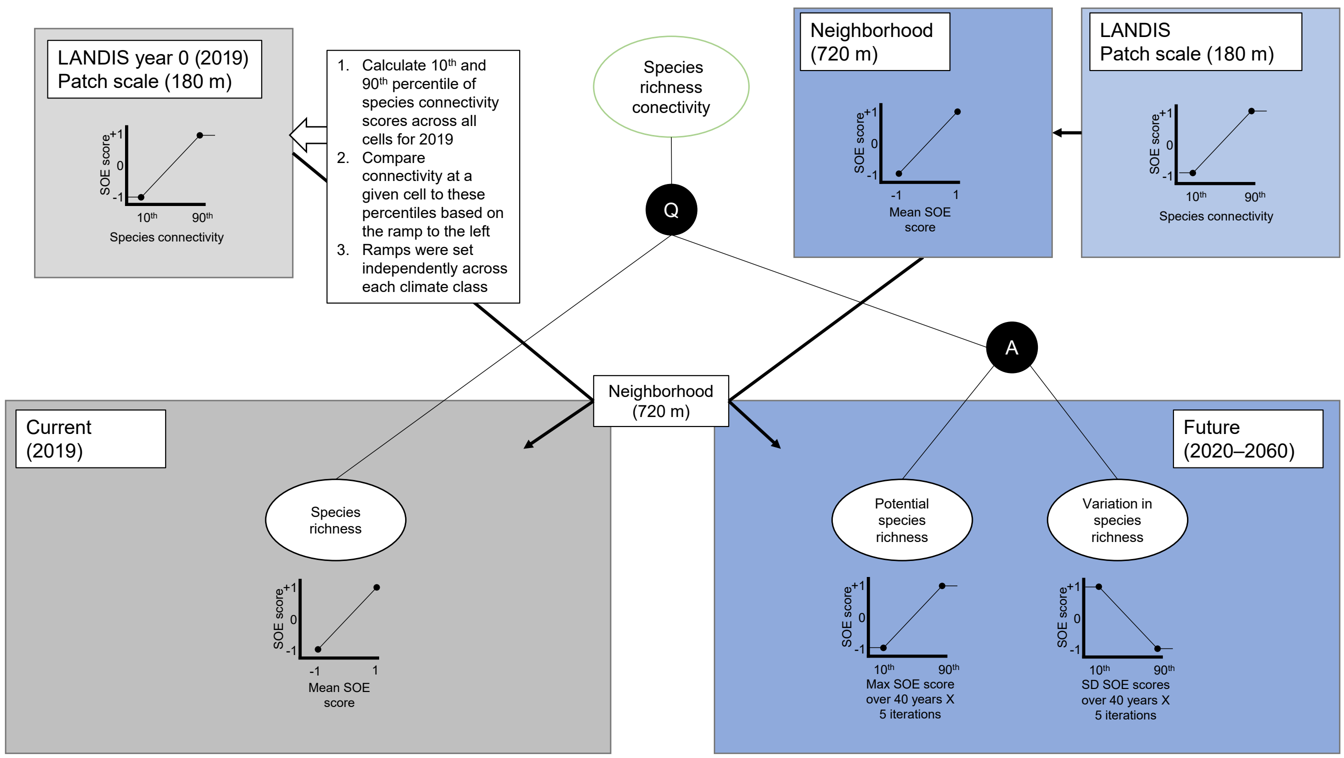


Figure 31—Species connectivity metric logic model in the species diversity element of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. Logic model operators: A = AND, Q = QUADRANT; SOE = strength of evidence.

Community Integrity Element

Overview—

The community integrity element is represented by six metrics of functional group diversity (M1) (fig. 32). Functional diversity is a component of biodiversity that describes the range of things that organisms do in communities and ecosystems. Species perform a range of critical ecosystem services. A primary consideration in management is to maintain conditions (resistance strategy), adapt to changing conditions (adaptation strategy), and transition to alternate but still productive conditions (transform) over time. The maintenance of ecosystem services is a primary concern with climate change.

M1: Functional group diversity—

Importance and relevance—A functional group is a set of species or collection of organisms that share similar characteristics within a community. Functional groups perform very specific roles within any given ecosystem and influence ecosystem level processes (Petchey and Gaston 2006). There are six functional groups, which include a range of trophic levels and ecosystem services (fig. 32), and they are represented by measures of both richness and connectivity. Measures of connectivity complement each functional group richness measure to indicate the greater or lesser value of the location based on its connectivity. High connectivity indicates a lower potential for species loss and a greater contribution for spatial adaptation to changing climates.

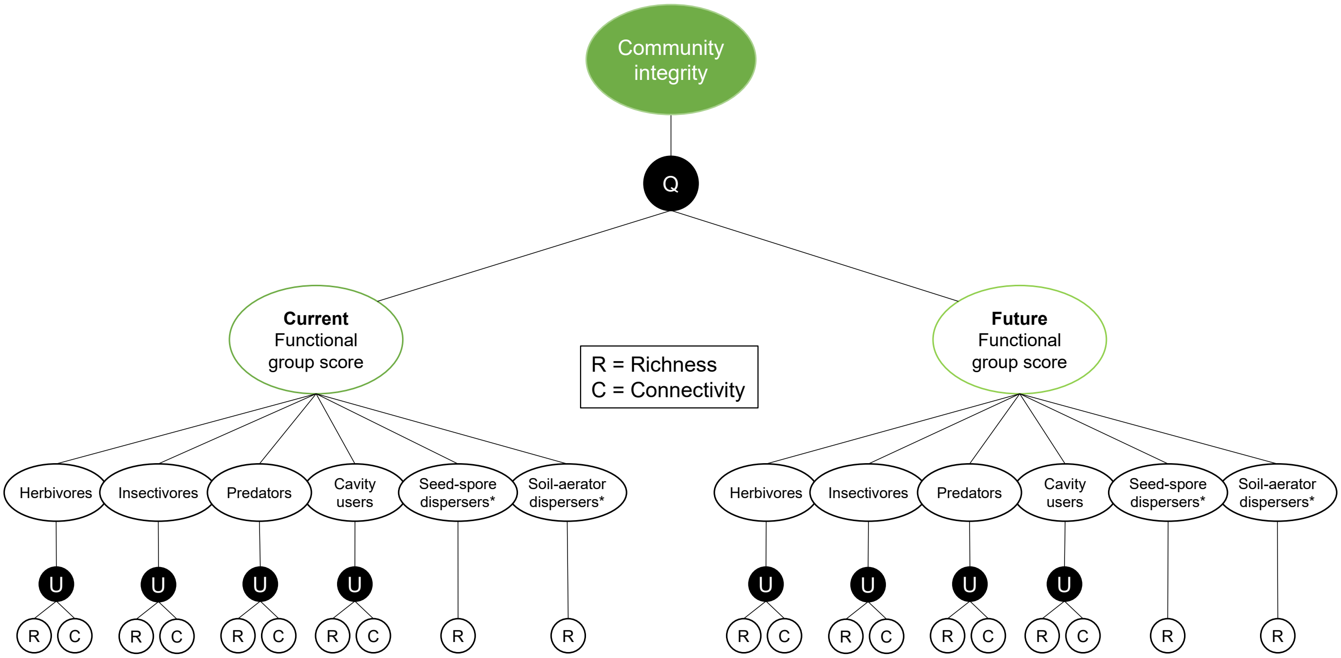


Figure 32—Community integrity element is represented by a range of six functional groups with current and future functional group scores that include a range of trophic levels and ecosystem services. Logic model operators: Q = QUADRANT, U = UNION.

Description and derivation—The diversity of each functional group is first determined by the number of species for which a given location provides suitable habitat and the degree to which it is connected currently. Current conditions for each functional group's richness and connectivity are based on 2019 LANDIS-II outputs interpreted in terms of CWHR habitat types and associated suitability for species in each functional group. Richness values are first calculated at the 15-m scale and then averaged across all 15-m cells at the 720-m neighborhood scale (about 125 ac) to represent area requirements for most species (fig. 33). Connectivity was calculated as described in the above "Biodiversity Modeling Methods" section.

Future conditions for each functional group's richness and connectivity are based on five replicates of LANDIS-II model outputs for scenario 1 (private timberlands and defense zone management only) for 40 years into the future (2020–2060). LANDIS-II outputs are interpreted in terms of CWHR habitat types and associated suitability for species in each functional group. Richness values are first calculated at the 180-m scale and then averaged across all 180-m cells at the 720-m neighborhood scale (about 50 ha) to represent area requirements for most species (table 17; fig. 33). Connectivity was calculated as described in the above "Biodiversity Modeling Methods" section.

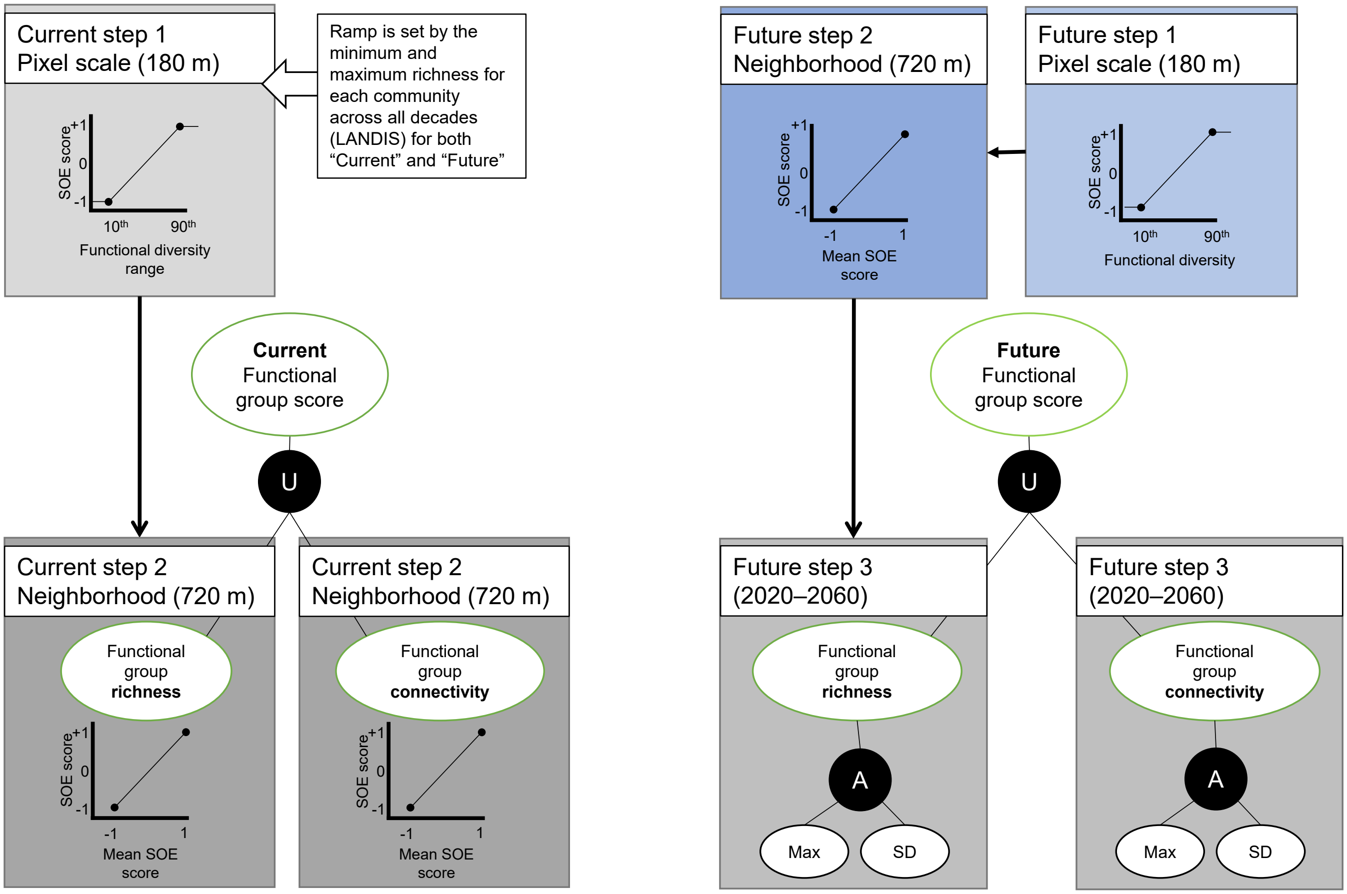


Figure 33—Functional group diversity metric logic model for each group in the community integrity element of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. Logic model operators: A = AND, Q = QUADRANT; SOE = strength of evidence; SD = standard deviation, SOE = strength of evidence.

Table 17—Community integrity element, functional group diversity metric condition interpretations (logic model) of the biodiversity conservation pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Scale	Data	Data source	Condition	Reference
Current functional diversity/ connectivity	15-m pixel	Diversity: sum of species for which the CWHR habitat is suitable for reproduction (0/1) Connectivity: connectedness of suitable habitat	LANDIS-II (2019)	Target: ≥90th percentile Fully departed: ≤10th percentile of full range of current and future conditions	N/A
Current functional diversity/ connectivity	720-m neighborhood	Average current condition score	LANDIS-II (2019)	Target: +1 Fully departed: −1	N/A
Future functional diversity/ connectivity	180-m patch	Maximum condition score over all decades	LANDIS-II (2020–2060)	Target: ≥90th percentile Fully departed: ≤10th percentile of full range of current and future conditions	N/A
Future functional diversity/ connectivity	720-m neighborhood	Average future condition score	LANDIS-II (2020–2060)	Target: +1 Fully departed: −1	N/A
Future variability in diversity/ connectivity score	720-m neighborhood	Standard deviation of decadal condition scores	LANDIS-II (2020–2060)	Target: ≤10th percentile Fully departed: >90th percentile	N/A

CWHR = California Wildlife Habitat Relationships, N/A = not applicable.

Carbon Sequestration Pillar

Overview

Carbon storage in forest biomass is an essential attribute of stable forest ecosystems and a key link in the global carbon cycle. Forests sequester and store large amounts of carbon, which is an important role in mitigating climate change. After carbon dioxide is converted into organic matter by photosynthesis, carbon is stored in forests for a period of time in a variety of forms before it is ultimately returned to the atmosphere through respiration and decomposition or disturbance. A substantial pool of carbon is stored in woody biomass (roots, trunks, and branches), while other portions are organic matter in forest floor litter and in soils.

Forests are at increasing risk of losing carbon owing to large-scale disturbance events, especially from high-severity wildfire. Forest management can reduce the potential for high-severity fire by reducing forest density, but there is a recognized tradeoff in that management incurs a short-term carbon cost to avoid substantial carbon losses from high-severity fires over longer time periods (Hurteau and North 2010). Although fuel treatments may lower the overall biomass stored, more biomass may survive a fire compared to untreated forests (Battles et al. 2018), and the treatments can shift carbon stock growth to larger and more resilient trees.

California has taken several legislative steps toward mitigating risks of carbon emissions and increasing carbon sequestration. In 2006, the California State Senate passed Assembly Bill 32, known as the Global Warming Solutions Act, which set a goal to reduce fossil fuel carbon emissions to 116 Tg and recognized the need to offset emissions through land management, including forest management. In 2018, California's Executive Order B-55-18 mandated that the state achieve carbon neutrality by 2045 and subsequently maintain net negative emissions. Natural and working lands are identified as essential to reaching this goal, with forests calculated to contribute about 20.5 Mt/year toward the goal of an additional 125 Mt/year of carbon captured and sequestered (i.e., negative emissions) statewide (Baker et al. 2020). Note that assumptions about the likelihood and severity of wildfire and any emissions that would result or be avoided were not included in these emissions calculations, and high-severity wildfire in unhealthy forests have contributed significant emissions to the atmosphere in recent years. Preliminary estimates from the 2020 wildfire year for California indicate that wildfires burning in California forests emitted more than 80 Mt of CO_2 (CARB 2020), with even higher levels of emissions from wildfires in 2021, according to Copernicus Climate Change Service (2021). This suggests that forests in California have been a net source of carbon to the atmosphere in recent years.

The desired outcome for the carbon sequestration pillar is that carbon is sequestered and stable. The primary focus of the carbon sequestration pillar is on stable carbon to inform management opportunities to improve conditions on the landscape. The focus on stable carbon reflects spatially explicit conditions that are valuable to maintain and also to reflect where conditions can be enhanced toward long-term gains in ecosystem conditions and services. To do this, the carbon sequestration pillar evaluation focuses on carbon in aboveground live tree biomass. There is one element in this pillar: carbon stability (figs. 34 and 35).

The pillars in the TCSI Blueprint are set up to be evaluated independent of one another; conflicts and synergies among the pillars can be examined. By representing these resilience objectives independent of one another, it enables managers to identify and resolve conflicts in more transparent and scientifically defensible manners. For example, the carbon sequestration and fire dynamics pillars are evaluated separately in the TCSI Blueprint, and then in project identification and planning, conflicts between carbon and fire can be observed and reconciled by evaluating where achieving both pillar objectives are consistent or in conflict.

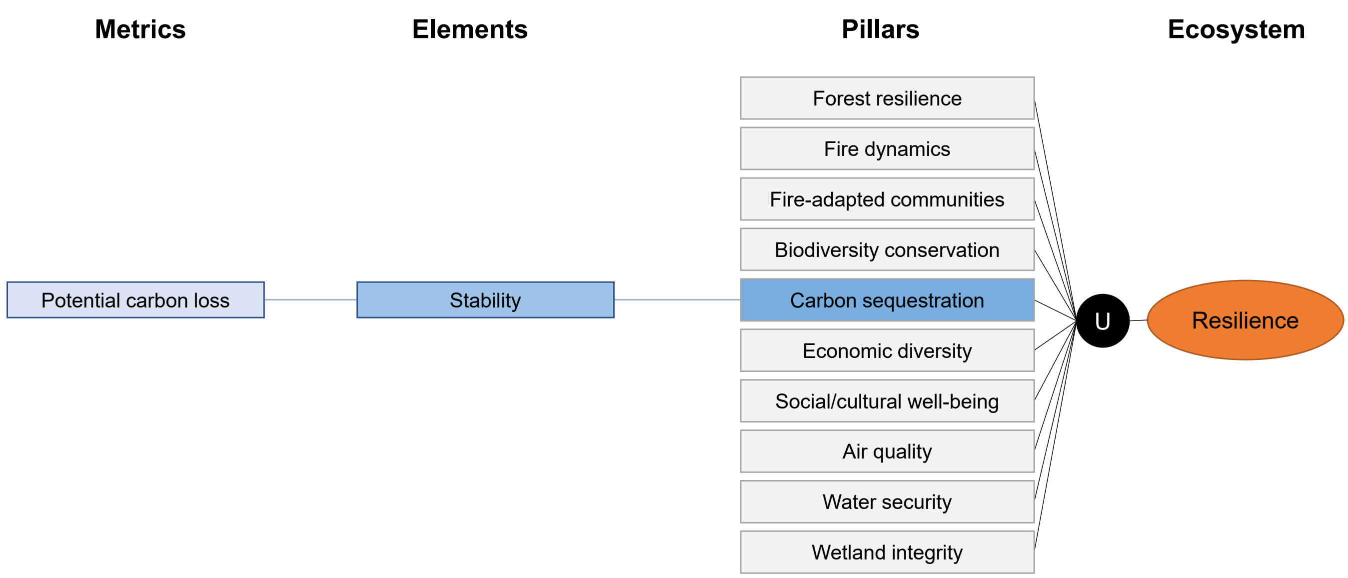


Figure 34—Elements and metrics representing the carbon sequestration pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. U = “UNION” logic model operator.

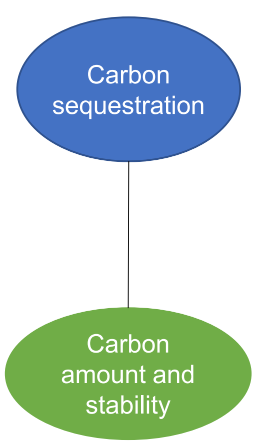


Figure 35—Carbon sequestration pillar logic model with associated elements in the Tahoe-Central Sierra Initiative Blueprint for Resilience.

Carbon Modeling Methods

General target conditions for carbon sequestration on the TCSI landscape are to increase net carbon sequestration over time. Given that the TCSI landscape comprises about 16 percent of California forested lands, a specific target for the TCSI landscape contribution to statewide carbon neutrality (Baker et al. 2020) would be about 3.3 Mt more per year. Estimates of current carbon sequestration rates are 3.1 Mt of CO_2 per year based on the TCSI resilience assessment (Wilson and Manley 2021a), which would mean that the TCSI landscape objective would be to roughly double the current carbon sequestration rate by 2045. However, in the past few years, the TCSI landscape has been a carbon source, not a sink, due to increased emissions associated with wildfires (CARB 2020, Maxwell and Scheller 2021).

We originally characterized total ecosystem carbon and the net ecosystem exchange for 2019 (Maxwell et al. 2022; Wilson and Manley 2021a, 2021b) using the LANDIS-II model in conjunction with a 2019 NCX base map, including soil carbon pools based on the 2017 gridded Soil Survey Geographic (SSURGO) data for California (USDA NRCS 2020) and dead carbon pools from an interpolation of FIA data of fine and coarse woody debris (Wilson et al. 2013). However, dead carbon in the form of dead wood is highly volatile, and in contrast, soil carbon is very stable. The measure of stable carbon that is most likely to be responsive to and representative of climate and management effects is live carbon.

The net ecosystem exchange (NEE) is primary productivity, the amount of carbon the forest acquires as it grows, minus ecosystem respiration (e.g., decomposition). A negative NEE value indicates a carbon sink (subtracting carbon from the atmosphere) and a positive NEE value indicates a carbon source (adding carbon to the atmosphere). NEE values vary in regard to climate conditions and therefore vary from year to year and over time. Emissions and NEE can vary significantly from year to year and are a function not only of forest dynamics but also represent the fate of woody material that is taken out of the forest for various uses (e.g., lumber and biochar).

In the TCSI Blueprint, we used estimates of carbon from live woody biomass as a proxy for carbon sequestration. Live woody biomass is a strong and actionable proxy for the contribution that forest ecosystems are making to carbon sequestration objectives. Tons of live carbon are calculated as woody biomass divided by 2, which represents a generalization of the proportion of woody biomass attributed to water versus carbon.

The carbon sequestration pillar is composed of one element, carbon stability, which represents carbon sequestration values and opportunities.

Stability Element

Overview—

Historically, low-intensity fires in dry forests promoted forest carbon storage by reducing surface and ladder fuels and thereby protecting carbon in soil and large, old trees. Today, the stability of carbon stored in forests is challenged by impacts from high-severity wildfire, climate-change-induced warming, and drought (Hurteau et al. 2019, Liang et al. 2017). Forest carbon management needs to balance disturbance-driven carbon loss with long-term, stable carbon storage.

M1: Potential carbon loss—

Importance and relevance—Stability is an important feature in carbon sequestration calculations because high levels of carbon loss, even when followed by high rates of carbon sequestration, are not as ecologically beneficial as high residency rates for carbon, particularly when stored in large, live trees that have many other ecological benefits.

Description and derivation—Carbon stability is measured as the variability in carbon stores per unit area over time. For current conditions, current live carbon levels were summed to HUC12 subwatersheds (table 18; fig. 36). Percentile values were calculated to compare the relative amounts across the subwatersheds. Similarly, a 720-m moving window analysis was used to sum carbon levels at a finer scale to capture variability in carbon amounts within individual HUC10 watersheds. Areas with higher carbon levels in the current time period resulted in higher scores in these areas.

Future carbon conditions were evaluated in a variety of ways. The proportion of total carbon in the current time period was compared to the maximum potential future levels at the 180-m scale. High scores were given to areas where current carbon levels were near their maximum. The probability of carbon loss from the current time period to the end of the LANDIS-II simulation (2060) was calculated as the number of model iterations that ended with less carbon than it began with for a given 180-m pixel. High scores were given to areas that rarely lost carbon over the simulation period.

Future potential conditions for each HUC12 subwatershed were based on maximum observed values over the next 40 years for that given HUC. Variability over time was represented by the standard deviation of the loss condition score for each decade. Calculated percentiles across all HUC12 subwatersheds and the SOE score is determined for a given HUC12 subwatershed based on its percentile. A similar analysis was done at the 720-m neighborhood scale to capture finer scale variability within HUC10 watersheds.

Table 18—Carbon stability element condition interpretations (logic model) of the carbon sequestration pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience

Data description	Scale	Data	Data source	Condition	Reference
Current live carbon biomass	180-m	Sum of all live aboveground carbon	LANDIS-II	N/A	N/A
Current live carbon biomass	HUC12	Sum of 180-m live carbon	LANDIS-II	Target: ≥90th percentile of potential Fully departed: ≤10th percentile of potential	N/A
Percentile live carbon within HUC10	720-m neighborhood	Sum of 180-m live carbon within 720-m window	LANDIS-II	Target: maximum C level within HUC10 Fully departed: minimum C level within HUC10	N/A
Proportion of maximum total C	180-m patch	Current C level/ maximum C level	LANDIS-II	Target: 90th percentile Fully departed: 10th percentile	N/A
Future probability of carbon loss	180-m patch	Proportion of model iterations where live carbon declines from current levels (2020–2060)	LANDIS-II	Target: 0% Fully departed: 100%	N/A
Future potential live carbon	180-m patch	Amount of live tree and shrub carbon	LANDIS-II	N/A	N/A
Future potential live carbon	HUC12	Maximum C amounts within HUC12 (2020–2060)	LANDIS-II	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A
Future live carbon variability	HUC12	Standard deviation HUC12 C amounts over time (2020–2060)	LANDIS-II	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A
Future potential live carbon	720-m neighborhood	Percentile maximum live C within HUC10	LANDIS-II	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A
Future live carbon variability	720-m neighborhood	Percentile standard deviation live C within HUC10	LANDIS-II	Target: ≥90th percentile Fully departed: ≤10th percentile	N/A

N/A = not applicable, C = carbon, HUC = hydrologic unit code.

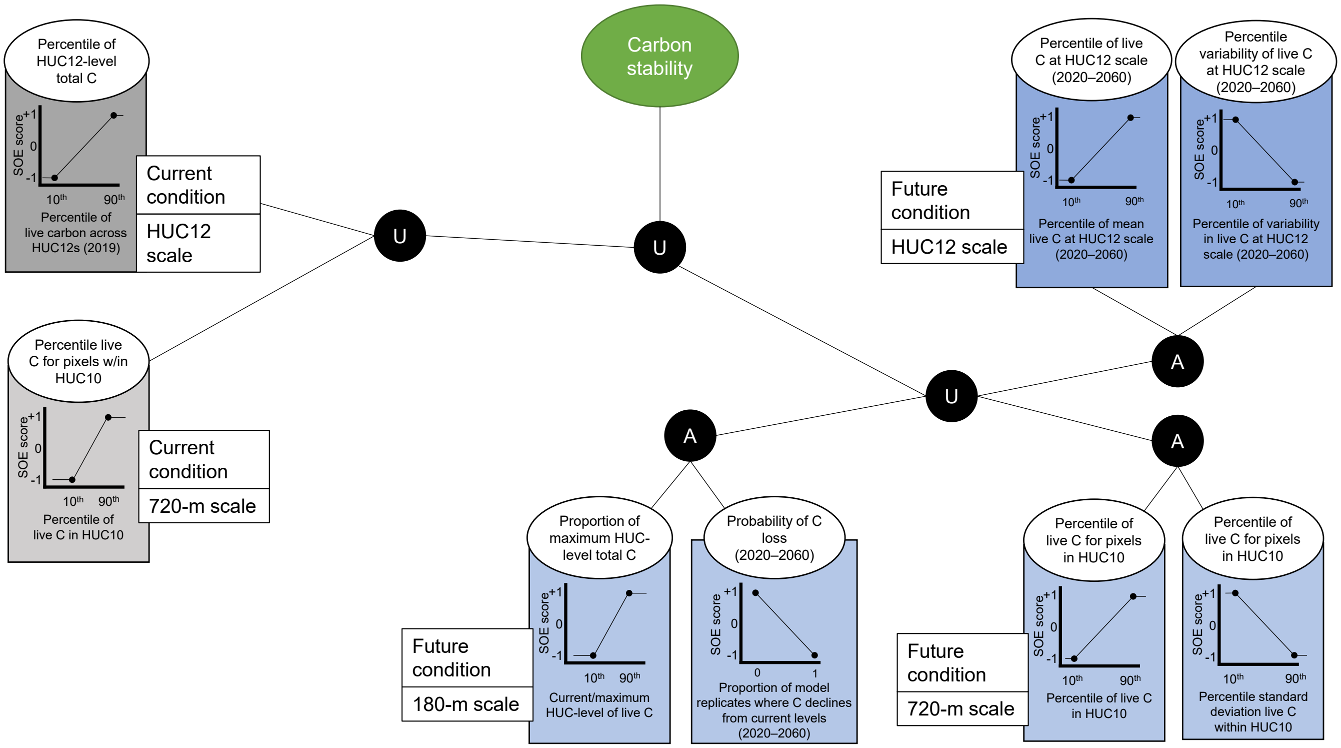


Figure 36—Potential carbon loss metric representing the stability element of the carbon sequestration pillar in the Tahoe-Central Sierra Initiative Blueprint for Resilience. HUC = hydrologic unit code, logic model operators: A = AND, U = UNION.

Acknowledgments

This work and the resulting Tahoe-Central Sierra Initiative (TCSI) Blueprint products would not be possible without the support and commitment of many individuals and agencies. None of this would have been possible without the foresight, commitment, and fortitude of the TCSI Steering Committee. Significant contributions of staff time were made by the Sierra Nevada Conservancy, the California Tahoe Conservancy, The Nature Conservancy, and the USDA Forest Service. Special thanks to the members of the TCSI Science Coordination Group and the Blueprint User Group for the many hours they contributed to discussion and review—they greatly improved the end product. Contributions from stalwart members of these two groups included those of Erin Ernst, Nic Enstice, Sarah Campe, Forest Schafer, Kristin Shive, Becky Estes, and Dave Fornier. Many thanks to Robert Scheller and Charles Maxwell (North Carolina State University) for their tremendous skill and patience in conducting the LANDIS-II modeling in support of the TCSI and the TCSI Blueprint.

U.S. and Metric Equivalents

U.S. Standard Equivalents

When you know:	Multiply by:	To find:
Centimeters (cm)	0.394	Inches
Meters (m)	3.28	Feet
Kilometers (km)	0.621	Miles
Hectares (ha)	2.47	Acres
Trees per hectare	0.405	Trees per acre

Metric Equivalents

When you know:	Multiply by:	To find:
Inches (in)	2.54	Centimeters
Feet (ft)	0.305	Meters
Miles (mi)	1.609	Kilometers
Acres (ac)	0.405	Hectares
Trees per acre	2.47	Trees per hectare
Ounces (oz)	28.4	Grams
Tons (t)	907	Kilograms

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Appendix 1: Tahoe-Central Sierra Initiative Blueprint for Resilience Data Sources and Terms

- **CAL FIRE Management Activity Project Planning and Event Reporter (CalMAPPER)**—The California Department of Forestry and Fire Protection (CAL FIRE) CalMAPPER is an internal geographic information system application that captures data on forest and fuels management projects and associated activities across programs within CAL FIRE. These data include active and completed project and treatment locations and basic activity information related to the treatments.
- **California Forest Observatory**—A data-driven forest monitoring system. This Web-based tool (https://forestobservatory.com) maps the drivers of wildfire hazard across the state, including forest structure, weather, topography, and infrastructure. Developed by Salo Sciences, Inc. and others, it combines high-resolution satellite imagery, airborne laser scanning, and artificial intelligence to provide current data at the individual tree scale. Imputed LiDAR data were used to assess canopy height and cover.
- **California Wildlife Habitat Relationships (CWHR)**—The CWHR system is a habitat classification scheme to categorize how the element stage classes and structures support California's regularly occurring birds, mammals, reptiles, and amphibians (Mayer and Laudenslayer 1988). There are 59 wildlife habitats in the CWHR System.
- **Contemporary regional reference condition dataset**—The landscape is stratified based on the biophysical setting of climate class and landscape management unit classifications (Jeronimo et al. 2019).
  - Climate classes are based on climatic water deficit, January minimum temperature, and actual evapotranspiration.
  - Landscape management units are classified into four topographic positions: ridge-, valley-, northeast-, and southwest-facing slopes. We developed a simplified four-class version of the landscape management unit layer using the Landscape Management Unit Tool, version 2 (Boynton et al. 2012, Underwood et al. 2010) that identified ridgetops, valley bottoms, northeast slopes, and southwest slopes.
  - Each landscape management unit is then attributed to a majority climate class; and defined the extrapolation of reference conditions based on climate class and landscape management unit stratification as the contemporary range of variability.
- **Ecosystem Disturbance and Recovery Tracker (eDaRT)**—The eDaRT (Koltunov et al. 2020) is an automated system that provides a suite of Landsat-derived products to identify and categorize changes in forest, shrubland, and herbaceous ecosystems. The eDaRT products are not publicly available, but recent efforts are focused on expanding operations by the USDA Forest Service

in California and elsewhere in the Western United States in support of daily ecosystem management tasks.

- **Fire and Resource Assessment Program (FRAP)—**The CAL FIRE FRAP assesses the amount and extent of California's forests and rangelands, analyzes their conditions, and identifies alternative management and policy guidelines.
- **FLEP-Gen/WildEST—**A deterministic method for generating flame-length probabilities (Scott 2020). Similar to FSim large fire simulator (see below), but it differs in the way it draws weather streams during a fire progression (i.e., a wider variety of weather conditions are used rather than matching historical weather) and adjusts fire intensity estimates based on whether a pixel burned with a heading or nonheading fire.
- **Forest Inventory and Analysis (FIA) data**—The USDA Forest Service FIA program provides a long history of status and trends in forest area and location; species, size, and health of trees; total tree growth, mortality, and removals by harvest; wood production and utilization rates by various products; and forest land ownerships.
- **ForSys**—A spatial scenario planning model designed to explore landscape management scenarios and optimize decisions in terms of where and how to achieve different outcomes and outputs at different scales (Ager et al. 2021b). Management tradeoffs can be identified by simulating a wide range of management scenarios in which activities are prioritized according to multiple agency land assessments on wildfire risk, economic opportunity, and ecological condition.
- **FSim large fire simulator—**A program that simulates the growth and behavior of hundreds of thousands of fire events for risk analysis across large land areas using geospatial data on historical fire occurrence, weather, terrain, and fuel conditions. Effects of large fire suppression on fire duration and size are also simulated.
- **Functional diversity**—The value and range of those species and organismal traits that influence ecosystem functioning (Laureto et al. 2015).
- **Integrated Climate and Land Use Scenarios (ICLUS), Version 2**—ICLUS scenarios are produced with a demographic model and a spatial allocation model (USEPA ORD 2017). The ICLUS to develop future scenarios of population, housing density, and impervious surfaces. The ICLUS includes use of dynamic future climate variables to draw on the most recent climate data and climate change scenarios. Though the effect of dynamic future climate variables on migration is small, the cumulative changes yield different settlement patterns that enable scenario-based analyses of impacts and vulnerabilities of environmental endpoints.
- **LANDFIRE—**A Web-based tool (https://landfire.gov) that provides more than 20 national geospatial layers (e.g., vegetation, fuel, disturbance, etc.), databases, and ecological models that are available to the public for the United States and

U.S. insular areas. The vegetation dataset was derived from LANDFIRE 2014 with modification to reflect fuel disturbances between 2015 and 2018.

- **Landscape Disturbance and Succession-II (LANDIS-II)**—The LANDIS-II landscape simulation model is used to represent future potential conditions for 2020–2060.
  - We focused specifically on LANDIS-II model runs that used the Model for Interdisciplinary Research on Climate (MIROC) 8.5 climate scenario and a "business as usual" management scenario.
  - The MIROC climate scenario was considered the warm and dry scenario and was found to best represent recent wildfire activity compared to other tested scenarios.
  - The business-as-usual management scenario represented potential conditions with minimal amounts of human intervention to determine where management could help direct natural forest dynamics toward more resilient conditions.
- **Light detection and ranging (LiDAR)—**LiDAR is a remote-sensing method that uses light in the form of a pulsed laser to measure ranges (variable distances) to the Earth.
- **Monitoring Trends in Burn Severity (MTBS)**—MTBS is a multiagency program designed to consistently map the burn severity and perimeters of fires across all lands of the United States since 1984.
- **NCX—**NCX uses modeling to assign an FIA tree list to each 15-m pixel based on similarities in environments and spectral characteristics of the FIA plot and candidate pixel.
  - Characterized tree density and basal area for each 1-ha pixel across the Tahoe-Central Sierra Initiative landscape and the contemporary reference sites based on 2018 NCX modeled vegetation.
- **R**—A programming language for statistical computing and graphics used to clean, analyze, and graph data.
- **Soil Survey Geographic (SSURGO) database**—The SSURGO is a soil database available through the USDA Natural Resources Conservation Service (NRCS). It is based on National Cooperative Soil Survey data collections over the past century. Tables or maps can be generated for most areas served by the NRCS, including states, territories, commonwealths, and island nations. The data are based on ground-based soil observations and sampling, collected at scales ranging from 1:12,000 to 1:63,360, and many soil samples were analyzed in laboratories. Map units describe soils and other components that have unique properties, interpretations, and productivity. The mapping is intended for natural resource planning and management by landowners, townships, and counties.

- **Strength of evidence (SOE) score—**A score assigned to a given pixel resulting from fuzzy logic models that is used to assess the level of departure from some target or desired condition for a given metric. Values run from −1 (fully departed) to +1 (fully within target).
- **USDA Forest Service Activity Tracking System (FACTS)**—The FACTS database links tabular data with geospatial maps to display where specific forest resource activities occur nationwide. It standardizes the data collection processes for diverse forest resource activities, such as fuels reduction, reforestation, and rangeland vegetation improvements. FACTS offers various outputs and maps for analysis, project planning, and required yearly reporting to meet national, regional, forest, and ranger district needs.
- **Wildfire datasets—**Fuel disturbances were incorporated based on wildfire datasets: MTBS, Rapid Assessment of Vegetation Conditions after Wildfire, and Geospatial Multi-Agency Coordination fire perimeter data. Additional disturbances from forest harvest were based on (FACTS) data and tree mortality data from the eDaRT. The fuelscape was created using the LANDFIRE Total Fuel Change tool.
- **Wildland-urban interface (WUI)**—The federal definition of the WUI (USDA and USDI 2001) follows the Western State Forester's definition: "the urban wildland interface community exists where humans and their development meet or intermix with wildland fuel.'' Generally, the focus is on communities that are described as "**interface**" **WUI**—which includes developed areas with sparse or no wildland vegetation but are within close proximity of a large patch of wildland—and "**intermix**" **WUI**—the area where houses and wildland vegetation directly intermingle.

Appendix 2: Species in the Biodiversity Conservation Analysis

The species lists below are the product of the species criteria process described in the biodiversity conservation pillar applied to birds (table A2.1), mammals (table A2.2) and reptiles (table A2.3). The California Wildlife Habitat Relationships (CWHR) database (CDFW CIWTG 2014) was used to identify species for use in the analysis. These species ranges covered at least 20 percent of the Tahoe-Central Sierra Initiative study area and have reproductive habitat within forested environments modeled by Landscape Disturbance and Succession-II (LANDIS-II).

For the habitat analysis, we queried CWHR software (v. 9.0) to select species that (1) were native; (2) overlapped with Alpine, Amador, Butte, El Dorado, Nevada, Placer, Plumas, Sierra, or Yuba counties; and (3) had year-long presence in those counties. We subsequently filtered out species that did not have reproductive habitat in any of the 16 cover types simulated by the LANDIS-II model (described previously) or were primarily associated with aquatic environments. This resulted in identifying 202 species for the habitat modeling: 95 birds, 81 mammals, and 26 reptiles. Species for the connectivity analysis have dispersal distances of at least 1200 m.

Functional group abbreviations are as follows:

A = soil aerators

C = cavity excavators and nesters

H = herbivores

I = insectivores

P = predators

S = seed dispersers

If a species belonged to more than two functional groups, we retained the two that species contributed to the most, with the exception of corvids. As they are true omnivores, more than two functional groups were retained for corvids.

Table A2.1—Bird species included in the biodiversity conservation pillar analysis of the Tahoe-Central Sierra Initiative Blueprint for Resilience

Species common name	Species scientific name	CWHR ID	Connectivity analysis	Functional group	Size
					Ounces
Sharp-shinned hawk	*Accipiter striatus*	B115	Yes	P	5.4
Cooper's hawk	*Accipiter cooperii*	B116	Yes	P	11.2
Northern goshawk	*Accipiter gentilis*	B117	Yes	P	35.2
Red-shouldered hawk	*Buteo lineatus*	B119	No	P	22.2
Red-tailed hawk	*Buteo jamaicensis*	B123	Yes	P	35.1
Golden eagle	*Aquila chrysaetos*	B126	Yes	P	160.95
American kestrel	*Falco sparverius*	B127	Yes	P, use C	4.3
Peregrine falcon	*Falco peregrinus*	B129	Yes	P	37.6
Prairie falcon	*Falco mexicanus*	B131	No	P	26.8
Sooty grouse	*Dendragapus fuliginosus*	B134	Yes	H	36.5
California quail	*Callipepla californica*	B140	No	H	6.5
Mountain quail	*Oreortyx pictus*	B141	Yes	H	8.3
Band-tailed pigeon	*Patagioenas fasciata*	B251	Yes	H	12.5
Mourning dove	*Zenaida macroura*	B255	Yes	H	4.3
Barn owl	*Tyto alba*	B262	Yes	P, use C	19.4
Western screech owl	*Megascops kennicottii*	B264	No	P, use C	7.2
Great horned owl	*Bubo virginianus*	B265	Yes	P, use C	60.2
Northern pygmy owl	*Glaucidium gnoma*	B267	Yes	P, use C	2.3
Burrowing owl	*Athene cunicularia*	B269	No	P, I	5.3
California spotted owl	*Strix occidentalis*	B270	Yes	P use C	21.2
Great gray owl	*Strix nebulosa*	B271	Yes	P	42.4
Long-eared owl	*Asio otus*	B272	No	P	11.6
Northern saw-whet owl	*Aegolius acadicus*	B274	Yes	P use C	3.8
White-throated swift	*Aeronautes saxatalis*	B282	Yes	I	1.2
Anna's hummingbird	*Calypte anna*	B287	Yes	I	0.2
Belted kingfisher	*Megaceryle alcyon*	B293	No	P	5.5
Lewis's woodpecker	*Melanerpes lewis*	B294	Yes	H, I	4
Acorn woodpecker	*Melanerpes formicivorus*	B296	No	H, C	2.8
Red-naped sapsucker	*Sphyrapicus nuchalis*	B298	No	I, C	1.7
Red-breasted sapsucker	*Sphyrapicus ruber*	B299	Yes	I, C	2.1
Nuttall's woodpecker	*Picoides nuttallii*	B302	No	I, C	1.4
Downy woodpecker	*Picoides pubescens*	B303	Yes	I, C	0.9
Hairy woodpecker	*Picoides villosus*	B304	Yes	I, C	2.4
White-headed woodpecker	*Picoides albolarvatus*	B305	Yes	I, C	2.1
Black-backed woodpecker	*Picoides arcticus*	B306	Yes	I, C	2.6
Northern flicker	*Colaptes auratus*	B307	Yes	I, C	4.8
Pileated woodpecker	*Dryocopus pileatus*	B308	Yes	I, C	10.6
Black phoebe	*Sayornis nigricans*	B321	No	I	0.7
Gray jay	*Perisoreus canadensis*	B345	No	P, I	2.5
Steller's jay	*Cyanocitta stelleri*	B346	Yes	P, S, H, I	4.2
Western scrub-jay	*Aphelocoma californica*	B348	No	P, S, H, I	3

Table A2.1 (continued)—Bird species included in the biodiversity conservation pillar analysis of the Tahoe-Central Sierra Initiative Blueprint for Resilience

Species common name	Species scientific name	CWHR ID	Connectivity analysis	Functional group	Size
					Ounces
Pinyon jay	*Gymnorhinus cyanocephalus*	B349	No	H, S	3.7
Clark's nutcracker	*Nucifraga columbiana*	B350	Yes	H, S	4.7
Black-billed magpie	*Pica hudsonia*	B351	No	P, H, I	6.3
American crow	*Corvus brachyrhynchos*	B353	No	P, H, I	16.6
Common raven	*Corvus corax*	B354	Yes	P, H, I	40.8
Mountain chickadee	*Poecile gambeli*	B356	Yes	H, I,	0.4
Chestnut-backed chickadee	*Poecile rufescens*	B357	Yes	I	0.4
Oak titmouse	*Baeolophus inornatus*	B358	No	H, I	0.5
Bushtit	*Psaltriparus minimus*	B360	No	I	0.2
Red-breasted nuthatch	*Sitta canadensis*	B361	Yes	I, C	0.4
White-breasted nuthatch	*Sitta carolinensis*	B362	Yes	H, I	0.9
Pygmy nuthatch	*Sitta pygmaea*	B363	Yes	I, H	0.4
Brown creeper	*Certhia americana*	B364	Yes	I	0.3
Rock wren	*Salpinctes obsoletus*	B366	Yes	I	0.6
Canyon wren	*Catherpes mexicanus*	B367	No	I	0.5
Bewick's wren	*Thryomanes bewickii*	B368	Yes	I, use C	0.4
House wren	*Troglodytes aedon*	B369	Yes	I, use C	0.4
Pacific wren	*Troglodytes hiemalis*	B370	Yes	I, use C	0.4
Golden-crowned kinglet	*Regulus satrapa*	B375	Yes	I	0.2
Ruby-crowned kinglet	*Corthylio calendula*	B376	Yes	I	0.3
Blue-gray gnatcatcher	*Polioptila caerulea*	B377	No	I	0.3
Western bluebird	*Sialia mexicana*	B380	Yes	I, H	1
Townsend's solitaire	*Myadestes townsendi*	B382	Yes	I, H	1.2
Hermit thrush	*Catharus guttatus*	B386	Yes	I, H	1
American robin	*Turdus migratorius*	B389	No	I, H	2.9
Wrentit	*Chamaea fasciata*	B391	No	I, H	0.6
California thrasher	*Toxostoma redivivum*	B398	No	I, H	3.1
Phainopepla	*Phainopepla nitens*	B408	No	I, H	0.8
Loggerhead shrike	*Lanius ludovicianus*	B410	No	I, P	1.5
Hutton's vireo	*Vireo huttoni*	B417	No	I	0.4
Yellow-rumped warbler	*Setophaga coronata*	B435	Yes	I, H	0.5
Spotted towhee	*Pipilo maculatus*	B483	Yes	I, H	1.5
California towhee	*Melozone crissalis*	B484	No	I, H	1.9
Rufous-crowned sparrow	*Aimophila ruficeps*	B487	No	I, H	0.7
Bell's sparrow	*Artemisiospiza belli*	B497	No	I, H	0.7
Fox sparrow	*Passerella iliaca*	B504	Yes	I, H	1.3
Song sparrow	*Melospiza melodia*	B505	No	I, H	1.2
White-crowned sparrow	*Zonotrichia leucophrys*	B510	No	I, H	1
Dark-eyed junco	*Junco hyemalis*	B512	Yes	I, H	0.9
Red-winged blackbird	*Agelaius phoeniceus*	B519	No	I, H	1.9
Western meadowlark	*Sturnella neglecta*	B521	Yes	I, H	3.6

Table A2.1 (continued)—Bird species included in the biodiversity conservation pillar analysis of the Tahoe-Central Sierra Initiative Blueprint for Resilience

Species common name	Species scientific name	CWHR ID	Connectivity analysis	Functional group	Size
					Ounces
Brewer’s blackbird	*Euphagus cyanocephalus*	B524	Yes	I, H	2.6
Gray-crowned rosy-finch	*Leucosticte tephrocotis*	B534	No	I, H	2
Pine grosbeak	*Pinicola enucleator*	B535	Yes	H	2.9
Purple finch	*Haemorhous purpureus*	B536	Yes	I, H	0.9
Cassin’s finch	*Haemorhous cassinii*	B537	Yes	I, H	1
House finch	*Haemorhous mexicanus*	B538	No	H	0.8
Red crossbill	*Loxia curvirostra*	B539	Yes	I, H	1
Pine siskin	*Spinus pinus*	B542	Yes	H	0.5
Lesser goldfinch	*Spinus psaltria*	B543	No	H, S	0.4
American goldfinch	*Spinus tristis*	B545	No	H	0.6
Evening grosbeak	*Coccothraustes vespertinus*	B546	Yes	H, I	2.3
Juniper titmouse	*Baeolophus ridgwayi*	B552	No	I, H	0.6
Barred owl	*Strix varia*	B699	No	P	26.8

Functional groups: C = cavity excavators and nesters, H = herbivores, I = insectivores, P = predators, S = seed dispersers.
CWHR = California Wildlife Habitat Relationships database; yes = included in analysis, no = not included.

Table A2.2—Mammal species included in the biodiversity conservation pillar analysis of the Tahoe-Central Sierra Initiative Blueprint for Resilience

Species common name	Species scientific name	CWHR ID	Connectivity analysis	Functional group	Size
					Ounces
Vagrant shrew	*Sorex vagrans*	M003	No	I	0.3
Montane shrew	*Microtus montanus*	M004	No	I	1.5
Trowbridge's shrew	*Sorex trowbridgii*	M012	No	A, I	0.3
Shrew-mole	*Neurotrichus gibbsii*	M015	No	A, I	0.8
Broad-footed mole	*Scapanus latimanus*	M018	No	A, I	1.8
Little brown bat	*Myotis lucifugus*	M021	No	I	0.4
Yuma myotis	*Myotis yumanensis*	M023	No	I	0.2
Long-eared myotis	*Myotis evotis*	M025	No	I	0.2
Fringed myotis	*Myotis thysanodes*	M026	Yes	I	0.2
Long-legged myotis	*Myotis volans*	M027	No	I	0.3
California myotis	*Myotis californicus*	M028	No	I	0.2
Small-footed myotis	*Myotis ciliolabrum*	M029	No	I	0.2
Silver-haired bat	*Lasionycteris noctivagans*	M030	No	I	0.3
Canyon bat	*Parastrellus hesperus*	M031	No	I	0.2
Big brown bat	*Eptesicus fuscus*	M032	Yes	I	0.8
Western red bat	*Lasiurus blossevillii*	M033	No	I	0.4
Hoary bat	*Lasiurus cinereus*	M034	No	I	1
Townsend's big-eared bat	*Corynorhinus townsendii*	M037	Yes	I	0.3
Pallid bat	*Antrozous pallidus*	M038	Yes	I	0.8
Brazilian free-tailed bat	*Tadarida brasiliensis*	M039	No	I	0.3
American pika	*Ochotona princeps*	M043	No	H	5.2
Brush rabbit	*Sylvilagus bachmani*	M045	No	H	24
Audubon's cottontail	*Sylvilagus audubonii*	M047	No	H	32
Snowshoe hare	*Lepus americanus*	M049	No	H	52.8
White-tailed jackrabbit	*Lepus townsendii*	M050	No	H	112
Black-tailed jackrabbit	*Lepus californicus*	M051	Yes	H	76.8
Mountain beaver	*Aplodontia rufa*	M052	No	H	39.7
Least chipmunk	*Tamias minimus*	M054	No	I, H, S	1.7
Yellow-pine chipmunk	*Tamias amoenus*	M055	No	H, S	1.8
Shadow chipmunk	*Tamias senex*	M057	No	H, S	3.1
Long-eared chipmunk	*Tamias quadrimaculatus*	M062	No	H, S	3.1
Lodgepole chipmunk	*Tamias speciosus*	M063	No	H, S	2.1
Yellow-bellied marmot	*Marmota flaviventris*	M066	No	H, S	120
Belding's ground squirrel	*Spermophilus beldingi*	M070	No	H	10.2
California ground squirrel	*Spermophilus beecheyi*	M072	No	H, S	20.8
Golden-mantled ground squirrel	*Spermophilus lateralis*	M075	No	H	7.4
Western gray squirrel	*Sciurus griseus*	M077	No	H, S	22.9
Douglas squirrel	*Tamiasciurus douglasii*	M079	No	H	8
Northern flying squirrel	*Glaucomys sabrinus*	M080	Yes	H	3.8
Botta's pocket gopher	*Thomomys bottae*	M081	No	H, A	4.1
Northern pocket gopher	*Thomomys talpoides*	M083	No	H, A	3.9

Table A2.2 (continued)—Mammal species included in the biodiversity conservation pillar analysis of the Tahoe-Central Sierra Initiative Blueprint for Resilience

Species common name	Species scientific name	CWHR ID	Connectivity analysis	Functional group	Size
					Ounces
Mountain pocket gopher	*Thomomys monticola*	M085	No	H, A	3.7
Great Basin pocket mouse	*Perognathus parvus*	M088	No	H, A	0.7
California pocket mouse	*Chaetodipus californicus*	M095	No	H, A	0.8
Heermann's kangaroo rat	*Dipodomys heermanni*	M104	No	H, A	2.6
California kangaroo rat	*Dipodomys californicus*	M105	No	S, H	3
Western harvest mouse	*Reithrodontomys megalotis*	M113	No	H	0.5
Deer mouse	*Peromyscus maniculatus*	M117	No	H, I	0.6
Canyon mouse	*Peromyscus crinitus*	M118	No	H, S	0.6
Brush mouse	*Peromyscus boylii*	M119	No	H, S	1
Pinyon mouse	*Peromyscus truei*	M120	No	H, S	0.7
Northern grasshopper mouse	*Onychomys leucogaster*	M121	No	I, P	1.1
Dusky-footed woodrat	*Neotoma fuscipes*	M127	No	H	9.3
Bushy-tailed woodrat	*Neotoma cinerea*	M128	No	H	11.8
California red-backed vole	*Myodes californicus*	M129	No	S, H	1
Heather vole	*Phenacomys intermedius*	M130	No	H	1.4
Montane vole	*Microtus montanus*	M133	No	A, H	2.1
California vole	*Microtus californicus*	M134	No	A, H	2.6
Long-tailed vole	*Microtus longicaudus*	M136	No	H, A	1.9
Common muskrat	*Ondatra zibethicus*	M139	No	H	40
Western jumping mouse	*Zapus princeps*	M143	No	I, H	0.7
Common porcupine	*Erethizon dorsatum*	M145	Yes	H	320
Coyote	*Canis latrans*	M146	Yes	P	488
Red fox	*Vulpes vulpes*	M147	No	P	288
Kit fox	*Vulpes macrotis*	M148	No	P	75.8
Gray fox	*Urocyon cinereoargenteus*	M149	Yes	P	193.8
Black bear	*Ursus americanus*	M151	Yes	H, I	7200
Ringtail	*Bassariscus astutus*	M152	Yes	P	38.1
Raccoon	*Procyon lotor*	M153	Yes	H, I	207.7
Marten	*Martes americana*	M154	Yes	P	27.9
Fisher	*Martes pennanti*	M155	Yes	P	123.3
Ermine	*Mustela erminea*	M156	Yes	P	2.5
Long-tailed weasel	*Mustela frenata*	M157	Yes	P	9.3
American badger	*Taxidea taxus*	M160	Yes	P	281.9
Western spotted skunk	*Spilogale gracilis*	M161	Yes	P, I	16.4
Striped skunk	*Mephitis mephitis*	M162	Yes	P, I	123.2
Mountain lion	*Puma concolor*	M165	Yes	P	2608
Bobcat	*Lynx rufus*	M166	Yes	P	328
Mule deer	*Odocoileus hemionus*	M181	Yes	H	3392
Pronghorn	*Antilocapra americana*	M182	Yes	H	2000
Big-eared woodrat	*Neotoma macrotis*	M233	No	H	7.2

Functional groups: A = soil aerators, H = herbivores, I = insectivores, P = predators, S = seed dispersers.
CWHR = California Wildlife Habitat Relationships database; yes = included in analysis, no = not included.

Table A2.3—Reptile species included in the biodiversity conservation pillar analysis of the Tahoe-Central Sierra Initiative Blueprint for Resilience

Species common name	Species scientific name	CWHR ID	Connectivity analysis	Functional group	Size
					Ounces
Great Basin collared lizard	*Crotaphytus bicinctores*	R017	No	I	0.8
Long-nosed leopard lizard	*Gambelia wislizenii*	R018	No	P, I	1.2
Western fence lizard	*Sceloporus occidentalis*	R022	No	I	0.5
Common sagebrush lizard	*Sceloporus graciosus*	R023	No	I	0.4
Common side-blotched lizard	*Uta stansburiana*	R024	No	I	0.1
Blainville's horned lizard	*Phrynosoma blainvillii*	R029	No	I	0.9
Desert horned lizard	*Phrynosoma platyrhinos*	R030	No	I	2.0
Western skink	*Plestiodon skiltonianus*	R036	No	I	0.5
Gilbert's skink	*Plestiodon gilberti*	R037	No	I	0.5
Tiger whiptail	*Aspidoscelis tigris*	R039	No	I	0.6
Southern alligator lizard	*Elgaria multicarinata*	R040	No	I, P	1.1
Northern alligator lizard	*Elgaria coerulea*	R042	No	I, P	1.0
Northern rubber boa	*Charina bottae*	R046	No	P	1.8
Ring-necked snake	*Diadophis punctatus*	R048	No	P	0.04
Common sharp-tailed snake	*Contia tenuis*	R049	No	I	
North American racer	*Coluber constrictor*	R051	No	I, P	56
Striped racer	*Coluber lateralis*	R053	No	P	17.5
Striped whipsnake	*Masticophis taeniatus*	R054	No	P	3.8
Gophersnake	*Pituophis catenifer*	R057	No	P	48
Eastern kingsnake	*Lampropeltis getula*	R058	No	P	35.2
California mountain kingsnake	*Lampropeltis zonata*	R059	No	P	52.8
Common garter snake	*Thamnophis sirtalis*	R061	No	P	5.3
Terrestrial garter snake	*Thamnophis elegans*	R062	No	P	5.3
Sierra garter snake	*Thamnophis couchii*	R063	No	P	5.3
Desert night snake	*Hypsiglena torquata*	R071	No	P	80
Western rattlesnake	*Crotalus oreganus*	R076	No	P	80

Functional groups: I = insectivores, P = predators.

CWHR = California Wildlife Habitat Relationships database; yes = included in analysis, no = not included.

This publication is available online at https://www.fs.usda.gov/research/psw.

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