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A closer look at novel climates: new methods and insights at continental to landscape scales

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Abstract

Novel climates – emerging conditions with no analog in the observational record – are an open problem in ecological modeling. Detecting extrapolation into novel conditions is a critical step in evaluating bioclimatic projections of how species and ecosystems will respond to climate change. However, biologically informed novelty detection methods remain elusive for many modeling algorithms. To assist with bioclimatic model design and evaluation, we present a first-approximation assessment of general novelty based on a simple and consistent characterization of climate. We build on the seminal global analysis of Williams *et al.* (2007 PNAS, 104, 5738) by assessing of end-of-21st-century novelty for North America at high spatial resolution and by refining their standardized Euclidean distance into an intuitive Mahalanobian metric called sigma dissimilarity. Like this previous study, we found extensive novelty in end-of-21st-century projections for the warm southern margin of the continent as well as the western Arctic. In addition, we detected localized novelty in lower topographic positions at all latitudes: By the end of the 21st century, novel climates are projected to emerge at low elevations in 80% and 99% of ecoregions in the RCP4.5 and RCP8.5 emissions scenarios, respectively. Novel climates are limited to 7% of the continent's area in RCP4.5, but are much more extensive in RCP8.5 (40% of area). These three risk factors for novel climates – regional susceptibility, topographic position, and the magnitude of projected climate change – represent *a priori* evaluation criteria for the credibility of bioclimatic projections. Our findings indicate that novel climates can emerge in any landscape. Interpreting climatic novelty in the context of nonlinear biological responses to climate is an important challenge for future research.

Keywords: bioclimate, climate change, climate envelope, Mahalanobis distance, model extrapolation, no-analog, novel climates, species distribution modeling

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Introduction

Anthropogenic climate change adds a daunting new dimension to one of the central projects of ecology – elucidating the role of climate in ecological function. In just a few decades, local climates are projected to change on scales comparable to the temperature gradients across hundreds of kilometers of latitude and hundreds of meters of elevation (IPCC 2014). Ecologists need climatically specific data to project how species and ecosystems will respond to these changes. Microclimate modification experiments in laboratories and the field provide crucial insight (Thompson *et al.*, 2013), but cannot capture the myriad ecological contexts – species, ecosystem states, and climate types – under the purview of ecosystem managers. As a complement to experimental data, observational studies provide a wealth of information on biological responses to diverse climatic conditions (Dawson *et al.*, 2011). If an ecosystem is projected to experience a warmer and drier climate in the future, we can obtain ecological insight from similarly warmer and drier conditions elsewhere on the landscape, in historical events, or in distant epochs. These similar conditions are called *climate analogs* (Mearns *et al.*, 2001). The climate analog approach is the explicit basis of statistical models, such as species distribution models (Elith & Leathwick, 2009), that use climate variables to predict ecological responses in space and/or time. Mechanistic ecological models are also dependent on observational data, and thus climate analogs, for parameterization and validation (Rastetter *et al.*, 2003). Given that most ecological models are at least partially dependent on observations mediated by the climates of the recent past, the emergence of novel climatic conditions is a serious challenge for projecting ecological responses (Williams & Jackson, 2007). 'No-analog' or 'novel' climates challenge the empirical basis of bioclimatic models (Webber *et al.*, 2011), which are only statistically valid under the

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climatic conditions in which their correlations to biology were developed (Fitzpatrick & Hargrove, 2009). In a formal sense, correlative inferences are not valid for novel climates. In practice, some amount of model extrapolation is necessary for ecological management in a changing climate. Nevertheless, the risk of inference error increases with the degree of extrapolation, and assessments of novel climatic conditions are due diligence in bioclimatic modeling (Peterson *et al.*, 2011).

Species distribution models have evolved in recognition of the pitfalls of model extrapolation (Thuiller *et al.*, 2004), and detection of multivariate model extrapolation continues to be an area of investigation (e.g., Mesgaran *et al.*, 2014). Williams *et al.* (2007) introduced the concept of fundamentally novel climates that are broadly relevant to the whole ecosystem, rather than being defined with respect to individual species. By measuring climatic differences relative to historical interannual climatic variability (ICV), Williams *et al.* (2007) demonstrated that the tropics and subtropics are susceptible to emergence of general novelty due to climate change in the 21st century. This result was corroborated at the global scale using an alternative method (Garcia-Lopez & Allue, 2013). The Williams *et al.* (2007) approach has been widely applied at regional and jurisdictional scales (e.g., Ackerly *et al.*, 2010; Ordonez & Williams, 2013). Alternative methods of assessing novelty have been applied at continental scales (Rehfeldt *et al.*, 2012; Roberts & Hamann, 2012), and the results of these studies suggest that novel climates may also emerge in temperate and Arctic climates. However, the relationship of these novelty inferences to each other, and to the global-scale assessment of Williams *et al.* (2007), is unclear. Further, the role of elevation gradients in moderating the emergence of novel climates has received little attention. A continental-scale analysis of climatic novelty in extratropical regions is required.

Strengths and weaknesses of standardized Euclidean distance

The standardized Euclidean distance (SED) metric for novel climate detection (Williams *et al.*, 2007) has enduring appeal because it measures climatic dissimilarities relative to the historical range of local climatic variability. In addition to the long-term average climate, the amount of year-to-year variability in climatic conditions is a defining characteristic of the environment to which biological species and economic systems are adapted (Jackson *et al.*, 2009). Any absolute amount of change in a climate element, such as mean annual temperature, is likely to be more important to locations and seasons with low ICV in that element (Mahlstein *et al.*, 2012). This logic underlies the widespread use of local ICV as a means of assessing the general ecological and economic significance of some amount of climate change in any given climate element (Hansen *et al.*, 2012; Hawkins & Sutton, 2012).

Despite exhibiting acceptable performance relative to several more complex analog detection metrics (Grenier *et al.*, 2013), the SED metric has two important shortcomings. First, it is susceptible to variance inflation due to correlations in the raw variables. Second, it does not account for the effect of dimensionality (number of variables) on the statistical meaning of distance. These shortcomings confound interpretation of SED, particularly when comparing measurements with different dimensionality. We improve on the SED approach by reworking it into a Mahalanobis distance, and by interpreting those distances against a null distribution.

The continental climate envelope

Most analyses of novel climates employ the conceptual model of the study-area climate envelope (*sensu* Williams *et al.*, 2007). The observed climates of a study area occupy an identifiable volume – the climate envelope – within a multivariate data space made up of several climate variables. In a changing climate, this climate envelope will shift its position in multivariate climate space, resulting in the emergence of novel climates along the leading edge of the shifting climate envelope.

The simplest concept of the climate envelope is a convex hull with a single leading edge (*sensu* Garcia-Lopez & Allue, 2013). This concept may be appropriate to small study areas or highly generalized climate classifications, but it neglects important features of observed climate envelopes. Two-dimensional seasonal climate envelopes for North America exhibit complex structure with several leading edges (Fig. 1). In all seasons, the climate envelope of the North American continent has four prominent lobes associated with global-scale atmospheric circulation: tropical rainforest climates associated with upwelling of the Hadley cell; hot-dry subtropical climates associated with the downwelling of the Hadley cell; cool-wet temperate climates of Ferrel-polar frontal convergence; and cold-dry Arctic climates associated with the polar vortex. In other words, global atmospheric circulation superimposes an oscillating spatial precipitation pattern onto the relatively monotonic poleward temperature gradient, creating several leading edges in the North American climate envelope. In higher-dimensional climate space, there is also potential for elevational gradients to create other leading edges. Hence, global warming can be expected to produce regional and local occurrences of novel

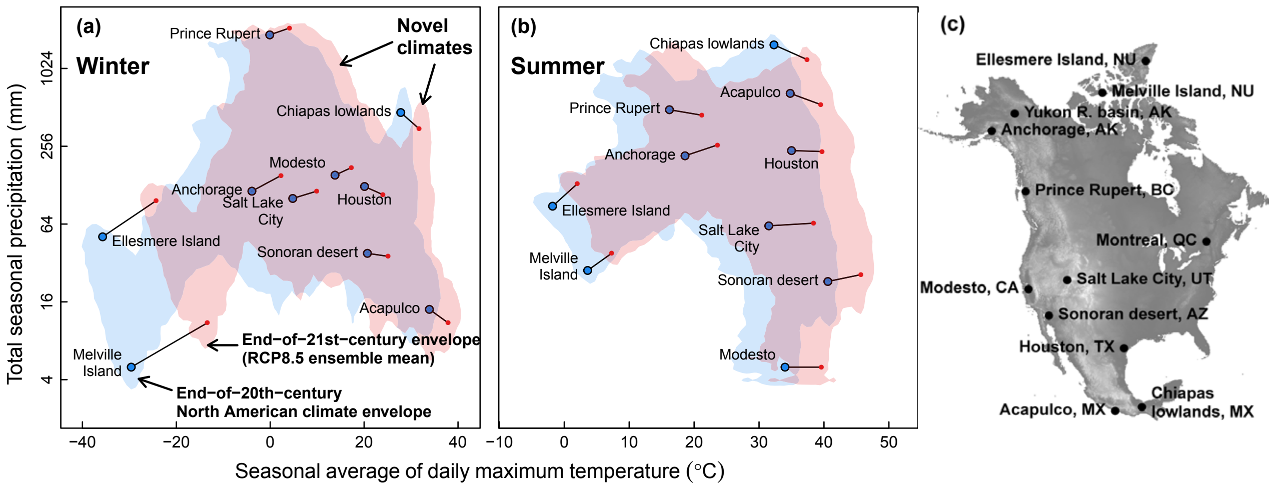

Fig. 1 Projected shifts in the North American temperature-precipitation envelope in winter (a) and summer (b). Even in just two dimensions, there are several leading edges along which novel climates can form. Climate change trajectories for representative locations (c) are shown for reference. [Colour figure can be viewed at wileyonlinelibrary.com]

climates at all latitudes, rather than just in the warmest southern margins of the continent.

Variable selection: defining climate

An investigation of novel climates hinges on how climates are differentiated. The climate of any given location can be defined in terms of hundreds of biologically relevant variables, such as growing season frosts, wind speed, fog, solar insolation, extreme events, snow-free period, and so on. No two locations or time periods have the same combination of all of these characteristics; hence, climate analogs cannot be defined in an objective sense. The climates of different locations can be considered ecologically equivalent only to the extent that some of their climatic differences are unimportant to the species or biological interactions under consideration. Climatic similarities are subjective; a climate analog from the perspective of one species may not be an analog for another species.

The biological specificity of climatic analogs dictates that climatic novelty ultimately is specific to each bioclimatic model. Nevertheless, we agree with Williams *et al.* (2007) that novelty in basic aspects of climate such as seasonal temperature and precipitation is likely to have broad ecological significance. This 'general novelty' represents an enhanced likelihood of species- or process-specific novelty relevant to modeling ecological impacts of climate change. Assessments of general novelty are useful to ecological modelers in that they provide a first approximation of geographical regions or time periods where the risk of model extrapolation is high. They are also useful for *post hoc* evaluation of studies that do not include an assessment of model extrapolation.

In analyses of general novelty, there is a balance to be struck between defining climate too generally (not enough climate variables), and defining climate too specifically (too many variables). The simple, 4-variable definition of climate used by Williams *et al.* (2007) ensured that the potential for declaring novelty in ecologically equivalent climatic conditions was low. In other words, their method carried a low risk of false novelty (analogous to Type I inference errors). This robust approach produced strong evidence that bioclimatic models of 21st-century ecological change in the tropics and subtropics are susceptible to model extrapolation errors. However, this robustness came at the cost of a high potential of false analogs (analogous to Type II inference errors). Consequently, Williams *et al.* (2007) should be considered inconclusive for areas where novelty was not detected, that is, the temperate and Arctic regions. A novelty analysis for these regions requires a more specific definition of climate.

The objective of this study is to provide a continental-scale assessment of general novelty that builds on the methods and results of Williams *et al.* (2007). Our study is distinct in several respects. First, we adapt the standardized Euclidean distance (SED) metric into a Mahalanobian dissimilarity metric. Second, we use a much higher spatial resolution to investigate the role of elevation gradients in climatic novelty. Finally, we elucidate some drivers of novelty at continental to landscape scales. Our results provide a first approximation of model extrapolation risk for use in North American bioclimatic studies. More generally, we advance conceptual and statistical models of climatic novelty that are globally applicable.

Materials and methods

We measure novelty as the dissimilarity between the projected end-of-21st-century climate of a location of interest and its best analog among the observed end-of-20th-century climates of North America (Fig. 2). Our methods follow the general approach of the standardized Euclidean distance (SED) metric (Williams *et al.*, 2007), which scales climate variables relative to the local range of ICV. However, we make two major modifications to the SED metric: (i) we adapt SED into a Mahalanobis distance and (ii) we interpret distances as percentiles of the chi distribution. Mahalanobis distance improves the scaling of variables relative to ICV and removes variance inflation due to correlations. Interpretation using the chi distribution accounts for the effect of dimensionality on the statistical meaning of distance. We call this new metric 'sigma dissimilarity'. In the supporting information to this paper, we provide R code and data for calculating and mapping climatic novelty using the sigma dissimilarity metric (section S15).

Calculation of Mahalanobis distance scaled to ICV

The source data for calculating a Mahalanobian extension of SED are the following:

- Gridded North American climate normal data: [A] and [B] are ($n \times K$) matrices of n spatially gridded observations of K climate variables over North America. [A] is comprised of 1971–2000 climate normals (30-year means), and [B] is comprised of projected 2071–2100 normals. The observations of these matrices, a_{ik} and b_{ik}, are normals for variable k at location i.
- Time series of reference ICV: [C_j] is a ($T \times K$) matrix of T concurrent annual observations of the K climate variables at a location, j, for which novelty is to be calculated. The observations of [C_j], c_{jtk}, are the values of variable k at year t of the reference period 1951–1990. s_{jk} is the standard deviation of ICV in variable k.

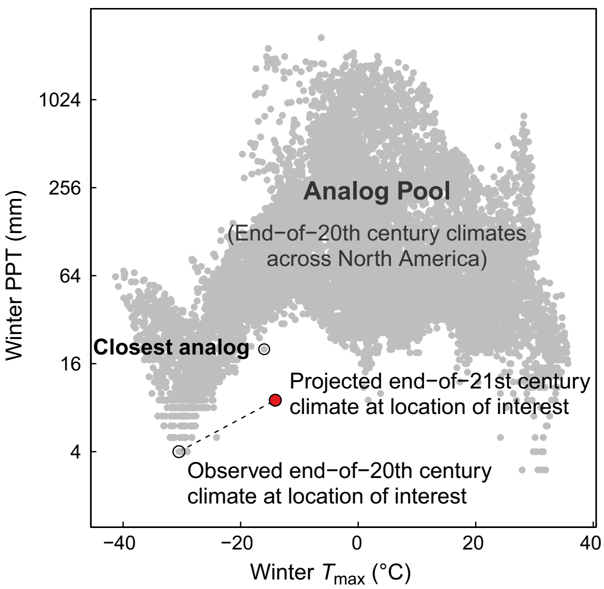

Fig. 2 Simplified illustration of the novelty assessment. Novelty is the distance between the projected future climate of a location of interest and its closest analog in the observed climates of the study area. [Colour figure can be viewed at wileyonlinelibrary.com]

The standardized Euclidean distance (SED_{ji}) between the projected climate normals of a focal location j and the observed climate normals of any location i, as formulated by Williams *et al.* (2007), is

$$\mathrm{SED}_{ji} = \sqrt{\sum_{k=1}^{K} \frac{\left(b_{jk} - a_{ik}\right)^2}{s_{jk}^2}}. \tag{1}$$

The corresponding Mahalanobis distance, D_{ji}, is

$$\mathrm{D}_{ji} = \sqrt{\mathrm{D}_{ji}^2} = \sqrt{\left[\boldsymbol{b}_j' - \boldsymbol{a}_i'\right]^T \left[\mathrm{R}_j\right]^{-1} \left[\boldsymbol{b}_j' - \boldsymbol{a}_i'\right]} \tag{2}$$

where [R_j] is the correlation matrix of [C_j] and $\boldsymbol{a}_i'$ and $\boldsymbol{b}_j'$ are row vectors of [A] and [B] at locations i and j, respectively, expressed as standardized anomalies of reference ICV [C_j].

Mahalanobis distance can be more intuitively understood as standardized Euclidean distance measured in the principal components of [C_j]. There are three steps to calculating Mahalanobis distance in this way (Fig. 3).

Step 1—Re-expression as standardized anomalies. Each observation in [C_j] can be expressed as a conventional standardized anomaly by subtracting the mean and dividing by the standard deviation of the time series for variable k:

$$c_{jtk}' = \frac{c_{jtk} - \bar{c}_{jk}}{s_{jk}}. \tag{3}$$

The result is a ($T \times K$) matrix [C_j'] containing the column-wise z-scores of [C_j'].

[A] and [B] can similarly be expressed as standardized anomalies of reference ICV:

$$a_{ik}' = \frac{a_{ik} - \bar{c}_{jk}}{s_{jk}} \tag{4}$$

resulting in ($n \times K$) matrices [A′] and [B′]. The outcome of this step is that each climate variable is scaled relative to ICV at focal location j (Fig. 3b). Simple Euclidean distance in this scaled data space is equivalent to SED in the raw data space.

Step 2—Principal components analysis. This step rotates the axes of the data space into alignment with the principal components of local ICV (Fig. 3c). [A′], [B′], and [C_j'] are projected onto the principal components of [C_j'], to produce linearly transformed matrices [X], [Y], and [Z_j], respectively. Principal components are discarded (truncated) if they have variance <0.01 (rationale provided in supporting materials, Appendix S2). In other words, the dimensionality of the data space is reduced from K to M climate variables if any of the principal components of

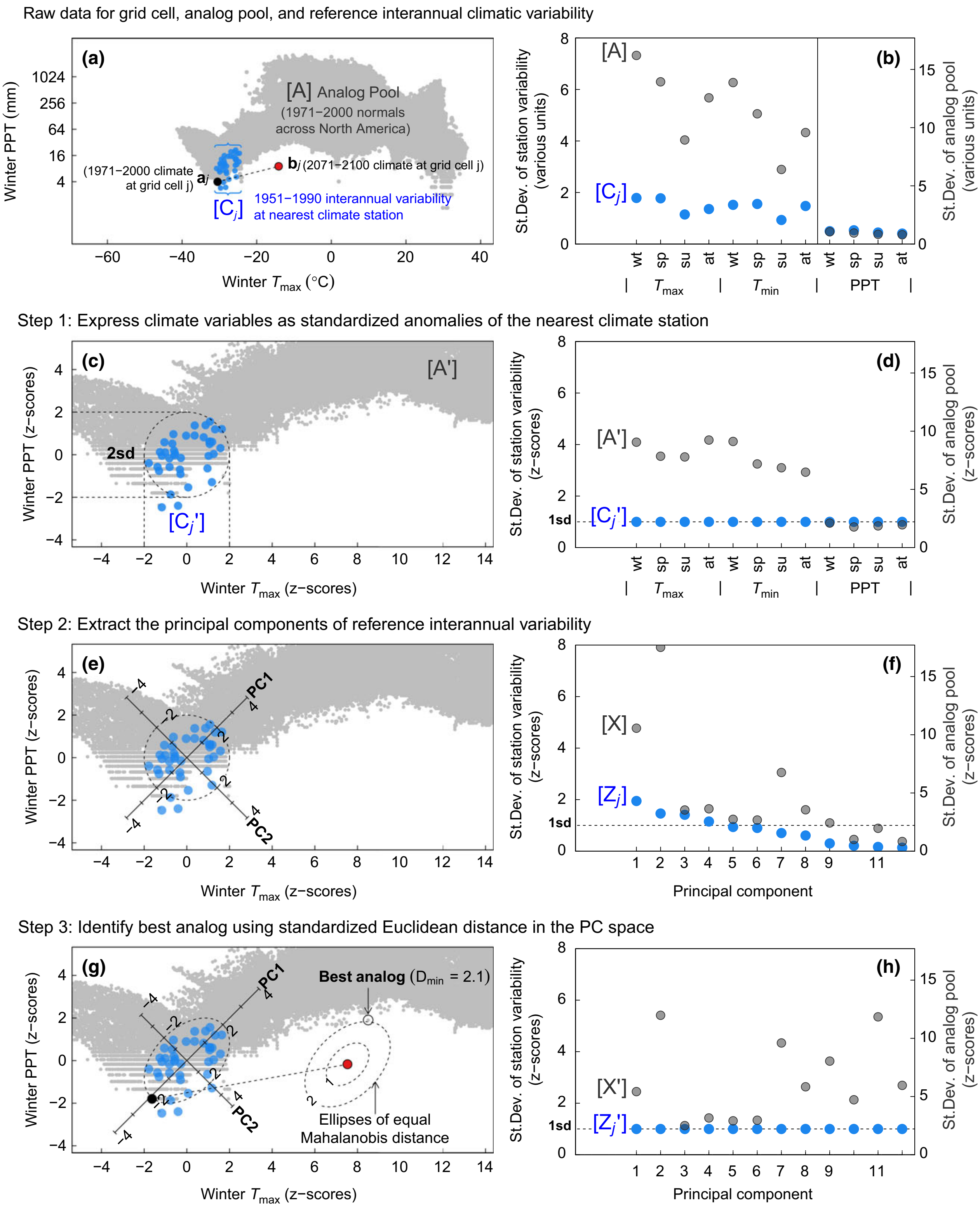

Fig. 3 Illustration of the procedure for analog identification using Mahalanobis distance scaled to local ICV, described mathematically in the text. Scatter plots (a, c, e, g) show the transformations of the data in two arbitrarily selected climate variables. Scree plots (b, d, f, h) show the relative spatial and temporal variation in the 12 dimensions of the data space at each step. The focal location in this example, grid cell *j*, is located on Melville Island (75°N, 107°W).

$[C_j']$ have trivial variance. Equations for this step are provided in Appendix S4.

Step 3—Calculation of Mahalanobis distance. Mahalanobis distance in the raw data, D_{ji}, can be calculated as standardized Euclidean distance (SED) in the rotated and truncated data space (Fig. 3d):

$$D_{ji} = \sqrt{\sum_{m=1}^{M} \frac{\left(y_{jm} - x_{im}\right)^2}{\sigma_{jm}^2}} \tag{5}$$

where σ_{jm}^2 is the standard deviation of ICV in each principal component, that is, the column standard deviations of $[Z_j]$.

For each focal location j, D_{ji} is measured to all of the other n grid locations in North America. The minimum of these distances, $D_{j\min}$, identifies the location with the best end-of-20th century analog for the projected end-of-21st-century climate of focal location j.

Sigma dissimilarity

The effect of dimensionality on expected distances is a critical consideration for interpreting distances as dissimilarity. The probability distribution of squared Mahalanobis distances in multivariate normal data is described by the chi-square distribution with degrees of freedom equaling the number of dimensions in which the distance is measured (Wilks, 2006). It follows that the chi distribution provides a null distribution for (nonsquared) Mahalanobis distances and that Mahalanobis distances can be expressed probabilistically as percentiles of the chi distribution (Fig. 4). Translation of distances into probabilities is necessary to account for the effect of dimensionality on the statistical meaning of distance. We express chi percentiles using the terminology of univariate z-scores; that is, 1σ, 2σ, and 3σ (sigma) to describe the 68th, 95th, and 99.7th normal percentiles, respectively. This 'sigma dissimilarity' metric serves as a multivariate z-score. We translated $D_{j\min}$ for each map grid cell into sigma similarity (Fig. 5).

As a statistical measure of the departure from historical variability, sigma dissimilarity provides an intrinsically meaningful metric of the general ecological significance of climatic dissimilarities. For this reason, we do not use a threshold analog dissimilarity level to define novelty. As a point of reference, however, we note that Williams *et al.* (2007) used a threshold of $SED_t = 3.22$ to define novel climates. Given that this SED_t was measured in a 4-dimensional climate space, it corresponds to a sigma dissimilarity of at least 2.11σ, depending on the correlations between the raw variables. We subjectively consider 2σ analog dissimilarity – the 95th percentile of local ICV – to be a moderate degree of novelty, and 4σ analog dissimilarity to be extreme novelty.

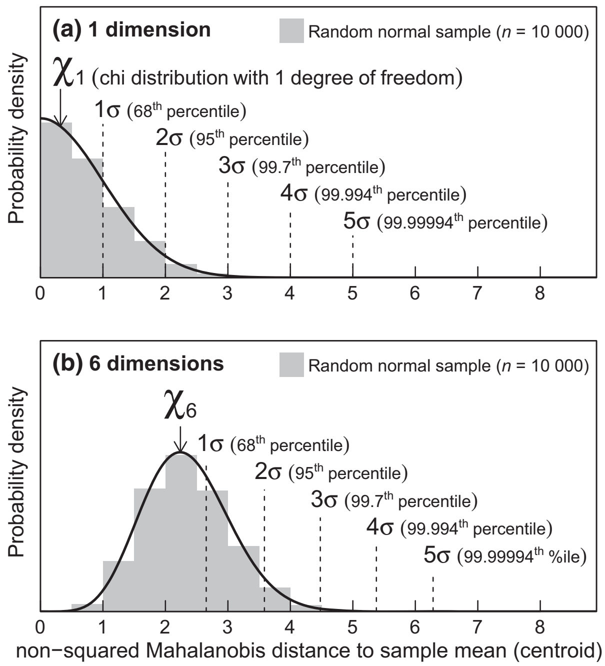

Fig. 4 The theoretical basis of the multivariate sigma dissimilarity metric. The chi distribution is the probability density function of the nonsquared Mahalanobis distances from multivariate normal observations to their mean. (a) The chi distribution in 1 dimension is a half-normal distribution, and distances correspond to the sigma percentiles of the normal distribution. (b) At increasing dimensionality, the sigma percentiles of the chi distribution shift away from the origin, providing a dissimilarity metric that accounts for the effects of dimensionality on the statistical meaning of distance.

Climate data

Variable selection. To facilitate continental- and landscape-scale novelty analyses, we use 12 seasonal climate variables to increase the differentiation of climates relative to Williams *et al.* (2007) four-variable analysis. This more specific definition of climate is intended to reduce the potential for false analogs (analogous to Type II errors) without unduly increasing the potential for false novelty (analogous to Type I errors). The 12 climate variables are mean daily minimum and maximum temperature ($T_{\min}$ and $T_{\max}$) and total precipitation (PPT) for the four climatological seasons: winter (DJF), spring (MAM), summer (JJA), and autumn (SON). We log-transformed precipitation variables to provide a re-expression of the data in terms of relative magnitude.

Climate normals. Gridded climate normals were obtained using CLIMATENA v5.10 (Wang *et al.*, 2016). This publicly available application uses the delta method to downscale CMIP5 projections. The 1971–2000 base climatology (Fig. 6) is compiled at 2.5-arcmin resolution from PRISM sources (Daly *et al.*, 2008; Pacific Climate Impacts Consortium and PRISM Climate Group 2014) for the contiguous United States and Western Canada, and generated using the ANUSPLIN methodology (McKenney *et al.*, 2011) for the remainder of the continent. We extracted data grids from CLIMATENA at 4 km resolution (2 km for inset maps and 8 km for sensitivity analyses) in a North American Equidistant Conic projection. The digital elevation models (DEMs)

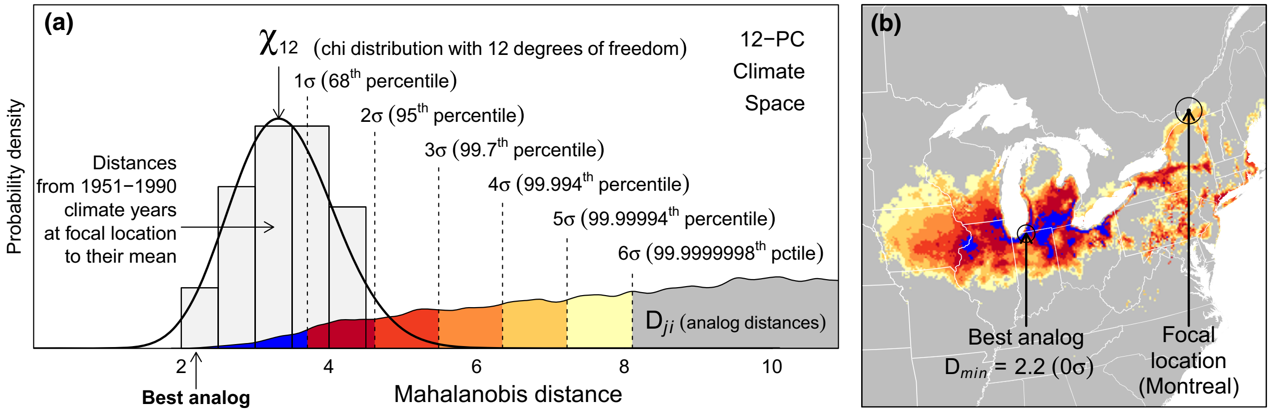

Fig. 5 Illustration of the use of the sigma dissimilarity metric to map analog dissimilarity. The projected climate of the focal location is the Ensemble Mean RCP4.5 projection for the 2071–2100 normal period. (a) The expected probability density of reference ICV for the focal location is described by the chi distribution with degrees of freedom equaling the dimensionality of the data space, assuming multivariate normality. Distances (D_{ji}) from the end-of-21st century focal condition to the end-of-20th century analogs are (a) classified and (b) mapped using the sigma percentiles of the chi distribution.

used to extract data from CLIMATENA are gridded subsamples of USGS GTOPO30, thus conserving the elevation variance of this 30-arc second DEM.

Analog pool. To improve computational speed while conserving North American climatic diversity, we reduced the analog pool (the [A] matrix) to n = 161 032 using a combination of regular and variable subsampling of the 30-arc second DEM. This 12% sample of the 4 km map grid adequately represents the diversity of climates present in the map grid and results in negligible bias to the results of this study (Appendix S3). We determined that outliers from the North American climate envelope are not a source of bias in the novelty assessment (Appendix S7).

Local ICV. We estimated local ICV, [C_j], using weather station data from the CRU TS3.23 (Harris *et al.*, 2014) source observations. Our use of point station data avoids variance reduction artifacts evident in gridded and interpolated time series (Director & Bornn, 2015). We used a reference period of 1951–1990, due to higher risk of inhomogeneities prior to 1951 and a sharp decline in station observations after 1990. Precipitation stations were assigned the temperature time series of the nearest temperature station, and discarded if no temperature station was available within 60 km. We discarded stations with <20 years of complete record north of 33°N. This process selected 2304 CRU TS3.23 stations within the study area (Fig. 6). We calculated sigma dissimilarity (novelty) separately for each of the four stations nearest to the focal location j and then averaged these values. Details of ICV data selection and processing are provided in Appendix S1.

CMIP5 ensemble projections. We conducted assessments of end-of-21st-century projections (2071–2100 climate normals) using an ensemble of the 15 CMIP5 projections (Taylor *et al.*, 2012) available in CLIMATENA: ACCESS1.0, CanESM2, IPSL-CM5A-MR, MIROC5, MPI-ESM-LR, CCSM4, HadGEM2-ES, CNRM-CM5, CSIRO Mk 3.6, GFDL-CM3, INM-CM4, MRI-CGCM3, MIROC-ESM, CESM1-CAM5, and GISS-E2R (Appendix S5: Table S2). The ensemble models were chosen to represent the major clusters of CMIP5 GCMs identified by Knutti *et al.* (2013) and further selected based on the validation statistics of their CMIP3 equivalents (Wang *et al.*, 2016). Our primary results are based on an 'ensemble mean projection' calculated from the mean monthly anomaly for each variable in all 15 models (Fig. 6).

Emissions scenarios. We evaluate novelty for the RCP4.5 and RCP8.5 scenarios (van Vuuren *et al.*, 2011). We use the term *emissions scenarios* for simplicity, recognizing that these scenarios encompass other major components of radiative forcing such as atmospheric chemical cycles and land use change. RCP4.5 and RCP8.5 are most closely comparable to the B1 and A1F1 scenarios of the preceding SRES scheme (Rogelj *et al.*, 2012). The RCP4.5 and RCP8.5 scenarios produce end-of-21st-century global warming of 2.4 °C (1.7–3.3 °C) and 4.3°C (3.2–5.5 °C), respectively, relative to the 1850–1900 period (IPCC 2013). The RCP4.5 scenario roughly corresponds to the 2.7 °C (2.1–3.2 °C) temperature rise consistent with the conditional INDCs of the Paris Agreement, and the RCP8.5 scenario roughly corresponds to the 4.1 °C (3.1–4.8 °C) warming consistent with an absence of emissions policies (Rogelj *et al.*, 2016).

Results

The RCP4.5 ensemble mean projection for the 2071–2100 normal period represents an increase of 3.5 °C in the mean annual temperature (MAT) of North America, relative to the 1971–2000 normal period. In this projection, 2σ novelty emerges over 7% of the area of the continent (Fig. 7a). Novel climates are primarily found adjacent to the Gulf of Mexico, the west coast of Mexico, the western high Arctic islands, and coast of

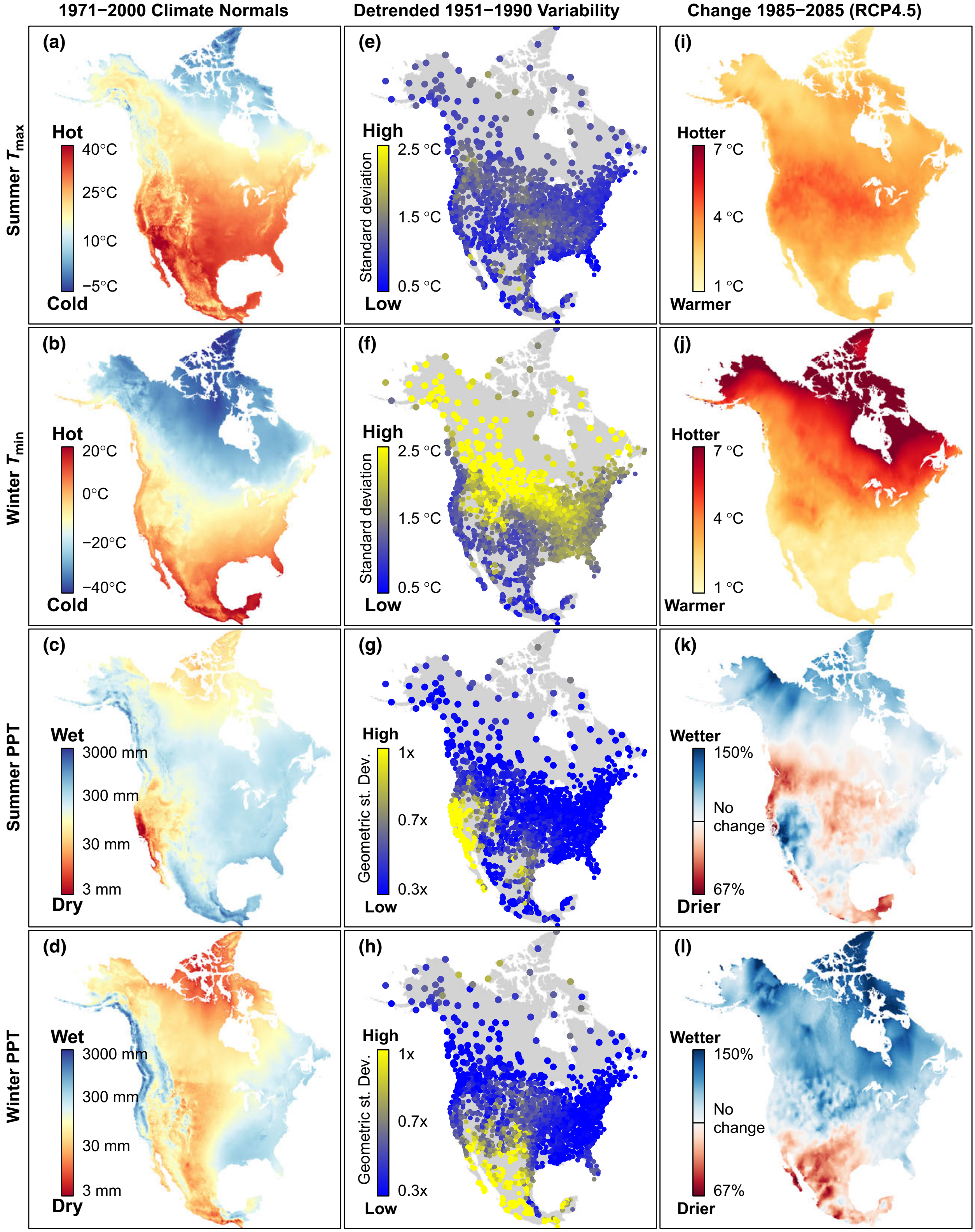

Fig. 6 An overview of the spatial variation in the input data to the novelty analysis. 1971–2000 climate normals (a–d) are obtained from PRISM for the contiguous United States and British Columbia, and ANUSPLIN elsewhere. Local ICV (e–h) is obtained from 2304 CRU TS3.23 source stations. Projected climate change for the 15-model ensemble (i–l) is downscaled by the CLIMATENA software using the delta method.

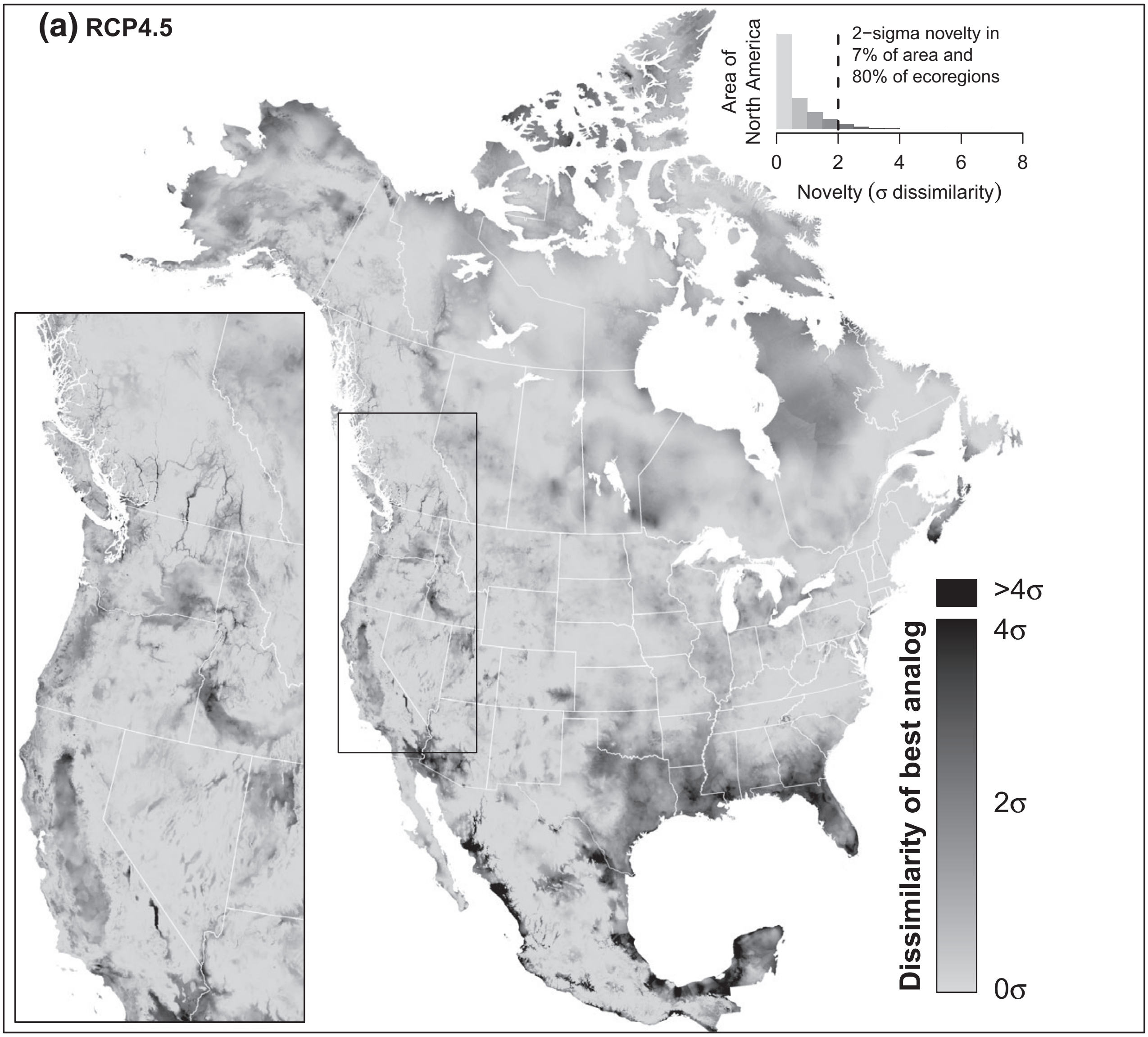

Fig. 7 Distribution of climatic novelty across North America in the (a) RCP4.5 and (b) RCP8.5 ensemble mean projections for the 2071–2100 normal period. The central Western Cordillera is shown in the inset to show elevation-related details. Spatial data for this figure are provided in Appendix S16.

northwest Alaska. Despite being limited in terms of area, novel climates are widespread: 80% of North American ecoregions contain some amount of 2σ novelty. Novelty is emergent in many of the major basins and valleys of the Western Cordillera, including Death Valley, the Snake and Columbia Rivers, Puget Sound, the major valleys of southern British Columbia, and the northern portion of the California Central Valley.

The RCP8.5 projection (6.2 °C average MAT increase) exhibits a much higher level of novelty, covering 40% of the area of the continent, and is found within 99% of ecoregions (Fig. 7b). Patterns of novelty observed for RCP4.5 are largely accentuated in RCP8.5. In addition, widespread novelty is emergent across the central and eastern portions of the continent with the exception of the Appalachian range and Labrador. Novelty is less widespread in the Western Cordillera than in eastern North America, and is limited to lower elevations. In addition to the areas of emergent novelty in the RCP4.5 projection, several areas of the temperate rainforest climates of coastal British Columbia, Washington, and Oregon show pronounced ($>3\sigma$) novelty in the RCP8.5 projection.

The range of variation in novelty calculated from the four ICV proxies is substantial in many grid cells, particularly in the RCP4.5 projection (Appendix S10). This variation suggests some potential for local bias associated with averaging of ICV proxies. However, there are

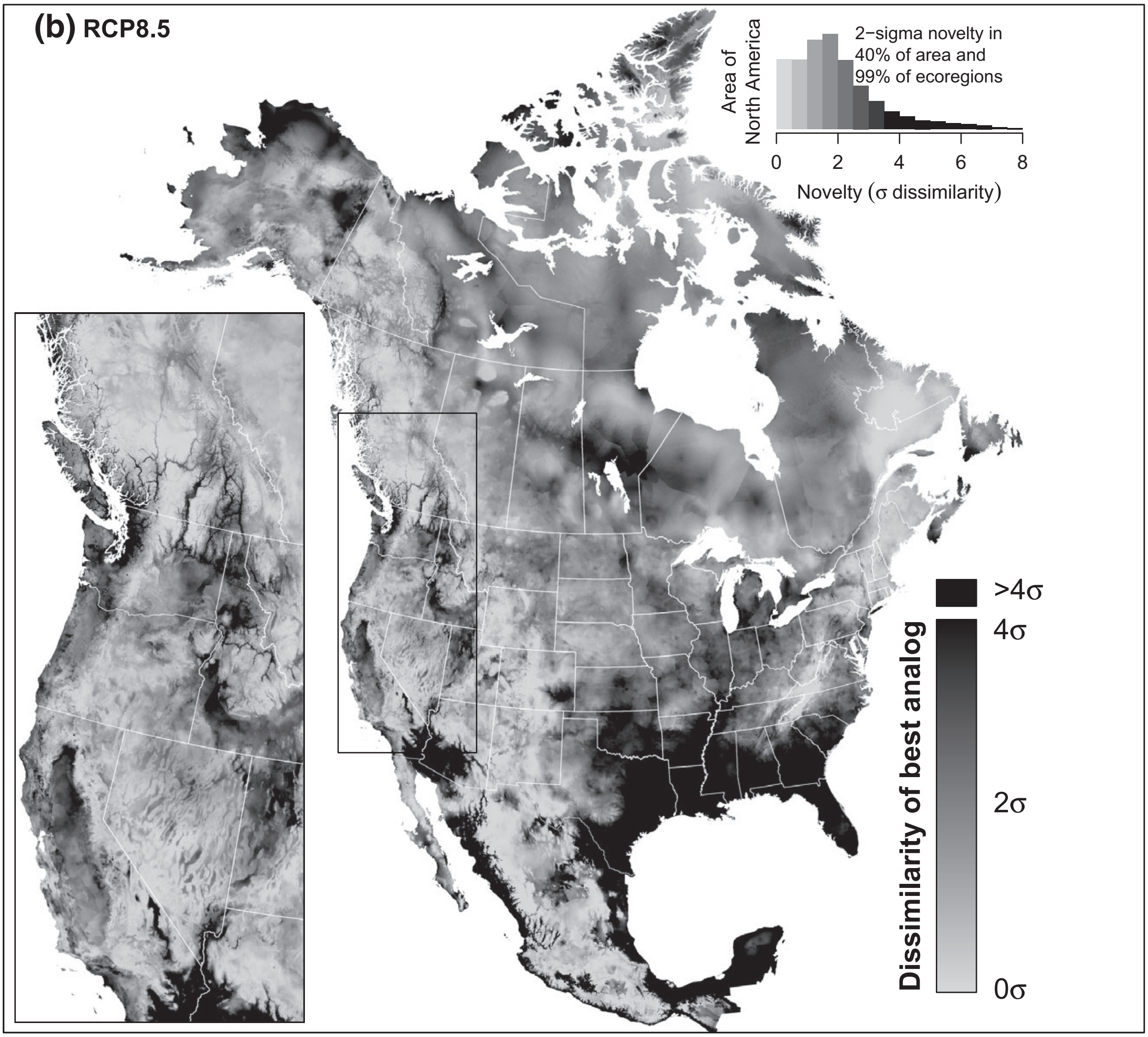

Fig. 7 continued

few locations with the potential for missed novelty or false novelty relative to a 2σ threshold. The main results of this analysis do not appear to be sensitive to differences between the four ICV proxies for each grid cell.

Variable selection

Novelty is sensitive to the variables used to define climate (Fig. 8). The four-variable climate used by Williams *et al.* (2007) – average temperature and precipitation in summer and winter (Fig. 8a) – produces a sharply reduced novelty throughout the continent, particularly in the Western Cordillera, boreal, and Arctic regions, even in RCP8.5. Much of this reduction is associated with the use of mean temperature (T_{ave}) instead of minimum and maximum temperature (T_{min}, T_{max}). The use of two instead of four seasons has a relatively small effect on novelty. The SED metric does not show this pronounced sensitivity to substituting T_{min} and T_{max} for T_{ave} (Appendix S13).

Figure 9 demonstrates the effect of variable selection on the climatic dissimilarity between a single location and all other locations in the 1971–2000 reference period. Consistent with Fig. 8, full seasonality has a marginal effect on climatic similarity, but variable sets including T_{min} and T_{max} yield a substantially more specific definition of climate than those using T_{ave}. In particular, equivalent climates (<1σ dissimilarity) are regionally limited in the 12-variable climate space, but extend throughout the southwest USA in the four-variable climate space. A

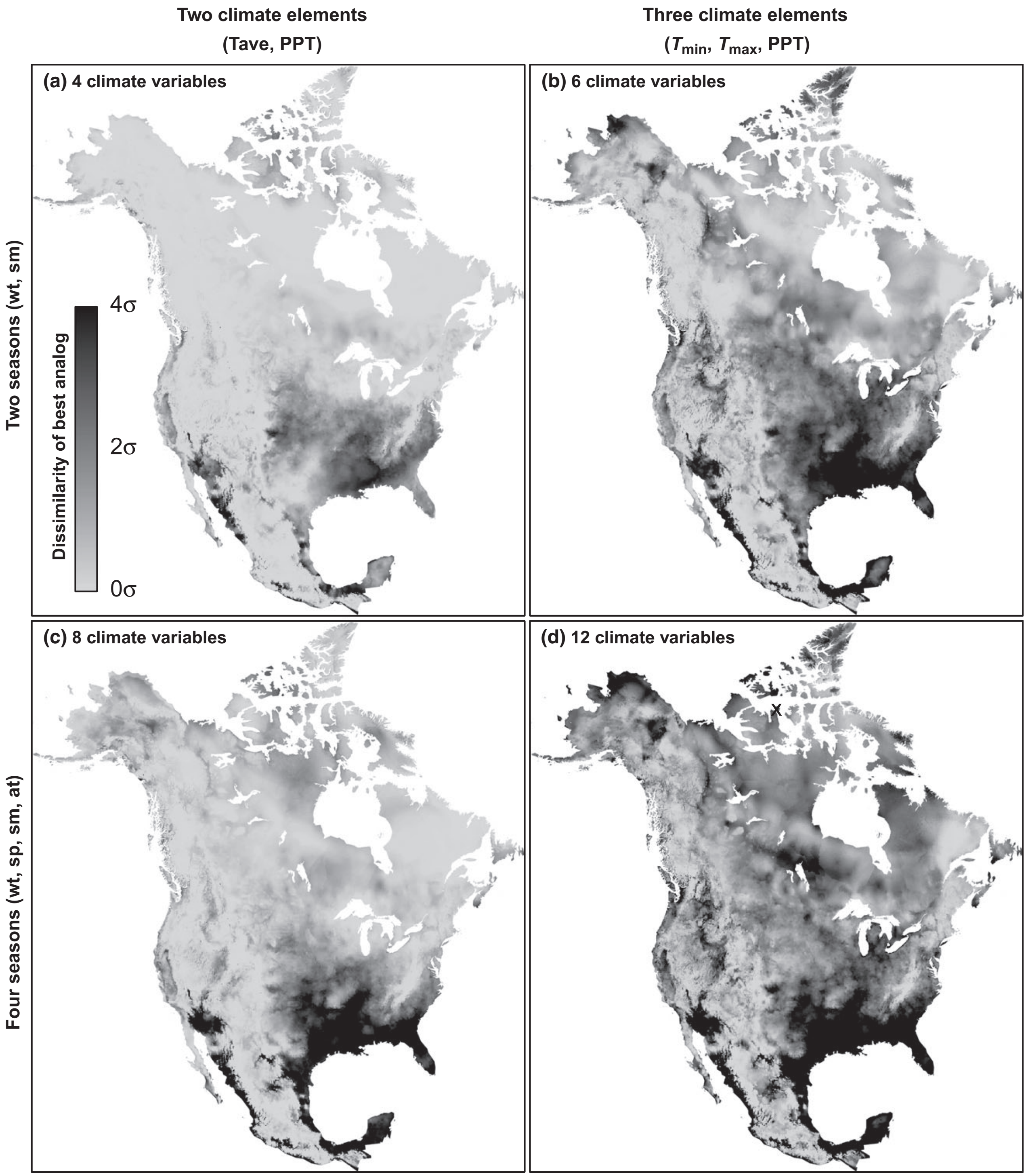

Fig. 8 Effect of variable selection on novelty of the RCP8.5 ensemble mean projection. The 12-variable novelty (panel d) is the same as the main results presented in Fig. 7. Novelty is highly sensitive to the use of seasonal mean daily temperature (T_{ave}) instead of seasonal mean minimum and maximum daily temperature (T_{min}, T_{max}). Novelty is less sensitive to the use of two seasons instead of four. Results for RCP4.5 are provided in Appendix S12.

subjective assessment of several locations indicates that the relative sensitivity to variable selection is highly inconsistent in different locations of the continent (Appendix S12: Figures S22–S33). In addition, different locations show very large variation in the climatic specificity associated with any given set of variables.

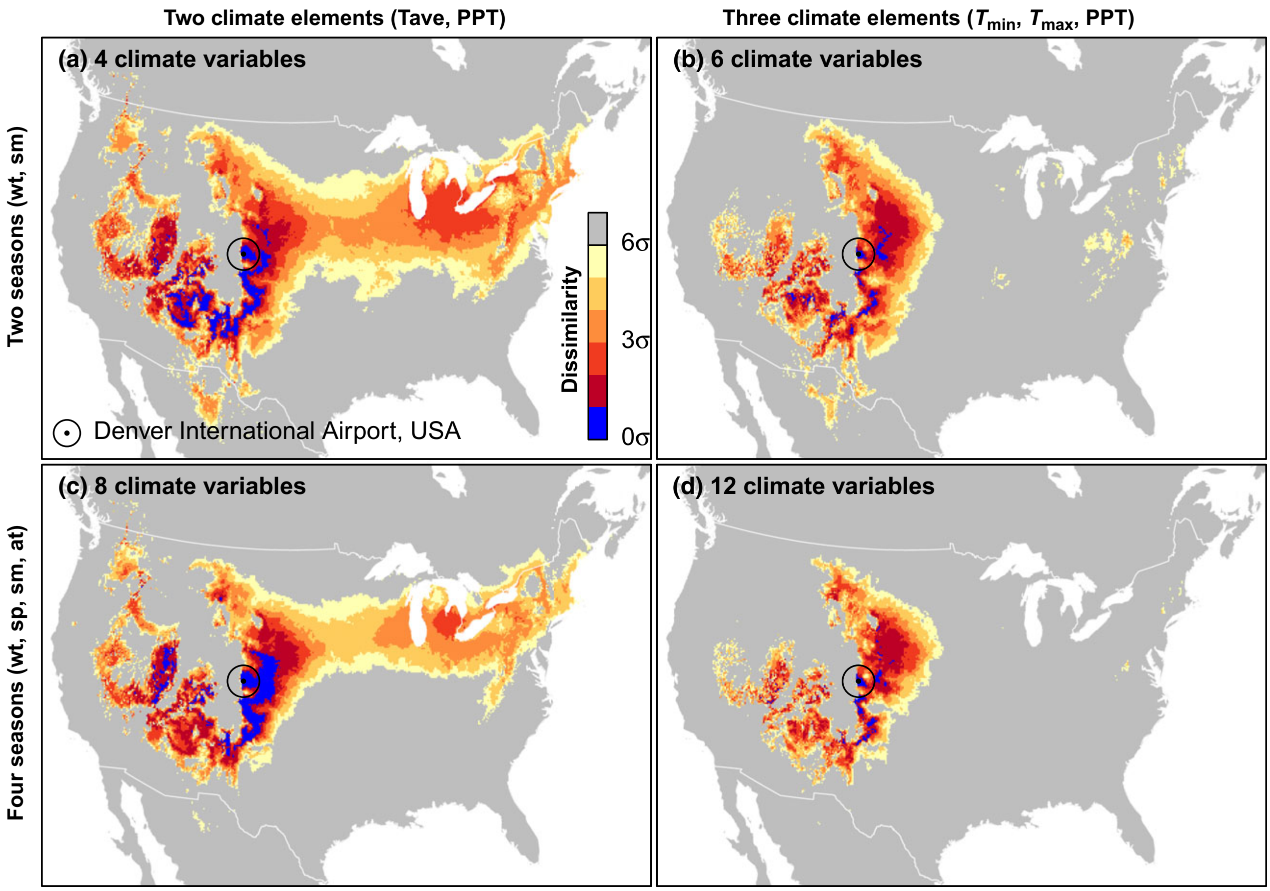

Fig. 9 Effect of variable selection on reference period (1971–2000) dissimilarity to a single location (Denver, CO). The 12-variable climate space (panel d) corresponds to the default variable selection this study. Seasonal mean minimum and maximum daily temperature (T_{min}, T_{max}) collectively provide a higher degree of climatic specificity than seasonal mean daily temperature (T_{ave}). Maps for other locations are provided in Appendix S12.

Inter-model variation

RCP4.5 novelty projections of the 15 individual models in the ensemble reveal large inter-model variation that exceeds the difference between mean projections for RCP4.5 and RCP8.5 (Fig. 10 and Appendix S6: Figure S10). Despite large inter-model variation, the RCP4.5 ensemble mean projection produces a pattern of novelty that is identical to the average of separate novelty calculations on the 15 individual ensemble models (Appendix S6: Figure S11). On average, the ensemble mean projection has a small bias toward lower novelty relative to the mean novelty of the individual ensemble models.

Drivers of novelty

Figure 11 provides a visualization of the mechanism of widespread emergence of novel climates over the eastern continental interior evident in the RCP8.5 scenario. This plot was generated by performing a PCA on the [X′] matrix of Montreal, Quebec. The principal components are the dominant modes of spatial climatic variation across North America relative to the local ICV of Montreal. In the first two dimensions of the climate space (PC1 and PC2), Montreal appears to be in the interior of the climate envelope. However, viewing the third dimension of the local climate space reveals that Montreal is located on or near an edge of the North American climate envelope that extends the length of the continent from the northern Gulf of Mexico coast (Houston, Texas) to the Arctic (Yukon Basin). This plot illustrates that novelty is a consequence of components of the climate change trajectory that do not align with locally relevant spatial climatic gradients. Topographically uniform landscapes have fewer spatial climatic gradients and consequently are more susceptible to the emergence of novel climates.

Despite being localized to Montreal, Fig. 11a also illustrates the basis for emergence of novel climates in several other regions of the continent. The tropical rainforest (e.g., Chiapas, Mexico) and subtropical desert

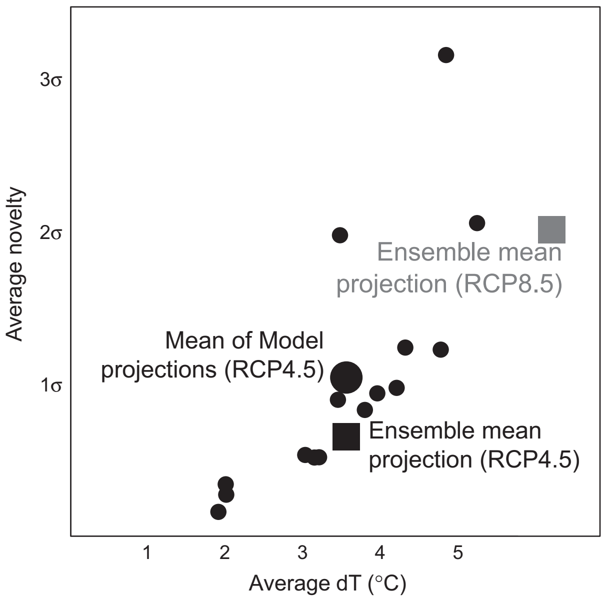

Fig. 10 Comparison of the ensemble mean projections to individual RCP4.5 projections of the 15 models in the ensemble. *X*-axis: North American average dT, the difference in mean annual temperature between the 2071–2100 and 1971–2000 periods. *Y*-axis: average novelty over North America.

climates (e.g., Sonoran desert) are on the leading edge of the temperature distribution of the continent. However, other leading edges are visible. The temperate rainforest climates represented by Prince Rupert, British Columbia, form a pronounced lobe in the North American climate envelope due to their high precipitation. Similar but smaller elevation-associated lobes are visible for the Yukon River Basin (locally warm/dry), and the upper elevations of Ellesmere Island (locally cold/wet). Each of these lobes has a leading edge relative to the climate change trajectory, resulting in the emergence of novel climates.

Relationship between novelty and topographic position

There is a strong relationship between topographic position and novelty (Fig. 12). In the RCP4.5 scenario, 2σ novelty is essentially limited to the lower half of the elevation range in all ecoregions with topographic relief (Fig. 12c), and $>4\sigma$ extreme novelty is limited to very low topographic positions. RCP8.5 novelty is also strongly associated with low topographic positions and suggests an upslope expansion of novelty as the magnitude of climate change increases. In addition, the low point density at the origin of Fig. 12d indicates that low ($<1\sigma$) novelty is uncommon at low topographic positions in the RCP8.5 scenario. Comparison to a null model (Fig. 12e, f) indicates that the relationship between topographic position and novelty is not simply an artifact of declining land area at higher topographic positions. The observed relationship between topographic position and novelty is statistically distinct from the null model in both RCPs at subsamples of the spatial grid (n = 199 059) as low as n = 15 (Appendix S9), which can be assumed to eliminate the confounding effects of spatial autocorrelation on statistical significance (Gotelli & Ulrich, 2012). This very high power provides strong evidence that the relationship between topographic position and novelty is greater than expected by chance.

Relationship between novelty and analog source distance

Maps of analog source distances demonstrate the effect of topographic diversity on the geographical distance from which analogs must be sourced (Fig. 13a, b). Analogs are primarily sourced from nearby downhill locations in the Western Cordillera and Appalachian range. In contrast, latitudinal analog distances are greater in the more topographically uniform central and eastern portions of the continent. Very high ($>4\sigma$) novelty is associated with low elevational and latitudinal analog source distances (Fig. 13c, d).

There are several locations where the best analog is sourced from substantially higher relative elevations (>1000 m), notably the great central valley of California, the Snake and Columbia basins of the Pacific Northwest, the Chilcotin plateau of British Columbia, and the Rocky Mountain foothills of Alberta (Fig. 13a). As would be expected, these uphill analogs are sourced from distant southern locations (Figs 13b and 14a). It is notable that these uphill analogs are associated with a moderate 1–2σ novelty (Fig. 13c, d), that is, low analog goodness of fit.

Figure 14 further summarizes the relationship between elevation, latitude, and novelty. Uphill (downhill) analogs are exclusively associated with distant southern (northern) sources. Highly novel climates are strongly associated with nearby analogs. The reverse does not hold, however: There are many locations with simultaneously low levels of elevational distance, latitudinal distance, and novelty (not shown).

Discussion

Our results build on the findings of Williams *et al.* (2007). Like Williams *et al.*, we found that the warmer southern margins of the continent and the western Arctic are particularly prone to the emergence of novel climates. In addition, we found localized emergence of novel climates in lower topographic positions throughout the continent. Novel climates cover a limited area in the ensemble mean projection for the RCP4.5

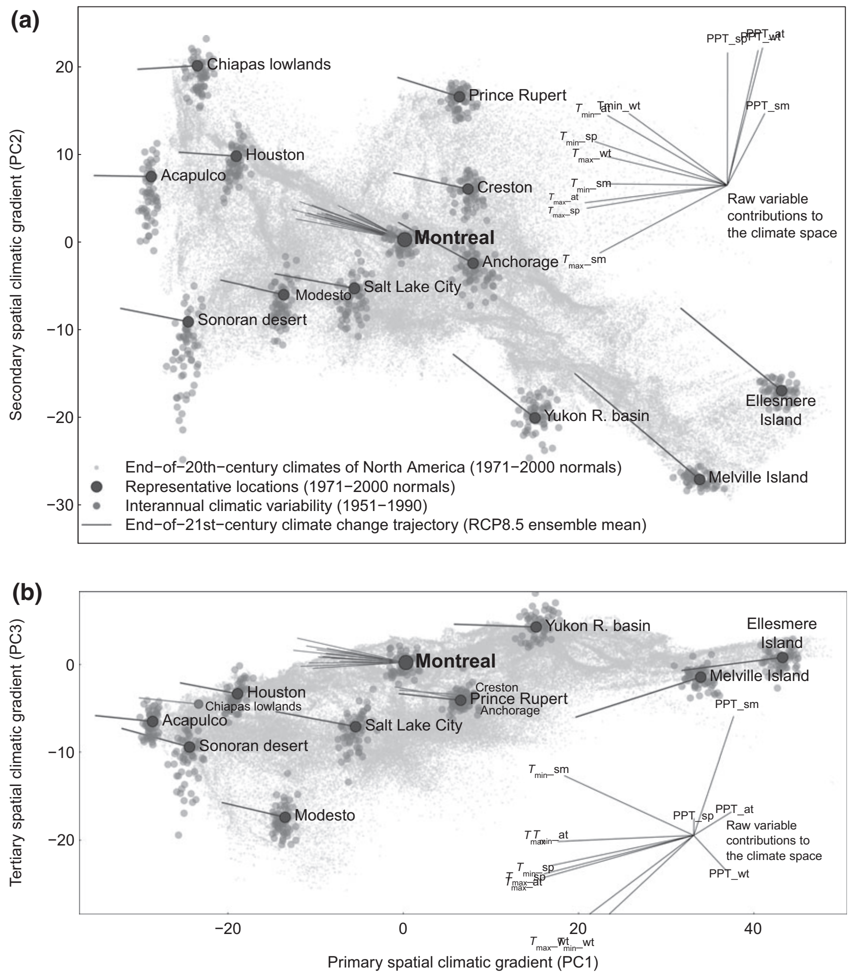

Fig. 11 The first three dimensions of the North American climate envelope plotted in the localized climate space of Montreal, Canada (a: PC1xPC2; b: PC1xPC3). The individual RCP8.5 climate change trajectories of the 15-model ensemble are plotted for Montreal. The RCP8.5 ensemble mean trajectory is plotted for several other locations (mapped in Fig. 1c).

emissions scenario (3.5 °C average warming over North America), but are widespread in RCP8.5 (6.2 °C warming). These three factors associated with a higher emergence of novel climates – regional susceptibility, topographic position, and the magnitude of projected climate change – can be viewed as *a priori* evaluation criteria for the credibility of bioclimatic projections. For example, species distribution model inferences for low topographic positions carry a higher burden of proof with respect to model extrapolation than other areas of the landscape. Other factors that limit analog availability, such as a sampling design that is truncated by a jurisdictional boundary, further increase the risk of model extrapolation and the burden of proof for proponents of bioclimatic models (Thuiller *et al.*, 2004). Our results are intended as a first approximation: Novelty is ultimately specific to each bioclimatic model. Our finding that most landscapes are prone to localized emergence of novel climates underscores the critical role of novelty assessments in validating projections of how species and ecosystems will respond to climate change.

Variable selection

We have demonstrated that variable selection is a critical consideration in novel climate detection. In the absence of a measure of biological response, there is no objective basis to prefer the 12-variable climate used for primary results in our paper over the four-variable climate of Williams *et al.* (2007). These variable sets sit on a continuum from a very general (i.e., one variable) characterization of climate, which would result in essentially no novelty, to a very specific one, which would result in nearly ubiquitous novelty. The art of novelty detection lies in finding an ecologically meaningful level of climatic specificity along this continuum. Broadly speaking, the four-variable climate produces a generalized, biome-scale definition of

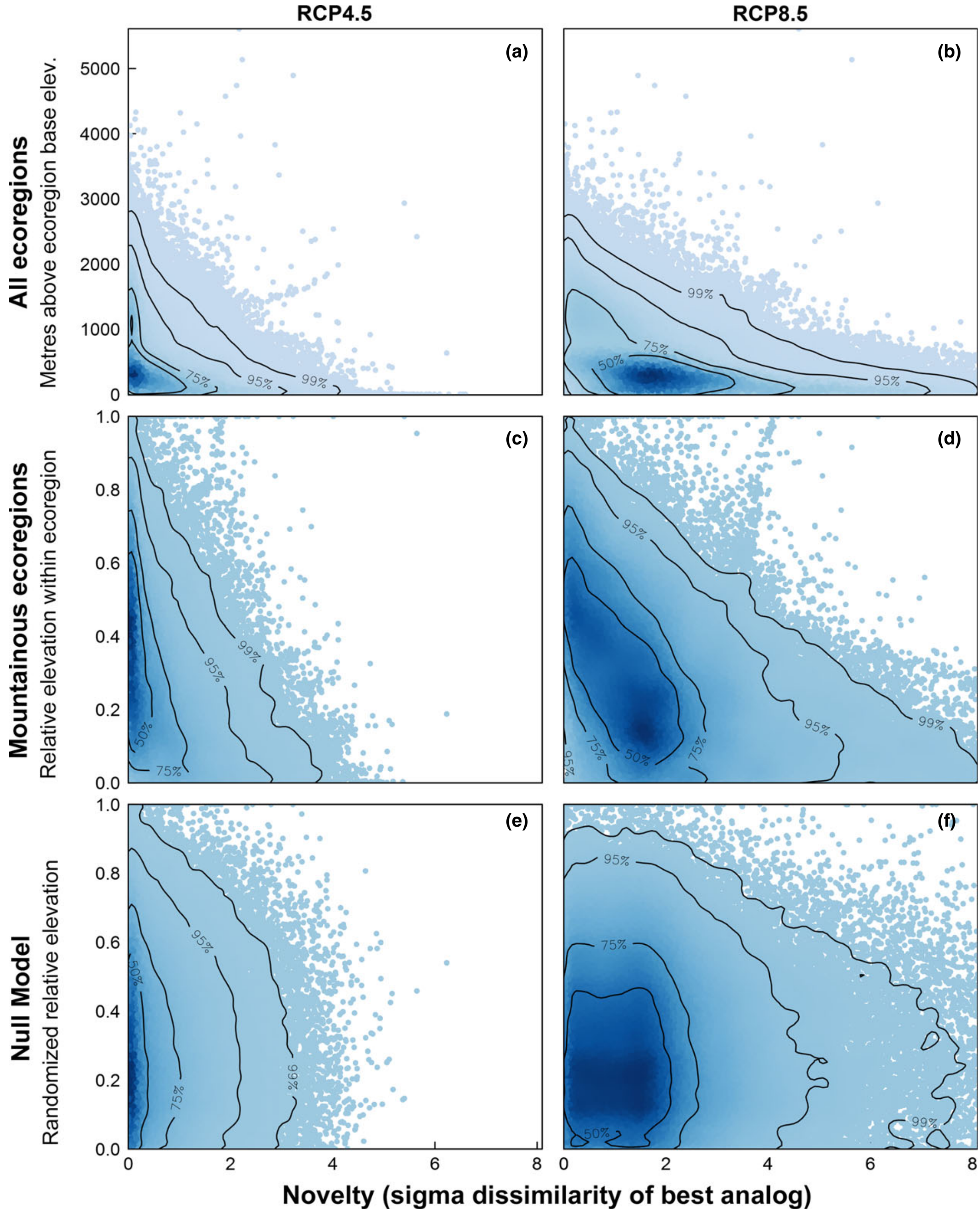

Fig. 12 Relationship between novelty and topographic position in RCP4.5 (a, c) and RCP8.5 (b, d). Topographic position is calculated as meters above the minimum elevation of each ecoregion (a, b), and alternately as a proportion of the elevation range within each ecoregion (c, d). (a) and (b) show results for all map cells in the continent (150 ecoregions, n = 331 360), but observations in (c, d) are limited to ecoregions with an elevation range >1000 m (97 ecoregions, n = 199 056). Color shading is in proportion to point density. (e) and (f) are null models for (c) and (d), generated by randomizing relative elevation; randomizing novelty produces an identical distribution. [Colour figure can be viewed at wileyonlinelibrary.com]

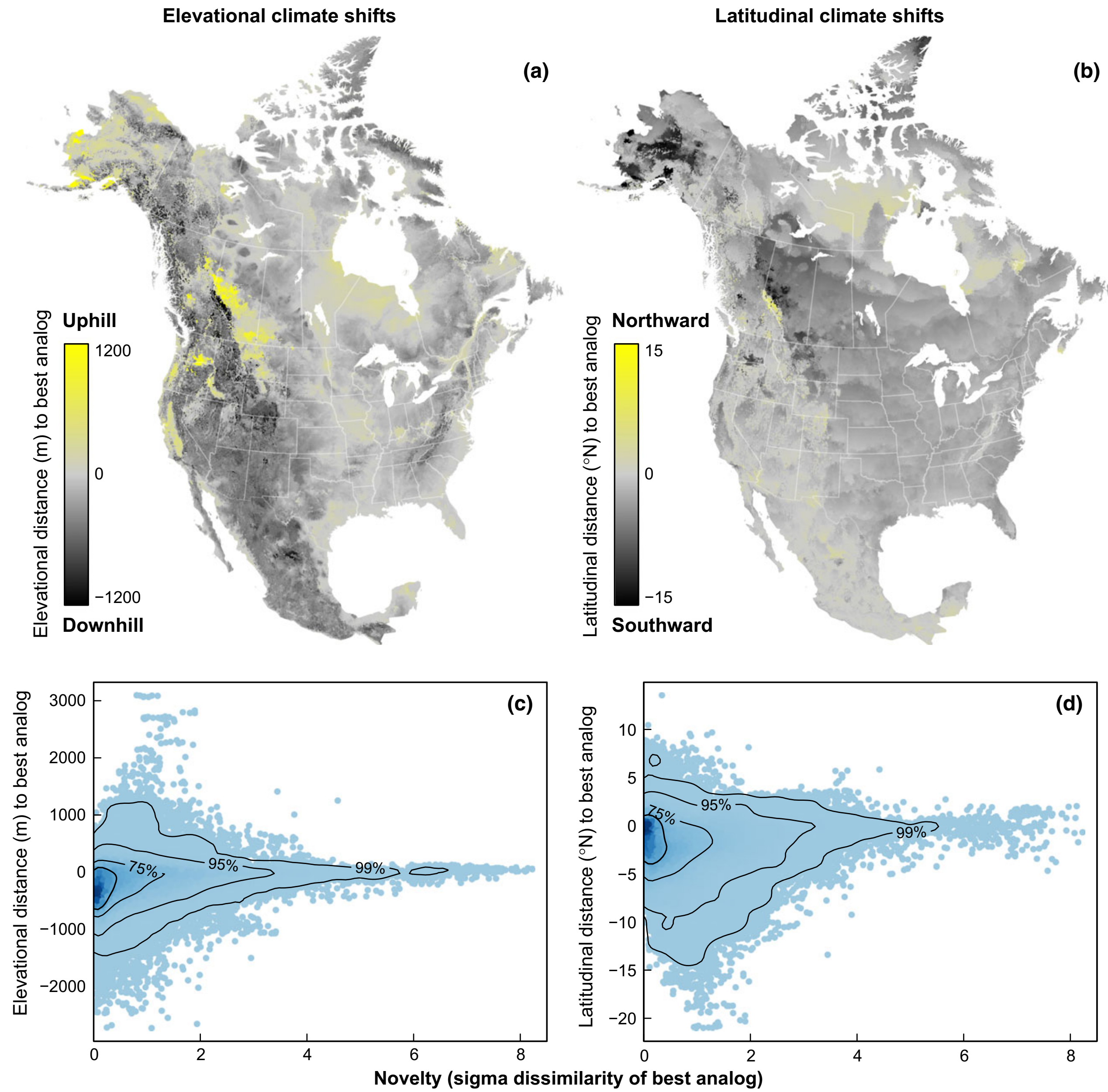

Fig. 13 Elevational and latitudinal climate shifts (distance to best analog) in the RCP4.5 ensemble mean projection, and their relationship to novelty. (a, b): Analogs are generally sourced from lower elevations and/or southern latitudes, but not always. Downslope analogs are widely available in western North America, but analogs must be sourced over larger latitudinal distances in eastern North America. (c, d): High novelty is associated with low elevational and latitudinal distances to the best analog. [Colour figure can be viewed at wileyonlinelibrary.com]

climate, while the 12-variable climate produces a much more spatially constrained pattern of climatic similarity relevant to a finer ecological scale (Fig. 9). However, the similarity maps for specific locations (Appendix S12: Figures S22–S33) suggest that the climatic specificity of any given set of climate variables is highly inconsistent between regions. This result suggests that the novelty associated with a single set of variables cannot be assumed to be relevant to a consistent scale of ecological differentiation, such as biomes or plant associations. Techniques for localized variable selection – mirroring the use of interannual variability for localized variable scaling – are an important priority in the future development of novelty detection methods. By generalizing distance measurements made at different dimensionalities, the

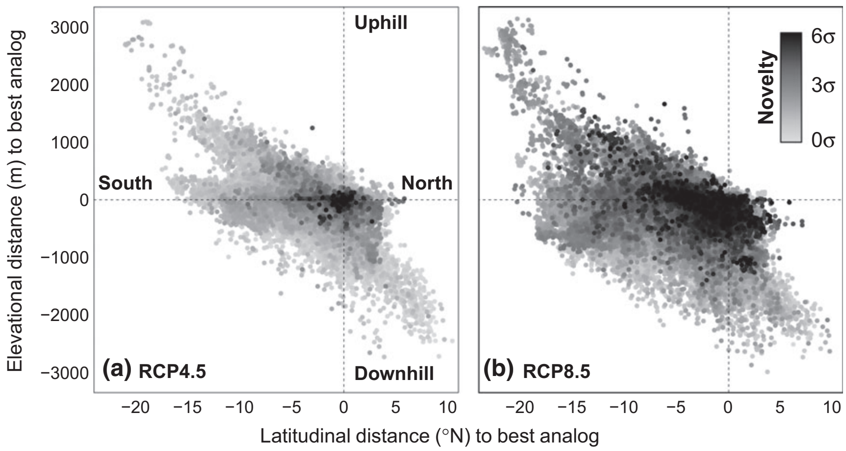

Fig. 14 Relationships between novelty with elevational and latitudinal climate shifts (distances to best analog), in the ensemble mean projection for the RCP4.5 (a) and RCP8.5 (b) scenarios. Highly novel climates are strongly associated with nearby analogs.

sigma dissimilarity metric can facilitate progress in localized variable selection.

The use of T_{ave} vs. T_{min} and T_{max} is the major factor driving the differences between novelty associated with the four-variable and 12-variable climates. This sensitivity to replacing T_{ave} with T_{min} and T_{max} is observed in the dissimilarity maps (Fig. 9 and Appendix S12) and therefore is not primarily attributable to inconsistencies between the observational (historical) and modeled (future) data. This sensitivity also cannot be attributed to an imbalance between the number of temperature and precipitation variables, since balancing the variable set with additional precipitation variables has little effect on climatic similarity (Appendix S12: Figure S34). These analyses indicate that replacing T_{ave} with T_{min} and T_{max} provides substantial additional information to differentiate distinct climates. Given that changes to the diurnal temperature range are a signature of an enhanced greenhouse effect (Braganza *et al.*, 2004), and to the extent that diurnal temperature range can be considered to be ecologically relevant, the use of T_{min} and T_{max} appears to be an important consideration in detecting novelty.

Added value of Mahalanobis distance over SED

Mahalanobis distance can either decrease or increase distance relative to SED, depending on whether or not the direction of measurement is aligned with the dominant variable correlations, which in this study are the dominant modes of historical climatic variability. We found that Mahalanobis distance generally increases novelty and spatial dissimilarity relative to SED, though SED produced higher novelty in some locations (Appendix S13). The differences between the two distance metrics were subtle in the four-variable climate definition of Williams *et al.* (2007), but pronounced when T_{ave} was replaced with T_{min} and T_{max} for the six- and 12-variable climates. The ability to accommodate the correlations of these variables is a key advantage of Mahalanobis distance over SED, given that goal of the distance measurement is to detect deviations from the historical pattern of variability. Our results suggest that the added value of Mahalanobis distance over SED may be marginal in simple definitions of climate (e.g., Williams *et al.*, 2007), but is substantial in the larger and more correlated variable sets required for continental- and landscape-level analyses.

Implications of ignoring interannual climatic variability (ICV) of the analog climate

Our method hinges on the ICV of the location of interest, but ignores the ICV of candidate analogs. This asymmetry creates the potential for equivalencies to be drawn between climates with biologically relevant (Jackson *et al.*, 2009) differences in modes of variability, such as the type and frequency of extremes. Metrics of goodness of fit of ICV, such as the multidimensional Kolmogorov–Smirnov statistic (Fasano & Franceschini, 1987), are preferable for small analog pools (e.g., Kopf *et al.*, 2008), but are computationally unfeasible for continental-scale analysis at high spatial resolution. Adding an ICV criterion to the analog dissimilarity metric would inevitably result in increased localization of climatic similarity, and thus higher novelty. For this reason, our method can be expected to underestimate novelty relative to a method that accounts for analog ICV, particularly at locations with geographically distant analogs.

Errors associated with observational data

An important methodological difference between our study and Williams *et al.* (2007) is our use of observational data for the base climatology and ICV, instead of the internal climatology and variability of the ensemble models. High-resolution observational data are critical to adequately sampling the analog pool of the continent and to eliminating systematic downward biases in ICV due to grid cell averaging (Director & Bornn, 2015). The disadvantage of combining high-resolution observational climatology with model projections is the loss of physical consistency in the analysis. For example, in the process of delta-downscaling, model projections may be transferred to regions of the climate space, such as hypermaritime and high-elevation climates, that are not represented in the coarse grid of the global climate model (Wilby *et al.*, 2004). Another example is that the timing of multidecadal variability in the model runs may not be in phase with the observed climate used for delta-downscaling, resulting in exaggeration or damping of the climate change signal. These and other discontinuities between the observed historical and modeled future climate are an unquantified source of error in this analysis. These errors could be reduced through more sophisticated downscaling approaches that were out of scope for this first-approximation analysis. Note also that sigma dissimilarity assumes multivariate normality of ICV, and our results are sensitive to this assumption (Appendix S8: Figure S16).

Errors associated with ICV proxies

We used weather station data as point-level estimates of climatic variability and covariance. Despite several advantages to this approach, it carries some particular sources of error. Incomplete years in the time series are unavailable to the PCA, which is expected to be unstable at small sample sizes. In our study, areas with very small sample size are limited (Appendix S14: Figure S38). Further, the similarity between the 12-dimensional results and the six-dimensional results (Fig. 8 and Appendix S12: Figure S21) suggests that limited sample size relative to dimensionality is not a major source of error in this analysis. However, reliable estimation of error in sigma dissimilarity is nontrivial (Appendix S14), and the ratio of time series observations to the dimensionality of the sigma dissimilarity calculation should be maximized wherever possible.

The potential for bias due to nonrandom weather station placement is an inevitable limitation of the use of weather stations as proxies for local variability. High topographic positions are systematically undersampled by weather stations and therefore are likely to be poorly represented by their ICV proxies. However, our inferences of novelty at low topographic positions are robust to this source of error. The potential for cross-contamination between the distinct ICV patterns of maritime and continental climates is another potential artifact of the use of weather stations as ICV proxies. Mexico, the contiguous United States, and coastal British Columbia have sufficient station density in the coast-interior transition that conflation of distinct regional climates can reasonably be ruled out as a source of error. In contrast, very low station density in the boreal and Arctic regions suggests that results for these regions should be interpreted at a coarse spatial scale (Appendix S11).

The weather station data for Mexico are of poorer quality than for Canada and the United States, with longer distances between coupled precipitation and temperature stations (Appendix S1: Figure S3), lower number of complete years (Appendix S1: Figure S5), and higher potential for PCA artifacts (Appendix S2: Figure S7). In addition, novelty in southern Mexico is expected to be exaggerated due to the arbitrary truncation of the study area at the border with Guatemala, and hence the unavailability of analogs in Central America. For these reasons, novelty results for Mexico should be viewed with caution. These issues do not affect the role of Mexico as an analog pool for the United States.

Inter-model variation

We found that inter-model variation in RCP4.5 novelty projections exceeds the substantial difference between novelty of the RCP4.5 and RCP8.5 ensemble mean projections. This finding mirrors several species distribution modeling studies with inter-model uncertainty greater than scenario uncertainty (e.g., Real *et al.*, 2010; Goberville *et al.*, 2015). Inter-model variation may be due to structural differences in the models, but may also be due to intrinsic variability of the modeled climate system (Hawkins & Sutton, 2009) and downscaling biases. Internal variability can dominate inter-model variation at local scales in North America (Kay *et al.*, 2015), particularly for precipitation variables (Deser *et al.*, 2012). Two of the high-novelty outliers in the RCP4.5 individual model projections, IPSL-CM5A-MR and GFDL-CM3, are based on only one model run (Appendix S5: Table S2), which increases the potential for these model projections to be influenced by internal variability. However, the greatest outlier, HadGEM-ES, is itself the mean of 4 runs of the model, which suggests that the very high novelty from this model is due to structural model differences rather than internal variability. Despite the limited extent of novelty in the RCP4.5 ensemble mean projection, the presence of high-novelty projections in the RCP4.5 ensemble suggests that the potential for widespread emergence of novel climates cannot be disregarded even under a scenario of substantial global emissions reductions.

Relationship between climatic novelty and climate velocity

The distance and elevation from which an analog must be sourced is relevant to several conservation and management considerations. Emergence of climates with distant analogs can, at first approximation, be considered to be more ecologically problematic than those with nearby downslope analogs, because climatically adapted organisms are less likely to be locally available (Hamann *et al.*, 2015). Distant analogs also are less credible, as they are more likely to have additional biologically important environmental differences not captured by the climate variables used in the analysis. The trade-off between elevation and geographical distance in sourcing analogs is central to the concept of climate velocity (Loarie *et al.*, 2009), the speed at which climate conditions shift over the landscape in a changing climate. In the context of novel climates, we are interested in 'backward velocity' from a future condition to a historical analog (Hamann *et al.*, 2015), which can be thought of as the geographical distance from which ecological data must be sourced to match the evolving climate in a location of interest. In this study, we found that novel climates are associated with analogs that are proximal to the focal location in both elevation and latitude. This result suggests an inverse relationship between climatic novelty and climate velocity, though the mechanism for this relationship is not clear from our results. Low climate velocity can be due to the availability of downslope analogs, but it can also be due to a lack of good analogs in the study area. Similar to climatic novelty, backward climate velocity is associated with low topographic positions (Hamann *et al.*, 2015), yet novelty and velocity represent distinct risks to ecological knowledge and the validity of ecological models. Our results indicate that novel climates are an important dimension in the measurement and interpretation of climate velocity.

Drivers of novelty at low topographic positions

The key outcome of our high-resolution analysis is the detection of novel climates at low topographic positions throughout the continent. This emergence of landscape-level novelty is strongly influenced by how specifically the climate is defined – it is absent in the four-variable climate but prominent in the six- and 12-variable climates – suggesting that localization of climatic similarity is the mechanism for this pattern of novelty. Warming climates at higher elevations are likely to have downhill analogs with a similar historical seasonality and diurnality. In contrast, analogs for the lowest topographic positions are inevitably in nonlocal regions that are more likely to have different patterns of seasonal and diurnal climatic variation, and thus higher sigma dissimilarity. The importance of this localized climatic signature is also suggested by the association of novel climates with geographically proximal analogs.

In some ways, this effect can be considered an artifact of the equal weight given to all variables within the sigma dissimilarity calculation, notwithstanding the scaling to ICV. For example, summer drought may be a critical factor driving a species or ecological community that can tolerate a wide range of winter conditions. In this hypothetical case, there may be many ecologically equivalent analogs in other regions that would not be detected by our method. However, novelty could conversely be underestimated in other ecological situations requiring a more specific definition of climate than we have used. This distinction highlights the ultimate necessity for case-specific novelty assessments that are informed by relevant biological responses. Given the current scarcity of methods for case-specific novelty assessments, discussed below, the detection of low-elevation novelty in our study represents a useful first approximation of extrapolation risk at the landscape scale.

The need for intrinsic model extrapolation detection

Techniques to detect model extrapolation have not kept pace with the development of sophisticated algorithms for bioclimatic modeling. Model extrapolation is typically assessed *extrinsically*, that is, outside of the model itself, with little connection to its nonlinear relationships. The most common extrinsic methods simply detect projections outside the numerical range of training data in individual variables (e.g., multivariate environmental similarity surfaces, Elith *et al.*, 2010), though applications of Mahalanobis distance for multivariate extrapolation detection are gaining recognition (Mesgaran *et al.*, 2014). *Intrinsic* extrapolation detection algorithms that account for the nonlinear, multivariate structure of today's bioclimatic models are preferable, but have largely been elusive. Opportunities for intrinsic novelty detection, such as those presented by the proximity matrix of Random Forest (Breiman, 2001), should be vigorously pursued.

Credibility of RCP8.5 bioclimatic projections

The widespread emergence of novel climates in the RCP8.5 projections for the end of the 21st century underscores the pitfalls of modeling ecological responses to extreme climate change (Wiens *et al*., 2009). The scale of climate change under this scenario requires that analogs be sourced at large geographical or elevational distances, which likely removes analogs from a meaningful biophysical context. Hence, even where analogs are found in an RCP8.5 end-of-century projection, their credibility is dubious. Our results suggest that bioclimatic model projections using the RCP4.5 scenario can be considered – at first approximation – to carry an acceptable risk of model extrapolation in areas where we did not find novel climates. However, the validity of end-of-century bioclimatic projections based on RCP8.5, in any location, should be carefully considered due to high risk of model extrapolation into novel climate space.

Managing novel climates

If bioclimatic models are unreliable in novel climates, what is the alternative? In the absence of directly applicable observational data, ecological prediction in novel climates is likely to be more art than science, demanding ecological wisdom that integrates diverse information sources (Dawson *et al*., 2011). Emerging novel climates will inevitably retain vestiges of their historical character, such as the relative characteristics of their seasonal cycle, ICV, and spatial pattern. Despite some enduring familiarity, however, novel climates are likely to be less tractable to accumulated ecological knowledge, and thus represent a higher risk of management failures (Williams & Jackson, 2007). The widespread novelty observed in the RCP8.5 scenario of this study likely represents a serious threat to the ability of ecological practitioners to plan for the future. Novel climates intensify the challenges of adaptation to climate change, and add to the urgency of greenhouse gas emissions reductions.

Since climate is a fundamental driver of ecological function, the use of climate analogs underpins ecology as a predictive science. When we use data collected from one place or time as ecological insight into another, we implicitly assume that the two climatic contexts are sufficiently similar for this knowledge to be transferable. Yet understanding and communicating the limits to the transferability of knowledge is equally foundational to ecology. Climate change is forcing ecologists to generalize available ecological information to locally unfamiliar conditions. Bioclimatic models are a valuable tool in this effort. Nevertheless, ecologists should be increasingly vigilant for climatic conditions that are poorly sampled by observational data. Identification of novel climates helps us to differentiate contexts in which bioclimatic models can be informative from those in which other approaches are necessary. This study provides *a priori* risk factors for emergence of novel climates. However, operational and ecologically specific detection of novel climates remains an open problem in the field of bioclimatic modeling.

Acknowledgements

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Selection of reference interannual variability data.
Appendix S2. Rationale for the PCA truncation threshold.
Appendix S3. Method of subsampling the analog pool.
Appendix S4. Equations for step 2 (PCA) of the Mahalanobis distance calculation.
Appendix S5. CMIP5 ensemble models.
Appendix S6. RCP4.5 novelty assessment for individual ensemble models.
Appendix S7. Investigating analog outliers.
Appendix S8. Accounting for non-normality in the distribution of ICV.
Appendix S9. Null model analysis of elevation-novelty relationship.

Appendix S10. Variation around mean novelty from multiple ICV proxies.
Appendix S11. Bias due to nonrandom weather station placement.
Appendix S12. Variable selection.
Appendix S13. Comparison to standardized Euclidean distance.
Appendix S14. Assessment of error due to ICV sample size.
Appendix S15. Basic Code for calculating and mapping climatic novelty using the sigma dissimilarity metric.
Appendix S16. Spatial data for Fig. 7.