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Novel climates: Trajectories of climate change beyond the boundaries of British Columbia's forest management knowledge system

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ABSTRACT

The non-stationary climates of the 21st century are compelling forest managers to seek non-local species, provenances, and silvicultural regimes that are better suited to the anticipated future climates of their operating areas. Ideally, forest managers can source this information from climate analogs within their jurisdictions, but the emergence of unfamiliar climates is a distinct possibility with particular challenges. Here, we present an assessment of the emergence of mid-21st-century climates with no analog in the 20th-century climates of British Columbia (BC), and the extent to which these novel climates are described by climate analogs elsewhere in North America. We use a recently developed linear method of novel climate detection in parallel with Random Forest classification to evaluate the robustness of novel climate inferences. Our results suggest that a majority of the province's area will remain free of novel climates over this time period, and therefore that BC's ecological knowledge system, the Biogeoclimatic Ecosystem Classification, can remain the dominant source of climate analogs for mid-21st-century forest management planning horizons. Nevertheless, we detected a robust pattern of climates that are novel to BC in mid-21st-century climate projections at low elevations in the coastal, southern interior, and northeastern regions of the province. There appears to be potential to inform forest management in some of these novel climates with analogs from adjacent states and provinces. We demonstrate that extrapolations into novel climates typically understate the magnitude of climate change and modeling uncertainty, creating a false impression of robust predictions in locations where model performance is poorest. By identifying portions of their landscapes that are prone to emergence of novel climates, forest managers can avoid management errors and prioritize the search for analogs beyond the boundaries of their knowledge systems.

1. Introduction

1.1. Emerging challenges to the "local is best" ethic in forest management

The necessity to adopt non-local practices in response to climate change is a major new dimension in forest management. Historically, forest managers have developed specialized management regimes for their local ecosystems (Puettmann et al., 2009). The complex interactions of productivity, competition, stress, and disturbance are often idiosyncratic to individual places, leading forest managers towards a "local is best" ethic with respect to silvicultural systems, stand-tending practices, and species and provenance selection (Seymour et al., 2002; Ying and Yanchuk, 2006). These local idiosyncrasies are strongly driven by climate (Pojar et al., 1987), but the climates of the 20th century were sufficiently stable for forest managers to understand climate as a stationary quality of place. The non-stationary climates of the 21st century are a fundamental challenge to this place-based understanding of climate and ecosystem function (Millar et al., 2007). Forest managers have entered an era in which the "local is best" ethic is no longer reliable, and are looking to other locations for species, provenances, and management regimes that may be better suited to the anticipated future climates of their jurisdictions (Potter and Hargrove, 2012; Williams and Dumroese, 2013). This use of non-local climate analogs is an emerging cornerstone of 21st century forestry management, and underlies assisted migration through remote provenance selection (Aitken and Whitlock, 2013), assisted range expansion (Rehfeldt and Jaquish, 2010), and *in situ* tree species conservation (Hamann and Aitken, 2013). Moreover, climate analogs are essential to maintaining the relevance of accumulated practitioner knowledge in a changing climate. As climate zones shift across the landscape, so must the ecological knowledge with which they are associated.

Where analogs for anticipated future climates are available within

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local jurisdictional boundaries—e.g., from downhill locations—forest managers are able to draw on their familiar local knowledge systems. However, the projected magnitude of climate change over forest management timescales is compelling forest managers to look for climate analogs in the relatively unfamiliar climates of other jurisdictions (Potter and Hargrove, 2012). While some locally unfamiliar climates may have historical analogs in nearby jurisdictions, previous research suggests the potential for novel climates that have no historical analogs at continental (Rehfeldt et al., 2012; Mahony et al., 2017) and even global (Williams et al., 2007; García-López and Allué, 2013) scales. These truly novel climates represent conditions for which little knowledge is available from observational experience (Williams and Jackson, 2007), and therefore for which ecological predictions are unreliable (Fitzpatrick and Hargrove, 2009). Forest management in a changing climate will inevitably involve some extrapolation of accumulated knowledge into novel, unfamiliar conditions. Nevertheless, the risk of management failures will likely increase with the degree of extrapolation (Peterson et al., 2011, pp. 126–8). Measurement of novelty in projections of climate change indicates the degree of confidence that can be placed in climate analogs for forest management guidance.

1.2. Novel climates in the British Columbia forest management context

The use of climate analogs for climate change adaptation is in the early stages of being operationalized in British Columbia. For the past 50 years, forest practices and legislation in British Columbia have been organized under a province-wide structured knowledge system named the Biogeoclimatic Ecosystem Classification (BEC; MacKenzie and Meidinger, 2017; Haeussler, 2011). BEC includes, as one of its central pillars, a hierarchical climate classification with 16 zones (Fig. 1), ~100 subzones, and ~200 subzone-variants. Though BEC climates were originally conceived as static map units, spatial shifts in BEC climate units have been projected by using these units as analogs for the future climates projected by global climate models (Hamann and Wang, 2006; Wang et al., 2012). BEC unit projections are being used in an overhaul of the BC government's tree seed transfer framework, in which seed transfer limits are defined by BEC units and shifted in space in accordance with their projected future spatial distribution (O'Neill et al., 2017). BEC unit projections are also being used to incorporate

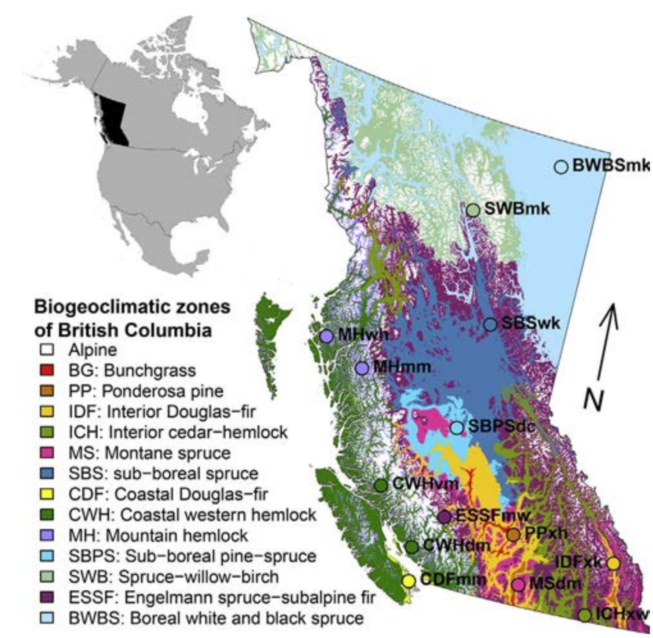

Fig. 1. Biogeoclimatic zones of British Columbia, the highest level of the BEC climate classification. Representative locations for a small sample of BEC subzones (see Supplementary Table S1 for full names) are provided for reference in subsequent figures.

climate change into provincial government's tree species suitability guidelines, by demoting or promoting individual species based on their historical suitability to the range of BEC units projected for a planting site. In providing a pool of climate analogs that are richly embedded with ecological knowledge, BEC is a coherent framework to guide the transfer of locally-adapted forest management strategies among regions and sites as their climates change.

The emergence of climates that are not described by the BEC system is an open problem in the use of climate analogs for forest management in British Columbia. Mismatch between future conditions of some locations and their BEC analogs should be expected, since current BEC projections do not draw on analogs from outside British Columbia. Two-dimensional seasonal temperature-precipitation envelopes for BC indicate that the warm edge of the BC climate envelope will develop novel climates (relative to historical BC climates) as it shifts due to climate change (Fig. 2). These simplified representations of climatic shifts suggest that the potential for novel climates is not limited to the warmest and driest areas of the province (e.g., the CDFmm subzone in the Georgia Basin and the PPxh subzone in the Okanagan Valley), but spans the warm margin of the climate envelope along the full range of precipitation regimes. The emergence of climates that are unfamiliar to the BEC system is an inevitable consequence of climate change. Further, previous research indicates the potential for future climates in British Columbia with no analogs in North America (Rehfeldt et al., 2012; Mahony et al., 2017).

The apparent potential for climate change to produce climate types that are novel to BC indicates that BEC projections are susceptible to extrapolation errors. Current BEC projections (Wang et al., 2012) provide the analog with the best match to projected conditions. The best match, however, is not necessarily a good match. Where extrapolation into novel climates results in a poor match between the projected future climate condition and its assigned analog within the BEC system, the BEC analog is likely to provide misleading guidance (Fitzpatrick and Hargrove, 2009). Undiagnosed use of poor-quality analogs has the potential to produce management failures due, for example, to inappropriate provenance or species selection for reforestation. It is essential to identify poor-quality analogs associated with novel climates, so that other more informative sources of guidance for management can be sought.

1.3. Measuring climatic novelty

Climatic novelty is subjective to the ecological context under consideration. The many variables with which climate can be characterized—growing season frosts, wind speed, fog, solar insolation, extreme events, snow-free period, and so on—have varying relevance to different species in different environments. The scales and thresholds at which these climate elements are relevant is similarly context-specific, due to differences in species' ecological tolerances. It follows that a climatic condition that is novel from the perspective of one ecological community may be functionally familiar to another.

The context-dependence of climatic novelty has important implications for how it is measured. The most prominent approach to novel climate detection defines novelty as the climatic distance (D_{min}) between the projected climate and its closest historical analog (Williams et al., 2007; Mahony et al., 2017). This distance is measured using a set of climate variables that is universal to all locations in the study. The relative magnitude (the scaling) of these climate variables is defined by standardizing them to their local interannual climatic variability. Although this linear scaling approach is localized, it does not necessarily reflect the complex and non-linear biological responses to climate that are idiosyncratic to each ecosystem. In contrast, BEC projections are currently produced using a machine learning algorithm, Random Forest (Breiman, 2001), that models the relationship between BEC units and climate using localized climate variable selection and non-linear scaling. Climatic novelty measured within the model

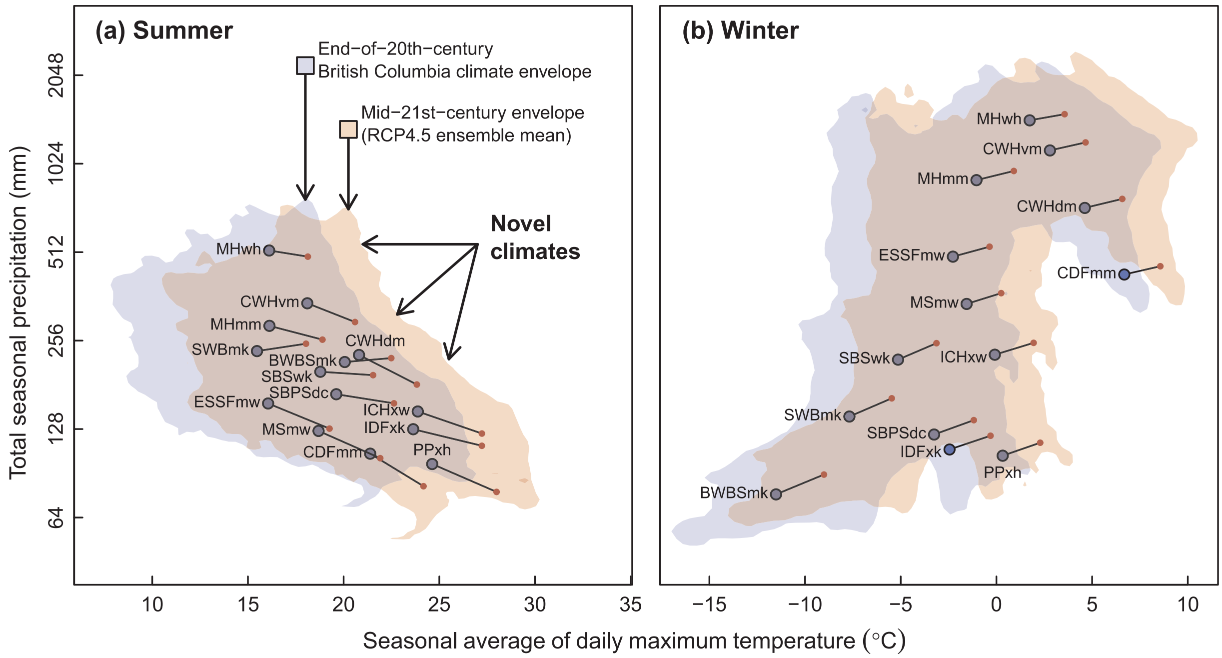

Fig. 2. Projected shifts in the British Columbian temperature-precipitation envelope in winter (a) and summer (b). RCP4.5 ensemble mean projection for the 2041–2070 period. Novel climates emerge along the leading edge of the shifting climate envelope. Climate change trajectories for a selection of BEC subzones (mapped in Fig. 1) are shown for reference, linking end-of-20th-century climates (blue dots) to the projected mid-21st-century climate (red dots). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

structure of Random Forest BEC classifications could be much more ecologically meaningful than novelty measured with the linear D_{min} approach. However, there currently are no established methods for novelty detection in Random Forest bioclimatic classifications, despite the availability of methods for simpler classification problems (Désir et al., 2013; Zhou et al., 2015) and the promising approach developed by Rehfeldt et al. (2012). In the absence of direct novelty detection with Random Forest, the D_{min} approach can provide a necessary approximation of which areas of British Columbia are susceptible to the emergence of novel climates. Further, the D_{min} approach can provide a point of comparison for evaluating indicators of novelty in Random Forest BEC projections and investigating how Random Forests behaves in the context of extrapolation.

1.4. Study objectives

The objectives of this study are to provide an assessment of where novel climates in British Columbia are likely to emerge by middle of the 21st century and to demonstrate the utility of this approach to forest management. We focus on the projected climates of the 2050s (2041–2070) as this period roughly corresponds with the midpoint of the 50–100-year harvest rotations typical of British Columbia and is of immediate significance to current reforestation and timber supply management decisions (O'Neill et al., 2017). We use our established linear method for detecting novel climates (Mahony et al., 2017) in parallel with Random Forest classification to evaluate (1) the robustness of novel climate inferences and (2) the extent to which these projected novel climates are described by climate analogs elsewhere in North America. In addition to providing specific insights for British Columbia, we find that overestimation of analog similarity and ensemble agreement are general characteristic errors of extrapolation into novel climates. We demonstrate that these quantities can be used as indicators of climatic novelty in machine learning bioclimatic projections.

2. Methods

2.1. Linear novelty detection method

The linear novelty detection method in this study follows the general approach of Williams et al. (2007) and the specific metric of Mahony et al. (2017). We calculate linear novelty (D_{min}) as the Mahalanobis distance (Mahalanobis, 1936) between the projected mid-21st-century (2041–2070) climate of a location of interest and its closest analog among the observed end-of-20th-century (1971–2000) climates of an analog pool (Fig. 3). The analog pool is either BC or North America depending on the analysis. This Mahalanobis distance is scaled to the historical interannual variability of the climate variables for the location of interest, as described in more detail below. This method is described mathematically in Supplementary Note S1. Unlike Mahony et al. (2017), we do not interpret Mahalanobis distances probabilistically using the sigma dissimilarity metric; novelty distances are instead interpreted in this paper in terms of the minimum distances between BEC units.

2.2. Random forest classification

2.2.1. Indicators of novelty in Random Forest projections

We propose two indicators of extrapolation into novel climates in Random Forest projections: Analog similarity and ensemble agreement (Fig. 4). We hypothesize that *analog similarity*—the similarity between a location's 20th-century climate and the 20th-century analog for its projected 21st-century climate—will tend to be greater for novel climates than for projected climates with good analogs. Where there is a good analog for the projected climate (location 1 in Fig. 4a), the analog dissimilarity (D_a) will be the same magnitude as the climate change trajectory (D_c). Where the climate change trajectory extends beyond the edge of the study area climate envelope (locations 2 and 3 in Fig. 4a), analog dissimilarity may in some cases (e.g., location 2 in Fig. 4a) be less than the magnitude of climate change ($D_a < D_c$). In extreme cases of novelty, where the climate change trajectory extends perpendicular from the leading edge of the study area climate envelope (e.g., the PPxh

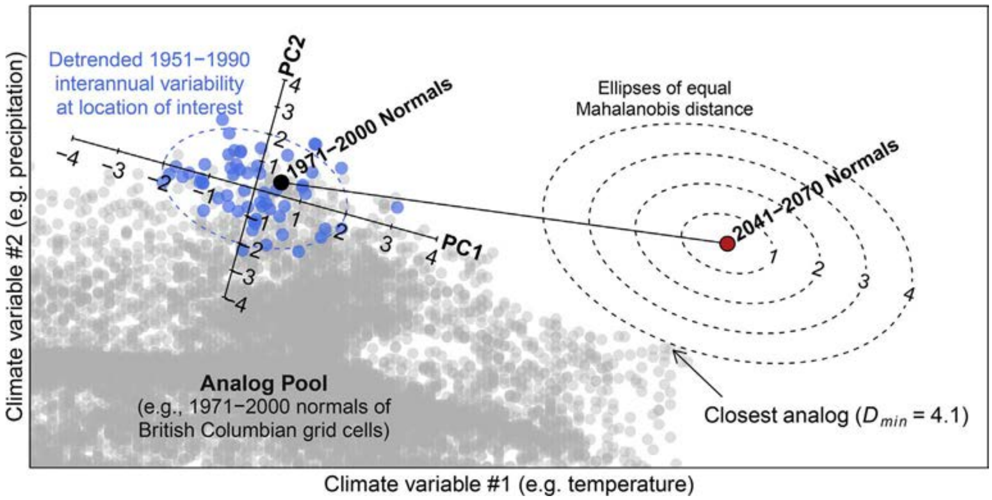

Fig. 3. Illustration of the linear method for measuring climatic novelty. The local interannual climatic variability (blue dots) of a location of interest is used to scale a Mahalanobis distance to identify the closest end-of-20th-century analog (grey dots) for the projected climate of the location of interest (red dot). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

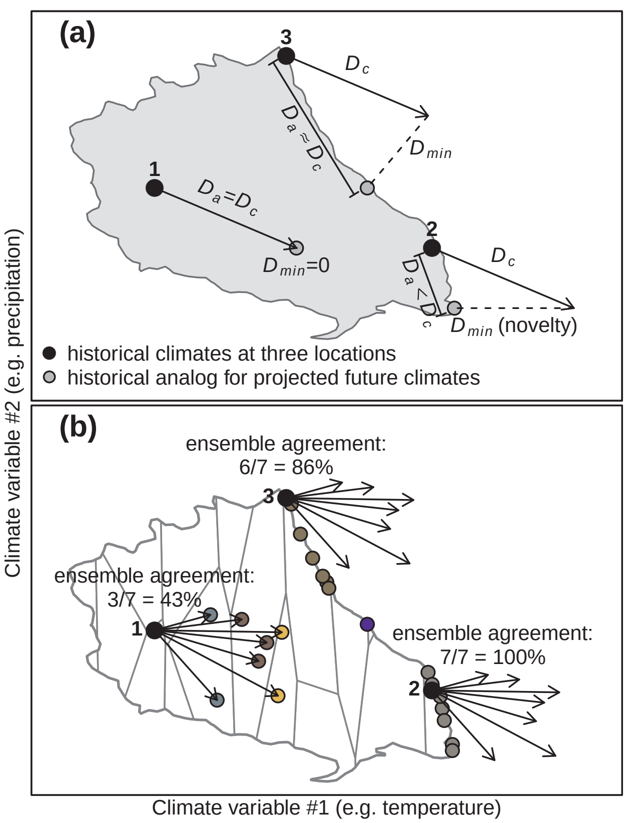

Fig. 4. Conceptual models of indicators of novelty in Random Forest projections: (a) Analog similarity and (b) ensemble agreement. The grey polygon signifies the study area climate envelope, and arrows indicate trajectories of climate change. (a) Novel climates can be reliably inferred where the analog dissimilarity (D_a) is less than the magnitude of climate change (D_c). (b) Novel climates are expected to produce higher agreement on the class (portrayed as subdivisions of the study area climate envelope; e.g., BEC subzones) assigned to the diverse projections of an ensemble of climate models.

trajectory in Fig. 2), analog dissimilarity will be near zero because the best analog for the end of the trajectory is its origin. This conceptual model of analog similarity suggests that it is a precise but not highly sensitive indicator: it is expected to produce few type I errors (novelty inferred when the climate is not novel), but many Type II errors (novelty not detected when the climate is novel; e.g., location 3 in Fig. 4a). Analog similarity can be measured as a distance (0-D_a) in linear classification and approximated in Random Forest using proximity matrices, as described in Section 2.2.3 and Supplementary Note S5.

Ensemble agreement—the uniformity of class (e.g., BEC subzone) predictions for different global climate model projections—is another potential fingerprint of novelty detectable in Random Forest projections (Fig. 4b). Where good analogs are available (location 1 in Fig. 4b), variation in the climate change trajectories of different global climate model projections willproduce variation in class predictions for any given location. In the absence of good analogs (locations 2 and 3 in Fig. 4b), the ensemble predictions are more likely to fall into a smaller number of classes located at the edge of the study area climate envelope. This conceptual model suggests that ensemble agreement is likely to be a more sensitive indicator of novelty than analog similarity (lower type II errors), but a less precise one (higher Type I errors). In particular, the precision of ensemble agreement as an indicator of novelty can be expected to be reduced by (1) variations in the volume of classes within the climate space and (2) variations the position of historical reference climates relative to the climatic boundary of each class. There are several ways to measure ensemble agreement; in this paper we use the proportion of models that predict the majority class, as illustrated in Fig. 4.

2.2.2. Random Forest classification

We trained Random Forest models to classify BEC subzone-variants from climate variables. Each model comprised 500 trees. To prevent class imbalances, each tree was grown using an n = 50 bootstrap sample of grid cells each BEC subzone-variant, a technique called “tree-level downsampling.” Analyses on the ensemble mean projection were performed on a 2-km grid, using BEC subzone-variants as the class variable. To reduce computation time, CMIP5 ensemble analysis was performed on a 4-km grid, using BEC subzones as the class variable.

2.2.3. BEC proximity matrix

The similarity between BEC subzone-variants within a Random Forest model was calculated with Random Forest proximity matrices. Random Forest proximity between two training observations is the proportion of trees within the forest in which the two observations are assigned to the same predicted class (same leaf node). For each RF model calculated on the full grid, we calculated a proximity matrix for an n = 10,100 stratified subsample of the grid (50 grid cells for each of the 202 BEC subzone-variants). The proximity between two BEC subzone-variants is estimated as the average of their 50 × 50 submatrix within the proximity matrix. This calculation results in a 202 × 202 proximity matrix between BEC subzone-variants. RF subzone-variant proximities are $\log_{10}$-scaled in this paper’s results.

2.3. Climate data

2.3.1. Climate variables

The primary climate variables used in this study are six "seasonal basic" variables: mean daily minimum and maximum temperature (T_{min}, T_{max}) and log-transformed total precipitation (PPT) for winter (Dec-Jan-Feb) and summer (Jun-Jul-Aug). These variables provide a simple characterization of climate, consistent with our objectives for the linear novelty analysis; they have been validated for novelty analysis (Mahony et al., 2017); they avoid the conflation of distinct seasonal climate signals (e.g. as with mean annual temperature); they have approximately linear responses to increasing mean temperature (unlike e.g., number of frost-free-days); and they do not have highly non-normal distributions of interannual climatic variability. Random Forest models were trained on 5 nested variable sets of increasing dimensionality: the 6-variable "seasonal basic" set, the 44-variable set of Wang et al. (2012), and also on intermediate nested sets of 3, 12, and 24 variables (Supplementary Note S6).

2.3.2. Observed and projected climate normals

Gridded climate normals for the 1971–2000 and 2041–2070 periods were obtained using ClimateNA v5.10 (Wang et al., 2016). We extracted data grids from ClimateNA at 2 km resolution for British Columbia and 8 km resolution for North America in a North American Equidistant Conic projection. Observed 1971–2000 climate normals are interpolated from the PRISM climate surfaces for British Columbia (Pacific Climate Impacts Consortium and PRISM Climate Group, 2014). Projected 2041–2070 climate normals are the ensemble mean of the 15 CMIP5 projections (Taylor et al., 2012; Supplementary Table S2) available in ClimateNA. 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). The ensemble mean projection is calculated from the mean monthly anomaly for each variable in all 15 models. We evaluate novelty for the RCP4.5 and RCP8.5 scenarios (van Vuuren et al., 2011). The RCP4.5 scenario roughly corresponds to the 2.7 °C (2.1–3.2 °C) temperature rise consistent with the conditional Intended Nationally Determined Contributions 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).

2.3.3. Local interannual climatic variability

We estimated local interannual climatic variation using weather station data from the CRU TS3.23 (Harris et al., 2014) source observations. Our use of point station data avoids variance reduction artefacts evident in gridded and interpolated time series (Director and Bornn, 2015). Since the purpose of the CRU station time series in this analysis is to estimate the covariance structure of local interannual climatic variability, matching the normal period used for the analog pool (1971–2000) is not strictly necessary. Maximizing the length and reliability of the time series, however, is critical. For this reason, we used a reference period of 1951–1990 due to higher risk of inhomogeneities prior to 1951 and a sharp decline in precipitation station density 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 fewer than 20 years of complete records. This process selected 91 CRU TS3.23 stations within British Columbia. We calculated Mahalanobis distance (novelty) separately for each of the four stations nearest to the location of interest, then averaged these values.

2.4. North American climate analogs

To identify North American analogs for the projected mid-21st-century climates of British Columbia, we conducted both a "backward" and a "forward" analysis (*sensu* Hamann et al., 2015). The backward analysis trained Random Forest models on the projected 2041–2070 climate normals of pooled BEC units and North American ecoregions, and used these models to classify the historical 1971–2000 normals of North American raster grids. The forward analysis trained the model on historical normals and made class predictions on the projected normals. Tree-level downsampling was applied in all Random Forest models at n = 15 per class per tree. For the purpose of sensitivity analysis, we created two alternative ecoregion classifications as class variables. The coarse-ecoregion set is composed of the World Wildlife Fund terrestrial ecoregions (Olson et al., 2001), totalling 145 ecoregions across the full extent of North America outside British Columbia. The fine-ecoregion set was compiled from US level IV ecoregions (Omernik, 1987) and Canadian ecodistricts (Ecological Stratification Working Group (ESWG), 1995), totaling 751 non-BC ecoregions in Western North America (33°N-62°N; 102°W-140°W). Each ecoregion set was gridded at 8 km resolution and pooled with a 2 km grid of BEC subzones (interior BC) and subzone-variants (coastal BC). Each of these two sets of training classes was paired with the 6-variable and 44-variable predictor sets, for a total of 4 Random Forest models each for the forward and backward analyses. Results of the 44-variable, coarse-ecoregion analysis are presented in this paper, and all four model predictions are presented as sensitivity analyses in the Supplementary Note S7.

3. Results

3.1. Distance between BEC units

Climatic distances between BEC units (Supplementary Fig. S1) provide ecological context for interpreting novelty distances. Coastal (maritime) and interior (continental) BEC units have distinct distributions of nearest-neighbour distances. Coastal units are further apart from each other in climate space, on average, than interior units; a difference that is increasingly evident at higher levels of the BEC hierarchy (Fig. S1c). This difference may be due to inconsistency in the application of the expert-based classification methodology between the two regions. However, the potential for this difference to be caused by lower vegetation sensitivity to climatic differences on the coast cannot be ruled out *a priori*. Although the ecological significance of the distinct distributions of coastal and interior regions is unclear, it nevertheless suggests that the two regions should be treated separately when interpreting climatic novelty. We use the median distance between nearest neighbour subzones as a threshold for novelty: $D_{min} > 2.7$ in the coast region and $D_{min} > 1.5$ in the interior region.

3.2. Detection of novel climates with linear classification

The pattern of novelty of projected mid-21st-century climates of British Columbia is consistent across emissions scenarios (Fig. 5a and b). Under RCP4.5 (Fig. 5a), BEC subzone-scale novelty ($D_{min} > 1.5$ in the interior) is projected for the major valley-bottoms of the southern interior, the Chilcotin Plateau, and northeastern BC. Under RCP8.5 (Fig. 5b), this spatial pattern of novelty intensifies to a level corresponding to the emergence of novel interior-region BEC zones ($D_{min} > 2.5$). On the coast, subzone-level novelty ($D_{min} > 2.7$) is limited to the small pockets of the coast under RCP4.5, but expands under RCP8.5 to large areas of the outer North Coast, Haida Gwaii, southern Vancouver Island, and the Lower Mainland. Expanding the analog search to all of North America substantially reduces novelty in Northeast BC, the Chilcotin Plateau (Central BC), and Rocky Mountain Trench (Southeast BC) (Fig. 5c and d). However, the pattern and magnitude of novel climates on the coast and the southern interior is essentially equivalent for the BC and North American analog pools. The lack of North American analogs for these locations in the linear novelty assessment indicates the potential for emergence of continental-scale climatic novelty in British Columbia.

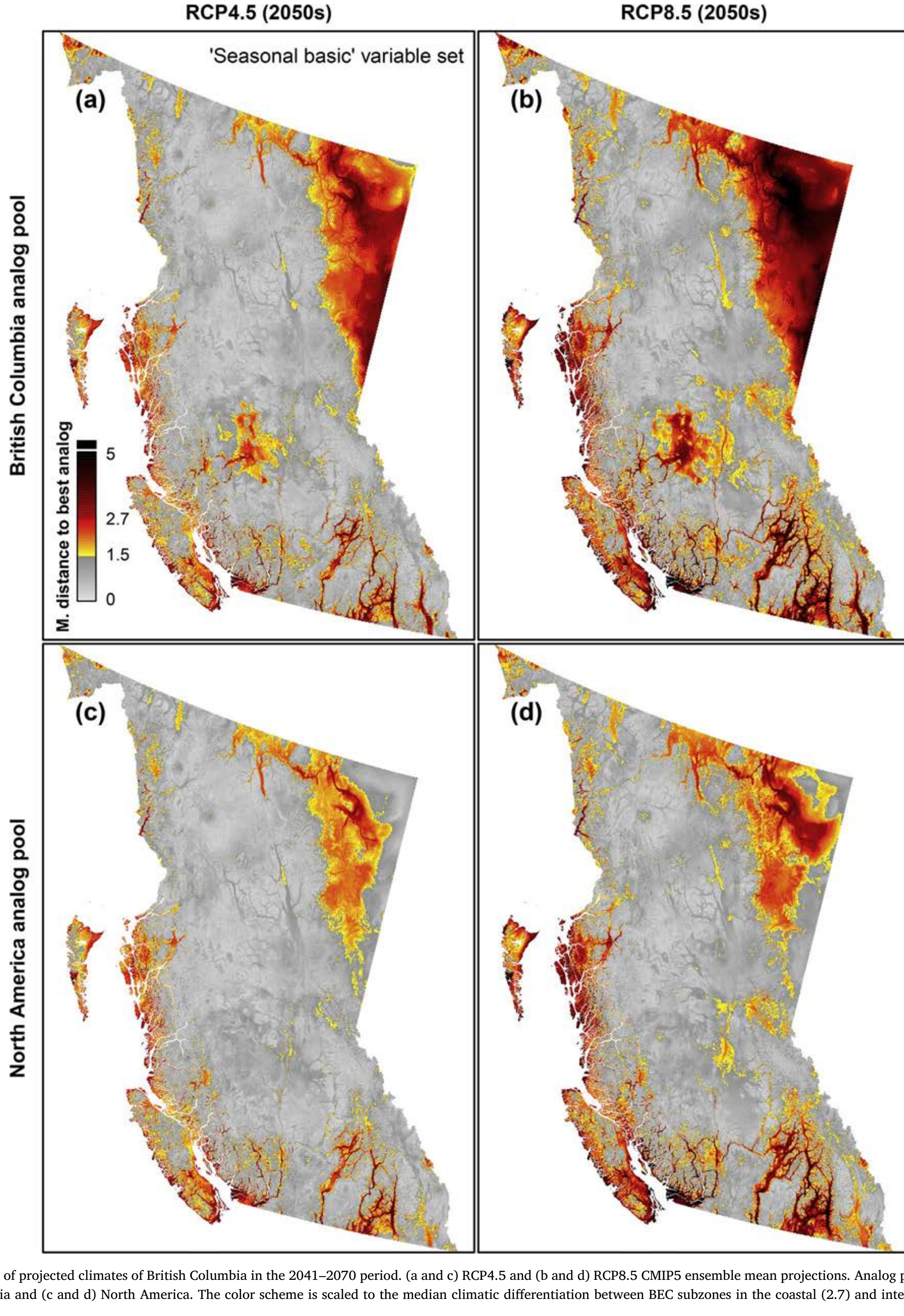

Fig. 5. Novelty of projected climates of British Columbia in the 2041–2070 period. (a and c) RCP4.5 and (b and d) RCP8.5 CMIP5 ensemble mean projections. Analog pools are (a and b) British Columbia and (c and d) North America. The color scheme is scaled to the median climatic differentiation between BEC subzones in the coastal (2.7) and interior (1.5) regions.

Linear novelty is strongly associated with topographic position: novel climates ($D_{min} > 1.5$) predominantly occur at low elevations and there are very few low-elevation locations (< 500 m) with low novelty ($D_{min} < 1$) (Supplementary Note S8). As expected, climate analogs are predominantly sourced from downhill and southward locations (Supplementary Note S4). However, there are instances of uphill and northward analog sources, indicating that that climatic shifts may not follow intuitive geographic trajectories.

The spatial distribution of projected novelty within the current map area of BEC zones is summarized in Fig. 6a and b. With the exception of the BWBS and CDF, novelty does not align well spatially with BEC zones: zones that contain some areas of high novelty—i.e., the ICH, PP,

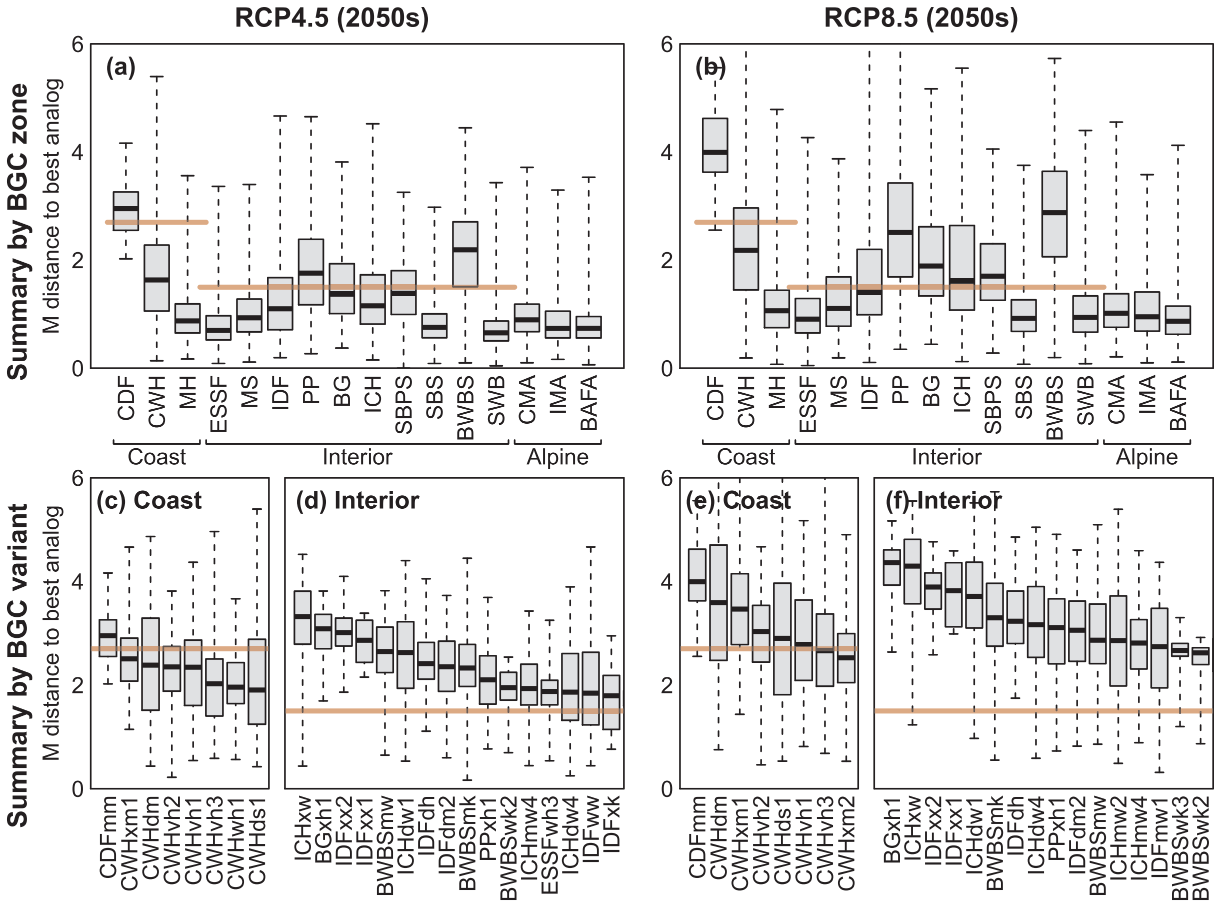

Fig. 6. Spatial distribution of linear climatic novelty (D_{min}) in current BEC zones and subzone-variants. (a and b) Boxplots of the spatial distribution of climatic novelty within the current BEC zone map units, using the 6-variable "seasonal basic" predictor set for the (a) RCP4.5 and (b) RCP8.5 ensemble mean projections. (c–f) BEC subzone-variants with the highest median novelty over their spatial range on the (c and e) coast and (d and f) interior for (c and d) RCP4.5 and (e and f) RCP8.5. Boxplot whiskers indicate minima and maxima. Red horizontal lines indicate the subzone-level novelty thresholds of $D_{min} = 2.7$ for the coast and $D_{min} = 1.5$ for the interior. BEC subzone-variant names are provided in Supplementary Table S3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

SBPS, and BG zones—also contain areas of low novelty. The BEC subzone-variant is a more effective level of the BEC hierarchy to capture the spatial distribution of novelty (Fig. 6c–f): in the interior, some BEC subzone-variants are occupied by novel climates on more than 75% of their area, even in RCP4.5. On the coast, however, few variants have a majority of their area as novel climates, even in RCP8.5.

3.3. Evaluation of indicators of novel climates using linear classification

Analog similarity and ensemble agreement are both moderately correlated with climatic novelty (r = 0.59 and r = 0.57, respectively) in the linear classification of the RCP4.5 ensemble mean projection (Fig. 7). High analog similarity exclusively occurs at high novelty (i.e., there are no Type I errors), indicating that analog similarity is a precise indicator of climatic novelty in the context of linear classification. Instances of simultaneously low analog similarity and high novelty (type II errors) indicate that the sensitivity of this proxy is not as high as its precision. Despite being correlated with novelty, ensemble agreement exhibits both type I and II errors (Fig. 7b), suggesting that it is not as precise a proxy of novelty as analog similarity. These results indicate that analog similarity and ensemble agreement have some utility in detection of model extrapolation in projections by machine learning algorithms such as Random Forest.

3.4. Indicators of novelty in Random Forest BEC projections

Random Forest and linear classification produce similar BEC projections based on the RCP4.5 "seasonal basic" variable set (Fig. 8a and d) despite their large methodological differences. The prominent trends of both of these projections, relative to the historical distribution of BEC zones (Fig. 1), are: (1) the uphill expansion of the CWH and ICH zones at the expense of the MH and wet belt ESSF, respectively; (2) the expansion of the IDF and ICH into the central interior at the expense of the SBPS, MS, and SBS zones; (3) the expansion of the ESSF and SBS zones into the Northern interior at the expense of the SWB and alpine (BAFA) zones; and (4) the expansion of the CWH zone into montane elevations of the West Kootenays.

As expected due to their correlation (Fig. 7a), analog similarity of the linear classification (Fig. 8b) reflects the patterns and magnitude of climatic novelty measured directly (Fig. 5a), notably the Alberta Plateau (BWBS zone), Okanagan valley, Georgia Basin, Chilcotin Plateau, and the outer coast. These patterns are also evident in the analog similarity of the Random Forest projection (Fig. 8e). More broadly, the Coastal valleys and mountains and the valleys of the southern interior exhibit low analog similarity in the Random Forest projection. The coarse-scale patterns of RF analog similarity (Fig. 8e) and ensemble agreement (Fig. 8f) are similar. However, there are some occurrences of high ensemble agreement that are not matched in analog similarity, notably the northern Cariboo region and central Rocky Mountain Trench. These mismatches may indicate areas of genuinely high projection confidence (ecological equivalence between model projections), as opposed to spurious ensemble agreement produced by novel conditions. Examples of BEC subzone-variant similarities are presented in Supplementary Note S5.

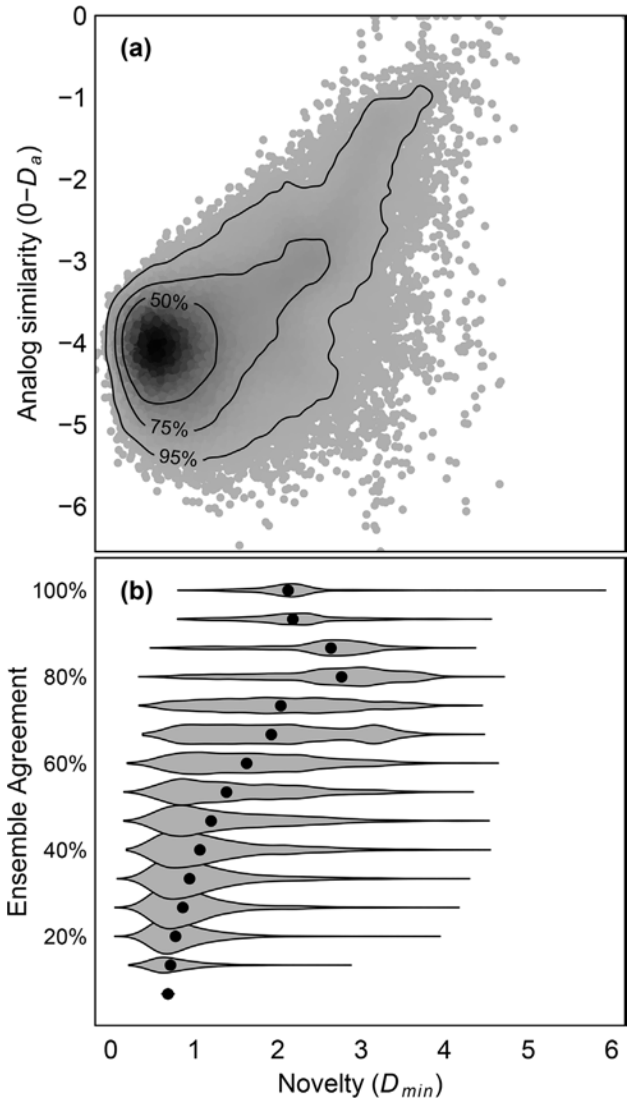

Fig. 7. Relationship between linear novelty (D_{min}) measured with Mahalanobis distance and two hypothesized indicators of novelty: (a) analog similarity and (b) ensemble agreement. RCP4.5 ensemble mean projection of the "seasonal basic" variable set for British Columbia grid cells. (a) Scatter plot of analog similarity shaded by grid point density and contoured by 50th, 75th, and 95th percentiles. (b) Violin plots indicating the novelty of grid points within each level of ensemble agreement, which is a discrete variable because it is the number of models voting for the majority class divided by the number of models in the ensemble. Conceptual models of novelty (D_{min}), analog similarity (0-D_a), and ensemble agreement are illustrated in Fig. 4.

Progressively increasing the predictors available from the 6 "seasonal basic" variables up to 44 variables produces similar but somewhat more conservative Random Forest BEC projections (Fig. S6), notably removing the small occurrences of questionable analogs such as IDF in far northern BC and CWH (a coastal zone) in the interior wet belt. Higher dimensionality produces subtle increases in analog similarity (Fig. S7) and ensemble agreement (Fig. S8), with some pronounced localized changes. Reducing the variable set to include only winter T_{min}, summer T_{max}, and mean annual precipitation produces an increase in questionable analogs (Fig. S6b) (e.g. extensive MS in the Boreal mountains), as would be expected due to insufficient predictors to differentiate distinct ecosystem climates. Analog similarity is somewhat higher in these 3-variable projections (Fig. S7b), but ensemble agreement is substantially lower (Fig. S8b), reflecting a higher level of analog availability in this low-dimensional climate space that is too simple to differentiate many ecologically distinct climates.

3.5. North American climate analogs

The "backward" search for North American analogs trains a Random Forest model on the projected climates within the mapped distributions of pooled BEC subzones (within BC) and WWF ecoregions (outside of BC). This model is then used to assign a class label (subzone or ecoregion) to the historical climates of North America. The proportion of classification trees in the Random Forest that voted for a BC climate (Fig. 9a) is an approximate measure of analog similarity to the future climates of British Columbia. Non-BC climate analogs are predominantly located in the Rocky Mountains as far south as Colorado and on the southwestern coast of Alaska. Southern climate analogs on the coast are limited to small areas of the Oregon Cascades and the Sierra Nevada. With the exception of some low-similarity analogs in the Great Lakes and Canadian Maritimes regions, climate analogs are generally absent from central and eastern North America.

The class assigned to a grid cell in the "backward" analog search indicates the current BEC unit of the location to which the historical analog is matched (Fig. 9b). For example, the large pink area in central British Columbia indicates analogs for the projected climates of the current subzones of the Montane Spruce (MS) BEC zone, and the purple areas in the Rocky Mountains of NW Montana indicate analogs for the projected climates of the current Engelmann spruce – subalpine fir (ESSF) subzones. This backward prediction produced analogs for the future climates of current BG, ESSF, MS, SBPS and IDF subzones in Washington, Oregon, Idaho, Montana, and Wyoming. There are relatively few analogs for ICH and PP subzones either within or outside of British Columbia. West-central Alberta contains large areas of analogs for BWBS subzones and small pockets of analogs for SWB subzones. Analogs for projected climates of CWH and CDF climates are limited to coastal Washington.

This analog mapping is highly sensitive to variable availability and ecoregion generalization. Reducing the variable availability from 44 variables to the six-variable "seasonal basic" set produces a large expansion of analogs in the Northwestern United States (Supplementary Figs. S9a and S10a). The fine-scale ecoregionalization (replacing 145 ecoregions of North America with 751 ecoregions for western North America) produces a large contraction of analogs (Supplementary Figs. S9d and S10d).

The "forward" search for North American analogs trains a Random Forest model on historical climates of pooled BEC subzones and WWF ecoregions and assigns a class label to the projected climates of BC (Fig. 10). The proportion of classification trees in the Random Forest that voted for a non-BC climate is an approximate measure of climatic novelty to BC. Non-BC votes are limited to the areas of novelty inferred from the linear analysis. However, some areas of novelty inferred from previous analyses are absent from the forward search of North American analogs. These absences, such as on the North Coast, suggest projected climates without North American analogs. In contrast to the backward analog search, the forward search is not sensitive to the coarseness of the non-BC classes (Supplementary Fig. S11c and d). However, the forward search is sensitive to variable availability: the 6-variable predictor set produces an increase in non-BC Random Forest votes relative to the 44-variable set, particularly in the Chilcotin and Thompson Plateaus (Supplementary Fig. S11a). Similar to linear novelty, non-BC Random Forest votes are strongly associated with low topographic positions (Supplementary Note S8).

4. Discussion

We have provided an assessment of the projected scale and pattern of novel climate emergence in British Columbia by the middle of the 21st century. The analysis followed two emissions scenarios: one which is consistent with the current national commitments to the Paris Agreement (RCP4.5) and one corresponding to continued uncontrolled increase in greenhouse gas emissions (RCP8.5). Our results suggest that

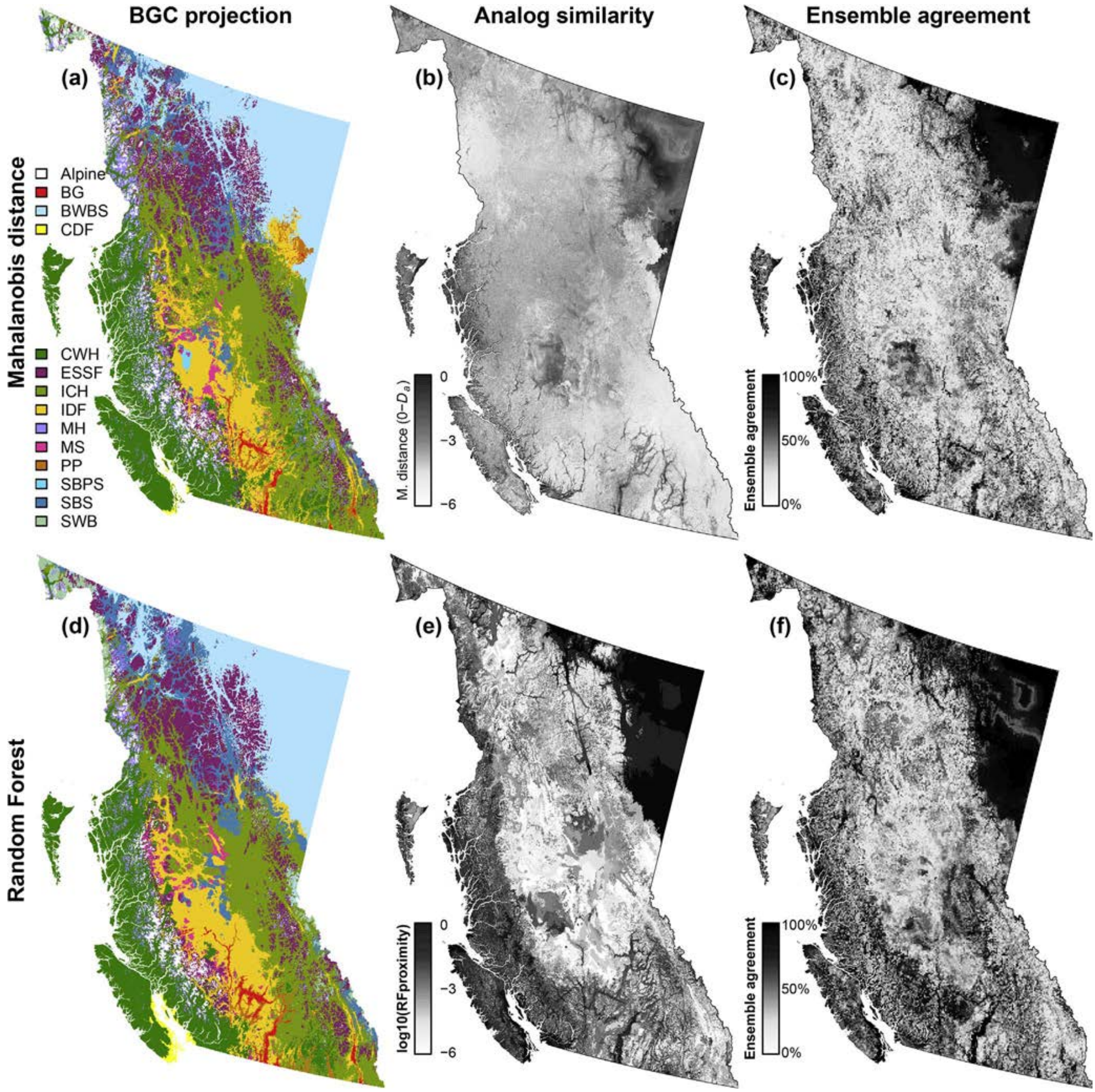

Fig. 8. Analog similarity and ensemble agreement in BEC projections made using Mahalanobis nearest neighbour (a-c) and Random Forest (d–f) classification; RCP4.5 ensemble mean projection for the 2041–2070 period, using the "seasonal basic" variable set. (a and d) BEC zone of best analog. (b and e) Climatic similarity between the best analog and the reference period condition. (c and f) Proportion of a 15-model ensemble that voted for the majority subzone.

a majority of the province's area will remain free of BC-level novel climates during the middle of this century, and therefore that the BEC system will remain the dominant source of climate analogs for mid-21st-century forest management planning horizons. Nevertheless, we detected a robust pattern of novel climates in mid-21st-century climate projections at low elevations in the Boreal Northeast interior (BWBS zone), the Georgia basin (CDF zone), the Chilcotin Plateau, the North Coast, and the major valley systems of the southern interior (BG, PP, IDF and dry ICH zones). Our analysis suggests that forest management in some of these novel climates can be informed by analogs from other jurisdictions in North America. However, the novel climates of the north coast do not have North American analogs in either the linear or Random Forest classifications. Further, the linear and Random Forest analyses disagree on whether there are North American analogs for the projected climates of the south coast and southern interior regions. We have demonstrated that projections of classification models into novel climates can be expected to under-represent the magnitude of climate change and overestimation of ensemble agreement. These characteristic extrapolation errors create the false impression of robust predictions in locations where model performance is poorest. The necessity to identify novel climates applies to the structured forest management knowledge systems of other jurisdictions—e.g., those of Yukon Territory (Environment Yukon, 2013) and Quebec (Saucier et al., 2003)—and also to the informal local knowledge base of individual land managers. By identifying portions of their landscapes that are prone to emergence of novel climates, forest managers can avoid misinterpretation of model projections and prioritize the search for analogs beyond the jurisdictional boundaries of their ecological knowledge systems.

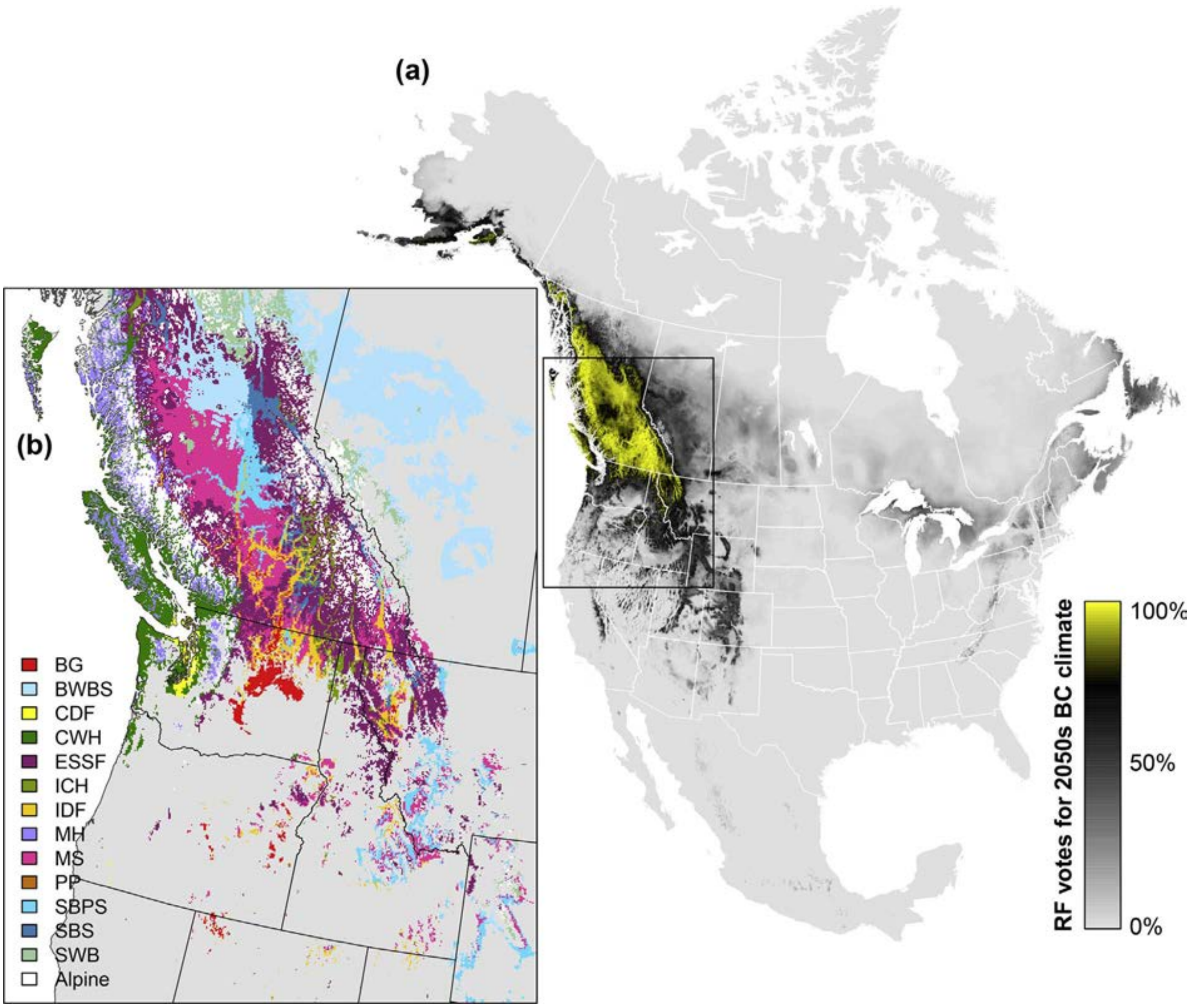

Fig. 9. End-of-20th century analogs for the mid-21st-century climates of BC, as predicted by a Random Forest model trained on the 44-variable RCP4.5 ensemble mean 2041–70 climates of BEC units (within BC) and WWF ecoregions (outside BC). (a) Random Forest proportional votes for climates projected to occur within BC. (b) Dominant BEC zone predicted by the RF model, indicating the BEC zone that each climate analog represents.

4.1. Novel climate detection in Random Forest projections

We have used a linear classification framework to validate two novelty indicators that are measurable in Random Forest projections—analog similarity and ensemble agreement. The similarities in the spatial distributions of these novelty indicators in linear and random forest classifications provide a robust indication of locations in British Columbia that are susceptible to emergence of novel climates. The novelty indicators also indicate the types of extrapolation errors that are induced by climatic novelty: analog similarity and ensemble agreement cannot be interpreted at face value in Random Forest projections. In the presence of substantial climate change, the absence of a shift in projected bioclimatic zones at certain locations should be interpreted as an artefact of novel climates, rather than as an indicator that climate change is relatively benign in those locations. Similarly, ensemble agreement cannot be assumed to indicate locations where the confidence in the ensemble projection is higher. On the contrary, ensemble agreement more likely indicates locations where lower confidence in the ensemble projection is warranted due to errors of extrapolation into novel climates. These artefacts of novel climates highlight the importance of developing a reliable novelty metric for random forest bioclimate classifications. Random Forest has proven to be a valuable tool for climate analog identification because it performs non-linear, localized variable selection and scaling appropriate to the complex relationships between climate drivers and ecological responses. Linear classification methods, though highly amenable to measurement of novelty, likely produce less reliable analogs because the variables and their relative scalings are universal to all of the ecosystem climates being modelled and are not necessarily relevant to each or any of them. Further development of machine learning novelty metrics, such as the novelty indicators proposed here and the "dummy class" approach demonstrated by Rehfeldt et al. (2012), will greatly assist the use of climate analogs for forest management.

4.2. Forest management hazards

The ecological hazards associated with errors of extrapolation into novel climates are likely to be diverse and case-specific. In some cases, poor analogs will fail to represent the crossing of critical ecological thresholds. For example, the presence of Southern-Alberta grassland-climate analogs for the projected climates of the Northeastern BC boreal forest region (Fig. 9b) suggests that a biome-level drought threshold may be undetected in current BEC projections (Wang et al., 2012), for which the analog pool is limited to British Columbia. However, novel climates do not intrinsically represent a direct hazard for tree productivity, as indicated by the successful introduction of Douglas-fir into Europe, where climatic conditions are distinctly novel to the North American native range of this species (Boiffin et al., 2017). Novel

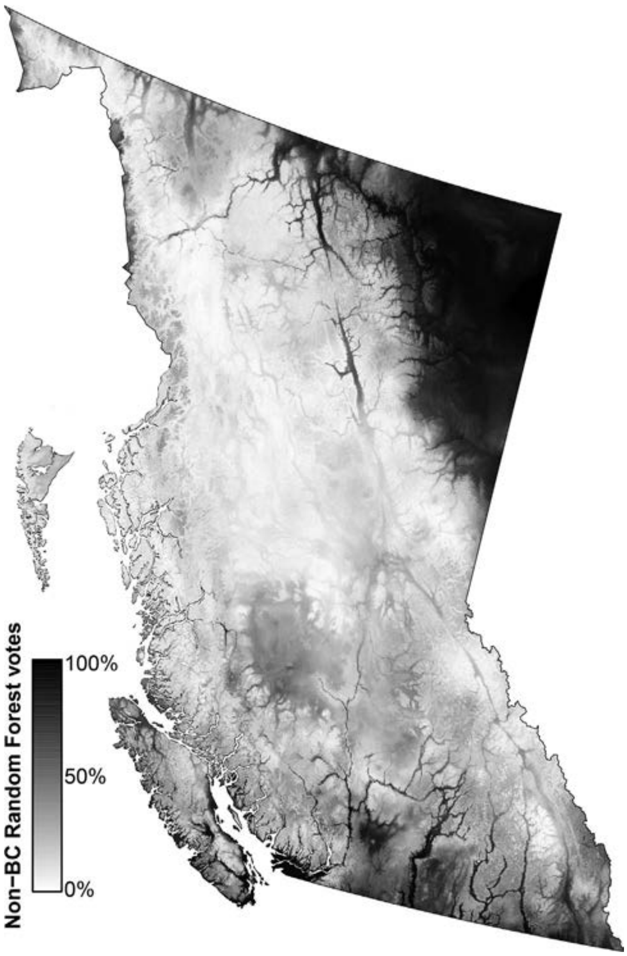

Fig. 10. Locations in BC with non-BC North American analogs for their RCP4.5 ensemble mean climate of the 2041–2070 period, as predicted by a Random Forest model trained on the 1971–2000 climates of BEC units (within BC) and coarse ecoregions (outside BC). The map is shaded by the proportion of classification trees in the Random Forest that voted for non-BC ecoregions.

climatic conditions may in some cases represent a relaxation of environmental constraints. For example, the central- and north-coast regions of BC are projected to become warmer and wetter overall, conditions which appear to have no North American analogs. These climatic conditions are unlikely to have any direct negative environmental consequences on native tree species, and indeed may be conducive to increased productivity in the absence of unforeseen biotic constraints. Current species selection guidance is likely to remain appropriate in these circumstances. These examples illustrate the importance of case-specific analysis and expert judgement in designing management strategies for identified novel climates.

4.3. Managing novel climates

Novelty to the British Columbia analog pool indicates projected climates that are not described by BEC, and which therefore have no associated forest management strategies that are formalized in provincial legislation (e.g. species selection guidelines) and local practice (e.g. stand establishment and tending regimes). One remedy, which is currently being implemented by the BC government, is to extend biogeoclimatic mapping into adjacent jurisdictions to access climate analogs from which management strategies and observational data can be drawn. The results of our North American climate analog assessment (Figs. 9 and 10) suggest that North American climate analogs are available for many of the projected novel climates of interior British Columbia, particularly in Alberta, Washington, Oregon, Idaho, Montana and Wyoming. The very high sensitivity of Random Forest analog identification to the bioclimate classification (Supplementary Figs. S9–11) suggests that extension of the BEC classification and mapping methodology into these jurisdictions is a prerequisite to accurate identification of climate analogs.

Drawing analogs from adjacent jurisdictions, however, can only partially ameliorate the problem of novel climates. For example, the scarcity of southern analogs for the coastal climates of BC in Fig. 9 is consistent with the prior expectation that the climate trajectory of coastal BC, towards warmer but still wet conditions, may not follow the observed north-to-south spatial climatic gradient of cool-wet to warm-dry (Mahony et al., 2017). The linear novelty assessment (Fig. 5), random forest novelty indicators (Fig. 8), and the North American analog search (Fig. 10) consistently indicate that the north coast in particular appears to be susceptible to the emergence of continental-scale novel climates. In such cases, a global-scale analog search may be informative, especially in locations where plantations of species native to British Columbia have been established. For example, species choices could be informed by the climates where Sitka spruce grows well in the British Isles (Cameron, 2015) or where Douglas-fir is planted in Europe (Isaac-Renton et al., 2014). However, management decisions in the absence of climate analogs must inevitably rely on other approaches, such as species-specific climatic suitability modeling (e.g. Leites et al., 2012; Rehfeldt et al., 2014), not just of tree species but also of their major pests, pathogens, and competitors. Indeed, disruption of pathosystems is among the earliest and most severe climate change impacts on forests and may be particularly difficult to predict in novel climates (Woods, 2011). Experimental climate modification experiments (e.g. Templer et al., 2017) can also be informative, especially at the regeneration stage, and managers should consider prioritizing these experiments in ecosystems that are more likely to transition into novel climates. Novel climates intensify the uncertainties of forest management under climate change. Strategies for dealing with these uncertainties—including lowering risk exposure (e.g., reducing rotation length), hedging (e.g., mixed-provenance regeneration), bolstering resistance (e.g., retention of intact ecosystems), and adaptive management (Spittlehouse and Stewart, 2003; Millar et al., 2007; Bolte et al., 2009; Vilà-Cabrera et al., 2018)—are particularly necessary in locations where novel climates are projected to emerge.

4.4. The limits to adaptation in unfamiliar climates

The accumulation of local ecosystem management regimes, and an understanding of the range of conditions over which they could be successfully applied, was one of the defining accomplishments of 20th-century forest management. This structuring of ecological knowledge into climatic and edaphic classes based on the concept of ecological equivalence is exemplified by BEC, which provides a framework to define limits to the spatial transferability of management regimes, genetic resources, and natural resources legislation. Climate change undermines a core underpinning of this knowledge base—that the future will resemble the past on the timescales over which forests are managed. Climate analogs can assist forest managers with redeploying their hard-won knowledge across the changing climates of their land base, and with sourcing non-local management strategies for the locally unfamiliar climates of the 21st century. However, a distinct problem of managing ecosystems in a non-stationary climate is that predicted ecosystem responses, and the applicability of knowledge derived from climate analogs, cannot be verified except by waiting for events to unfold (Rastetter, 1996), at which point the predictions are moot. In addition, the future state of local climates is subject to many uncertainties stemming from global climate models (Deser et al., 2012; Knutti and Sedláček, 2012). These factors constrain the time horizon over which forest managers can place confidence in guidance from climate analogs.

The intensity of these constraints is determined by the magnitude and pace of climate change. A greater magnitude of climate change requires sourcing analogs from more distant biogeographical contexts, which may have low ecological equivalency due to non-climatic factors such as photoperiod and biotic interactions, and from beyond jurisdictional boundaries, which involves the formidable task of assimilating new management regimes into the jurisdictional knowledge system. Further, the magnitude of climate change increases the potential for climates with no analog and thus no observational knowledge base. The RCP4.5 scenario represents a disruptive change in climate that nevertheless stabilizes by the end of this century. This stabilization implies that the shifting climatic zones will settle into place, and that forest managers at the end of the 21st century may be able to reinitiate the accumulation of locally-specific ecosystem knowledge. In contrast, it is questionable whether forest managers and other applied ecologists will be able to keep pace with the perpetually transitory and increasingly novel climates projected under the RCP8.5 scenario (Williams and Jackson, 2007). The limits to which the forestry knowledge base can be brought to bear on the problem of climate change adaptation is a basis for forest managers to advocate for global emissions reductions.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2017.12.036.

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