CONSERVATION SCIENCE PARTNERS

TECHNICAL REPORT

5 November 2021

For the project entitled:

Informing the identification and protection of public lands to help mitigate the impacts of climate change and biodiversity loss in the United States.

Recommended citation: Conservation Science Partners. 2021. Informing the identification and protection of public lands to help mitigate the impacts of climate change and biodiversity loss in the United States. Technical Report. Truckee, CA.

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1. BACKGROUND

To mitigate the impacts of climate change and stem the loss of biodiversity, scientists have recommended substantial increases in the amount of protected land area (Noss et al. 2012), leading to calls for ambitious new protection targets, including the Aichi Target 11 (Dinerstein et al. 2019) and the Biden administration's recent commitment to protecting 30% of public lands in the United States by 2030 (Exec. Order No. 14008 2021). Achieving these ambitious targets in the US will require protecting millions of acres of public lands managed by the Bureau of Land Management (BLM) and the US Forest Service (USFS), two of the largest land management agencies in the nation. However, prioritizing which acres of public land to protect remains a considerable challenge given multiple land use objectives, the variety of ecological and environmental benefits that any given landscape might provide (e.g., carbon storage, wildlife habitat, ecological connectivity), and potential trade-offs among these co-benefits.

To address this challenge, we integrated multiple ecological and environmental variables (hereafter, "indicators") into a set of three model-based indices, each of which provides a coherent measure of conservation value and incorporates multiple ecological and environmental attributes. We applied an innovative approach to address correlations among ecological indicators and ensure that composite index values are as interpretable as possible. Specifically, we developed three model-based indices for the conterminous United States (hereafter, 'CONUS') and Alaska, a state frequently omitted from large-scale ecological and conservation studies of the US. Each of the three indices was hypothesized to reflect unique sets of conservation priorities: preserving biodiversity, mitigating climate change, and quantifying overall conservation value (see also Dickson et al. 2014). The three indices and underlying indicator variables were specified in close collaboration with project partners and stakeholders, with the goal of leveraging the best available science to meet diverse resource management and policy-making needs.

We incorporated these composite indices and indicators into an open-access, web-based tool enabling managers, planners, decision makers, and others to examine the estimated conservation value of a given location, along with the ecological and environmental variables driving that value. Users can then identify the highest value landscapes within their area of interest based on indicator values and one or multiple composite indices. The tool is user-friendly and allows for transparent, interpretable comparisons of potential areas to prioritize for additional protections (hereafter, 'priority areas') based on a range of desired outcomes. We anticipate that this tool will be useful in guiding the prioritization of landscapes for new protections across multiple spatial scales (e.g., from local area protections to nationwide planning efforts).

This technical document describes the approaches we used to identify and develop indicator layers and formulate the model-based indices, with particular emphasis on our efforts to maximize the interpretability of indices by ensuring that all indicators exert equal influence on index values. We also describe the intended uses of our data and models and highlight potential applications of our web-based tool to identify priority areas for conservation on federal lands in the US.

2. INDICATORS

Selection of indicators was guided by expert knowledge and driven by the goals and values of project partners and expected end users who are directly engaged in conservation policy-making and advocacy (Dickson et al. 2014). Specifically, we chose a contemporary, parsimonious set of indicators that reflected key or emerging conservation priorities related to the protection of biodiversity and mitigation of climate change. We endeavored to keep our indicator set sufficiently concise to ensure that it is clear to users what information is being integrated into each index and to maximize interpretability of resulting index values. We also ensured indicators were developed using the most recent available spatial data (i.e., maps or 'layers') at the highest spatial resolution we could obtain, with the goal of minimizing coverage gaps across CONUS and Alaska.

Total carbon estimates the total ecosystem carbon (above and below ground biomass, soil organic carbon) that currently exists in a given location. This 300-m resolution dataset represents the best available information on current carbon storage (circa 2010) across the US (Goldstein et al. 2020, Noon et al. 2021). Total carbon was determined based on ecosystem type, using the average carbon content per unit area for each of 13 terrestrial ecosystems and three coastal biomes (Goldstein et al. 2020, Spawn et al. 2020). Ecosystem-specific values of average above ground biomass carbon per hectare were derived from applicable databases (e.g., ForC database of forest carbon stocks [Anderson-Teixeira et al. 2018] and global grassland carbon database [Xia et al. 2014]), while below ground biomass carbon was estimated for each ecosystem type based on below ground:above ground (root:shoot) biomass ratios (Mokany et al. 2006) for the dominant vegetation type in that ecosystem. See Goldstein et al. (2020) for a definition of ecosystem types included. Soil organic carbon stocks were estimated using the SoilGrids database (Hengl et al. 2017).

Climate resilience estimates the degree to which the current climate conditions in a given location will be accessible in the future. Areas of high climate resilience are those that contribute to the ability of organisms to adapt to climate change through both local and long-distance movements (Carroll et al. 2015). Climate resilience was derived as the multiplicative inverse of *climate velocity*, a measure of the instantaneous velocity of climate change at a given location. The climate velocity metric used here was developed by Hamann et al. (2015) by integrating 11 climate variables via principal component analysis (PCA; see Hamann et al. 2015 for details on climate variables) and calculating velocity based on the distance between sites with matching present climate conditions (averaged from 1981 to 2010) and future climate conditions (2055). The Hamann et al. (2015) algorithm can be implemented in either forward (find future climate locations that match the focal location's current climate) or backward (find current climate locations that match the focal location's future climate) directions. We derived our estimate of climate resilience based on backward velocity, which asks: given the projected future climate conditions of a focal location, what is the minimum distance an organism has to migrate in order to colonize the focal location from another location with similar present day climate?

Climate stability describes the similarity between present climate (averaged between 1981 and 2010) and future climate (2055) at a given location. Climatically stable areas will have future climates that are similar to present conditions. Our estimate of climate stability was derived as the multiplicative inverse of climatic dissimilarity (Williams et al. 2007, Carroll 2018), with dissimilarity being a frequently used metric to estimate how different the future climate at a given location will be from its present climate conditions (Mahony et al. 2017). This dissimilarity metric is based on the 11 climate variables listed above, integrated via PCA (Belote et al. 2018). Multivariate local climate dissimilarity (LCD) is calculated as

$$\text{LCD} = \sqrt{\left(PC1_{future} - PC1_{current}\right)^2 + \left(PC2_{future} - PC2_{current}\right)^2}$$

where PC1 is strongly associated with temperature and PC2 is strongly associated with precipitation and moisture variables (Belote et al. 2018).

Ecological intactness estimates the degree to which a given location remains in a natural state (i.e., unmodified by human land use). Ecologically intact landscapes are those with minimal or no influence from human activities and which are therefore able to support natural evolutionary and ecological processes (Angermeier and Karr 1996, Parrish et al. 2003) as well as communities of organisms similar in species composition, diversity, and functional organization to those of undisturbed habitats (Parrish et al. 2003). We calculated ecological intactness as *1 - AI*, where *AI* is the degree of anthropogenic impact on a landscape. Drawing on our previous work (CSP 2019, see also Theobald 2013), we derived estimates of anthropogenic impact for CONUS (circa 2017) and Alaska (circa 2014), quantifying the intensity and extent of multiple human activities, including residential and commercial development, agriculture, energy production and mining, transportation, and forestry (CSP 2019). Given differences in the availability of data inputs between CONUS and Alaska, ecological intactness was calculated separately for each of these extents and was derived at 90-m resolution for CONUS and 270-m resolution for Alaska.

Species richness estimates the total number of species likely to occur in a given area. For CONUS, we used a model of imperiled species richness (NatureServe 2020). This layer integrates habitat suitability maps for 2,216 of the nation's most imperiled species, including vertebrates (birds, mammals, amphibians, reptiles, freshwater fishes; 309 species), freshwater invertebrates (228 species), pollinators (43 species), and vascular plants (1,636 species). The 990-m resolution layer includes species designated by NatureServe as imperiled or critically imperiled, and species listed as threatened and endangered under the Endangered Species Act. Because this data layer is currently available only for CONUS, we estimated vertebrate species richness separately for Alaska based on 500-m resolution species range data from the USGS Gap Analysis Project (i.e., GAP; Gotthardt et al. 2014). We calculated species richness by overlaying GAP range maps for 330 terrestrial vertebrate species in Alaska, including birds (255 species), mammals (72 species), and amphibians (3 species), following Soto-Navarro et al. (2020).

Ecological connectivity estimates the ability of a given location to support the natural movement of organisms through processes such as dispersal, migration, and gene flow, and to provide linkages between areas of high-quality habitat (Dickson et al. 2017). Maintaining areas of high ecological connectivity is also considered a key strategy for supporting species migrations and range shifts under climate change (Heller and Zavaleta 2009). We used the procedure described by Dickson et al. (2017) to derive resistance surfaces for connectivity models by rescaling our anthropogenic impact layers for CONUS and Alaska (described above under *ecological intactness*) and incorporating a modest penalty for steep slopes (Dickson et al. 2017), which may present barriers to movement for many terrestrial organisms. We used mammal species richness layers to estimate source strength (the likelihood that a given location will act as starting/end point for animal movement), and treated source strength as proportional to the number of mammal species estimated to occur in a given location. Again, we estimated mammal richness by overlaying mammal species range maps, and generated richness layers separately for CONUS and Alaska due to differences in data availability and quality. For CONUS, we downloaded International Union for Conservation of Nature (IUCN) range maps for mammals (408 species) and restricted these ranges based on recently published maps of IUCN habitat (Jung et al. 2020). Richness maps for CONUS were produced at 2-km resolution, as recommended for IUCN range data. For Alaska, we used the 500-m resolution GAP mammal species range data (described above under *species richness*). We used a circuit theory-based approach (McRae et al. 2008, Dickson et al. 2019) to model the flow of organisms across CONUS and Alaska, using Omniscape software (Landau et al. 2021) to implement omni-directional connectivity models for each extent at 1-km resolution (after McRae et al. 2016).

3. MODEL-BASED INDICES

Combinations of the indicators described above were integrated into three model-based indices, with each index providing a single estimate of conservation value for each location (i.e., pixel) across the focal extent. Model-based indices are a popular approach to synthesizing complex, multivariate phenomena into a unidimensional, easily understood metric (Greco et al. 2019), with well known examples including the UN's Human Development Index and the Environmental Performance Index (Hsu and Zomer 2016). Model-based indices are mathematical combinations of (in this case) ecological and environmental variables that otherwise have no common meaningful unit of measurement (Burgass et al. 2017). As such, they are sensitive to assumptions regarding which indicator variables are included and how those variables are combined. As noted above, our choice of specific indicator variables was based on our previous published work (Dickson et al. 2014) and close collaboration with partner organizations involved in conservation science and policy-making. Here we describe how those indicators were combined in each of three model-based indices, as well as our efforts to develop a transparent and well-justified approach to the mathematical combination of indicators for each index.

3.1 Indices and model extents

We developed three model-based indices based on combinations of ecological and environmental indicator variables with each index addressing a unique set of conservation objectives. The **composite index** incorporates all six indicators described above to provide a comprehensive assessment of conservation value across CONUS and Alaska. The **carbon and climate index** emphasizes areas important for mitigating the impacts of climate change and includes three indicators: total carbon, climate resilience, and climate stability. The **biodiversity index** emphasizes areas important for maintaining connected ecosystems and mitigating species loss, and includes three indicators: ecological connectivity, ecological integrity, and either imperiled species richness (CONUS) or vertebrate species richness (Alaska).

As noted in Section 2 above, several indicators were derived separately for CONUS and Alaska due to differences in dataset availability between these two extents. We therefore calculated each of the three indices separately for CONUS and Alaska, yielding six different models. The process for deriving each of these models was identical (described in detail below), but the underlying set of indicators differed in each case. All indices were derived in Google Earth Engine at a 90-m resolution.

3.2 Deriving the model-based indices

There are several key decisions related to how indicator values are mathematically combined in a model-based index – including whether and how indicators are transformed, aggregated, and weighted – that will affect the ultimate interpretation of index values and resulting planning and prioritization decisions. Indeed, a lack of clarity and transparency around such decisions has been a major critique of such indices (Burgass et al. 2017, Greco et al. 2019). Here, we describe the decisions undertaken when computing each of the model-based indices, paying special attention to the issue of indicator weights, a complicated problem in the transparent calculation of indices given the often considerable difference between an indicator's weight and it's actual influence on the resulting index value (Becker et al. 2017).

The first major decision is whether and how to transform indicator variables. Some investigators choose to normalize highly skewed variables by applying certain transformations (e.g., a log-transformation of a right-skewed continuously distributed quantity with non-negative values). However, such transformations, by definition, change the values of an indicator and its behavior and influence in a model-based index (e.g., in the case of a log-transformation, the new values, log(x), become a nonlinear function of x). The difference between (and proportionality of) values on their native scale changes as a function of any transformation applied. Although in some cases these transformations are desirable (e.g., if the value of connectivity saturates at some point) the specific transformation, including any parameters in the transforming function, would need to be justified. Lacking strong justification for any particular transformation, we choose not to alter the distributions of any of the indicators we used.

The next decision entails the mathematical function used to place all indicators on a common scale. This step is necessary because the indicators we used have non-comparable units (e.g., tonnes of carbon per hectare, number of vertebrate species). To ensure comparability across indicators, each indicator was standardized (converted to z-scores) such that

$$z_{ij} = \frac{x_{ij} - mean(x_j)}{sd(x_j)} \qquad \text{(eq. 1)}$$

where x_{ij} is the vector of $i = 1, 2, \ldots, N$, observations of indicator j and z_{ij} are the z-transformed values. Converting to z-scores has the effect of centering the distribution of each indicator on zero and converting the unit of measurement for all indicators to standard deviations, thereby allowing direct comparison between indicators with very different native measurement units.

We calculated the value of the model-based index, *y*, at each location, *i*, as the weighted linear combination of indicator variables. We used a weighted sum of indicators (Paruolo et al. 2013, Becker et al. 2017) such that

$$y_i = \sum_{j=1}^{J} z_{ij} w_j \qquad \text{(eq. 2)}$$

where w_j is the weight applied to indicator *j*. It is tempting to assume that the weights represent the relative importance of each indicator in determining the resulting index, but this is not always the case (Paruolo et al. 2013, Becker et al. 2017). When indicators are correlated, as ecological and environmental variables often are, weights may not be truly representative, or even intuitively predictive, of indicator 'importance,' which we define as the degree to which a single indicator can explain observed variation in the model-based index. Note that similar problems can also occur when indicators do not have equal variance. However, this was addressed in our analyses because all indicators were standardized by converting to z-scores, as described above.

Given this complex relationship between weights and indicator influence, the naive application of weights can lead to non-intuitive index values for which particular indicators are more or less influential than expected. Therefore, rather than simply basing our analysis on equal weighting of each indicator, as is frequently done in analyses aggregating multiple ecological datasets, we instead adapted a method proposed by Becker et al. (2017) to determine the set of weights needed to achieve *equal importance* across all indicator variables. This approach, which involves using an optimization algorithm to find the set of weights that yields a predetermined importance value for each indicator, is described in detail in Appendix A.

In Table 1, we illustrate the value of considering indicator *importance* in our analyses by demonstrating that, when indicators are weighted equally, their contribution to the value of the model-based index is in some cases far from equal. In addition, when weights are optimized to yield equal importance, the weights themselves can vary substantially between indicators.

Table 1. Optimized vs. equal indicators weights and their effect on estimated indicator influence over two spatial extents. For each indicator, the weight (w_j) used in eq. 2 is shown, along with the resulting importance of that indicator (in parentheses), where importance is defined as the degree to which variation in the given indicator explains the variance observed in the model-based index *y*. Note that weights and importance were calculated separately for each combination of index and model extent.

	Index	Model extent	Indicators						
			Total carbon	Climate resilience	Climate stability	Ecological intactness	Ecological connectivity	Vertebrate species richness*	Imperiled species richness*
Optimized weights	Composite	CONUS	0.48 (0.17)	0.57 (0.17)	0.64 (0.17)	0.36 (0.17)	0.41 (0.17)	--	0.57 (0.17)
	Carbon and climate	CONUS	0.49 (0.33)	0.5 (0.33)	0.53 (0.33)	--	--	--	--
	Biodiversity	CONUS	--	--	--	0.65 (0.33)	0.30 (0.33)	--	0.81 (0.33)
	Composite	Alaska	0.68 (0.17)	0.47 (0.17)	0.36 (0.17)	0.69 (0.17)	0.37 (0.17)	0.40 (0.17)	--
	Carbon and climate	Alaska	0.59 (0.33)	0.56 (0.33)	0.35 (0.33)	--	--	--	--
	Biodiversity	Alaska	--	--	--	0.63 (0.33)	0.26 (0.33)	0.49 (0.33)	--
Equal weights	Composite	CONUS	1 (0.17)	1 (0.16)	1 (0.12)	1 (0.21)	1 (0.21)	--	1 (0.13)
	Carbon and climate	CONUS	1 (0.35)	1 (0.34)	1 (0.32)	--	--	--	--
	Biodiversity	CONUS	--	--	--	1 (0.38)	1 (0.42)	--	1 (0.20)
	Composite	Alaska	1 (0.12)	1 (0.18)	1 (0.19)	1 (0.11)	1 (0.20)	1 (0.20)	--
	Carbon and climate	Alaska	1 (0.30)	1 (0.32)	1 (0.38)	--	--	--	--
	Biodiversity	Alaska	--	--	--	1 (0.24)	1 (0.40)	1 (0.37)	--

* See section 2 above for details on species richness layers. Vertebrate species richness was used in calculating composite and biodiversity indices for Alaska and imperiled species richness was used in the analogous CONUS indices.

4. RESULTS SUMMARY

Mapping the three model-based indices across CONUS and Alaska resulted in the identification of different potential priority areas based on the particular index used, with each index representing distinct conservation objectives as described above. In many cases, incongruent regions were identified as high value for mitigating impacts of climate change versus protecting biodiversity. However, there were also priority areas that overlapped for multiple objectives, where conservation actions might provide a variety of benefits for both climate mitigation and biodiversity.

For example, a large portion of the southeastern and southern coastal plains of the US (including much of Georgia and Florida) was identified as a priority area in both the overall composite index and the carbon and climate index. A quick comparison of maps of all three indices and their underlying indicators suggested this prioritization was largely driven by climate stability, total carbon, and imperiled species richness. Despite the fact that species richness values were high for this region, however, lower values for ecological intactness and ecological connectivity resulted in relatively low values for the biodiversity index, suggesting this may be a complicated region to prioritize if protecting biodiversity is the main objective.

Conversely, several montane regions stood out as high priority areas for all three indices. Examples include the Sierra Nevada and Coast Ranges of California, the Boston and Ouachita Mountains south of the Ozarks, and the Blue Ridge Mountains in the central Appalachian region. These areas were identified as high value conservation areas based on a combination of high total carbon and climate resilience, as well as relatively high imperiled species richness, ecological intactness, and ecological connectivity.

The web application also includes analytical tools to evaluate priority areas of unprotected federal lands, allowing users to readily identify BLM and USFS lands that fall within the top percentiles (i.e., 5, 10, or 20%) of conservation value based on the index of choice. For example, to meet a target of protecting one million additional acres of BLM lands in California, end users might choose to focus on the top 10% of unprotected BLM lands based on the overall composite index, which prioritizes over 825,000 acres in the northern and southern Coast Ranges and western Sierra Nevada foothills. Additional BLM lands might be considered in the Klamath Mountains from the top 10% of priority areas based on the carbon and climate index, or in the Sierra Nevada and Peninsular Ranges from the top 10% of priority areas based on the biodiversity index. Again, the three indices identify several overlapping areas of high conservation value, while other areas are prioritized only for climate mitigation or biodiversity protection.

The variation in priority areas revealed by these indices illustrate their utility for identifying and comparing high value areas for different conservation objectives. Ready access to interactive, web-based maps of all three indices and their input indicators allows end users to quickly compare and contrast priority areas for a range of desired outcomes. Importantly, the parsimonious set of input indicators representing key conservation objectives also ensures the factors underlying index values are clear to users, facilitating straightforward and transparent interpretation of model outputs.

5. DATA USES AND LIMITATIONS

We intend for these data to be used to inform identification and prioritization of high value public lands in CONUS and Alaska, allowing the user to identify the top areas required to achieve their particular target in terms of acreage or percent of land area protected. The three model-based indices and associated indicators provide the flexibility to compare and contrast priority areas based on a range of conservation values and desired outcomes. The indices were produced at a spatial resolution of 90 m and derived from input layers ranging from 90 m to 2 km, reflecting what we determined to be the best available data. Because we used input layers produced at varying resolutions, we anticipate these data will be most relevant for landscape-scale, coarse-filter assessments, and may be unsuitable for finer-scale, localized analyses. To facilitate landscape-scale analyses that are relevant to management decision making, our interactive web tool highlights federal lands containing pixels in the top percentiles of each model-based index. These top percentiles were calculated based on index layers that were smoothed by averaging index values in a 5,000-acre moving window (corresponding to the federally mandated minimum size for wilderness areas in the US). Thus, the high value pixels in these top percentiles represent a minimum 5,000-acre area of high conservation value.

It is worth reiterating that all model-based indices represent numerical representations of values and objectives rather than a statistical quantification of some measurable phenomenon, and that index results will depend on the exact indicators used and the relative importance values they are assigned. We have endeavored to (1) choose a comprehensive set of indicators that reflect a range of conservation goals based on partner need and expertise, and (2) ensure that all indicators have equal influence in determining the value of the resulting index. However, we acknowledge that these decisions may not reflect the specific goals or values of all users. In addition to examining index results, we encourage users to explore and compare patterns based on the individual indicator layers themselves, several of which are likely to be highly relevant to decision making, depending on user objectives and priorities. Of the three indices provided, the combined composite index offers the most comprehensive measure of overall conservation value of a given landscape.

We caution prospective users to assess the suitability of the data for the question of interest, and to consider any scale-dependent limitations in the data that may affect their applicability or interpretation. In particular, we note that the indicator layers for climate resilience and climate stability are derived from 1-km resolution data, which may be too coarse to evaluate finer-scale climatic variability (e.g., temperature variation driven by topographic complexity; Ackerly et al. 2010). We also acknowledge sources of potential uncertainty in the indicator layers, including variability in spatial and temporal scales and potential error in modeled pixel values. While we are unable to directly incorporate indicator uncertainty into the model-based indices given the deterministic nature of this modeling approach, we expect any influence on index values to be minor given our efforts to obtain the highest quality indicator datasets available. Lastly, we recommend that applications or publications drawing on these data in novel analyses, reports, peer-reviewed articles, theses, or other forms, should be undertaken in consultation with the authors of this report. The source of the data should be properly referenced using the citation provided on the cover page.

6. COMPARISON TO SIMILAR TOOLS

Our project builds on previous research and increasing efforts to identify and prioritize high value landscapes for climate mitigation and biodiversity protection. However, our study adds to this body of work in several novel and important ways.

First, although many studies mapping conservation priority areas have focused on identifying ‘hotspots’ for conservation of biodiversity, few incorporate carbon storage and climate mitigation as major conservation objectives. During initial reviews, partners and stakeholders expressed a need for metrics quantifying the value of landscapes based on the potential to protect biodiversity and to mitigate climate change. In response to these needs, we incorporated what we ascertained to be the best available data on carbon storage, along with well-developed indicators of local climate impacts to ensure that our indices address both sets of conservation goals.

Second, Alaska is often omitted from large-scale ecological and conservation studies of the continental US, given the distinctiveness of environments at high latitudes and disparities in the quality and availability of data for Alaska relative to CONUS. Yet Alaska encompasses an area nearly one-fifth the size of the lower 48 states combined, including expansive wilderness areas and extensive public lands. Based on high stakeholder interest in identifying priority landscapes in Alaska in addition to CONUS, we made particular efforts to identify the best available data layers for Alaska. We also derived novel species richness, ecological intactness, and connectivity layers for Alaska to fill fundamental data gaps.

Third, by advancing the methodological approach of influence optimization, our study also contributes to an active area of research in the derivation of model-based indices. Our use of influence analysis and optimization is a subtle but consequential improvement on similar composite measures in ecology and conservation. Ensuring that the perceived importance of each indicator corresponds to its actual importance, and that all indicators have equal influence on our model-based indices, makes interpretation of index values more straightforward, transparent, and robust.

Lastly, the development of these model-based indices and underlying indicators was driven by early and continued engagement with our project partners. Our main objective was to address their priorities with the best available data in an analytical and web-based platform that allows for responsive and rapid updates, given new data or changing priorities. The provision of these data layers in a user-friendly, interactive format is a critical component of ensuring these tools can be readily accessed and implemented by conservation practitioners for science-informed decision-making and advocacy efforts.

Acknowledgements

We thank the Conservation Lands Foundation, with whom this project was co-developed, as well as our other partner organizations, including Audubon Alaska, Campion Foundation, and the WildSpaces Foundation. Total carbon data were generously provided by A. Goldstein and M. Noon from Conservation International. We also thank three anonymous reviewers who provided valuable comments that greatly improved this work. This report and the technical aspects of this project were conceived and implemented by J. Anderson, B. Dickson, L. Farwell, J. Gage, V. Landau, J. Suraci, H. Wang, and L. Zachmann.

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APPENDIX A. Optimizing indicator weights for equal importance in composite indices

We used a composite index approach (see Greco et al. 2019) to combine several individual indicators into a single metric of conservation "value". In our case, we used a simple linear combination of indicators with weights applied to each indicator. The values of the composite index, y (a column vector of length I), are calculated as

$$y = Xw. \tag{1}$$

X is an $I \times J$ matrix of indicator values, where x_{ij} is the value of indicator j for observation i, and w is a column vector of weights of length J, where w_j is the weight for indicator j. We should note that the observations, i, in our case correspond to the values of individual pixels in spatially-gridded indicator data.

It is tempting to assume, in the case of the linear combination in Eq. 1, that the weights represent the relative importance of each indicator in determining the overall composite index, but this is not always the case (Paruolo et al. 2013, Becker et al. 2017). When indicators are correlated, as environmental variables and metrics often are, weights are often not truly representative, or even intuitively predictive, of importance. Similar problems can also occur when indicators do not have equal variance; however, this is not relevant to our analysis, because all indicators were standardized – scaled to zero mean and unit variance – prior to computing the composite index (Eq. 1). Paruolo et al. (2013) and Becker et al. (2017) offer a simple metric of "importance", S_j, for indicator j, that accommodates correlation among indicators.

$$S_j = \frac{\sum_{i=1}^{I} \left(E(\hat{y}_i|x_{ij}) - \bar{y}\right)^2}{\sum_{i=1}^{I} \left(y_i - \bar{y}\right)^2} \tag{2}$$

S_j, also called the Pearson correlation ratio, is a measure of the degree to which a single indicator can explain observed variation in the composite index, y. $E\left(\hat{y}_i|x_{ij}\right)$ is the expected value of the composite index given the value of indicator j for observation i, $\bar{y}$ is the mean observed composite index value across all observations, and y_i is the observed composite index value for the i^{th} observation. $E\left(\hat{y}_i|x_{ij}\right)$ can be defined using any regression of indicator j on y, including nonlinear and non-parametric regression. This feature is important because – in the case of correlated indicators – the relationship between indicator j and the composite index y can be nonlinear. Becker et al. (2017) suggest that Gaussian process or penalised splines regression offer the most generalizable solution for defining $E\left(\hat{y}_i|x_{ij}\right)$ because it can accommodate highly complex nonlinear correlations among indicators. For our purposes, we found that polynomial regression with degree 4 could sufficiently capture nonlinear relationships between indicators and composite index scores resulting from correlations among indicators. We opted to use this simpler regression function because it is less subject to parameterization decisions than penalized splines (e.g. number of knots, degree, and order) and offers vast improvements in computation speed compared to Gaussian process regression.

With Eq. 2, we now have a way to measure the *importance* of each indicator.[1] The challenge then becomes how to reverse engineer the weights from a set of desired importances. Following Becker et al. (2017), we use an optimization algorithm to determine the set of weights that yields, based on Eq. 2, the desired set of importances. To do this, we used the Nelder Mead() function (with bounds [0, 1] for individual weights) in the lme4 package in R (Bates et al. 2007), and optimized weights to determine the set of weights that minimizes the difference between our desired and observed importances. As Becker et al. (2017) discuss, there is not always a perfect solution to the "inverse problem", but the optimizer will nonetheless find the "best" solution. For this reason, it is important to verify using Eq. 2 that the optimal weights do indeed result in importances that are acceptably close to the desired importances.

[1] The process of determining weights is often expert-driven. It may be necessary to solicit expert opinion on what the desired *importances* should be, rather than weights, as it is much more intuitive. Lacking a formal process by which such importances could be estimated or derived, we have chosen to use equal importance as the basis for all indicators in our composite indices.

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