

RESEARCH ARTICLE

Combining value and vulnerability of pinyon–juniper ecosystems for climate-smart management: A case study in Black Canyon of the Gunnison National Park

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Abstract

1. Land management and natural resource conservation involve assessment of multiple factors, including climate vulnerability and resource value, yet rarely do research efforts or decision-making processes involve both facets in tandem.
2. We develop a 'climate-smart' conservation framework which combines an analysis of potential future climate impacts to vegetation derived from moderate-resolution remote sensing imagery, random forest modelling and water-balance projections with resource value scores as determined by local experts in order to identify management goals within the 'resist-accept-direct' framework.
3. Our framework is applied through a case study in the context of pinyon–juniper ecosystems in Black Canyon of the Gunnison National Park and demonstrates how spatially explicit understandings of vegetation value and vulnerability to climate conditions interact in the context of natural resource management.
4. Of the eight areas identified as management priority areas, three areas show an expected increase in productivity and thus managers may 'accept' the trajectory of change. Four of the management priority areas with relatively small expected decreases in productivity and/or very high value are determined to be areas in which managers might 'resist' the trajectory of change. We find one area of lower management importance and large expected vegetation decline, which may be considered a candidate to 'direct' to a desirable state compatible with future climate conditions.
5. *Solution.* The proposed framework is readily adaptable to all natural, managed lands and serves as a template for future land-management research and decision-making processes which are pragmatic and value-informed in the face of climate change.

KEYWORDS

climate impacts, conservation, land management, natural resource value risk assessment

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1 | INTRODUCTION

1.1 | Land-management frameworks

National parks around the world are vital for the protection and conservation of diverse, natural ecosystems and cultural sites. Further, they provision ecosystem services, including watersheds that provide drinking water (Null, 2016), forests that store carbon (Melillo et al., 2016) and habitat for a myriad of species (Johnston et al., 2013). Management of protected areas is becoming increasingly relevant and complex given the rapidly changing climate conditions and impacts to highly valued resources such as glaciers (Marzeion et al., 2014), wildlife (La Sorte & Thompson, 2007; Moritz et al., 2008) and vegetation (Van Mantgem et al., 2009) in parks. In the United States (US), it has recently been shown that land area managed by the US National Park Service (NPS) is more susceptible to the effects of climate change than the US area as a whole (Gonzalez et al., 2018).

Given the diversity of resources protected in national parks, their potential vulnerability to future environmental conditions and their unique status as managed lands intended for conservation, recent and extensive efforts have focused on creating climate-informed management principles and guidelines. The framework used by the NPS is centred around the 'Climate Smart Conservation Cycle' (National Park Service, 2021) (Figure 1a). Climate-smart conservation is a management framework created by a consortium, including the NPS, other federal agencies and non-governmental organizations that offers general principles for successful climate

adaptation (Stein et al., 2014). These principles include: identifying management goals, determining resource vulnerability, identifying management options and implementing selected options that are feasible and likely to succeed. These steps can be expanded to clarify aspects of the process, which has resulted in many different and often complementary frameworks in practice (Janowiak et al., 2022; Lim et al., 2005; National Park Service, 2021; Schmitz et al., 2015; Schuurman et al., 2020).

Action-oriented guidance that meets these principles and is emphasized by the NPS considers three intentions for management options: resist, accept or direct (RAD) (Lynch et al., 2021; Schuurman et al., 2020, 2022) (Figure 1b). RAD directly challenges the assumption that ecosystems and natural resources are managed to resemble their historical state, a common management approach in the last several decades. Indeed, management guidelines with the goal of maintaining or restoring historical conditions were encouraged by most US land-management agencies as recently as the early 2000s (Fischman, 2004; Schuurman et al., 2022; United States National Park Service, 2006). However, there is increasing evidence that such a goal is often impractical or infeasible given climate non-stationarity, which may force transitions to new ecological states (Bueno de Mesquita et al., 2021; Hirsch, 2011; Milly et al., 2008; Slater et al., 2021). Thus, frameworks that acknowledge the inevitability for ecological transformations, like RAD, are becoming increasingly employed to guide contemporary land-management decisions, as they likely can lead to more realistic and achievable management goals that may lead to successful outcomes.

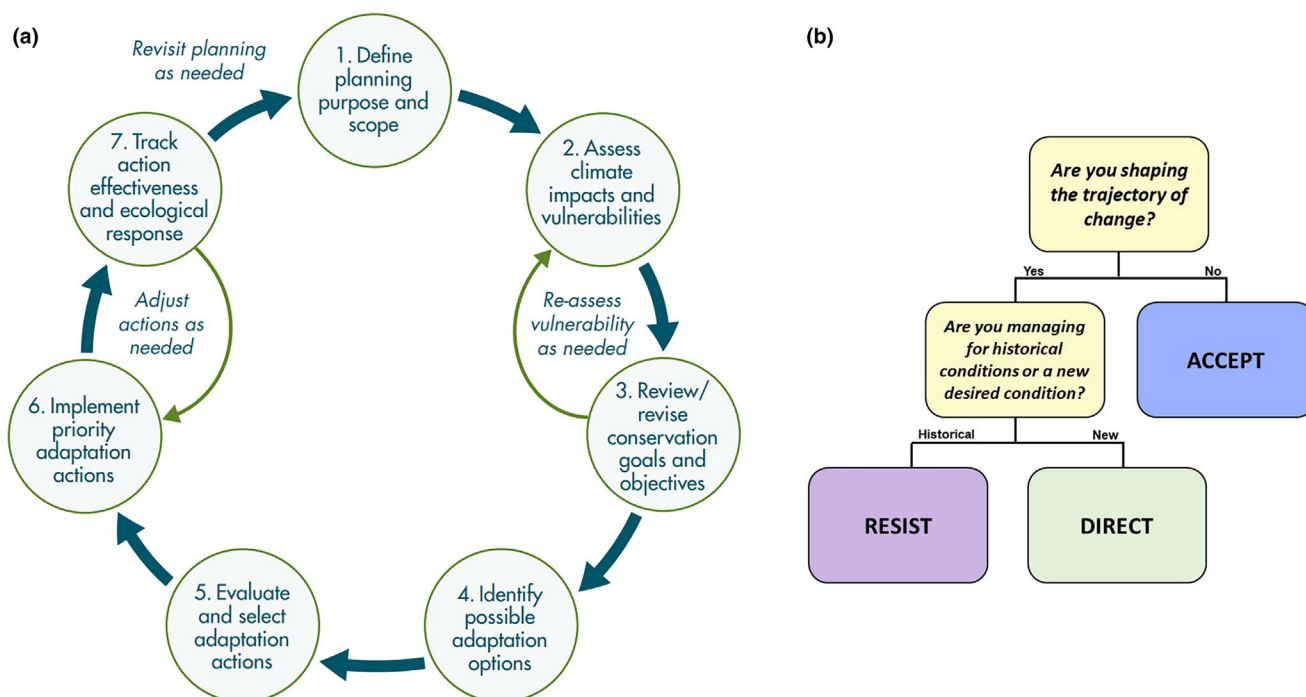


FIGURE 1 Land-management framework schematics employed in this work. (a) Climate-smart conservation cycle (as in Stein et al., 2014). (b) Resist-Accept-Direct [RAD] decision tree (as in Schuurman et al., 2020). Note that identifying and selecting adaptation strategies (aided by RAD) are only a small part of the climate-smart conservation cycle. Thus, we envision that the RAD framework is most appropriately implemented in Steps 3 through 5 of the climate-smart conservation cycle.

Selecting management options in the face of climate change that acknowledge management goals and resource vulnerability is challenging, and yet other considerations can be equally relevant. Many management actions are carried out to reflect human perceptions of natural resource values that are linked to intrinsic ecological functions and societal importance. For example, high value placed on giant sequoia (*Sequoiadendron giganteum*) trees because they are endemic, rare and culturally important, in part due to their enormous size and stature, may justify resource-intensive measures to protect them from wildfire (Parsons, 1990, 1994). Similarly, endangered species or rare habitats may justify more effort or cost to protect them from stressors. The work described here represents the first time that expert-assigned resource values have been explicitly and quantitatively used within the RAD framework to help guide management decisions.

1.2 | Scope and outline

To explicitly demonstrate how quantitative vulnerability assessments can be used in tandem with resource values, we provide a detailed case study regarding the management of pinyon (*Pinus edulis*)—juniper (*Juniperus* spp.) (PJ) ecosystems in Black Canyon of the Gunnison National Park (BLCA). Our objective is to merge the assessment of PJ vulnerability to future climate change with management resource values to identify spatially explicit conservation goals for PJ in BLCA. The broad categories of conservation goals considered here are from the RAD framework and include management targets that fall into the resisting, accepting or directing vegetation transitions. This work is conducted in the context of future PJ distributions that are expected to persist in BLCA (Noel et al., 2025). However, the importance of high-value PJ ecosystems, including old-growth stands (Miller et al., 1999), may prompt a prioritization of a management action even if a climate-induced transition may be inevitable.

We organize this work according to Steps 1 through 5 in the climate-smart conservation cycle, with the present methods most applicable to Steps 2 and 3 (Figure 1a). First, we explore the purpose and scope of our case study in Section 2.1 by reviewing relevant background and the importance of PJ in the western United States and specifically in BLCA. In Section 2.2, we develop a method to assess climate impacts and vulnerabilities. Specifically, we establish historical relationships between satellite imagery-based vegetation productivity metrics and ecohydrology from a water-balance model driven by reanalysis data which we use to predict future vegetation conditions using an array of general circulation model (GCM) projections. In Section 2.3, we discuss how conservation goals and objectives are determined by eliciting resource value scores from local experts. Finally, Section 2.4 establishes how the vulnerability and value metrics can be combined to identify and evaluate possible adaptation options by employing the RAD decision-making framework (Figure 1b).

This work reveals how a decision-making process can be executed in a repeatable and transparent way to identify how PJ stands may be managed differently based on their vulnerability to future climate conditions, relative importance for wildlife habitat, cultural

significance or recreational value. Our method for assessing vulnerability is unique for its relatively fine resolution and adaptability to any land area in the United States for general vegetation classes. Then, by fusing satellite imagery and park-specific vegetation maps, our results are relevant and updateable for management decision-making processes tuned to particular locations and dominant species of interest. While previous research has explored the vulnerability of PJ in the United States to climate change, these studies are limited by sparse or low-resolution observations or reliance on intensive field-based measurements (Breshears et al., 2005; Flake & Weisberg, 2019; Hartsell et al., 2020; Noel et al., 2023; Shaw et al., 2005; Shriver et al., 2022). Finally, our work uniquely combines resource values with climate vulnerability to help guide management goals in the context of climate-smart conservation and RAD management frameworks. We demonstrate the workflow via application to PJ ecosystems in BLCA, but note that the methods are broadly applicable across managed lands in the United States.

2 | MATERIALS AND METHODS

2.1 | Study area

Pinyon–juniper (PJ) ecosystems comprise culturally and ecologically important ecosystems across an estimated 40 million hectares in the western United States (Romme et al., 2009). PJ ecosystems are vital to Native Americans for food, firewood, building material and ceremonial purposes (Gottfried et al., 1995; Janetski, 1999; Koyiyumptewa, 1993). They also provide habitat for mammals and birds, including the pinyon jay, whose population has declined by 85% in the last 50 years and is the primary seed dispersal agent for pinyon pine (Boone et al., 2021; Rosenberg et al., 2016). PJ stands are threatened by direct impacts of climate change via drought and wildfire and indirectly via disease agents that are favoured in warmer conditions when trees are drought stressed and more susceptible to attack (Breshears et al., 2005; Shaw et al., 2005). In the past few decades, die-off of pinyon and juniper trees has occurred in large areas of the south-western United States (Breshears et al., 2005; Flake & Weisberg, 2019; Shriver et al., 2022). The trajectory of PJ ecosystems is locally dependent on species composition and adaptive capacity, thus responses to climate change are expected to vary by location (Noel et al., 2023, 2025).

Black Canyon of the Gunnison National Park (BLCA), located in western Colorado, has approximately 4742 ha of PJ-dominated landscape accounting for 37.5% of its total area (Figure 2). PJ in BLCA maintains ecological integrity, species diversity and wildlife habitat, and provides for visitor recreation (Hartsell et al., 2020). Major management considerations are conservation and protection of old-growth PJ for ecological benefits to wildlife, including bighorn sheep (*Ovis canadensis*) and pinyon jay (*Gymnorhinus cyanocephalus*), buffering adjacent critical habitat for Gunnison sage-grouse (*Centrocercus minimus*) and management of recreation (i.e. protecting trees that offer shade to visitors).

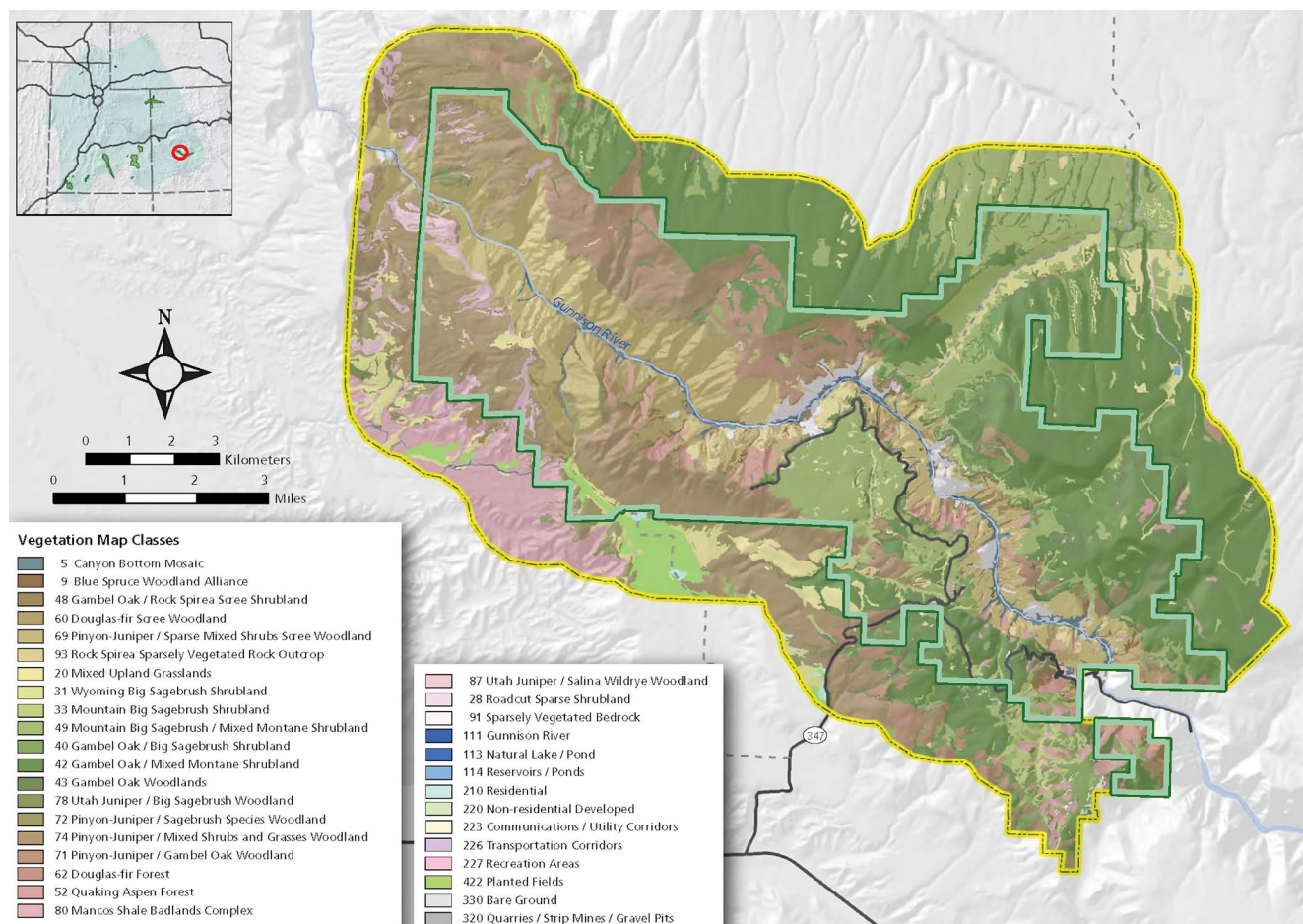


FIGURE 2 Vegetation type classifications in Black Canyon of the Gunnison National Park (green outline), adapted from Coles et al. (2010).

The National Land Classification Database (NLCD) was used to determine general vegetation types for locations in and around the park (Dewitz, 2023). Prior to analysis, we masked out pixels that were classified as water, snow/ice, barren, developed or cultivated. In doing so, we removed the influence of regions with extremely sparse or no vegetation or vegetation supported by non-natural water inputs. In addition to NLCD, we used fine-scale vegetation type classifications (Coles et al., 2010) to further refine our study area, centred on PJ ecosystems in BLCA. Throughout the results in this paper, we highlight results in PJ-dominated areas or pixels, which we define as in land classes 69—'Pinyon-Juniper/Sparse Mixed Shrubs Scree Woodland', 71—'Pinyon-Juniper/Gambel Oak Woodland', 72—'Pinyon-Juniper/Sagebrush Species Woodland' and 74—'Pinyon-Juniper/Mixed Shrubs and Grasses Woodland' in Coles et al. (2010) (Figure 2).

2.2 | Vulnerability assessment

We assessed historical climate sensitivities and future vulnerabilities of PJ stands in BLCA. Given our focus on vegetation growth and health, we used satellite imagery to derive the integrated enhanced vegetation index (iEVI) (Section 2.2.1), a proxy for gross primary productivity. We then related estimated productivity to different

components of water balance (Section 2.2.2) using random forest regression (Section 2.2.3). To include the effects of future climate exposure on vegetation, we employed projections of temperature and precipitation from GCMs (Section 2.2.4).

2.2.1 | Vegetation indices

We estimated annual gross primary production by processing a vegetation index derived from remote sensing imagery (Bunting et al., 2019). Our approach largely follows the methods for assessing primary production in Thoma et al. (2019), with a few slight differences. First, we used the enhanced vegetation index (EVI), which uses optical and near-infrared bands and improves upon the commonly used normalized difference vegetation index because EVI is less sensitive to soil and atmospheric effects (Huete et al., 2002). Second, we used a spatially explicit growing season (GS) defined by actual evapotranspiration (AET) to provide more specific bounds on growth periods than fixed GS periods. Third, the relatively large time range of our data from 2001 to 2023 provides a robust indicator of inter-annual variability in production. Finally, we used per-pixel calculations and analyses and avoided averaging statistical results and quantities over polygons, preserving a fine

spatial resolution for detecting vegetation responses to water balance.

The Moderate Resolution Imaging Spectrometer (MODIS) sensor on the Terra satellite provides remote sensing images since early 2000, which have been processed into high-quality, convenient data products. We utilized the version 6.1 EVI product, available as a time series of 16-day maximum value composites at a 250m resolution from 2000 through 2023 for the entire continental United States (CONUS) (Didan, 2021). Observations affected by clouds, aerosols and snow were removed and then gap-filled with linear interpolation to create daily values. The final time series was smoothed using a Savitzky–Golay filter from Python's SciPy library (Virtanen et al., 2020).

The smoothed, daily EVI values were summed per pixel over the GS to obtain an estimate of total annual production. Actual evapotranspiration, equal to the amount of water evaporated or transpired from surfaces and plants, is available from the water-balance model described in Section 2.2.2 and used to define the GS. Specifically, the start of the GS, GS_{start} , is the first day (d) of the first 14-day period satisfying daily $AET > 0.25$ mm for each pixel (x, y) and year t . Similarly, the end of the GS (GS_{end}) is the last day of the final 14-day period of daily $AET > 0.25$ mm.

$$GS_{start}(x, y, t) = \underset{d}{\operatorname{argmin}} \left\{ \sum_{i=0}^{13} \mathbf{1}\{AET(x, y, t, d+i) > 0.25\} = 14 \right\} \quad (1)$$

$$GS_{end}(x, y, t) = \underset{d}{\operatorname{argmax}} \left\{ \sum_{i=0}^{13} \mathbf{1}\{AET(x, y, t, d-i) > 0.25\} = 14 \right\}.$$

The 0.25-mm threshold was chosen based on visual inspection of representative AET curves as the value that indicated consistent, above-zero AET at the beginning of the GS and near-zero AET at the end of the GS.

A per-pixel approximation of GS was defined as the period between median start and end dates across years $t = 2001, \dots, 2023$.

$$GS(x, y) = \left\{ d \in \{1, 2, 3, \dots, 365\} : \operatorname{median}_{t} GS_{start}(x, y, t) \leq d \leq \operatorname{median}_{t} GS_{end}(x, y, t) \right\} \quad (2)$$

Actual GS start and end dates vary temporally as well as spatially, so we used temporally stationary GS dates in order to simplify our analysis. Furthermore, the tails of the seasonal growth curves contribute minimal production to annual sums relative to the growth during the peak of the GS, so this simplification does not affect our results. The GS length is equal to the number of days between the median GS start and end dates (Figure 3).

The GS defined by Equations (1 and 2) was used to bound the numeric integration of daily, smoothed EVI values to obtain a gross estimate of annual vegetative production. To distinguish from daily values, we refer to the GS integrated, smoothed EVI as iEVI. Specifically, for a location (x, y) and year t , we summed the smoothed EVI values over days d in the local GS:

$$iEVI(x, y, t) = \sum_{d \in GS(x, y)} EVI(x, y, t, d). \quad (3)$$

The average over time of historical iEVI values is given by

$$\overline{iEVI}(x, y) = \frac{1}{23} \sum_{t=2001}^{2023} iEVI(x, y, t). \quad (4)$$

2.2.2 | Water balance

We leveraged water-balance variables to explain variation in iEVI, a proxy for gross primary production. Each water-balance variable describes a component of a Thornthwaite-type water-balance model, identical to that described in Tercek et al. (2021). The model partitions precipitation into runoff, storage or evapotranspiration on a daily basis. The movement of water between compartments depends on the amount of energy in the system and available water.

The water-balance variables included in this work were accumulated snow water equivalent (ASWE), AET, deficit (D), potential evapotranspiration (PET), runoff (RO) and soilwater (SW). SW is the quantity of water stored in the top metre of soil. RO consists of water that precipitates or melts after the soil water holding capacity is satisfied. PET is the amount of water that could be evapotranspired with available energy if water availability was unlimited to a short grass. AET is the daily loss of water from soil via transpiration and evaporation. D is the amount of additional

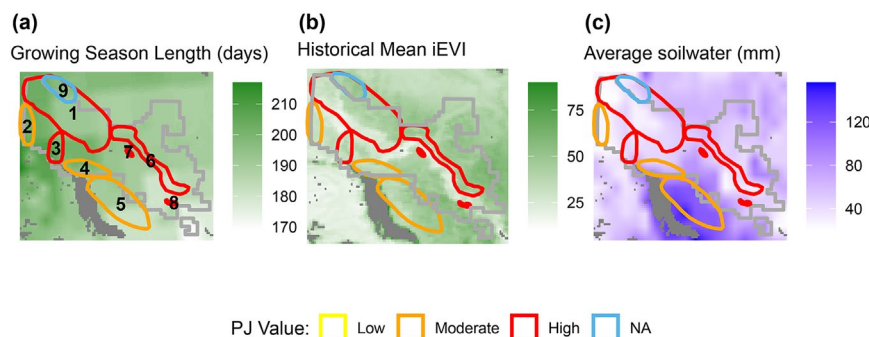


FIGURE 3 Historical values of (a) growing season length, (b) growing season mean integrated enhanced vegetation index (iEVI) and (c) water year average soil water over the period 2000–2023. Grey areas are masked due to an unsuitable land classification status. Each of these variables is overlaid with polygons of resource importance as determined by park managers. Centred on each polygon is the identification (ID) number, with the colour of the polygon outline indicating the resource value score. The grey outline designates the park boundary.

water vegetation could use if it was available, calculated as the difference between AET and PET (Tercek et al., 2021).

Water-balance variables can capture aspects of plant water extraction and use that are more biologically relevant than traditional precipitation and temperature measurements (Thoma et al., 2019). Yet, for comparison, we also considered models that incorporated traditional climate metrics: precipitation (Pr) and minimum and maximum temperature ($T_{\min}$ and $T_{\max}$). These three variables were downloaded at a daily, 4 km resolution directly from gridMET (Abatzoglou, 2013) and subsequently refined to a 250 m resolution using bilinear interpolation.

Daily values of each of the nine aforementioned variables were summarized over the biologically relevant water year (e.g. 1 October 2000 to 30 September 2001 constitutes the water year 2001) via averaging (SW), summation (AET, D, PET, RO, Pr, $T_{\min}$, $T_{\max}$) or maximum (ASWE) and projected using bilinear interpolation to match the 250 m MODIS resolution. Each variable was available from historical data beginning in 1980, but to match the MODIS data record, we only analysed climate data from the water year 2001 through water year 2023.

2.2.3 | Random forest models

In order to relate explanatory, historical water-balance variables (Section 2.2.2) to iEVI, we fit random forest models, as they have been shown to be effective regression options for spatial data (Cracknell & Reading, 2014; Li et al., 2023; Wylie et al., 2019). We utilized the R package `randomForest` with R software (R Core Team, 2025) to implement the regression algorithm (Liaw & Wiener, 2002). To avoid overfitting and optimize computational costs, hyperparameters were tuned to test three variables at each decision level of 500 trees. To assess model performance, 30% of the historical data were withheld during training for validation.

We fit random forests for several different combinations of explanatory variables, summarized in Table 1. First, we used water-balance variables alone to model iEVI, and refer to this model as 'water-balance only'. Second, our 'water-balance/xy' model utilized water-balance variables as well as latitude and longitude (y and x,

respectively) in the decision trees. Third, we fit a model that included water-balance variables and the additional climate variables temperature and precipitation, which we call the 'water-balance/climate' model. Finally, we fit a model, including all variables and spatial coordinates, the 'water-balance/climate/xy' model.

Several diagnostic results of the random forest models are also highlighted in Table 1. The most influential variables for each model were determined by the variables with the largest mean decrease in accuracy when that variable was randomly permuted (given by %IncMSE in the `randomForest` output). To compare and assess the models, we computed the mean proportion error ($MPE = \frac{|\text{observed} - \text{modelled}|}{\text{observed}}$), the root mean squared error (RMSE) and the percentage of variation explained (R^2) for the withheld test data.

2.2.4 | Future projections

Finally, we created and analysed predictions of future vegetation conditions over the period 2030–2100. As in Tercek et al. (2023), temperature and precipitation data from 13 different GCMs were used as inputs to the water-balance model, yielding annual predicted values for each water-balance variable analogous to the historical water year summaries (Section 2.2.2). To address the potential impacts of various climate mitigation strategies, we used GCM projections from two different representative concentration pathway (RCP) scenarios that represent moderate greenhouse gas emissions (RCP 4.5) and higher emissions (RCP 8.5). Each of the 13 GCMs was analysed for both RCP 4.5 and RCP 8.5, although data formatting errors prohibited the projections from one GCM under RCP 4.5. Thus, we were left with 25 sets of predicted future water-balance variables resulting from models that demonstrate a wide range of future changes in temperature and precipitation.

These future water-balance predictions were then input to the random forest model (Section 2.2.3) to estimate yearly iEVI for each GCM/RCP combination. To compare the future iEVI projections to historical conditions, we calculated a relative vegetation metric, Rel.Veg. Note that although projections were available until the end of the 21st century, we primarily considered a mid-century period (2030–2064) for its relevance to land managers. In addition,

Model name	Explanatory variables	RMSE	R^2
Water-balance only	ASWE, AET, PET, D, SW, RO	5.71	0.77
Water-balance/xy	ASWE, AET, PET, D, SW, RO, x , y	2.89	0.94
Water-balance/climate	ASWE, AET, PET, D, SW, RO, $T_{\min}$, $T_{\max}$, Pr	4.03	0.89
Water-balance/climate/xy	ASWE, AET, PET, D, SW, RO, $T_{\min}$, $T_{\max}$, Pr, x , y	3.11	0.93

Note: The four most influential explanatory variables determined by percentage increase in mean square error for each model are bolded. We report the iEVI root mean squared error (unitless) and the percentage of variation explained by the model predictions compared with the withheld test data.

Abbreviations: AET, actual evapotranspiration; ASWE, accumulated snow water equivalent; D, deficit; PET, potential evapotranspiration; R^2 , coefficient of determination; RMSE, root mean square error; RO, runoff; SW, soilwater; $T_{\max}$, maximum temperature; $T_{\min}$, minimum temperature; x, longitude; y, latitude.

TABLE 1 Performance statistics of four random forest models with varying predictors.

preliminary investigations into end-of-century vegetation predictions showed extremely similar patterns to the mid-century results and were omitted for concision.

First, we computed the expected relative vegetation for each of the 25 GCM projections as the ratio of the mid-century mean of predicted $\widehat{iEVI}$ and the historical average $\overline{iEVI}$. These ratios were then aggregated by RCP scenario, and in order to capture a range of possible outcomes, the per-pixel minimum, median and maximum over GCMs were calculated. Thus, we obtained a measure of expected average vegetation relative to historical averages for each RCP scenario and quantile (corresponding to the zeroth, fiftieth and hundredth percentiles) combination.

$$\text{Rel. Veg.}_{\text{quantile}}^{\text{RCP}}(x, y) = \text{quantile}_{\text{GCM}} \left\{ \frac{\frac{1}{35} \sum_{t=2030}^{2064} \widehat{iEVI}_{\text{GCM}}^{\text{RCP}}(x, y, t)}{\overline{iEVI}(x, y)} \right\}. \quad (5)$$

The relative vegetation metric may be interpreted as the proportion changed compared with historical values, that is $\text{Rel. Veg.} = 1.5$ corresponds to a 50% increase in vegetation compared with the baseline.

Finally, for the management-determined polygons of interest (to be defined in Section 2.3), we determined polygon-level vulnerability scores as the median of relative vegetation over pixels within the polygon. That is,

$$\text{Vuln}^{\text{RCP}}(\text{polygon}) = \text{median}_{(x,y) \in \text{polygon}} \left\{ \text{Rel. Veg.}_{\text{median}}^{\text{RCP}}(x, y) \right\}. \quad (6)$$

2.3 | Resource value assessment

Even with quantitative indicators of vulnerability, land managers often face the difficult decision of allocating finite resources between vulnerable areas. Adaptation actions are selected based on many factors, including potential effectiveness, cost, compliance with policy, law and also values. Such considerations are increasingly relevant as socioeconomic limitations may constrict resources for conservation management but could be needed over increasingly larger areas (Walls, 2018, 2022).

In addition to the novel combination of the climate-smart conservation and RAD frameworks, our work directly considers quantitative management 'value scores'. The value scores consider human values for cultural importance, view shed, wildlife habitat and ecosystem services like water, nutrient and energy cycles, as well as protection from soil erosion and intrinsic qualities like old-growth tree forms.

At a conference for the NPS's Northern Colorado Plateau Network Inventory and Monitoring Program in March 2024, we asked a local expert to provide 'value scores' for various PJ stands within BLCA. They were asked to identify regions of varying conservation priority. A score of 1 (less important), 2 (moderately important) or 3 (most important) was given to each region, as well as a brief

rationale for the assigned score. A copy of the complete, detailed instructions document for this evaluation is included in [Supporting Information, Document S1](#). The nine identified regions are described in [Table 2](#) and geographically shown in [Figures 3 and 4](#); [Figure S1](#).

Ideally, in other national parks and protected areas, input from multiple experts could be solicited before RAD decisions are made. However, due to the relatively small size and rural location of BLCA, we proceeded with the input of a single local expert, also noting that the assessments of each expert are likely informed by reports and research papers on park-relevant resources. Further, in cases with multiple involved and informed stakeholders from differing backgrounds, it may be beneficial to survey across all invested parties.

2.4 | RAD management goals

Finally, we combined the value scores of Section 2.3 with the vulnerability metrics of Section 2.2.4 to project each polygon into a management outcome category of the RAD framework. While the importance of integrating both resource value and vulnerability in management decision has been recognized for at least several decades, it is still rare that the combination is quantitatively realized, as we show here. In particular, we used resource values and vulnerability scores for each polygon to answer the questions posed by the RAD framework ([Figure 1b](#)). First, 'Are you shaping the trajectory of change?' If the polygon vegetation was expected to increase or remain stable, as measured by the $iEVI$ -based vulnerability metric in [Equation \(6\)](#), the answer was 'no', and that polygon received an 'accept' designation. Here, we made the assumption that non-decreasing vegetation production trajectories are desirable outcomes, and that under the projected climate conditions, this can occur naturally, without intervention, when $\text{Vuln} \geq 1$. For polygons that projected a decrease in production ($\text{Vuln} < 1$), we weighed the magnitude of the expected decrease along with the resource valuation. For instance, if the change was large and the resource value score was low, the polygon was likely to undergo a vegetation transition, and due to its low value, managers may 'accept' whatever outcome may occur and consider this an opportunity to monitor natural response to climate change.

For polygons where managers may wish to shape the trajectory of change, the next question addressed in the RAD framework was 'Are you managing for historical conditions or a new desired condition?' Again, the magnitude of change and the resource valuation were considered in tandem; if the polygon was projected to only experience a small change (i.e. less than a 10% decrease in $iEVI$), management of these areas may not likely require many management resources. Combining this with a high-value score indicated that managers may want to maintain historical conditions, therefore 'resisting' change. Note that the amount of expected change that managers consider acceptable may vary according to the value score. Polygons with a large magnitude of change and intermediate or large resource value scores may be candidates for managers to 'direct' the vegetation to a new desired condition.

TABLE 2 Polygon ID, valuation and rationale for the identified regions of interest.

ID	Value score	Value information	Vuln. (RCP4.5)	Vuln. (RCP8.5)	RAD
1	High	Old growth. Research benefit. Pinyon jay (<i>Gymnorhinus cyanocephalus</i>), Bighorn sheep (<i>Ovis canadensis</i>) habitat., Keep intact to resist cheatgrass [<i>Bromus tectorum</i>] and other invasives. Limit disturbances. Adjacent to critical occupied Gunnison sage-grouse (<i>Centrocercus minimus</i>) habitat, Manage grazing trespass.	0.94	0.92	Resist
2	Moderate	Wilderness with sparse PJ. Hotter, drier than other polygons, Cattle & sheep trespass.	0.88	0.87	Direct
3	High	Wilderness. High recreational & Bighorn sheep value in Red Rock Canyon.	0.99	0.99	Resist
4	Moderate	Increased insect pest/drought susceptibility. Shade for visitors. Increase resilience through visitor management to decrease soil erosion.	1.08	1.07	Accept
5	Moderate		1.06	1.07	Accept
6	High	Rimside trees. Protection strategies to decrease visitor impacts—e.g., fences, signs, block off social trails, Decrease soil erosion. High value for shade on overlooks.	0.97	0.95	Resist
7	High		0.89	0.87	Resist
8	High		1.18	1.16	Accept
9	NA	NA	0.86	0.85	

Note: Horizontal lines group the polygons by Value Information (i.e. Polygons 6, 7 and 8 each share the adjacent value information). Vulnerability (Vuln.) scores are determined via Equation (6), such that Vuln. < 1 indicates a decrease in production, whereas Vuln. > 1 indicates an increase in production relative to the historical (2001–2023) mean.

Abbreviations: NA, Not applicable; RCP, representative concentration pathway.

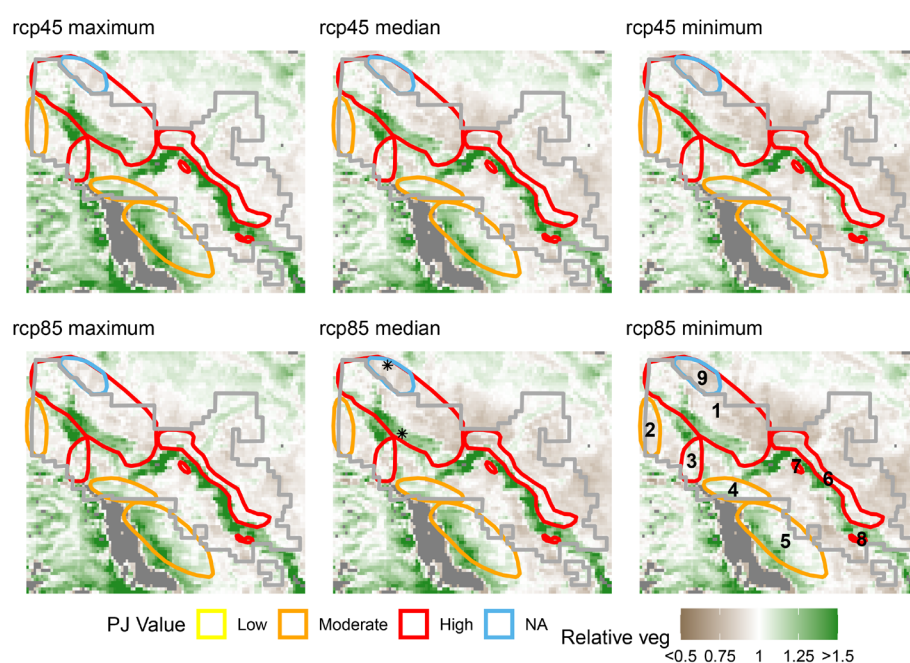


FIGURE 4 Relative change in vegetation production over the mid-century period compared with historical values (Equation 5). Predictions are determined from the water-balance/xy model in Table 1 when vegetation production is projected for scenarios of climate change. Shading is used to emphasize pinyon-juniper ecosystems. Panels represent maximum, median and minimum projected vegetation change, providing the range of projected vegetation change across all of the RCP combinations evaluated. Each plot is overlaid with polygons of importance as determined by a land manager. Centred on each polygon is the identification (ID) number, with the colour of the polygon outline indicating the resource value score (refer to Table 2). The * symbols in the bottom/centre panel designates the locations of two representative pixels further analysed in Figure 5. The grey outline designates the park boundary.

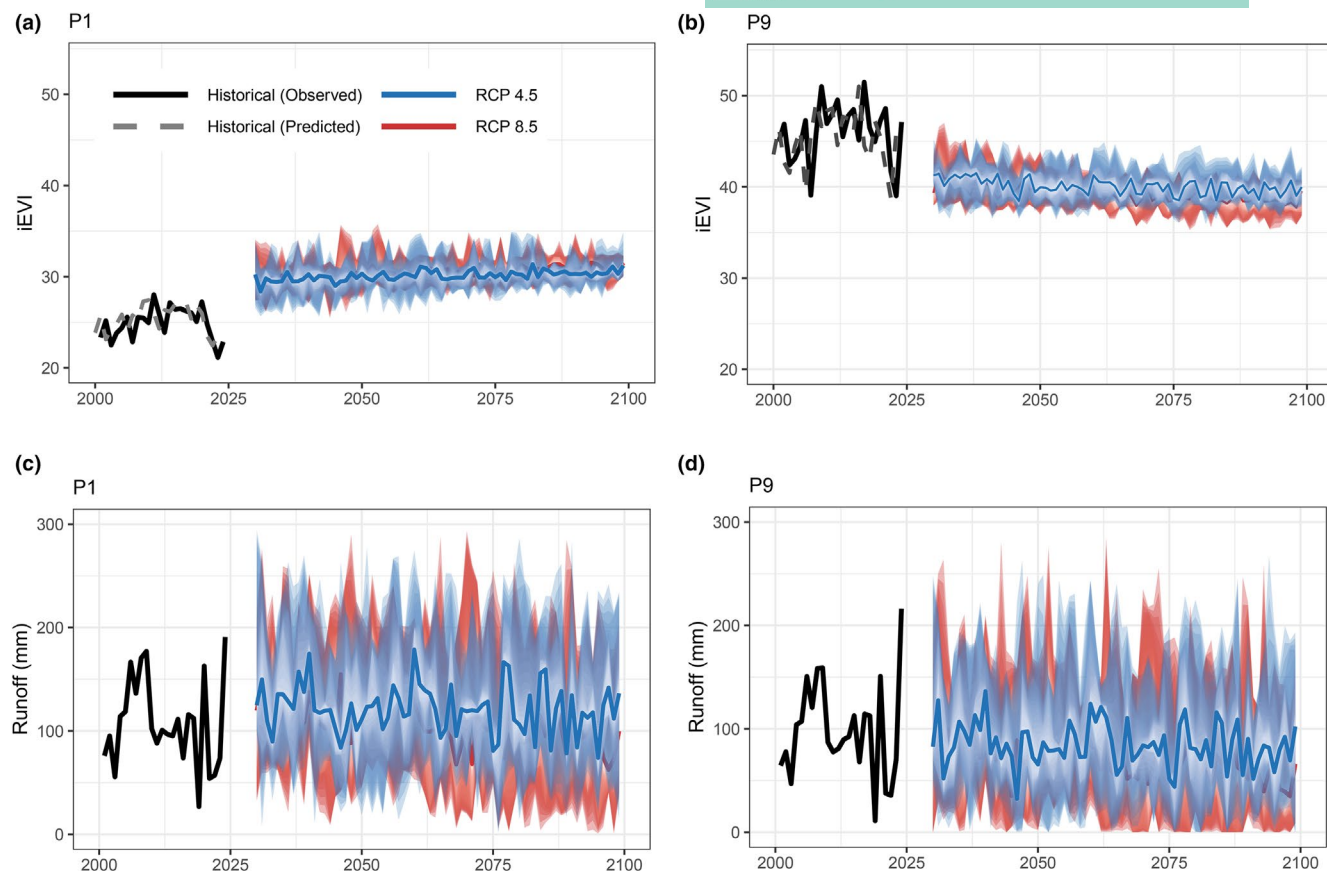


FIGURE 5 Historical (black) and predicted (blue and red) growing season integrated enhanced vegetation index (iEVI) (top) and projected runoff (bottom) for two representative pixels from Polygons 1 (left) and 9 (right) [i.e. (a) an iEVI time series from Polygon 1, (b) an iEVI time series from Polygon 9, (c) a runoff time series from Polygon 1, and (d) a runoff time series from Polygon 9]. Dashed grey line gives the model fit over historical data. Blue and red projections indicate representative concentration pathway (RCP) 4.5 and 8.5, respectively, with shading according to density over the set of general circulation model projections and the thick line corresponding to the median.

Although these polygons have high value, if they experience a large magnitude of change, they may be prohibitively costly to manage directly against the natural trajectory. Thus, by managing the transition to a new vegetation state, managers may be able to preserve some valuable properties of the area (shade, nutrient cycling, habitat) while adapting to future climate conditions.

3 | RESULTS

3.1 | Model fit

The best fit random forest model with the lowest RMSE and the largest percentage of variation explained was the water-balance/xy model, which employed water balance and spatial coordinate variables, but not temperature or precipitation variables (Table 1). Of the water-balance variables, RO was highly influential in all four models, and SW was the next most influential across the models. We note that ASWE was only influential when x , y coordinates were not included. This may be due to its unique relationship to geographic factors, mainly elevation. Thus, in the water-balance only

and water-balance/climate models, ASWE may serve as a proxy for explicit spatial information.

For the remainder of this work, we show results and predictions based on the water-balance/xy model of Table 1. Though not shown here, the broad patterns of the three other models were very similar, and therefore we opted for the best fit using water-balance data and x and y coordinates. The model fit was indeed good for historical data, the mean proportion of absolute error was rarely larger than 10% (Figure S1). The spatial regions with the largest MPEs were primarily outside the polygons of interest.

3.2 | Vegetation vulnerability

We compared the predicted annual GS production averaged over 2030–2064 to historical averages based on 2001–2023 values (Figure 4). There were largely similar spatial patterns across the range of RCP scenarios and GCM quantiles, but the magnitude differed. In all future scenarios, vegetation is expected to increase in productivity along a central portion of the park bordering the Gunnison River, which falls largely within the vegetation class Pinyon-Juniper/Sparse Mixed

Shrubs Scree Woodland (Figure 2). In general, the largest expected decreases are along the north-eastern side of the park.

There was a considerable range between the largest expected increase (18%) and the largest expected decrease (~13%) in vegetation across polygons as indicated by vulnerability score (Table 2). However, between the RCP scenarios, there appears to be very little variation, with the more extreme pathway (RCP 8.5) corresponding to at most a 2% difference in average expected vegetation change. Note that the time period containing our historical training data (2001–2023) corresponds to a period of megadrought in the south-western United States. Under RCP8.5, the probability of multidecadal droughts increases, and thus the relatively small spread between RCP scenarios may be influenced by similarity to climate conditions under which the vegetation indices and predictor variables were derived (Garfin et al., 2022). Vulnerability scores in Table 2 represent averages over GCMs, years and spatial pixels. Yet any one model, year or pixel could exhibit extreme outcomes. Thus, it can be helpful to consider the range of potential vulnerability predicted by an ensemble of GCMs via depictions over space (Figure 4) and time (Figure 5).

Over a longer time-scale, primary production time series may diverge on a per-pixel basis (Figure 5; locations of representative pixels denoted by * in Figure 4, bottom/centre panel). Although there was considerable spread associated with the 25 GCM projections, the difference between RCP scenarios was slight, with the largest difference occurring approximately after 2060 for the pixel from Polygon 9. For comparison, we also include the time series for projected runoff, which was a highly influential variable in the random forest models. Direct comparisons, however, between the dependent iEVI variable and the independent runoff variable could be approached with caution, as random forests generally allow for nonlinear and non-monotonic effects. Furthermore, even though runoff was found to be one of the most influential variables in the model, it is still one of several independent variables contributing to iEVI prediction.

3.3 | Management mapping

Polygons 4, 5 and 8 are valued for their relevance to park visitors and are projected to increase in vegetation productivity. Thus, we expect that managers may not choose to shape the trajectory of change and can 'accept' the changes within these areas. Next, model projections for Polygons 1, 3 and 6 projected only small changes from historical conditions, along with high-value scores due to 'old growth', 'recreational value' and 'shade for visitors', respectively. The expected change in productivity is less than 10% in these areas, and so they are likely to require less management resources to maintain their condition. Thus, managers may want to 'resist' change to retain the identified values. While Polygon 7 had a slightly larger magnitude of expected change, due to the high value of PJ as a source of shade to visitors, managers may still want to 'resist' change.

Finally, Polygon 2 covers a hotter, drier area that is less frequented by visitors and is expected to see a large change in vegetation production and has a relatively lower value score. Thus, it may

be a candidate to 'direct' the transition to a favourable vegetation state. We note that in this demonstration, no polygons were given the lowest value score. Seeing as parks are 'protected areas', it may be professionally difficult for a park manager to assign a low value score to any location in the park, barring disturbance. This provides further justification for having a low number of value scores to work into the analysis, given managers' biases as stewards of protected landscapes. As a low value score could also lead to 'accepting' a polygon's (positive or negative) trajectory, it may be of research interest to study the conditions for which managers assign the minimum value score.

4 | DISCUSSION

In this work, we demonstrated a framework to aid land managers in determining appropriate, climate-smart goals for naturally vegetated environments. By incorporating both the resource value score assigned by experts of that landscape with predicted vulnerability to future climate conditions, our results indicate more efficient and effective options than with either factor alone. We demonstrate a methodology to perform a robust and quantitative assessment of vulnerability by pairing remote sensing imagery and climate data, and note that the same steps could be followed using a qualitative vulnerability assessment based on expert elicitation as well. Our demonstration covers the first several stages of the 'climate-smart conservation cycle' for natural lands management (Figure 1). A manager following the steps of this framework could next be tasked with selecting and implementing adaptation options that are consistent with the RAD goals determined here. While a thorough description and comparisons of such management actions are beyond the scope of this work, in the case of PJ, recent work has explored where and what specific types of management actions, and at what intensity, are the most appropriate for managing PJ ecosystems for different management goals (Noel et al., 2023; Phillips et al., 2024; Redmond et al., 2023). For example, a list of management priorities, including 'maintain healthy ecosystems' (accept), 'assisted migration' (direct) and 'increase ecosystem resilience' (resist) with associated treatment types is available in Redmond et al. (2023, Table 1). A manager following this framework might use this tool as they continue through steps 4 and 5 of the climate-smart conservation cycle.

The utility of our proposed framework is readily seen through our case study, which identified spatially explicit vulnerability and management goals for PJ in BLCA. We determined potential management intentions for identified regions of particularly valuable vegetation throughout BLCA (Table 2). We see that for polygons of identical value (e.g. 6, 7 and 8—all of which are highly important for their rimside trees, which provide shade for visitors), a spatially explicit understanding of vulnerability resulted in variable management expectations. Specifically, the southernmost rimside polygon 8 is expected to increase production and may not increase further with management intervention, whereas rimside polygons 6 and 7 may benefit from management action to preserve important PJ function

for visitor benefit. Conversely, for polygons with nearly identical vulnerability, differing resource values led to variable management goals. For example, Polygon 2, which covers hot, dry wilderness and Polygon 7, a highly trafficked rimside area, are both expected to see large decreases in productivity. However, the resource value scores of 'mid-level importance' and 'highest importance', respectively, resulted in directing change of the wilderness polygon 2 versus resisting change in rimside polygon 7.

In the realm of vulnerability, there is a high level of spatial heterogeneity within each scenario (Figure 4). Indeed, while some areas of the park may experience more than a 50% increase in annual production, neighbouring vegetation may be reduced by half. These findings are consistent with previous work that shows variable trends of suitability between and within pinyon and juniper species across the south-western United States (Noel et al., 2025, 2023). The spatial differences may allow further insight into the importance of including latitude and longitude in the random forest models (Table 1). By incorporating coordinates as potential predictors, the model can fit different relationships between water balance and vegetation in different areas. This may have led the model to account for variables not explicitly included in the analysis, for instance, species composition or soil type, which can modulate the interaction between productivity and water use and availability (Munson et al., 2015). This may be further supported by viewing historical runoff compared with iEVI. RO was one of the most influential water-balance variable across all models. However, its long-term trend is less clear compared with iEVI (Figure 5), providing some evidence that its effect could be modulated by some other factor or factors in the model.

Focusing on the management priority areas, the high-value, rimside polygon 6 is likely to experience increases in vegetation production. While this may be a positive outcome, increasing greenness may be a sign of increasing undesirable invasive species, including cheatgrass (*Bromus tectorum*) (Condon et al., 2011; Flake & Weisberg, 2021). Indeed, a large-scale study of vegetation index–water balance relationships indicates that the association between gross annual productivity and hydrology is strongest for grasses and blackbrush shrublands across the Colorado Plateau (Thoma et al., 2019). This illustrates how the 'Re-assess vulnerability as needed' step in the climate-smart framework can help refine assessments. We do not intend for nor foresee managers completely neglecting or ignoring regions identified as having relative vulnerability scores greater than one. Rather, such a score may serve as a general indicator of vegetation health. Opposing evidence from park staff, visitors or scientific research that indicates that vegetation in a certain locale is stable or vulnerable may indicate further review and an update of management goals and intentions may be helpful.

Our framework is related to conservation triage, which helps prioritize environmental management actions to conserve valuable assets by judiciously using scarce resources (Bottrill et al., 2008; Johnson et al., 2015). Conservation triage has produced many nuanced perspectives that have been utilized across a wide array of land-management contexts (Martínez-Harms et al., 2024, Table 1). We propose that our framework could have applications in

conservation triage when decisions are made about which species and/or places justify investment relying on quantitative inputs, especially in the development of the existing NPS RAD framework.

The framework in this study provides a tool for understanding potential vegetation production into the future. However, there are several limitations of our study. First, these projections include only the effects of water-balance variables and notably exclude the effects of fire and invasive species, for instance. Furthermore, though the vulnerability metric employed here captures annual relationships between climate and productivity, extreme events such as prolonged or intense heat waves or drought over multiple time-scales not necessarily captured by the model can cause widespread plant mortality that leads to large community changes. Thus, we emphasize that species-specific or functional-group-specific data and modelling could complement the vulnerability results presented here. Nevertheless, the assignment of resource value scores, as shown by this work, can help managers decide when and where they might want to prioritize resisting the effects from threats not explicitly considered here.

Other caveats include the presence of non-target vegetation in pixels, the effects of a prolonged drought that was severe near the beginning of the study, and imperfect parameterizations and climate/soil data used in the water-balance model. Furthermore, the scale and resolution of GCMs did not always match the remotely sensed enhanced vegetation index we analysed in this study. We tried to address these mismatches by averaging or summing water-balance variables and using interpolations to match the 250-m MODIS pixel resolution, but acknowledge that these relationships could be refined to improve vulnerability assessments. Apparent discontinuities between historical values and projections based on GCMs (Figure 5, P1) may be attributed to biases in the model or in the projections, although we attempt to minimize the latter by relying on gridMET historical reanalysis data (Abatzoglou, 2013).

As land management becomes an increasingly challenging task given rapidly changing climate conditions and uncertainty, this work demonstrates a 'climate-smart' approach that can help facilitate informed decision-making by the NPS and other land managers.

AUTHOR CONTRIBUTIONS

David Thoma contributed to the conceptualization and supervision. Julie Sherman and Carolyn Lober conducted all analyses. Julie Sherman generated the figures. Michael T. Tercek generated the water-balance data and projections. Danguole B. Bockus conducted BLCA value assessment. Julie Sherman and David Thoma wrote the main manuscript. All authors reviewed and edited the manuscript.

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names is for descriptive purposes only and does not imply endorsement by the US Government.

CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

Primary model results of future projections of relative vegetation indices compared with historical values under 25 different GCM forcings are publicly archived at Sherman (2026). Analysis scripts are available from the corresponding author upon request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Figure S1. Mean proportion error for withheld, historical test data under model 2 of Table 1, shaded to emphasize PJ ecosystems. Grey areas are masked due to land classification status. Plot is overlaid with polygons of importance as determined by a land manager. The number centred on each polygon is the ID, and the colour of the outline signifies the resource value score (Table 2). The grey outline designates BLCA park boundary.

Document S1. Establishing management priorities by mapping values to PJ stands in NCPN parks.

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