OXFORD

BioScience, 2025, **75**, 362–378
https://doi.org/10.1093/biosci/biaf031
Advance access publication date: 6 May 2025
Overview Article

Spatial climate analogs in climate change research, impact assessment, and decision-making

Svetlana V. Yegorova, Solomon Z. Dobrowski, Laurie Yung, Sean A. Parks, R. Kyle Bocinsky, Kimberley T. Davis, Caitlin Littlefield, Marco P. Maneta, Carina Wyborn, Patrick Wurster, Robin Rank, Douglas Brinkerhoff and Thomas Colligan

Svetlana V. Yegorova (svetlana1.yegorova@umconnect.umt.edu) and Solomon Z. Dobrowski are affiliated with the Department of Forest Management at the University of Montana, in Missoula, Montana, in the United States. Robin Rank is affiliated with PivotBio, Seventh St, Berkeley, California, United States. Laurie Yung is affiliated with the Department of Society and Conservation at the University of Montana, in Missoula, Montana, in the United States. Sean A. Parks is affiliated with the Aldo Leopold Wilderness Research Institute, at the Rocky Mountain Research Station, US Forest Service, in Missoula, Montana, in the United States. R. Kyle Bocinsky is affiliated with the Montana Climate Office, at the University of Montana, in Missoula, Montana, in the United States. Kimberley T. Davis is affiliated with the Rocky Mountain Research Station, US Forest Service, in Missoula, Montana, in the United States. Caitlin Littlefield is affiliated with Conservation Science Partners, in Truckee, California, in the United States. Marco P. Maneta and Patrick Wurster are affiliated with the Department of Geosciences at the, University of Montana, in Missoula, Montana, in the United States. Carina Wyborn is affiliated with the Institute for Water Futures, at the Fenner School of Environment and Society, at Australian National University, in Canberra, Australia. Douglas Brinkerhoff and Thomas Colligan are affiliated with the Department of Computer Science at the University of Montana, in Missoula, Montana, in the United States.

Abstract

Climate adaptation requires actionable scientific information about potential climate impacts. Spatial climate analogs answer the question, 'where does the future climate of a focal location occur today?' Analogs provide a means to develop measures of climate change exposure and can be applied to project climate change impacts. Although analogs are the basis for empirical models, recent applications of analogs have been structured as spatial models, which can contribute distinct information compared to more commonly used nonspatial approaches. Analogs may improve our ability to communicate climate change impacts for science and nonscience audiences. We review approaches for identifying analogs, summarize their applications, highlight understudied features, and examine evidence of their utility for science communication. We conclude by identifying research needs: the establishment of best practices for analog identification, the adoption of validation methods for analog impact models, and the evaluation of the utility of analogs for communication.

Keywords: climate change impacts, spatial climate analogs, climate exposure, climate impacts communication

The ongoing climate crisis highlights the need to adapt to the climate-driven changes in socioecological systems that are already unavoidable (hereafter, *climate impacts*; Bierbaum et al. 2013). To be effective, adaptation practices must be location and context specific (Reckien et al. 2022), which, in turn, requires location-specific information about how systems are likely to respond to climate change. Spatial analogs, which are used to estimate climate change exposure, can also be used to project specific climate impacts. We use the term *analog impact model* (AIM; see box 1 for term definitions) to describe this class of empirical models. Our objective in this review is to summarize methodologies for identifying climate analogs, synthesize existing applications for estimating climate change exposure, and highlight the use of AIMs for projecting climate impacts.

Climate analogs are locations that share a similar climate across space and time. In the context of climate change, analogs can refer to incoming (reverse analog) or outgoing (forward analog) climates with respect to a focal location. Using spatially referenced climate projections, a *forward climate analog* identifies where the *current* climate of a focal location will occur in the future (figure 1a). Forward climate analogs are used to calculate forward climate velocity, identify climates that are likely to disappear in the future (Carroll et al. 2015, Hamann et al. 2015), and identify potential dispersal areas for focal species (Parks et al. 2023). In contrast, *reverse climate analogs* identify locations where the *future* climate of a focal location is found today (figure 1b; Carroll et al. 2015, Hamann et al. 2015). Reverse analogs are used to identify reverse climate velocities, climates that are novel with respect to a reference time period (Williams et al. 2007, Mahony et al. 2017), and to project climate impacts. AIMs characterize ecosystem state variables (e.g., vegetation type, species occurrence) at reverse analog locations and interpret these state variables as a model of future state variables at a focal location. (figure 1c). State variables can be represented by gridded data sets, including dominant vegetation types (Parks et al. 2018), crop productivity (Pugh et al. 2016, Chaudhary et al. 2023), and energy use (Hallegatte et al. 2007), among others.

Analogs can be applied as supervised and unsupervised models. In an unsupervised approach analogs are agnostic to a particular species or system of interest, and instead are defined by broadly relevant climate characteristics. Examples of unsupervised analog applications include measures of climate change velocity and climate novelty (Williams et al. 2007, Hamann et al. 2015, Mahony et al. 2017). In contrast, as a supervised approach, analogs are used to project climate impacts for specific state variables (e.g., changes in species occurrence) in AIMs. Having a response variable in supervised modeling provides a mechanism to optimally characterize climate for a system of interest.

Analogs have been used across many disciplines, including meteorology (Van den Dool 1994), climate downscaling

Received: November 5, 2023. **Revised:** January 24, 2025. **Accepted:** February 25, 2025

Box 1. Glossary of climate-analog related terms.

Analog impact model (AIM): uses features of the reverse analogs to model impacts or features of the focal location under future climate (figure 1c).

Climate analog: spatiotemporal climate analog used to find sites that share similar climatic and other characteristics (figure 1) to a focal location.

Climate change exposure: an umbrella term for various metrics quantifying the degree to which a location or a potential organism may be exposed to climate change effects. Climate velocity is an example of a climate exposure metric.

Climate change impact: an anticipated change to a response variable of interest (e.g., forest type, crop yield, fire regime) associated with a change in climate.

Climate distance and climate dissimilarity and climate similarity: sometimes used interchangeably, a measure of climate similarity, when comparing climates of two locations.

Climate space: univariate or multivariate space constructed by climate variables, in which climate dissimilarity of two locations or time periods is measured.

Climate variable: variables considered for defining climate space. Climate variables consist of a climate element (temperature), temporal specification (hourly, daily, monthly, annual) and a statistic (mean, variance, etc.). For example, mean annual temperature and precipitation.

Climate velocity: a climate change exposure metric quantifying the rate (distance per year) of climate movement in space. Can be thought of as the rate at which an organism has to move to maintain its preferred climate.

Constrained analog: analogs that are defined not only by climatic similarity, but other factors that are important for the specific climate change impact being projected (e.g., soil type) or for the specific user group (e.g., “knowable” analogs). Constrained analogs are always a subset of the full set of climate analogs (i.e., those only defined by climate).

Focal climate: climate at a focal location.

Focal location: location of interest represented by a pixel, city, or weather station, sometimes referred to as a “target” location.

Forward analog: location that is projected to have historic (or reference period) climate of a focal location in the future (figure 1a). Answers the question, where is the current climate of the focal location projected to occur in the future?

Functional analog: the analog resulting after applying all known constraints.

Nonanalog climate: climates (generally future climates) that are not observed under the contemporary or reference period climate in the chosen search space (province, continent, or Earth).

Reverse analog: location that currently has focal location’s future climate (figure 1b). Answers the question, where does the future climate of the focal location occur today?

Spatiotemporal or spatial climate analog: used interchangeably with climate analog.

(Maurer and Hidalgo 2008), and paleoecology (Overpeck et al. 1985), although what constitutes an analog and how analogs translate into projections of system states varies across these applications. The analog applications we discuss in this review are most similar to those of paleoecology, where climate analog approaches are used to reconstruct past climates from fossil records (Overpeck et al. 1985 and the citations within it, Williams and Shuman 2008). Paleoecologists compare present day and past ecosystems and use transfer functions to translate these comparisons into projections of past climate states. The AIM applications we discuss differ in the direction of reasoning and can be thought of as reverse transfer functions where comparisons of the twentieth century and projected future climate are used to infer future ecosystem states. Our focus reflects the increasing attention AIMs have garnered for projecting and communicating potential climate impacts.

In the broadest sense, analogs are synonymous with the substitution of space for time (Mahony 2017, Mahony et al. 2017) and are, therefore, the basis for empirical approaches that project biological responses to climate (Pickett 1989, Currie 2001, Lester et al. 2014, Lovell et al. 2023). The use of space-for-time substitution comes with many assumptions, including the assumptions that observed spatial patterns are due to variation in climate, and that climate and the response variable are in a pseudoequilibrium (Johnson and Miyanishi 2008, Lovell et al. 2023). The validity of the space-for-time approach appears to be more robust over long time horizons (millennial time scale), where climate and biotic responses are more likely to be in equilibrium with climate fluctuations (Blois et al. 2013, Adler et al. 2020). At finer timescales, where disequilibrium dynamics are prevalent (Svenning and Sandel 2013), projections with space-for-time substitution require more careful interpretation. These caveats apply not just to AIMs but to other empirical modeling approaches that rely on space-for-time substitution and, to a more limited degree, mechanistic models that are often parameterized using spatial data. Nonetheless, space-for-time approaches applied at decadal time frames can predict the correct direction, if not the magnitude of change (Lauenroth and Sala 1992, Elmendorf et al. 2015).

Although AIMs are conceptually similar to empirical bioclimatic models (they both rely on space-for-time substitution), differences emerge in the model support between the two approaches. AIMs characterize the climate envelope of a specific location, whereas bioclimatic models characterize the climate envelope of a species or a system of interest. The focus on location and the methodological decisions associated with this focus (i.e., how to characterize climate, where and how far to search for analogs, and how many analogs to use) geographically constrain the data used for making projections at a focal location (figure 1c).

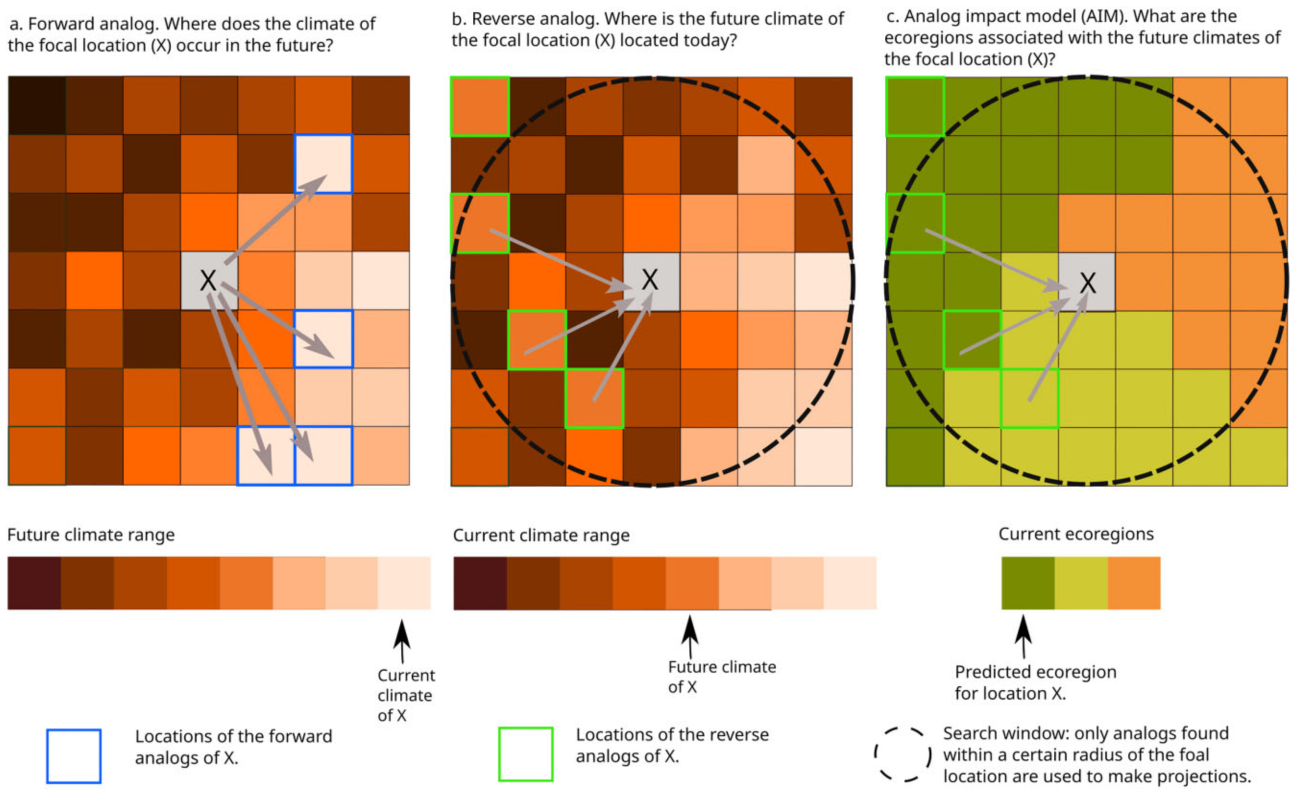

Figure 1. Climate analogs and analog impact models. For a focal location X, forward climate analogs (a) are locations where the focal pixel's current climate can be found in the future. Forward analogs are used to calculate climate velocity (see the "Climate change exposure" section), assess potential migration patterns, and map disappearing climates—locations that do not have forward analogs in the future climate. Reverse climate analogs (b) are the locations that currently have the focal pixel's future climate. Analog impact models (see panel (c) and the "Analog impact models" section) use state variables found at the locations of reverse analogs to project features at focal pixel X under a future climate. Reverse analogs are used to project climate impacts, such as climate-driven ecoregion transitions (see panel (c) and the "How are climate analogs used in climate change research and climate adaptation?" section) and locate areas expected to develop novel climates (i.e., locations that have no reverse analogs in the contemporary time period, not visualized). The search radius for climate analogs can be unconstrained or chosen to reflect biotic processes such as assumed dispersal constraints. In panels (b) and (c), only analogs found within a limited radius of the focal location are used.

Consequently, AIMs can function as spatial models (similar to other spatial modeling approaches that use a geographically limited moving window) and can therefore capture the effects of spatially structured variables and processes not directly included in the model.

Most commonly used empirical modeling approaches are not spatially explicit (Brown et al. 2011, Crase et al. 2014, Gaspard et al. 2019) and are therefore not well equipped to accommodate sources of spatial structure in data, beyond those associated with the explanatory variables. Nonspatial models translate spatial information (e.g., georeferenced observations) into nonspatial information (e.g., climate space) and then transfer forecasts back into geographic space, losing any spatially structured information that is present in the observations, but is not associated with the explanatory variables in the model. As a result, nonspatial models can suffer from spurious inferences because of confounding factors and omitted variable bias, both of which can manifest as spatial autocorrelation in model residuals (Brown et al. 2011, Walker 2014). AIMs follow a similar process, but they create individual models for each focal location, using a geographically limited data set. AIMs consider data that are geographically proximate to each focal location as a consequence of the spatial proximity between focal and analog locations (Hamann et al. 2015). This type of geographically limited search can preserve other spatially encoded information including the influence of exogenous (e.g., soil orders) and endogenous (e.g., dispersal dynamics) variables not included in the model. In contrast, nonspatial models are likely to attribute the influence of these omitted variables to the climate variables in the model. Whether the spatial nature of AIMs leads to different projections of climate impacts than nonspatial models would is not clear. In general AIMs have not been formally compared with more commonly used bioclimatic models, although a limited comparison suggests that AIMs provide qualitatively similar forecasts of future impacts (Coffield et al. 2021). In this review, we explore potential distinctions between AIMs and nonspatial models.

Climate analogs are often advanced as an effective means to communicate climate impacts to nonscientists and to inform climate adaptation decisions in multiple sectors (Hallegatte et al. 2007, Veloz et al. 2012, Rohat et al. 2017, Fitzpatrick and Dunn 2019, Chaudhary et al. 2023). Analogs have been used in innovative ways to communicate climate impacts and stimulate discussion in agricultural and urban planning settings (e.g., Hallegatte et al. 2007, Retchless 2014, Fitzpatrick and Dunn 2019, Chaudhary et al. 2023). For example, climate analog locations can be visualized, providing an engaging way to communicate anticipated future changes to broad audiences (e.g., plus2c.org, https://fitzlab.shinyapps.io/cityapp). However, we note that there is limited empirical evidence of the utility of analogs for communication and actual decision-making.

In this article, we review approaches for identifying climate analogs and for projecting climate impacts using AIMs. We summarize how climate analogs have been used to model climate impacts in ecological, built and agricultural contexts, highlight traits of analog approaches that remain underappreciated or unexplored, and contrast AIMs with commonly used empirical modeling approaches. To assess their utility in climate adaptation, we review evidence from social science regarding the effectiveness of analogs as a communication and decision-making tool. We conclude by identifying existing gaps in knowledge and suggest future areas of research. We provide a brief description of our review methods in the supplemental material.

How are climate analogs defined?

Identifying climate analogs relies on quantifying the climatic similarity between sites (or the same site over time). This is done by characterizing a climate space, quantifying climate distance between locations in the climate space and comparing those distances with a threshold value—a value within which climates are considered analogous.

More formally, for a focal location *i* in time period *a*, (x_i, t_a), and a set of candidate analog locations *j* in time period *b*, (x_j, t_b), analogs are the set of (x_j, t_b)s such that

$$D_{f(xi,ta),f(xj,tb)} < D_{\max} \quad (1)$$

where $D_{f(xi,ta),f(xj,tb)}$ is a measure of climatic distance between the focal and potential analog location in a defined climate space. $D_{f(xi,ta),f(xj,tb)}$ can be any algorithm for measuring distances in a multivariate space, such as Euclidean distance or others (e.g., McCune et al. 2002, Grenier et al. 2013). Although $D_{f(xi,ta),f(xj,tb)}$ is referred to as either *climate dissimilarity* or *climate similarity*, we opt to use *climate similarity* in most cases because it improves clarity. $D_{\max}$ is a threshold value, and $f(x, t)$ is a function that maps geographic locations to locations in climate space at time period *t*. $D_{\max}$ is crucial to determining which candidate locations are sufficiently climatically similar to be considered analogous (see the "Climate similarity measures and thresholds" section). The dimensions of this climate space are characterized by the variables used to define climate or by synthetic climate variables produced by ordination to reduce data dimensionality (Littlefield et al. 2017). In the reference time period, climate data are often derived from gridded data or weather station observations. For future time periods, climate is commonly characterized using downscaled data from general circulation models.

In addition to climate similarity, analogs can consider spatially structured nonclimatic variables that represent exogenous and endogenous processes relevant for understanding a system of interest. For example, analog definitions can include physiographic characteristics such as soil properties, topography (Dunn et al. 2019) and land use (Pugh et al. 2016). In addition, studies can limit the search window for analogs to represent dispersal limitations (Williams et al. 2007, Parks et al. 2019, Kling and Ackerly 2020, Coffield et al. 2021), which can be further refined to consider network constraints and connectivity (Dobrowski and Parks 2016, Littlefield et al. 2017). Analogs intended for climate adaptation and decision-making can also be limited by perceptual constraints, which can be thought of as a type of connectivity constraint. The pool of potential analogs can be limited to those knowable, familiar or those considered relevant to the end user or audience (Jost et al. 2016, Fitzpatrick and Dunn 2019). The decision to limit analog selection by physical distance, or other factors, is also a pragmatic one, because it reduces the computational cost of finding analogs.

After climatic and other constraints are applied to find all analogous climate locations, a subset of analogs is selected for climate exposure or climate impact estimates (see the "How are climate analogs used in climate change research and climate adaptation?" section). This subset is usually chosen to minimize climate dissimilarity, $D_{f(xi,ta),f(xj,tb)}$, between focal and analog locations (Mahony et al. 2017), but it can also prioritize other features—for example, the physical proximity between focal and analog locations (Parks et al. 2019).

Characterizing climate space

The definition of the climate space used for measuring climate similarity is critical to identifying analogs (Pugh et al. 2016, Mahony et al. 2017, Dunn et al. 2019). Climate can be characterized across multiple dimensions, each of which carries unique information (Garcia et al. 2014). Relevant aspects of climate are subjective to each species and will vary by the intended analog use. Whether climate analogs are used as supervised or unsupervised models influences the approach for defining climate space. Analogs intended for estimates of climate exposure (unsupervised approach; see the "Climate change exposure" section) often use broadly applicable climate variables (e.g., mean seasonal temperature and precipitation). In contrast, analogs used to project impacts to a specific response (a supervised approach; see the "Analog impact models" section) may use a more refined set of climate variables chosen through expert opinion or by evaluating how the choice of different climate variables affects AIM performance (see the "Future research" section). We describe the choices for defining climate space using three broad categories: the selection of climate variables (e.g., growing degree days, total annual precipitation, mean monthly temperature), the spatial resolution of climate data (1 square kilometer [km^2], 0.5- × 0.5-degree cells, counties), and climate variable standardization, weighting, and transformation. The lessons from existing studies suggest that these decisions influence the total number and the spatial distribution of candidate climate analogs (Pugh et al. 2016, Mahony et al. 2017, Dunn et al. 2019, Chaudhary et al. 2023).

A climate variable consists of a climate element (e.g., temperature, precipitation), its temporal specification (daily, monthly, seasonal, etc.) and a statistic that summarizes the element (e.g., mean, variance, percentile, minimum). Climate variables are usually chosen on the basis of the intended use of analogs. For example, urban climate analog studies commonly use the number of heating and cooling degree days, reflecting interest in estimating energy needs (Kopf et al. 2008). Agricultural studies include crop-specific growing degree days (Pugh et al. 2016) and soil properties (Dunn et al. 2019), whereas ecosystem-centered studies include annual measures of energy and water balance (Parks et al. 2018, Holsinger et al. 2019), because these variables influence plant distributions (Stephenson 1990). Characterizing climate space with a greater number of variables (i.e., narrowing climate definition) will restrict the overall number and the geographic distribution of analogs. Although the effect of increasing the number of variables will vary depending on how much unique information is added with each additional variable. Variables carrying more unique information will be associated with a greater restriction of analog distribution and numbers (Mahony et al. 2017). One could assess correlation of climate variables as a step in characterizing climate. However, the collinearity of variables may vary by location, and a "global" assessment of variable correlation may mask that variation. Mahony and colleagues (2017) show that the effect of additional climate elements varies by location and suggest that climate is most meaningfully defined in a site-specific manner.

However, current methods for site-specific characterizations of climate are lacking and need further exploration.

Among summary statistics, annual or seasonal means are common, whereas statistics describing interannual variability and seasonality are less common but represent important dimensions of climate. Interannual variability of a climate variable influences whether populations can persist on the landscape (Jackson et al. 2009), species life history strategies (Huey et al. 2009), and design principles of infrastructure. Similarly, information about seasonality—that is, how much climate varies within a year between seasons—is not captured by the annual mean. Seasonality is strongly associated with patterns of biological diversity and community composition (for a review, see Tonkin et al. 2017), crop cultivation (Dunn et al. 2019), and drives human infrastructure needs (e.g., heating and cooling). Including information about interannual variability or seasonality constrains the geographic distribution, and the number of potential climate analogs (Mahony et al. 2017, Dunn et al. 2019).

Extreme climatic events are also important for modeling socioecological state variables but are poorly captured in means or variance statistics (Katz et al. 2005). Extremes are critical for shaping social and ecological systems; they drive or modify distributions of species (Gutschick and BassiriRad 2003, Zimmermann et al. 2009, Morán-Ordóñez et al. 2018) and are crucial for designing infrastructure (e.g., Wang et al. 2019). However, incorporating climate extremes as variables for defining climate analogs may require the use of novel climate distance measures. Commonly used climate distance measures assume multivariate normality of the data and rely on the information captured in means and variance (Mahony et al. 2017). However, the distributions of extreme values are known to be poorly approximated by the statistics of mean and variance and, instead, are modeled with extreme value statistics (Katz and Brown 1992). This mismatch between data and methods may undermine the validity of inference of climate departures calculated on the basis of extremes. For example, King (2023) found that climate similarity of focal and analog climates increased when climate was defined by extremes compared with means. King (2023) attributed this effect to high interannual variability of extreme climatic events. The increased climate similarity in King (2023) may be an artifact of the use of a method of inference that assumes multivariate normality. This area of inquiry deserves further attention, including an exploration of data transformations that can match the extreme value data to the distributional assumptions embedded in the methods.

In a different application, Wang and colleagues (2019) used extreme value theory to find analogs for rare precipitation events in a case study. They calculated and visually compared exceedance probability curves for rainfall events for a focal city and three potential analog cities. Their promising approach requires further development to be applicable to a larger data set. The use of extremes for defining climate analogs deserves further attention given the increase in climate extremes with warming (Seneviratne et al. 2012, AghaKouchak et al. 2020) and their importance for driving ecosystem processes and engineering of built infrastructure.

The spatial resolution of climate data affects the degree to which spatial variability of climate is captured and represents a series of trade-offs between data availability, computational feasibility, and needs of the end users. Coarse resolution climate data preserves information about the mean climate of an aggregated area but may underestimate minima and maxima in complex landscapes (Hijmans et al. 2005). For instance, in several studies, the use of coarse resolution data was associated with greater distances (and therefore greater climate velocities) between focal locations and their closest analogs, compared with distances derived with fine resolution climate data (Hamann et al. 2015, Dobrowski and Parks 2016, Ordonez et al. 2016, Heikkinen et al. 2020). This suggests that coarse resolution climate data may overlook proximal analogous climates. Similarly, using fine resolution climate data in topographically complex terrain resulted in smaller estimates of area with novel climates compared with coarse resolution data (Mahony 2017). AIMs have been developed with climate data of varying spatial resolution (1–50-km^2 pixels or counties as the spatial unit) for extents ranging from regional to global; however, the effect of varying spatial resolution on AIM projections and skill has not been systematically examined.

Climate distance measures are sensitive to the absolute magnitude of the variables used in their development. Therefore, variables that make up the climate space should be standardized (e.g., subtracting the mean and dividing by the standard deviation) to ensure climate variables are weighted equally in contributing to climate similarity measurements. The standardization procedure is most meaningful for variables that are approximately normally distributed, which may not be the case for skewed variables, such as daily precipitation. A nonnormally distributed variable can be aggregated to a different temporal unit (e.g., from daily to monthly totals) and transformed to meet the normality assumption before they are standardized. After standardization, climate variables can be assigned weights to represent their assumed importance. For example, Bos and colleagues (2015) increased the weight of precipitation in calculating climate dissimilarity for finding farming analogs. They note that they "had to rely on research intuition in selecting these [weights]." In other words, variable weighting in analog selection is usually based on the modeler's opinion, as opposed to a formal weight selection procedure. We suggest an approach to variable selection and weighting in for AIMs in the "Methodological challenges and natural science research needs" section.

Climate similarity measures and thresholds

Among many approaches to quantify climate similarity in multivariate climate space (Grenier et al. 2013; e.g., Kopf et al. 2008), three are commonly used for defining climate analogs: binning, standardized Euclidean distance (SED), and Mahalanobis distance (MD). A full comparison of the relative strengths of different distance measurements is beyond the scope of this review, but see Grenier and colleagues (2013) for further details.

Measures of climate similarity can be discrete or continuous (figure 2), and both types require a climate similarity threshold to delineate analogous and nonanalogous climates. Discrete approaches treat all analogous climates as equally similar to the focal climate, whereas continuous approaches evaluate climate similarity on a continuous scale. The choice between discrete and continuous metrics is often based on data availability, computational feasibility, and simplicity of interpretation.

Binning is a discrete approach based on whether climate values of candidate analogs fall within specific bin widths around a focal climate (figure 2a). Setting the bin widths is equivalent to defining a climatic similarity threshold (D_{max}). Analogs that fall within the defined bins are considered equally climatically similar to the focal climate. For practical reasons, binning approaches tend to be applied to a limited number of climate variables, although many variables can be collapsed using principal components (or other data-dimension reduction approaches), with binning applied to a limited set of those components (Hamann et al. 2015,

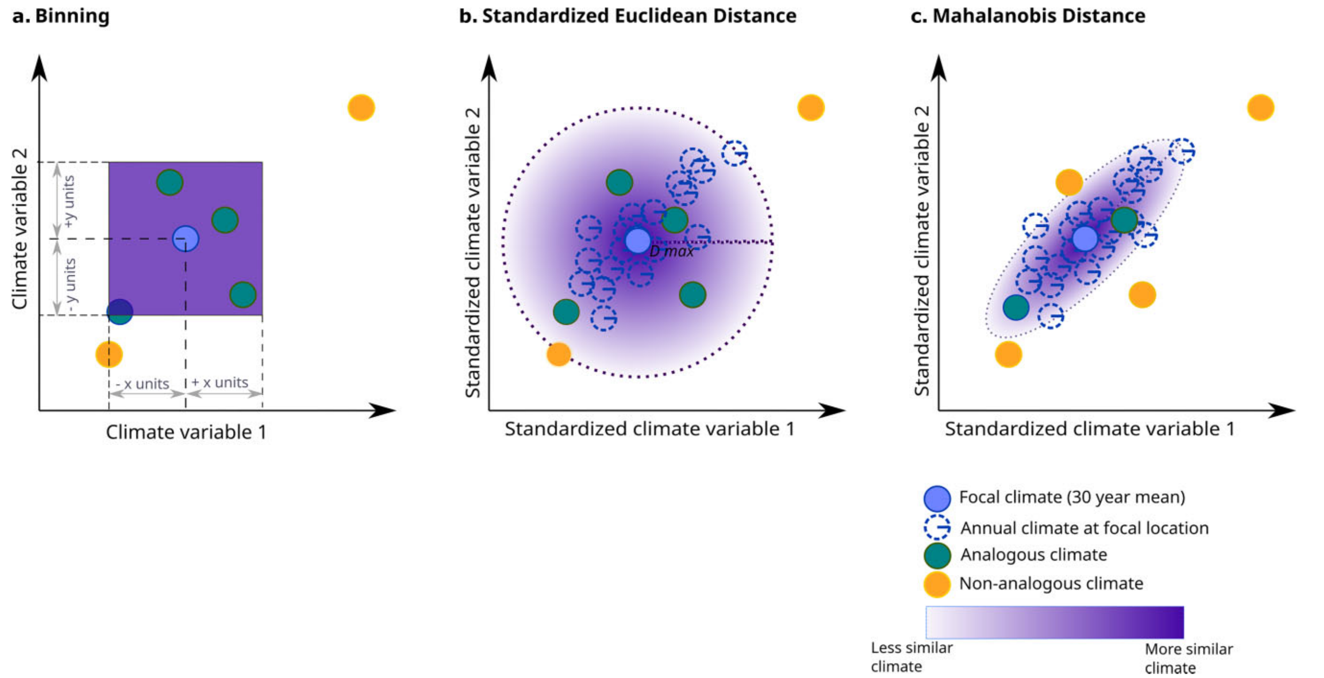

Figure 2. Approaches for quantifying climate distance. In this example, climate space is characterized with two variables. Binning (a) is a discrete approach and considers all climates that fall within the bin limits as equally analogous. The climate variable bin widths (±x, ±y in figure 2a) also function as thresholds (D_{max}). Continuous climate metrics, such as standardized Euclidean distance (SED; b) and Mahalanobis distance (MD; c) differentiate among analogs on the basis of their proximity to the focal climate in climate space. Climatic similarity threshold (D_{max}) sets the limit, beyond which climates are considered nonanalogous. SED does not account for climate variable correlation, and considers departures in any direction from the mean focal climate as equally meaningful (figure 2b versus 2c). In contrast, MD considers covariance among climate variables when measuring climatic distance. In panels (b) and (c), the dashed circle and ellipse, respectively, represent lines of equal climatic distance from the focal point. MD will report a lesser climatic distance compared with SED for a candidate analog falling along the dominant axes of the focal location's climate variation, and larger climate distances for those that do not (figure 2b and 2c).

Littlefield et al. 2017). Bin widths have been determined on the basis of expert opinion (McDonald et al. 2009, Dunn et al. 2019), the observed climatic niches of organisms (Littlefield et al. 2017), arbitrary criteria (Hallegatte et al. 2007), or current vegetation patterns or biome distributions (Parks et al. 2019)—an approach equivalent to system-based thresholding (described below).

In contrast to binning, continuous similarity measures can distinguish among more and less climatically similar analogs (figure 2b and 2c). Two commonly used climate distance measures are SED (Williams et al. 2007) and MD (Mahalanobis 1936, Mahony et al. 2017). Both SED and MD standardize the difference in climate between a focal and analog location by the focal climate's interannual variability. Therefore, the same absolute change in, for example, temperature, is interpreted as more meaningful in an area with low interannual temperature variability than in an area of high interannual temperature variability. In addition, unlike SED, MD considers the covariance structure among climate variables and weights climate departures on the basis of the climate variable covariance structure (figure 2c); departures that are orthogonal to the main axes of climate variation are considered larger by MD than by SED (figure 2b versus 2c).

Continuous similarity measures require a threshold (D_{max}) to judge whether a potential climate analog is sufficiently similar to be considered analogous. Future climates that do not have a sufficiently similar climate in the reference period are considered novel (see the "How are climate analogs used in climate change research and climate adaptation?" section). There are two approaches to setting D_{max}: supervised, or system specific, and unsupervised, or location specific. With the supervised approach, D_{max} is calibrated to optimally classify climates into groups of interest, such as climates associated with species presence or absence, ecoregion type, etc. (Williams et al. 2007). In the unsupervised approach, D_{max} is set with respect to the interannual climate variability at a focal location (Mahony et al. 2017). The distribution of distances between the mean climate and the climates of individual years at a given location follows the chi distribution with degrees of freedom equivalent to the number of climate variables used (Mahony et al. 2017). The distance between centroids of focal and analog climates can then be interpreted in percentiles of focal location's interannual variability. Mahony and colleagues (2017) suggested setting D_{max} at two standard deviations of the local interannual climate variability (two standard deviations of the chi distribution). This provides an intuitive approach for framing analogous and nonanalogous climates on the basis of a focal site's interannual climate variability.

How are climate analogs used in climate change research and climate adaptation?

Current applications of climate analogs fall into two broad categories: assessing climate change exposure (e.g., climate velocity) and projecting impacts to ecological or social systems using AIMs. These two categories represent the unsupervised (modeling climate exposure) and supervised (AIMs) uses of climate analogs. *Climate change exposure* is defined as an umbrella term for various metrics that quantify the degree to which a location (and organisms associated with that location) will be exposed to climatic conditions that are different from those currently observed (Houghton et al. 2001). Climate change exposure metrics are particularly useful when data on climate tolerance and sensitivity of biota are absent, as is the case for many species.

Climate change exposure

Climate change exposure can be estimated with climate velocity (Garcia et al. 2014) and climate novelty (Williams et al. 2007). Greater climate velocities imply higher climate change exposure: The faster the climate moves in space, the lower the chances that biota will be able to keep pace with these changes. Forward climate velocity is calculated by dividing the geographic distance between the focal site and its forward analog (figure 1a) by the elapsed time between considered time periods. The result is the average speed at which an organism at a focal location would have to move to maintain its current climate (Hamann et al. 2015, Batllori et al. 2017). Reverse climate velocity uses a similar approach based on reverse climate analogs and indicates how fast an organism has to move to colonize a focal location (Hamann et al. 2015). Climate velocity estimates depend on the projections of climate change and on how the distance between focal and analog locations is measured. Euclidean distance between focal and analog locations provides the lower boundary of climate velocity. Accounting for the actual dispersal or migration routes of organisms, and resistance or barriers to movement will increase velocity estimates. For example, to reach analog locations organisms may have to cross areas of high resistance to movement, such as unfavorable climates (Dobrowski and Parks 2016, Parks et al. 2020) and areas of high human modification (Littlefield et al. 2017, Carroll et al. 2018, Parks et al. 2020), all of which increase estimates of climate velocity if we assume that organisms will avoid high resistance areas.

Climate novelty refers to future climate conditions that are not observed in the reference period. Therefore, focal locations with a future climate that does not have analogous climates in the reference period identify areas with potential novel climates (Williams et al. 2007). Analogs are not the only method to identify the locations of future novel climates; several others have been proposed across different modeling techniques (Fitzpatrick and Hargrove 2009, Rehfeldt et al. 2012, Mesgaran et al. 2014, Mahony et al. 2018). The distribution and extent of novel climates in a given study is contingent on the geographic area searched for prospective analogs. In theory, the search for an analog can be global; however, there are legitimate reasons to constrain the search for analogs on the basis of biological constraints, such as dispersal limitations, or human perceptual constraints (see the “How are climate analogs defined?” section; Jost et al. 2016). Limiting the search to a specific radius around a focal location may increase the area of projected climatic novelty; a future climate may be regionally novel but not globally novel.

Understanding where climate novelty is likely to emerge may aid adaptation practices and climate-informed management. In these areas, ecological communities may reassemble in unfamiliar ways (Williams and Jackson 2007, Ordonez et al. 2016), and therefore, impact models based on observed correlations are likely to be invalid. For example, Fitzpatrick and colleagues (2018) showed that species distribution model performance decreased with increasing climate novelty between the model training (contemporary) and testing (paleo) periods. They also reported that the levels of novelty expected under high emission scenarios were likely to exceed those observed in the paleoecological past. For this reason, AIM applications generally avoid projecting impacts in areas of no analog climates. Climate novelty is expected to emerge or is already emerging in climates with low interannual variability and regionally warmest locations in topographically uniform locations (e.g., valleys; Williams et al. 2007, Mahony et al. 2017). In fact, the tropics, which are both the warmest areas and areas with low interannual variability, may have already crossed into the novel climate conditions (Garcia et al. 2014, Abatzoglou et al. 2020).

Analog impact models

In contrast to climate change exposure metrics, AIMs project climate impacts on specific response variables or systems of interest. AIMs use state variables (e.g., forest type) at reverse analog locations to project changes or a lack thereof to focal locations under a future climate (figures 1c and 5). Examples of ecological applications of AIMs include projections of crop production (Chaudhary et al. 2023), shifts in vegetation composition (Holsinger et al. 2019), and climate-informed forest management targets (Churchill et al. 2013), among others. We focus this section on highlighting that AIMs can be structured as spatial models and describing approaches to quantifying AIM projection uncertainty.

AIMs can be structured to behave like spatial models and therefore represent the effect of both climate and location on the response variable, similarly to other spatial models (Miller et al. 2007). Spatial modeling approaches lie on a spectrum defined by nonspatial models on one end and models based on spatial interpolation (coordinate-based) models on the other. Nonspatial models consider a set of environmental covariates as the primary drivers of a response and do not explicitly consider the influence of geographic location on the response. Spatial interpolation models (e.g., ordinary kriging, inverse distance weighting, or coordinate-only models) fit the response as a function of geographic location only. Although geographic location is not a biologically relevant driver by itself, it is an effective proxy for many spatially structured exogenous (climate, vegetation, etc.) and endogenous processes (dispersal, fecundity, etc.). Therefore, purely spatial models implicitly include many spatially structured processes as the drivers of model responses without attempting to identify them. This ability to capture location-relevant information allows spatial interpolation models to perform as well as or better than nonspatial models at reconstructing observed patterns (e.g., Bahn and McGill 2007, Hijmans 2012, Ploton et al. 2020).

Nonspatial and spatial interpolation models both have drawbacks. Nonspatial models are prone to misattributing the explanatory power of omitted variables to the ones included in the model (Lennon 2000, Kühn 2007, but see Diniz-Filho et al. 2003). This misattribution can result in misleading climate impact projections (e.g., Peterson et al. 2019). On the other hand, coordinate-based models do well in reproducing observed patterns and are often used as spatial null models for comparative purposes (e.g., Bahn and McGill 2007, Ploton et al. 2020) but are incapable of projecting climate-driven ecosystem changes.

AIMs have traits of both purely spatial and nonspatial modeling approaches and may balance the strength and weaknesses of both. AIMs use environmental covariates (e.g., climate) and can capture the effects of spatially structured processes. The relative weight of environmental covariates or spatially structured processes can be adjusted through methodological choices when identifying analogs. For example, limiting the search radius for analogs (e.g., Williams et al. 2007) and considering a limited number of most-climatically similar analogs (Parks et al. 2019) both have the effect of constraining the geographic scope from which analogs are drawn and therefore increase the influence of

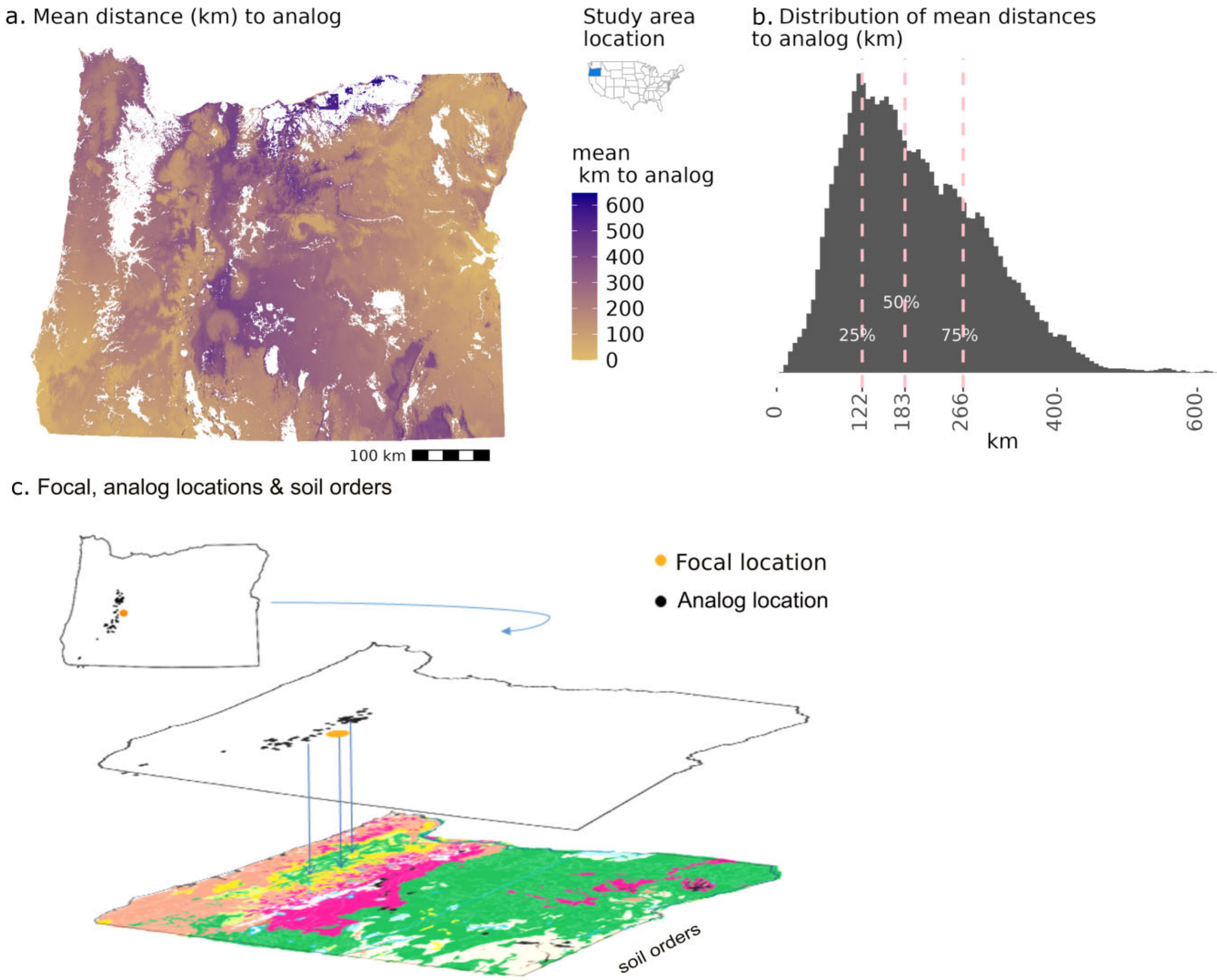

Figure 3. Spatial structuring of analogs and spatially encoded information. Geographic distribution of mean distances to 100 most climatically similar reverse analogs for the state of Oregon 2041–2070 period, RCP 8.5 (a). The histogram in panel (b) shows the distribution of values in panel (a); the dashed vertical lines indicate 25th, 50th, and 75th percentiles. (c) A focal location and the location of its100 reverse analogs for the 2041–2070 time period under RCP 8.5. The analog locations were defined using climate variables only, but the geographic distribution of the reverse analogs coincides with similar soil orders (Soil Survey Staff 1999), and therefore implicitly captures the effect of similar edaphic conditions.

space. AIMs are not unique in their ability to represent the effects of environmental covariates and geographic location. There are many spatially explicit approaches that are used for ecological modeling (e.g., Fotheringham et al. 2002, Dormann et al. 2007, Miller et al. 2007, Rollinson et al. 2021). However, in general, spatially explicit models are underused in ecology (Brown et al. 2011, Crase et al. 2014, Gaspard et al. 2019).

AIMs implicitly capture the effect of geographic position by summarizing the influence of climate on the response individually for each focal location and by using a geographically constrained subset of data to do so. The degree to which data informing AIMs is geographically constrained is an emergent property of the spatial structure of climate and climate velocity. Climate analogs tend to be found proximally to their focal locations, although the degree of this proximity varies (figure 3; Hamann et al. 2015, Mahony et al. 2017). The distribution of analogs and the variation in proximity between focal and analog locations is likely driven by physiography. For example, areas of complex topography usually source analog from nearby locations, whereas areas of uniform topography or regionally low positions source analogs from distant locations (Hamann et al. 2015, Mahony et al. 2017). In addition, other aspects of physiography influence both reference period and future climates (Dobrowski et al. 2009), thereby affecting the relative location of analogs. Analogs that are geographically proximal to their focal location are likely to share similar spatially structured drivers and, therefore, implicitly represent their influence if they are not included as variables in a model. For example, we show a focal location in Oregon, in the United States, and its 100 most climatically similar reverse analogs under RCP 8.5 in figure 3c. The geographic distribution of analogs allows them to share similar edaphic conditions with the focal location—one of many spatially structured drivers of ecosystem response. The geographic constraining of data in AIMs is conceptually similar to modeling approaches based on geographically moving windows (Fotheringham et al. 2002).

The spatial proximity of analogs—and, therefore, the information that analogs carry—can vary widely (figure 3a and 3b; Hamann et al. 2015). A user could elevate the relative importance of spatially structured information by defining an inclusion radius for analog searches, potentially at the expense of

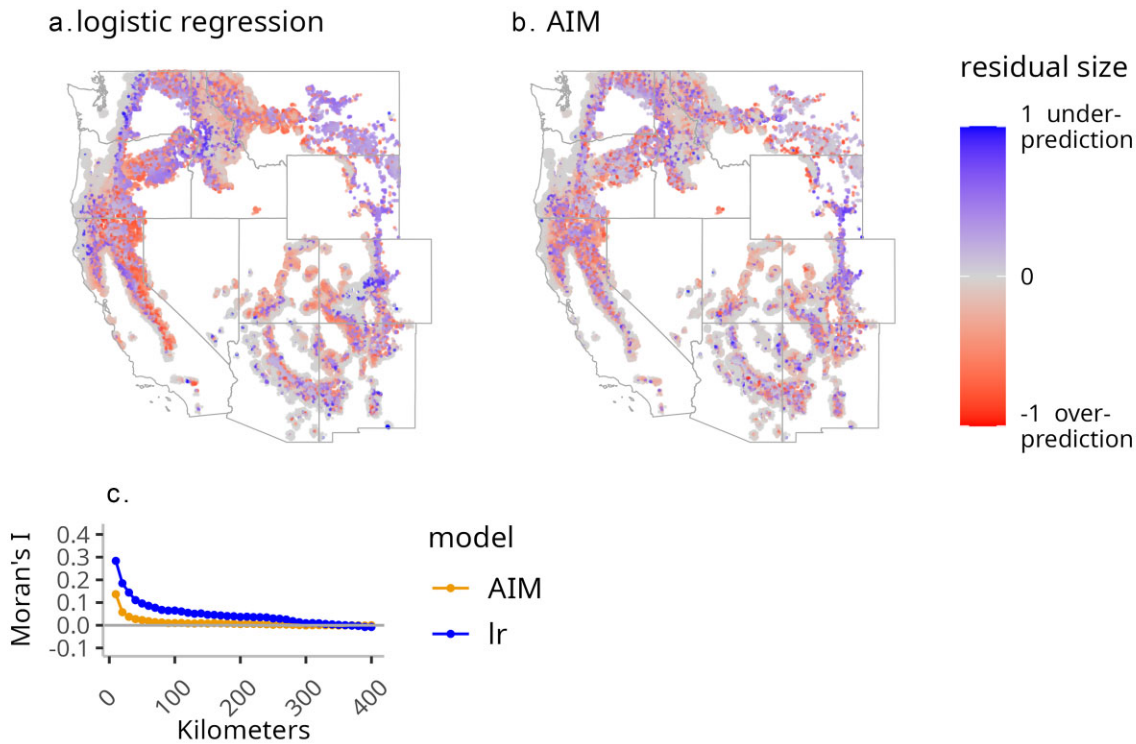

Figure 4. AIM and generalized linear model comparison. Comparing the spatial distribution of residuals and skill of second order polynomial logistic regression (a) and an AIM (b) at reconstructing present-day ponderosa pine distribution at a subset of the Forest Inventory and Analysis (FIA) plots (Bechtold et al. 2005) in the western United States. For the AIM, we calculated climate similarity between the reference period climate of each FIA plot and the reference climate of all the other FIA plots in the data set. We then used 100 best contemporary analogs for each plot to project the probability of ponderosa pine presence at each focal plot (p(present) = analog plots with ponderosa pine/100). Residuals = (observed – p(present)) for both models. Logistic regression AUC is 0.85, AIM's AUC is 0.9. The blue hues in panels (a) and (b) indicate underprediction, red—over prediction. (c) Test of spatial autocorrelation (Moran's I) of model residuals at 10 kilometer bandwidths for both models. Positive nonzero values of Moran's I indicate positive autocorrelation. Values close to zero indicate no spatial autocorrelation.

maximizing climate similarity of analogs or by weighting the degree to which each analog's input is considered by the inverse of its distance to focal location. Although several studies have limited the geographic range from which analogs are selected for computational feasibility (Dobrowski et al. 2021, Parks et al. 2023), there has not been a systematic analysis of the trade-offs between choosing analogs on the basis of spatial proximity and climate similarity.

AIMs can represent the spatial variability of climate–system relationships by estimating them individually for each focal location and basing them on data sets that are geographically constrained around focal locations. Climate–system or climate–species relationships are often nonstationary in space (Miller and Hanham 2011, Miller 2012, Rollinson et al. 2021), because they are modified by regional or local processes that are hard to capture in a global model. For example, plant species' relationship with climate is often nonstationary because individual populations evolve local adaptations (Peterson et al. 2019). Averaging across populations' individual responses rather than accounting for population differences in response can lead to contrasting projections of climate impacts on species (Peterson et al. 2019, Klesse et al. 2020, Perret et al. 2024). AIMs capture this spatial nonstationarity through selecting regionally relevant data to define system–climate relationship for each focal location. In contrast, nonspatial models estimate a "global" parameter for the influence of each climate variable and are therefore often unable to reflect this nonstationarity, which manifests in spatially autocorrelated residuals (Rollinson et al. 2021).

To provide a concrete example of the spatial features of AIMs, we model and compare the distributions of ponderosa pine (*Pinus ponderosa*) in the western United States using an AIM and a generalized linear model (figure 4). The generalized linear model tends to overpredict ponderosa pine presence in the middle and southern Rockies, and underpredict it in Eastern Montana, eastern Washington and Oregon (figure 4a). AIM overpredictions and underpredictions, on the other hand, have a more random distribution pattern (figure 4b), suggesting that the AIM better represents the distribution of the species. Overall, the AIM shows less spatial bias in model residuals (figure 4c) and lower model error (figure 4b) than logistic regression (figure 4a). AIM also shows greater skill (the area under the curve [AUC] = .90) than logistic regression (AUC = .85). The reduced spatial bias in residuals and lower Moran's *I* than in logistic regression are indicative of the AIM implicitly capturing spatial variation in climate–species relationship or the effect of other spatially encoded variables not directly included in the model. The details of our modeling can be found in the supplemental material.

Understanding the uncertainty of projected climate impacts is imperative to operationalize climate impact projections into adaptation decisions (Beier et al. 2017). The many sources of uncertainty in climate impact modeling are generally grouped into the following broad categories: the uncertainty of observed data, the uncertainty of future climate, and the uncertainty of specifying models correctly (Elith and Leathwick 2009, Beale and Lennon 2012, Wenger et al. 2013). To date, studies using AIMs have quantified uncertainties associated with climate projections and model specification. To our knowledge there has not been a formal evaluation of the relative importance of climate and model uncertainty in AIMs. Grenier and colleagues (2013) demonstrated that the choice of climate data (variability between general circulation models) has a larger influence on analog location than the choice of climate dissimilarity measure (model uncertainty). However, it is not clear whether variation in analog locations because of climate and model uncertainty would result in different impact projections from an AIM.

To quantify uncertainty associated with climate projections, Hallegatte and colleagues (2007) examined the influence of the choice between two global circulation models on the projection of energy needs in Paris, France. Each climate model was associated with a unique analog city and a unique projection of energy use. The range of potential energy needs served as one of the measures of climate projection uncertainty (Hallegatte et al. 2007).

In a study projecting ecoregion distribution under a warmer climate, Dobrowski and colleagues (2021) used two complementary measures to estimate uncertainty in model specification: analog agreement and mean climate similarity of analogs. To project future ecoregion at a focal pixel, they summarized the ecoregions associated with 100 reverse analogs of a focal pixel and selected the ecoregion supported by the greatest number of analogs out of 100—a plurality projection. However, presenting a single ecoregion may communicate an undue certainty, particularly in cases where the probability of the plurality ecoregion is only marginally higher than for the next most supported one. For this reason, Dobrowski and colleagues (2021) expressed projection uncertainty as the proportion of analogs supporting the plurality ecoregion projection at any given location (which we simply call *analog support*). The lower the analog support, the greater the probability of alternative ecoregion types, and the higher the projection uncertainty. For example, using vegetation classes instead of ecoregions, figure 5a and 5b show projections of potential natural vegetation types at two pixels in western Oregon, in the United States, under a warmer climate. Western hemlock (*Tsuga heterophylla*) is the vegetation class with the greatest analog support at both locations, receiving 80 and 46 votes (out of 100), respectively. We consider the projection made with 80 votes (figure 5a) more certain than the projection made with 46 votes (figure 5b), where western hemlock and tanoak (*Notholithocarpus densiflorus*) classes may be equally plausible (46 versus 43 analog votes; figure 5b). Projections of multiple vegetation classes at a focal location may indicate that the future climate could support either class. However, it could also indicate the model's inability to meaningfully distinguish environmental conditions of multiple vegetation classes. For example, if an analog's definition is missing an important biotic or abiotic factor (e.g., serpentine soil types, marine fog layer), the analog may not be able to meaningfully distinguish between environmental conditions of two (or more) vegetation communities. Distinguishing between these possibilities may require pixel-by-pixel or region-by-region consideration. However, both possibilities suggest projection uncertainty.

A further improvement on analog support, as a measure of uncertainty, could be an index that accounts for the distribution of support among possible classes. For example, the Gini index or Shannon diversity index would be more informative of cases where the distribution of analog votes fell approximately equally among several classes, and where, therefore, the plurality projection is uncertain, versus where lower plurality support (less than 50%) is still strongly informative (e.g., the rest of the votes are spread among many poorly supported classes).

A second measure of model uncertainty used by Dobrowski and colleagues (2021) was climatic similarity of analogs used for projections. Although all climates used in AIMs are considered analogous (i.e., the climate distances between focal and analog locations are below $D_{\max}$), actual climate similarity can vary widely from their respective focal climates (figure 2). Overall, we consider projections made with analogs of higher climate similarity to be more reliable than projections made with poorer analogs. Analog support and climate similarity of analogs should be considered together. Two climatically similar analogs may provide different vegetation projections. This suggests that either a single climate can support multiple vegetation types (e.g., alternative vegetation states at ecotones) or our model is lacking relevant characteristics to discern among environmental conditions of different vegetation types. Similarly, poorer analogs may agree on a single vegetation projection, but the weaker climate match should be separately considered as a source of uncertainty.

Assessing and expressing projection uncertainties is an ongoing challenge for the interpretation of AIMs and all modeling approaches more broadly. There are currently no broadly accepted best practices for reporting projection uncertainty of AIMs. We suggest that uncertainty estimates for AIMs described in this section (or an improvement on them) should be routinely developed to aid in using AIMs for decision-making and conservation planning.

How are climate analogs used in communication and decision-making?

Climate analogs and AIMs have been explored in research contexts, but are they useful as communication tools and are they actionable for decision-makers? Veloz and colleagues (2012) described analogs as "a powerful alternative method for decision-makers planning for climate change and a tool for better communicating the significance of climate change to broad audiences." According to Hallegatte and colleagues (2007), AIMs "translate a complex and abstract amount of information from climate models into metrics more usable for decision-makers and stakeholders" and "allow one to appreciate the magnitude of uncertainties about its level, rate, and location." Analogs are promoted as decision-support tools for adaptation related to urban heat waves (Rohat et al. 2017, Fitzpatrick and Dunn 2019), ski resorts (Dahinden et al. 2017), tree plantation productivity (Leibing et al. 2013), flood risk (Fekete 2009), protected area management (Holsinger et al. 2019, Parks et al. 2022), and agriculture (Ramírez-Villegas et al. 2011, Dunn et al. 2015).

Research on usable climate science, not specific to analogs, indicates that climate information needs to fit with specific audiences and decision contexts to be useful (Dilling and Lemos 2011, Kirchhoff et al. 2013). Climate analogs meet many of the criteria to be effective tools for communication and decision-making. Analogs provide local, tangible information about future change; they enable people to envision a future that is different from the past; and when represented through maps, they provide engaging visualizations (Nicholson-Cole 2005, Sheppard 2005, O'Neill and Nicholson-Cole 2009). However, the extent to which climate analogs can be useful rests on two specific assumptions: that analogs enable decision-makers to understand climate impacts in ways that are less abstract and more useful than existing alternative methods (Fitzpatrick and Dunn 2019) and that policies and practices in analog locations are adapted to and driven

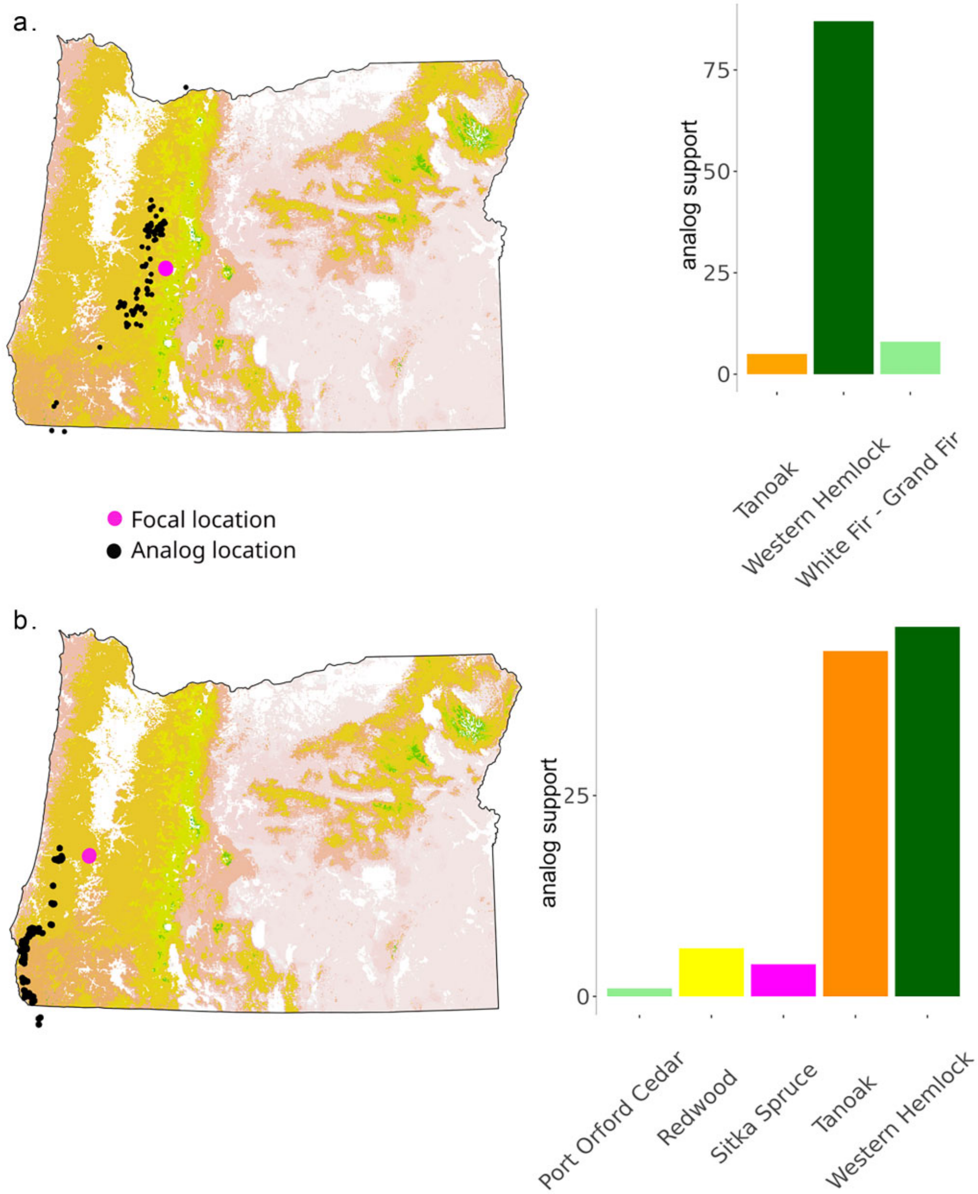

Figure 5. Expressing projection uncertainty with climate analogs. Focal locations, pink points in panels (a) and (b), and locations of 100 best reverse analogs (the black points). Analog locations are intersected with a vegetation data set—USFS Region 6 Potential Nature Vegetation layer. The bar graphs summarize the vegetation types intersected by reverse analogs. In panel (a), the 100 analogs intersect three different vegetation types: Western hemlock is the most commonly selected vegetation type, receiving 80 out of 100 analog votes. In panel (b), the 100 analogs intersect five different vegzones, with western hemlock receiving a narrow plurality of the analog votes (46 votes) over tanoak (43 votes). We use the proportion of votes received by the most supported vegetation category as a measure of projection certainty. Therefore, we consider the projection made in panel (a) as more certain than the projection made in panel (b), where tanoak and western hemlock vegetation types could be considered equally plausible projections.

by current climate and are therefore useful and informative to decision-makers in the focal location (Hallegatte et al. 2007, Kellett et al. 2015). Because only a handful of studies have tested the efficacy of climate analogs in nonresearch contexts, most claims about the communication and decision-making benefits of analogs have not yet been supported by research. Below we describe the existing empirical research on the utility of analogs.

Many papers assert that analogs are useful for communicating with the public about future change (Kopf et al. 2008, Rohat et al. 2017, Fitzpatrick and Dunn 2019), but this assumption remains largely untested. In one of the few studies examining analogs as a communication tool, Jylhä and colleagues (2010) found that a climate analog approach elicited largely accurate perceptions of changing climate zones in Finland among self-selected respondents to an online survey. The vast majority of survey participants reported that the maps depicting climate zone shifts were clear and comprehensible. In a study in the United States, Retchless (2014) examined how perceptions of future climate differed on the basis of whether projections were presented as climate analog locations versus as text-only temperature changes. Participants who were given climate analogs perceived climate change as less severe and less harmful than participants who were given specific temperature changes (Retchless 2014). Retchless (2014) speculates that knowledge of the analog location may have led the participants to view future climate as somewhat desirable, because nonclimate related features at the analog location were viewed positively (e.g., analog city has a thriving economy). On the basis of these results, Retchless (2014) urged "caution before using spatial-analog approaches" for communicating climate change to the public, because the nonclimatic characteristics of the analog location may influence perceptions of climate change in unpredictable ways.

Existing empirical research on the utility of analogs in decision-making comes mostly from agricultural and urban settings. The lessons from these disciplines are instructive for conservation and natural resources management. Dunn and colleagues (2015) examined the value and usefulness of analogs and other climate information for the wine grape sector in Australia, including the utility of different temporal and spatial scales. Decision-makers in the wine grape sector found analogs just as valuable as information about projected change to specific climate variables, such as temperature and precipitation. They preferred analog information for longer-term decisions (beyond 10–20 years) and found climate analogs valuable because they enabled them to compare regions and cultivars, plan new plantings, and choose new wine styles. The decision-makers in the wine grape sectors wanted analogs at the spatial scale of the growing region (as opposed to more localized scales). Furthermore, a majority indicated that uncertainty in projections would not stop them from using the information in decision-making. Because the Australian wine grape sector is competing in a global marketplace, there was also interest in both domestic and international analogs, to get a sense for overall market changes.

Studies that examined the utility of analogs for smallholder farmers in Africa and Asia concluded that farmers need to have knowledge of the analog location (or means to gain that knowledge) so that they understand what kind of agriculture may be adaptive in the future climate (Jost et al. 2016). Farmers were interested in learning practices from analog sites that may become adaptive at their location in the future but were constrained by the difficulty of visiting these locations to learn from them (Jost et al. 2016).

Analogs intended to inform agricultural decision-making may need to include additional nonclimatic variables that are as important to farming output as climate. Nyairo and colleagues (2014) and Bos and colleagues (2015) examined farming practices at the reverse analog location with the goal of learning adaptive farming practices. They found that practices at reverse analog locations were either similar to the focal location's or driven by nonclimatic factors, such as soils, farm size, market access, cultural traditions, and land-use legacies. These findings are echoed by Kellet and colleagues (2015), who examined reverse climate analogs among Australian cities to help focal cities fast track policy responses to climate change. They concluded that nonclimatic factors, including politics, culture, economics, and resources were driving policy decisions at analog locations more so than climate. They caution that determining if a particular policy or practice in the analog community is actually adaptive is subjective and requires a value judgment.

Chaudhary and colleagues (2023) attempted to make analogs more relevant to a particular socioecological system by using specific climate metrics relevant to agriculture, with the goal of facilitating dialogue about adaptation for US specialty crop production. They found that analogs tailored to the decision context may have the potential to catalyze discussion of adaptation alternatives among extension and outreach professionals.

In a novel application, Hallegatte and colleagues (2007) used an analog exercise to examine the relative costs of adaptation for Paris, France, given climate model uncertainty. The geographic distance between Paris's reverse analogs identified under two different climate models became a proxy for uncertainty. The two different analogs were used to examine which adaptation actions result in committed pathways that are difficult to reverse and sunk costs and therefore which investments are robust and cost effective. Although Hallegatte and colleagues (2007) did not study how decision-makers might perceive this information, their analysis demonstrated the potential utility of reporting multiple analog locations to ensure that adaptation pathways account for uncertainties about future climate.

From existing social science, we know that analogs are described as useful by decision-makers in some contexts (e.g., Australian winegrowers; Dunn et al. 2015) and that analogs have been used to identify cost effective adaptations in the context of uncertainty (e.g., adaptation pathways for Paris, France; Hallegatte et al. 2007). The utility of analogs depends on the ability to learn from the analog (e.g., capacity to visit or know the analog location; Jost et al. 2016) and on developing an analog based on variables relevant to the modeled process (e.g., including edaphic information when it is an important component of the modeled system; Dunn et al. 2019). Climate analogs might not communicate the magnitude of change or severity of impacts as effectively as more conventional climate information (e.g., for Pennsylvania residents; Retchless 2014), and, for some sectors, the differences between the target and analog locations are too small to be useful or driven primarily by nonclimatic influences (e.g., land-use policy; Kellet et al. 2015). However, the limited size and scope of these studies mean that these conclusions are preliminary and apply to specific contexts. We provide further suggestions for improving our understanding of analogs as communication and decision-making tools in the " Social science research needs" section.

Future research

As the uses of climate analogs grow, there is an emergent need to develop best practices for analog identification and application. However, recommendations for best practices are contingent on a better understanding of the influence of different methodologies on AIM projections and how analogs are perceived and used by end users. We broadly organize suggested research needs into methodological and social science sections. A common thread between these two areas is the need to evaluate the skill of analog based approaches for projecting climate impacts and for aiding climate-related decision-making.

Methodological challenges and natural science research needs

We identify three broad areas for future methodological research: the development and testing of advanced approaches to defining climate and measuring climate similarity in a biologically relevant way, the assessment of AIMs' skill at projecting climate impacts, and comparisons of AIM with a broader suite of modeling approaches to better understand how AIMs contribute to the climate impact projection toolbox.

More research is needed on formal approaches to variable selection and weighting when defining climate space for using analogs. Currently, researchers use informal or expert-based selection of variables to characterize climate analogs for both unsupervised and supervised analog applications. Mahony and colleagues (2017) refered to the choice of climate variables as an art more than science—pointing to the fact that a modeler makes a personal choice about the specificity and breadth of climate description. However, when analogs are used for supervised modeling—that is, to model climate impacts to specific systems—one could use cross-validation (or contemporary validation, as is described below) to examine the effects of climate variable selection on model skill. For example, one could use mean absolute error or AUC to assess model fit. A series of analyses examining the effect of selecting different climate variables, as well as different spatial and temporal resolutions, would clarify the effect of these methodological choices on AIM performance.

There is a need to investigate additional approaches to measuring climate similarity. The most commonly used methods for analog identification have important drawbacks. MD and SED compare multivariate means of focal and analog climates and assume multivariate normality, which is difficult to assess (Mahony et al. 2017). In addition, previous implementations of MD and SED have considered interannual climate variability at either focal or analog locations, but have not considered both simultaneously. Usually, a focal location's interannual climate variability is considered. However, ignoring interannual climate variability at analog locations creates the possibility of mismatched focal and analog climate variances and extreme values (also discussed by Mahony et al. 2017). A potential solution is to verify reciprocity of analogousness: calculate climate distance between a focal and an analog climate, reverse their labels, and make the computation again. However, this solution would double the already significant computational load of analog identification.

Comparing the distributions of climate variables at focal and analog locations instead of mean climate conditions is another important area of future research. Comparing distributions has the benefit of leveraging high temporal resolution of climate data without having to make a priori assumptions about the appropriate degree of temporal aggregation. Kullback–Leibler (KL) divergence and Earth-mover distance are two indices that quantify multivariate distributional differences that could be leveraged for analog identification (among many others). We note that Grenier and colleagues (2013) explored KL divergence for analog identification, but they used it on climate normals and, therefore, did not leverage the broader suite of distributional information.

Comparing multivariate climate variable distributions can be computationally expensive (Mahony et al. 2017) and may require flexible dimension-reduction techniques. Using machine-learning approaches to effectively encode the many dimensions of climate in a synthetic two-dimensional space could alleviate the computational burden of multivariate distributional comparisons. Variational autoencoders (VAEs; Kingma and Welling 2014) are an unsupervised machine-learning approach that has not been used for analog definition, but provides an interesting perspective. VAEs have the ability to encode high dimensional variables into a normalized low dimensional latent space. Therefore, high-dimensional climate representations can be collapsed to a two-dimensional space where climate similarity can be then calculated. The ability of VAEs to handle high dimensional data may allow for efficient representation of the distributional characteristics of climate data that are not readily captured by summary statistics, such as climatic extremes.

The majority of studies employing AIMs do not assess model skill, an important step to understanding the reliability of forecasts they produce. Validating climate impacts that are yet to unfold is not possible. Instead, we suggest that AIMs are evaluated either on their ability to reproduce state variables observed in the reference period (what we term *contemporary validation*; figure 4) or on their ability to capture patterns in a simulated data set. Both of these approaches are routinely employed to evaluate more commonly used empirical and mechanistic models but are rarely applied to AIMs. In the context of AIMs, a contemporary validation approach asks if contemporary analogs of a focal location accurately project the features of interest at the focal location (e.g., figure 4). A handful of studies provide examples of contemporary validation of AIMs and suggest that AIMs' performance may vary, depending on the study system. Studies projecting forest loss in western United States (Parks et al. 2019) and global agricultural yield (Pugh et al. 2016) both indicated that AIMs have a satisfactory performance. However, Bos and colleagues (2015) found that contemporary analogs could not reproduce smallholder farm outputs with sufficient precision and used this result to discourage climate analog use in that context. Alternatively, one could simulate different forms of species–climate relationships and test the skill of AIM at reproducing the synthetic data sets (Zurell et al. 2010, Miller 2014).

We recommend future work that provides a systematic comparison of AIMs with other modeling approaches to understand how their forecasts correspond and differ. Specifically, we need a comparison with approaches that fall under the broad umbrella of bioclimatic models that are often used to project range shifts in species distributions or impacts in the agricultural sector (Elith and Leathwick 2009). A limited example of AIMs- and random forest-derived forecasts shows that their outputs are qualitatively similar (Coffield et al. 2021). However, our comparison of a generalized linear model and AIMs in figure 4 highlights differences between model performances. We suggested key distinctions between the commonly used nonspatial species distribution modeling approaches and AIMs in the "Analog impact models" section and figure 4, highlighting the inherent and implicit spatial nature of AIMs. The implications of these differences for climate impact forecasting need to be further explored. Comparisons of the impacts projected by AIMs, mechanistic models, and correlative models can serve as a reality check on each approach (Parry and Carter 1989, Pugh et al. 2016, Coffield et al. 2021). A more systematic set of comparisons of standardized and simulated data sets is needed to understand the relative advantages of each modeling approach.

Social science research needs

Realizing the potential of analogs for communication and decision-making requires going beyond anecdotes. We need rigorous social science research to develop a body of empirical evidence about how people perceive analogs, how analogs influence perceptions of change, what kinds of decisions benefit from analogs, and how analogs can be improved to better meet the needs of decision-makers. Assumptions about how climate analogs influence people's perceptions of climate impacts, especially in comparison with other types of climate information, need to be examined. Emphasis should be placed on understanding how analogs can be used by decision-makers in particular sectors and assessing their communication value with different types of users. Focusing on what types of analogs are useful for specific sectors would help tailor analog development to the needs of decision-makers and therefore enhance their role in supporting decisions about adaptation. For example, research could examine whether including all of the constraints—physiographic, network, and perceptual—in climate analog definition improves its usability. A better understanding of relevant temporal and spatial scales by sector would allow developers to produce analogs that are helpful to end users. We also need to understand which sectors need to pinpoint a specific analog location (e.g., perhaps cities need other cities as analogs) versus a broader region (e.g., perhaps farmers need a regional focus).

Understanding whether and how analogs communicate uncertainty, especially compared with other types of climate information, and how decision-makers perceive and act on uncertainty in analogs will improve analog usability. This knowledge can also improve the design of analogs by helping determine when it will be useful to provide multiple analogs that illustrate different futures in order to enable decision-makers to plan in the face of uncertainty. Providing a single analog location or a single average projection of climate impact based on several analogs may suggest a level of confidence in future projections that cannot be justified by the science and could undermine resilience in the long term.

Multiple research communities are embracing the use of climate analogs for climate impact modeling (e.g., Pugh et al. 2016, Fitzpatrick and Dunn 2019, Parks et al. 2022). Whether the type of insights offered by AIMs are usable for climate adaptation remains largely untested. We suggest that designing analogs that are useful for adaptation requires an iterative process that enables end users and social science research to inform and feed back into the development and design of the analogs so that analogs intended for adaptation are actionable beyond the scientific community (Dilling and Lemos 2011). For example, dialogue across scientists and end users is needed to determine what kinds of uncertainties in future projections are important to particular sectors and how these uncertainties can be communicated in analogs. Similarly, understanding the relationship between the constraints included in developing analogs and the usability of analogs for decision-makers requires a dialogue between scientists, who can explain what is scientifically possible, and decision-makers, who can explain what constraints or analog features are relevant to their situation.

Conclusions

Spatial climate analogs are currently used to develop climate impact projections for both the research and practitioner communities. Three main themes emerge from our review. First, there is a need to establish best practices for defining analogs and a clear understanding of the effects of making different methodological choices on impact projections. Second, the spatial nature of AIMs and the potential benefits that come with it are mostly underused and need further study. Finally, the potential strengths of climate analogs require rigorous testing and additional empirical information to support their validity, both as climate impact projection tools and as communication and decision-making tools. This dual need provides unique opportunities for interdisciplinary collaborations that span natural and social sciences.

Acknowledgments

We acknowledge the support of the National Science Foundation Division of Graduate Education (grant no. 1633831) and the US Geological Survey Northwest Climate Adaptation Science Center (grant no. G17AC000218 to SVY). The project described in this publication was supported by Grant or Cooperative Agreement G23AC00072-00 from the United States Geological Survey. Its contents are solely the responsibility of the authors and do not necessarily represent the views of the Northwest Climate Adaptation Science Center or the USGS. This manuscript is submitted for publication with the understanding that the United States Government is authorized to reproduce and distribute reprints for Governmental purposes. We thank five anonymous reviewers for providing constructive feedback that greatly improved the manuscript.

Author contributions

Svetlana V. Yegorova (Conceptualization, Funding acquisition, Visualization, Writing - original draft, Writing - review & editing), Solomon Z. Dobrowski (Conceptualization, Funding acquisition, Visualization, Writing - original draft, Writing - review & editing), Laurie Yung (Conceptualization, Writing - original draft, Writing - review & editing), Sean A. Parks (Conceptualization, Writing - original draft, Writing - review & editing), R. Kyle Bocinsky (Conceptualization, Visualization, Writing - original draft, Writing - review & editing), Kimberley T. Davis (Writing - review & editing), Caitlin Littlefield (Writing - review & editing), Marco P. Maneta (Conceptualization, Writing - review & editing), Carina Wyborn (Writing - review & editing), Patrick Wurster (Writing - original draft, Writing - review & editing), Robin Rank (Writing - original draft, Writing - review & editing), Douglas Brinkerhoff (Conceptualization), and Thomas Colligan (Conceptualization, Writing - original draft).

Supplemental material

Supplemental data are available at *BIOSCI* online.

Data availability statement

The FIA data (Bechtold et al. 2005) used in this study's illustrations are publicly available at FIA DataMart (https://research.fs.usda.gov/products/dataandtools/tools/fia-datamart). The TerraClimate data are also available publicly at https://www.climatologylab.org/terraclimate.html. The United States Forest Service Region 6 Potential Natural Vegetation and the RCP 8.5 climate data were obtained from a third party and are expected to be publicly released by December 2026.

References cited

Abatzoglou JT, Dobrowski SZ, Parks SA. 2020. Multivariate climate departures have outpaced univariate changes across global lands. *Scientific Reports* 10: 3891.

Adler PB, White EP, Cortez MH. 2020. Matching the forecast horizon with the relevant spatial and temporal processes and data sources. *Ecography* 43: 1729–1739. https://doi.org/10.1101/807057.

AghaKouchak A, Chiang F, Huning LS. 2020. Climate extremes and compound hazards in a warming world. *Annual Review of Earth and Planetary Sciences* 48: 519–548. www.annualreviews.org/content/journals/10.1146/annurev-earth-071719-055228

Bahn V, McGill BJ. 2007. Can niche-based distribution models outperform spatial interpolation? *Global Ecology and Biogeography: A Journal of Macroecology* 16: 733–742.

Batllori E, Parisien M-A, Parks SA, Moritz MA, Miller C. 2017. Potential relocation of climatic environments suggests high rates of climate displacement within the North American protection network. *Global Change Biology* 23: 3219–3230.

Beale CM, Lennon JJ. 2012. Incorporating uncertainty in predictive species distribution modelling. *Philosophical Transactions of the Royal Society of London B* 367: 247–258.

Bechtold WA, Patterson PL, eds. 2005. *The Enhanced Forest Inventory and Analysis Program: National Sampling Design and Estimation Procedures*. USDA Forest Service, Southern Research Station.

Beier P, Hansen LJ, Helbrecht L, Behar D. 2017. A how-to guide for coproduction of actionable science. *Conservation Letters* 10: 288–296.

Bierbaum R, et al. 2013. A comprehensive review of climate adaptation in the United States: More than before, but less than needed. *Mitigation and Adaptation Strategies for Global Change* 18: 361–406.

Blois JL, Williams JW, Fitzpatrick MC, Jackson ST, Ferrier S. 2013. Space can substitute for time in predicting climate-change effects on biodiversity. *Proceedings of the National Academy of Sciences* 110: 9374–9379.

Bos SPM, Pagella T, Kindt R, Russell AJM, Luedeling E. 2015. Climate analogs for agricultural impact projection and adaptation: A reliability test. *Frontiers of Environmental Science and Engineering in China* 3: 65.

Brown CJ, et al. 2011. Quantitative approaches in climate change ecology. *Global Change Biology* 17: 3697–3713.

Carroll C, Lawler JJ, Roberts DR, Hamann A. 2015. Biotic and climatic velocity identify contrasting areas of vulnerability to climate change. *PloS One* 10: e0140486.

Carroll C, Parks SA, Dobrowski SZ, Roberts DR. 2018. Climatic, topographic, and anthropogenic factors determine connectivity between current and future climate analogs in North America. *Global Change Biology* 24: 5318–5331.

Chaudhary S, et al. 2023. Climate analogs can catalyze cross-regional dialogs for US specialty crop adaptation. *Scientific Reports* 13: 9317.

Churchill DJ, Larson AJ, Dahlgreen MC, Franklin JF, Hessburg PF, Lutz JA. 2013. Restoring forest resilience: From reference spatial patterns to silvicultural prescriptions and monitoring. *Forest Ecology and Management* 291: 442–457.

Coffield SR, Hemes KS, Koven CD, Goulden ML, Randerson JT. 2021. Climate-driven limits to future carbon storage in California's wildland ecosystems. *AGU Advances* 2: e2021AV000384. https://doi.org/10.1029/2021av000384

Crase B, Liedloff A, Vesk PA, Fukuda Y, Wintle BA. 2014. Incorporating spatial autocorrelation into species distribution models alters forecasts of climate-mediated range shifts. *Global Change Biology* 20: 2566–2579.

Currie DJ. 2001. Projected effects of climate change on patterns of vertebrate and tree species richness in the conterminous United States. *Ecosystems* 4: 216–225. https://doi.org/10.1007/s10021-001-0005-4

Dahinden F, Fischer EM, Knutti R. 2017. Future local climate unlike currently observed anywhere. *Environmental Research Letters* 12: 084004. https://doi.org/10.1088/1748-9326/aa75d7

Dilling L, Lemos MC. 2011. Creating usable science: Opportunities and constraints for climate knowledge use and their implications for science policy. *Global Environmental Change: Human and Policy Dimensions* 21: 680–689.

Diniz-Filho JAF, Bini LM, Hawkins BA 2003. Spatial autocorrelation and red herrings in geographical ecology. *Global Ecology and Biogeography* 12: 53–64.

Dobrowski SZ, Abatzoglou JT, Greenberg JA, Schladow SG. 2009. How much influence does landscape-scale physiography have on air temperature in a mountain environment? *Agricultural and Forest Meteorology* 149: 1751–1758.

Dobrowski SZ, Littlefield CE, Lyons DS. 2021. Protected-area targets could be undermined by climate change-driven shifts in ecoregions and biomes. *Communications Earth and Environment* 2: 198.

Dobrowski SZ, Parks SA. 2016. Climate change velocity underestimates climate change exposure in mountainous regions. *Nature Communications* 7: 12349.

Dormann F, et al. 2007. Methods to account for spatial autocorrelation in the analysis of species distributional data: A review. *Ecography* 30: 609–628.

Dunn MR, Lindesay JA, Howden M. 2015. Spatial and temporal scales of future climate information for climate change adaptation in viticulture: A case study of user needs in the Australian winegrape sector. *Australian Journal of Grape and Wine Research* 21: 226–239. https://doi.org/10.1111/ajgw.12138

Dunn M, Rounsevell MDA, Boberg F, Clarke E, Christensen J, Madsen MS. 2019. The future potential for wine production in Scotland under high-end climate change. *Regional Environmental Change* 19: 723–732.

Elith J, Leathwick JR. 2009. Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics* 40: 677–697. www.annualreviews.org/content/journals/10.1146/annurev.ecolsys.110308.120159

Elmendorf SC, et al. 2015. Experiment, monitoring, and gradient methods used to infer climate change effects on plant communities yield consistent patterns. *Proceedings of the National Academy of Sciences* 112: 448–452.

Fekete A. 2009. Validation of a social vulnerability index in context to river-floods in Germany. *Natural Hazards and Earth System Sciences* 9: 393–403. https://doi.org/10.5194/nhess-9-393-2009

Fitzpatrick MC, Dunn RR. 2019. Contemporary climatic analogs for 540 North American urban areas in the late 21st century. *Nature Communications* 10: 614.

Fitzpatrick MC, Hargrove WW. 2009. The projection of species distribution models and the problem of non-analog climate. *Biodiversity and Conservation* 18: 2255–2261. https://link.springer.com/article/10.1007/s10531-009-9584-8

Fitzpatrick MC, Blois JL, Williams JW, Nieto-Lugilde D, Maguire KC, Lorenz DJ. 2018. How will climate novelty influence ecological forecasts? Using the quaternary to assess future reliability. *Global Change Biology* 24: 3575–3586.

Fotheringham SA, Brunsdon C, Charlton M. 2002. *Geographically Weighted Regression*. Wiley.

Garcia RA, Cabeza M, Rahbek C, Araújo MB. 2014. Multiple dimensions of climate change and their implications for biodiversity. *Science* 344: 1247579.

Gaspard G, Kim D, Chun Y. 2019. Residual spatial autocorrelation in macroecological and biogeographical modeling: A review. *Han'gug Hwan'gyeong Saengtae Haghoeji (Korean Journal of Environment and Ecology)* 43: 19.

Grenier P, Parent A-C, Huard D, Anctil F, Chaumont D. 2013. An assessment of six dissimilarity metrics for climate analogs. *Journal of Applied Meteorology and Climatology* 52: 733–752.

Gutschick VP, BassiriRad H. 2003. Extreme events as shaping physiology, ecology, and evolution of plants: Toward a unified definition and evaluation of their consequences. *New Phytologist* 160: 21–42. https://doi.org/10.1046/j.1469-8137.2003.00866.x

Hallegatte S, Hourcade J-C, Ambrosi P. 2007. Using climate analogues for assessing climate change economic impacts in urban areas. *Climatic Change* 82: 47–60.

Hamann A, Roberts DR, Barber QE, Carroll C, Nielsen SE. 2015. Velocity of climate change algorithms for guiding conservation and management. *Global Change Biology* 21: 997–1004.

Heikkinen RK, Leikola N, Aalto J, Aapala K, Kuusela S, Luoto M, Virkkala R. 2020. Fine-grained climate velocities reveal vulnerability of protected areas to climate change. *Scientific Reports* 10: 1678.

Hijmans RJ. 2012. Cross-validation of species distribution models: Removing spatial sorting bias and calibration with a null model. *Ecology* 93: 679–688.

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A. 2005. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* 25: 1965–1978.

Holsinger L, Parks SA, Parisien M, Miller C, Batllori E, Moritz MA. 2019. Climate change likely to reshape vegetation in North America's largest protected areas. *Conservation Science and Practice* 1: e50. https://doi.org/10.1111/csp2.50

Houghton JT, Ding Y, Griggs DJ, Noguer M, van der Linden PJ, Dai X, Maskell K, Johnson CA. 2001. *Climate Change 2001: The Scientific Basis*. Cambridge University Press.

Huey RB, Deutsch CA, Tewksbury JJ, Vitt LJ, Hertz PE, Alvarez Pérez HJ, Garland T, Jr. 2009. Why tropical forest lizards are vulnerable to climate warming. *Proceedings of the Royal Society B* 276: 1939–1948.

Jackson ST, Betancourt JL, Booth RK, Gray ST. 2009. Ecology and the ratchet of events: Climate variability, niche dimensions, and species distributions. *Proceedings of the National Academy of Sciences* 106 (suppl. 2): 19685–19692.

Johnson EA, Miyanishi K. 2008. Testing the assumptions of chronosequences in succession. *Ecology Letters* 11: 419–431.

Jost C, et al. 2016. Understanding gender dimensions of agriculture and climate change in smallholder farming communities. *Climate and Development* 8: 133–144.

Jylhä K, Tuomenvirta H, Ruosteenoja K, Niemi-Hugaerts H, Keisu K, Karhu JA. 2010. Observed and projected future shifts of climatic zones in Europe and their use to visualize climate change information. *Weather, Climate, and Society* 2: 148–167.

Katz RW, Brown BG. 1992. Extreme events in a changing climate: Variability is more important than averages. *Climatic Change* 211: 289–302.

Katz RW, Brush GS, Parlange MB. 2005. Statistics of extremes: Modeling ecological disturbances. *Ecology* 86: 1124–1134.

Kellett J, Hamilton C, Ness D, Pullen S. 2015. Testing the limits of regional climate analogue studies: An Australian example. *Land Use Policy* 44: 54–61.

King AD. 2023. Identifying historical climate changes in Australia through spatial analogs. *Environmental Research Letters* 18: 044018.

Kingma DP, Welling M. 2014. Stochastic Gradient VB and the Variational Auto-Encoder. *Paper presented at the Second International Conference on Learning Representations; 14–16 April 2014*, Banff, Alberta, Canada. https://pdfs.semanticscholar.org/60ea/adac49b19d1f41925df3bbbb7983a113acec.pdf

Kirchhoff CJ, Carmen Lemos M, Dessai S. 2013. Actionable knowledge for environmental decision making: Broadening the usability of climate science. *Annual Review of Environment and Resources* 38: 393–414.

Klesse S, DeRose RJ, Babst F, Black BA. 2020. Continental-scale tree-ring-based projection of Douglas-fir growth: Testing the limits of space-for-time substitution. *Global Change Biology* 26: 5146–5163, https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.15170

Kling MM, Ackerly DD. 2020. Global wind patterns and the vulnerability of wind-dispersed species to climate change. *Nature Climate Change* 10: 868–875.

Kopf S, Ha-Duong M, Hallegatte S. 2008. Using maps of city analogues to display and interpret climate change scenarios and their uncertainty. *Natural Hazards and Earth System Sciences* 8: 905–918. https://doi.org/10.5194/nhess-8-905-2008

Kühn I. 2007. Incorporating spatial autocorrelation may invert observed patterns. *Diversity and Distributions* 13: 66–69.

Lauenroth WK, Sala OE. 1992. Long-term forage production of North American shortgrass steppe. *Ecological Applications* 2: 397–403.

Leibing C, Signer J, van Zonneveld M, Jarvis A, Dvorak W. 2013. Selection of provenances to adapt tropical pine forestry to climate change on the basis of climate analogs. *Forests* 4: 155–178. https://doi.org/10.3390/f4010155

Lennon JJ. 2000. Red-shifts and red herrings in geographical ecology. *Ecography* 23: 101–113.

Lester RE, Close PG, Barton JL, Pope AJ, Brown SC. 2014. Predicting the likely response of data-poor ecosystems to climate change using space-for-time substitution across domains. *Global Change Biology* 20: 3471–3481. https://doi.org/10.1111/gcb.12634

Littlefield CE, McRae BH, Michalak JL, Lawler JJ, Carroll C. 2017. Connecting today's climates to future climate analogs to facilitate movement of species under climate change. *Conservation Biology* 31: 1397–1408.

Lovell RSL, Collins S, Martin SH, Pigot AL, Phillimore AB. 2023. Space-for-time substitutions in climate change ecology and evolution. *Biological Reviews of the Cambridge Philosophical Society* 98: 2243–2270.

Mahalanobis PC. 1936. On the generalized distance in statistics. *Proceedings of the National Institute of Science of India* 2: 49–55.

Mahony CR. 2017. *Detecting Novel Climates in Projections of 21st Century Terrestrial Ecosystem Change. PhD dissertation. University of British Columbia, Vancouver, British Columbia*.

Mahony CR, Cannon AJ, Wang T, Aitken SN. 2017. A closer look at novel climates: New methods and insights at continental to landscape scales. *Global Change Biology* 23: 3934–3955.

Mahony CR, MacKenzie WH, Aitken SN. 2018. Novel climates: Trajectories of climate change beyond the boundaries of British Columbia's forest management knowledge system. *Forest Ecology and Management* 410: 35–47. www.sciencedirect.com/science/article/pii/S0378112717319175

Maurer EP, Hidalgo HG. 2008. Utility of daily vs. monthly large-scale climate data: An intercomparison of two statistical downscaling methods. *Hydrology and Earth System Sciences* 12: 551–563.

McCune B, Grace JB, Urban DL. 2002. Analysis of ecological communities (Vol. 28). MjM software design Gleneden Beach, OR.

McDonald A, Riha S, DiTommaso A, DeGaetano A. 2009. Climate change and the geography of weed damage: Analysis of U.S. maize systems suggests the potential for significant range transformations. *Agriculture, Ecosystems, and Environment* 130: 131–140. https://doi.org/10.1016/j.agee.2008.12.007

Mesgaran MB, Cousens RD, Webber BL. 2014. Here be dragons: A tool for quantifying novelty due to covariate range and correlation change when projecting species distribution models. *Diversity and Distributions* 20: 1147–1159.

Miller JA. 2012. Species distribution models: Spatial autocorrelation and non-stationarity. *Progress in Physical Geography: Earth and Environment* 36: 681–692.

Miller JA. 2014. Virtual species distribution models: Using simulated data to evaluate aspects of model performance. *Progress in Physical Geography: Earth and Environment* 38: 117–128.

Miller JA, Hanham RQ. 2011. Spatial nonstationarity and the scale of species–environment relationships in the Mojave Desert, California, USA. *International Journal of Geographical Information Science* 25: 423–438.

Miller J, Franklin J, Aspinall R. 2007. Incorporating spatial dependence in predictive vegetation models. *Ecological Modelling* 202: 225–242.

Morán-Ordóñez A, Briscoe NJ, Wintle BA. 2018. Modelling species responses to extreme weather provides new insights into constraints on range and likely climate change impacts for Australian mammals. *Ecography* 41: 308–320. https://doi.org/10.1111/ecog.02850

Nicholson-Cole SA. 2005. Representing climate change futures: A critique on the use of images for visual communication. *Computers, Environment and Urban Systems* 29: 255–273.

Nyairo R, Onwonga R, Cherogony K. 2014. Applicability of climate analogues for climate change adaptation planning in Bugabira Commune of Burundi. *Sustainable Agriculture Research* 3: 46–62. www.ccsenet.org/journal/index.php/sar/article/view/38493

O'Neill S, Nicholson-Cole S. 2009. "Fear won't do it": Promoting positive engagement with climate change through visual and iconic representations. *Science Communication* 30: 355–379.

Ordonez A, Williams JW, Svenning J-C. 2016. Mapping climatic mechanisms likely to favour the emergence of novel communities. *Nature Climate Change* 6: 1104–1109. https://doi.org/10.1038/nclimate3127

Overpeck JT, Webb T, Prentice IC. 1985. Quantitative interpretation of fossil pollen spectra: Dissimilarity coefficients and the method of modern analogs. *Quaternary Research* 23: 87–108.

Parks SA, Holsinger LM, Miller C, Parisien M. 2018. Analog-based fire regime and vegetation shifts in mountainous regions of the western US. *Ecography* 41: 910–921. https://doi.org/10.1111/ecog.03378

Parks SA, Dobrowski SZ, Shaw JD, Miller C. 2019. Living on the edge: Trailing edge forests at risk of fire-facilitated conversion to non-forest. *Ecosphere* 10: e02651.

Parks SA, Carroll C, Dobrowski SZ, Allred BW. 2020. Human land uses reduce climate connectivity across North America. *Global Change Biology* 26: 2944–2955.

Parks SA, Holsinger LM, Littlefield CE, Dobrowski SZ, Zeller KA, Abatzoglou JT, Besancon C, Nordgren BL, Lawler JJ. 2022. Efficacy of the global protected area network is threatened by disappearing climates and potential transboundary range shifts. *Environmental Research Letters* 17: 054016.

Parks SA, Holsinger LM, Abatzoglou JT. 2023. Protected areas not likely to serve as steppingstones for species undergoing climate-induced range shifts. *Global Change Biology* 29: 2681–2696. https://onlinelibrary.wiley.com/doi/abs/10.1111/gcb.16629

Parry ML, Carter TR. 1989. An assessment of the effects of climatic change on agriculture. *Climatic Change* 15: 95–116. https://doi.org/10.1007/bf00138848

Perret DL, Evans MEK, Sax DF. 2024. A species' response to spatial climatic variation does not predict its response to climate change. *Proceedings of the National Academy of Sciences* 121: e2304404120.

Peterson ML, Doak DF, Morris WF. 2019. Incorporating local adaptation into forecasts of species' distribution and abundance under climate change. *Global Change Biology* 25: 775–793.

Pickett STA. 1989. Space-for-time substitution as an alternative to long-term studies. Pages 110–135 in Likens GE, ed. *Long-Term Studies in Ecology: Approaches and Alternatives*. Springer.

Ploton P, et al. 2020. Spatial validation reveals poor predictive performance of large-scale ecological mapping models. *Nature Communications* 11: 4540.

Pugh TAM, Müller C, Elliott J, Deryng D, Folberth C, Olin S, Schmid E, Arneth A. 2016. Climate analogues suggest limited potential for intensification of production on current croplands under climate change. *Nature Communications* 7: 12608.

Ramírez-Villegas J, Lau C, Köhler A-K, Signer J, Jarvis A, Arnell N, Osborne T, Hooker J. 2011. *Climate Analogues: Finding Tomorrow's Agriculture Today.* Research Program on Climate Change, Agriculture, and Food Security. Working paper no. 12.

Reckien, Viner, Adler, Cheong, Conde. 2022. Decision-making options for managing risk. Pages 2539–2654 in Pörtner H-O, et al., eds. *Climate Change 2022: Impacts, Adaptations, and Vulnerability*.

Rehfeldt GE, Crookston NL, Sáenz-Romero C, Campbell EM. 2012. North American vegetation model for land-use planning in a changing climate: A solution to large classification problems. *Ecological Applications: A Publication of the Ecological Society of America* 22: 119–141.

Retchless DP. 2014. Communicating climate change: Spatial analog versus color-banded isoline maps with and without accompanying text. *Cartography and Geographic Information Science* 41: 55–74.

Rohat G, Goyette S, Flacke J. 2017. Twin climate cities: An exploratory study of their potential use for awareness-raising and urban adaptation. *Mitigation and Adaptation Strategies for Global Change* 22: 929–945. https://doi.org/10.1007/s11027-016-9708-x

Rollinson CR, Finley AO, Alexander MR. 2021. Working across space and time: Nonstationarity in ecological research and application. *Frontiers in Ecology and the Environment* 19: 66–72.

Seneviratne S, et al. 2012. *Changes in Climate Extremes and Their Impacts on the Natural Physical Environment*. Columbia University. https://doi.org/10.7916/D8-6NBT-S431

Sheppard SRJ. 2005. Landscape visualisation and climate change: The potential for influencing perceptions and behaviour. *Environmental Science and Policy* 8: 637–654.

Soil Survey Staff. 1999. *Soil Taxonomy: A Basic System of Soil Classification for Making and Interpreting Soil Surveys 2nd ed*. US Department of Agriculture, Natural Resources Conservation Service.

Stephenson NL. 1990. Climatic control of vegetation distribution: The role of the water balance. *American Naturalist* 135: 649–670.

Svenning J-C, Sandel B. 2013. Disequilibrium vegetation dynamics under future climate change. *American Journal of Botany* 100: 1266–1286.

Tonkin JD, Bogan MT, Bonada N, Rios-Touma B, Lytle DA. 2017. Seasonality and predictability shape temporal species diversity. *Ecology* 98: 1201–1216.

Van den Dool HM. 1994. Searching for analogues, how long must we wait? *Tellus A* 46: 314–324.

Veloz S, Williams JW, Lorenz D, Notaro M, Vavrus S, Vimont DJ. 2012. Identifying climatic analogs for Wisconsin under 21st-century climate-change scenarios. *Climatic Change* 112: 1037–1058. https://doi.org/10.1007/s10584-011-0261-z

Walker JA. 2014. The effect of unmeasured confounders on the ability to estimate a true performance or selection gradient (and other partial regression coefficients). *Evolution* 68: 2128–2136.

Wang AK, Dominguez F, Schmidt AR. 2019. Extreme precipitation spatial analog: In search of an alternative approach for future Extreme precipitation in urban hydrological studies. *Water* 11: 1032.

Wenger SJ, Som NA, Dauwalter DC, Isaak DJ, Neville HM, Luce CH, Dunham JB, Young MK, Fausch KD, Rieman BE. 2013. Probabilistic accounting of uncertainty in forecasts of species distributions under climate change. *Global Change Biology* 19: 3343–3354.

Williams JW, Jackson ST. 2007. Novel climates, no-analog communities, and ecological surprises. *Frontiers in Ecology and the Environment* 5: 475–482.

Williams JW, Shuman B. 2008. Obtaining accurate and precise environmental reconstructions from the modern analog technique and North American surface pollen dataset. *Quaternary Science Reviews* 27: 669–687.

Williams JW, Jackson ST, Kutzbach JE. 2007. Projected distributions of novel and disappearing climates by 2100 AD. *Proceedings of the National Academy of Sciences* 104: 5738–5742.

Zimmermann NE, Yoccoz NG, Edwards TC, Jr, Meier ES, Thuiller W, Guisan A, Schmatz DR, Pearman PB. 2009. Climatic extremes improve predictions of spatial patterns of tree species. *Proceedings of the National Academy of Sciences* 106 (suppl. 2): 19723–19728.

Zurell D, et al. 2010. The virtual ecologist approach: Simulating data and observers. *Oikos* 119: 622–635.

Received: November 5, 2023. **Revised:** January 24, 2025. **Accepted:** February 25, 2025