Indicators of vegetation productivity under a changing climate in British Columbia, Canada

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Abstract

Understanding the relationship between vegetation and climate is essential for predicting the impact of climate change on broad-scale landscape processes. Utilizing vegetation indicators derived from remotely sensed imagery, we present an approach to forecast shifts in the future distribution of vegetation. Remotely sensed metrics representing cumulative greenness, seasonality, and minimum cover have successfully been linked to species distributions over broad spatial scales. In this paper we developed models between a historical time series of Advanced Very High Resolution Radiometer (AVHRR) satellite imagery from 1987 to 2007 at 1 km spatial resolution with corresponding climate data using regression tree modeling approaches. We then applied these models to three climate change scenarios produced by the Canadian Centre for Climate Modeling and Analysis (CCCma) to predict and map productivity indices in 2065. Our results indicated that warming may lead to increased cumulative greenness in northern British Columbia and seasonality in vegetation is expected to decrease for higher elevations, while levels of minimum cover increase. The Coast Mountains of the Pacific Maritime region and high elevation edge habitats across British Columbia were forecasted to experience the greatest amount of change. Our approach provides resource managers with information to mitigate and adapt to future habitat dynamics. Forecasting vegetation productivity levels presents a novel approach for understanding the future implications of climate change on broad scale spatial patterns of vegetation.

Key words: Climate change, Productivity, Dynamic Habitat Index, Forecast, Remote sensing, British Columbia.

Introduction

Given ongoing climate change, there is a need to understand potential changes in the spatial distribution of vegetation into the future. Baseline information on the spatial distribution of vegetation patterns is required; however, such data are often costly and difficult to acquire. Archival sources of remotely sensed data provide opportunities for the generation of vegetation productivity data, which can then be used to observe past conditions and to support model-based predictions of future changes to vegetation across time and space.

Recent advances in image correction and time series analysis have resulted in improved spatial resolutions and temporal depth of archived satellite data (Kerr & Ostrovsky, 2003), and as a result, remote sensing based indicators of landscape conditions can provide significant time series of observations. Data can then be incorporated into a broad ecosystem approach to gain information on landscape dynamics and vegetation productivity (Hawkins, Field, Cornell, Currie, Guégan, Kaufman, Kerr, Mittelbach, Oberdorff, O'Brien, et al., 2003; Coops, Wulder, Duro, Han, & Berry, 2008; Field, Hawkins, Cornell, Currie, Diniz-Filho, Guégan, Kaufman, Kerr, Mittelbach, Oberdorff, O'Brien, & Turner, 2009; Andrew, Wulder, & Coops, 2011). With overall temperatures increasing and precipitation regimes varying, several hypotheses can be made about the impact of climate change on vegetation productivity dynamics (i.e., Li, Xie, Brown, Bai, Hua, & Judd, 2013). Within western North America we anticipate mid to high elevation forests to be impacted the most with increases in productivity associated with warmer temperatures and a general lengthening of the growing season (Mote, Parson, Hamlet, Keeton, Lettenmaier, Mantua, Miles, Peterson, Peterson, Slaughter, et al., 2003). Environments that experience highly seasonal fluxes in vegetation, such as deciduous forests or perennial grasslands, will also likely be impacted with reduced snow cover (Kawabata, Ichii, & Yamaguchi, 2001) and a general shift towards more productive, coniferous, vegetation types. In the interior of western North America warmer temperatures without a commensurate increase in precipitation may lead to a reduction in production due to drought stress (Latta, Hailemariam, & Barrett, 2009).

The Dynamic Habitat Index (DHI), proposed by Mackey, Bryan, & Randall (2004) and later developed by Berry, Mackey, & Brown (2007) and Coops, Wulder, Duro, Han, & Berry (2008), is an example of a vegetation productivity indicator that has been shown to be highly correlated to species richness and abundance. The DHI utilizes estimates of fPAR (the fraction of Photosynthetically Active Radiation), which measures the amount of radiation absorbed by the plant canopy at the 400–700 nm wavelength (Asrar, Fuchs, Kanemasu, & Hatfield, 1984). Acting as a proxy for landscape vegetation primary productivity, fPAR has been demonstrated as a surrogate measure for species distributions (Xiao & Moody, 2005). The DHI generates a broad-scale spatial representation of vegetation productivity dynamics, which have been shown to also provide metrics for assessing change to species richness and variety (Duro, Coops, Wulder, & Han, 2007; Andrew, Wulder, & Coops, 2011). Three fPAR metrics are used in the DHI: cumulative greenness, coefficient of variation, and minimum cover. Cumulative greenness represents the total annual radiation absorbed by the canopy; low greenness values indicate barren land with no productivity, while high values indicate more productive habitat. The coefficient of variation indicates the seasonality of plant productivity; high values indicate seasonal habitats, like alpine environments, while low seasonality values indicate vegetation regimes that do not change significantly throughout the year, such as a coastal evergreen forest. Finally, minimum cover represents baseline levels of recurrent vegetation cover (Coops, Wulder, Duro, Han, & Berry, 2008); high minimum cover values indicate a stable year-round productive habitat, such as a coastal valley or evergreen forests, while low values indicate environments that have snow cover for at least part of the year, such as the tundra or arctic. By assessing the DHI components simultaneously, considerable information can be obtained on vegetation and landscape dynamics. Examples of the benefits of using DHI to represent landscape conditions include the findings by Coops, Wulder, & Iwanicka (2009) that changes in DHI were significantly correlated to avian species richness across different functional groups in the United States. Additionally, in Ontario grassland bird species richness was found to be highly correlated with the minimum cover and seasonality derived from DHI (Coops, Wulder, & Iwanicka (2009). Andrew, Wulder, & Coops (2011) found that beta diversity of Canadian butterfly communities was positively correlated with DHI minimum and cumulative annual productivity. Michaud, Coops, Andrew, Wulder, Brown, & Rickbeil (2014) found that DHI metrics were significant contributions to moose (*Alces alces*) occurrence and abundance models in Ontario.

To date, most of these studies have utilized multi-year DHI layers derived from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery, which has been available since 2000. With the availability of the re-processed NOAA Advanced Very High Resolution Radiometer (AVHRR) data since 1987, each of the three components can now be monitored over longer time periods in order to more completely characterize the dynamics of the habitat conditions. In addition, it is possible to develop relationships between past climate and DHI responses over this 25-year period and then make predictions of DHI based on future anticipated changes in climate as developed by climate modelers. The goal of this research is to model and map past and future changes in vegetation production using the DHI across British Columbia, Canada and make inferences about the potential impacts on biodiversity. To meet this goal we utilized archived remotely sensed data to extract DHI components from 1987 to 2007. We then characterized the relationships between simple climate variables and the DHI components during this time using regression tree modeling. Future climate information was then used to predict and map possible scenarios of DHI components to the year 2065. We hypothesized that our predictions will show that future DHI cumulative greenness and minimum cover indices will increase and the DHI coefficient of variation indicator will decrease in response to a changing climate; however, the magnitude of change will vary across the diverse environments of British Columbia.

Methods

Study Area

The province of British Columbia spans 944,735 km^2 and has a variety of ecosystems due to its large size, diverse topography, and climate, which are driven principally by climatological forcing due to the proximity to the Pacific Ocean, Rocky and Coast Mountains, and continental air masses (Austin, Buffett, Nicolson, Scudder, & Stevens, 2008; Murdock & Burger, 2010). A broad ecosystem classification of the province exists and subdivides the province into areas of similar climate and other biophysical characteristics (soil, topography, and vegetation) represented by biogeoclimatic regions, from largest to smallest: ecozones, ecoprovinces, and ecodistricts (BC Ministry of Forests, 2009). For model development we partitioned the province into six broad regions of similar size based on ecoprovinces: Taiga Plain, Boreal Cordillera, Mountain Cordillera, Pacific Maritime, Okanagan Caribou, and Kootenay (Figure 1). Within each ecoprovince we represent spatial datasets, described below, using the average value of the ecodistrict. That is, each of the 106 ecodistricts across the province acted as the sampling unit for our study. Within each ecodistrict (more recently updated and renamed “ecosections” by the provincial government) only minor physiographic and macroclimatic variations occur (BC Ministry of Environment, 2011).

DATA

Climate

To obtain climate surfaces over the region, we utilized interpolations of climate station data derived using non-linear adjustments for mountainous terrain as produced and described by Hamann and Wang (2005). The products of Hamann & Wang (2005) provided spatially continuous interpolated climatic data for British Columbia that incorporated elevation and microclimatic drivers as seen in Climate-BC (Hamman & Wang, 2005). A 90 m-Digital Elevation

Model (DEM), obtained from the Shuttle Radar Topography Mission (SRTM), was converted to 1 km to provide comparable spatial data with our remote sensing data. Climate data were extracted using the 1 km by 1 km resolution DEM, as the analyst uploads a DEM to the website to download data at the resolution of the DEM. Annual climate variables from 1987 to 2007 were extracted for integration with the remote sensing data to establish the relationship between climate and landscape productivity.

To simulate conditions under a future projected climate, we utilized the Special Report on Emission Scenarios (SRES) climate scenarios developed by the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report, AR4 (Nakicenovic & Swart, 2000; IPCC, 2007). We contrasted three scenarios: "a business as usual" scenario (A1); a less extreme scenario (B1) that assumes current emissions rates will remain steady until around 2040 and then slowly drop to about half of the current rate by the end of the century; and A2, the most extreme scenario in terms of emission rates. We used scenarios from the Canadian Climate Centre's Modelling and Analysis (CCCma) third generation general circulation model (CGCM3), which includes improvements in the treatment of clouds, solar radiation, and land surface processes along with a simple ocean mixed-layer model with a thermodynamic sea ice component (von Salzen, McFarlane, & Lazare, 2005; Scinocca, McFarlane, Lazare, Li, & Plummer, 2008). Model selection was based on using the full range of possible scenarios that were available from respected institutions and were recommended by the Pacific Climate Impacts Consortium (Murdock & Splittlehouse, 2011). As with the historical climate data, we uploaded a 1 km by 1 km raster to extract the future projections of climate at a 1 km by 1 km scale (Hamann & Wang, 2005).

A literature review of the most relevant climate variables to extract from Climate BC indicated that temperature (Running & Nemani, 1988), precipitation (Slayback, Pinzon, Los, & Tucker, 2003; Potter, Kumar, Klooster, & Nemani, 2007), or a hybrid of both (Carey, 1996; Hamann & Wang, 2006), represented landscape dynamics well (Daly, Halbleib, Smith, Gibson, Doggett, Taylor, Curtis, & Pasteris, 2008) (Table 1). Selected temperature-based variables consisted of mean annual temperature, temperature difference (difference between mean warmest month temperature and mean coldest month temperature), growing degree days, number of frost free days, mean coldest month temperature, and Julian date on which frost free period begins (green up date). Derived-precipitation climate variables were mean annual precipitation, precipitation falling as snow, and mean summer precipitation. Hybrid climate metrics consisted of climate moisture deficit and evapotranspiration. Though not a climate variable, elevation is often an indirect measure of climate processes and elevation data were also extracted from the 1 km spatial resolution digital elevation model. All twelve listed variables were available as annual means for the 1 km x 1 km provincial grid in each past climate (annual 1987–2007 and 1961–1990 mean) as well as 2065 climate scenarios (B1, A1, A2).

Remote Sensing Imagery

In this research we utilized a long-term AVHRR dataset that was processed by Fontana, Coops, Khlopenkov, Trishchenko, Riffler, & Wulder (2012). The approach used to process the AVHRR is described in detail in Fontana, Coops, Khlopenkov, Trishchenko, Riffler, & Wulder (2012) and the generation of the DHI from the AVHRR described in Coops, Fontana, Harvey, Nelson, & Wulder (2014). For completeness, a brief summary of these processing steps is provided here; however, for more information readers are invited to refer back to the papers that accompany the processed data. The Advanced Very High Resolution Radiometer (AVHRR) on board the satellites of National Oceanic and Atmospheric Administration (NOAA) offer a unique source of long term information on vegetation dynamics. AVHRR data was compiled from 1985 to 2007 over Canada, the northern United States, and Greenland. Data were initially preprocessed using the Canadian AVHRR Processing System (CAPS), developed by the Canada Centre of Remote Sensing (CCRS). Once this was complete, two clear-sky composites for each 10-day period were developed from the forward or backward look angles of the instrument. This allowed different correction parameters to be developed based on the surface anisotropy, following recommendations of Los, North, Grey, & Barnsley (2005). As the data was acquired from a number of different AVHRR sensors over the time period, reflectance values were normalized to the AVHRR/3 on board NOAA-17 to account for differences in the spectral response functions, using available relative spectral correction coefficients (Fontana, Coops, Khlopenkov, Trishchenko, Riffler, & Wulder, 2012). Atmospheric correction was then performed using the Simplified Method for Atmospheric correction (SMAC) algorithm (Rahman & Dedieu, 1994). The Normalized Difference Vegetation Index (NDVI) was then calculated based on atmospherically corrected red and near infrared channels (Fontana, Coops, Khlopenkov, Trishchenko, Riffler, & Wulder, 2012).

To ensure a smooth temporal sequence of the 10-day NDVI data, Coops, Fontana, Harvey, Nelson, & Wulder (2014) utilized the TIMESAT software (Jönsson & Eklundh, 2004). TIMESAT fits a mathematical function through a remote sensing vegetation time series using a Savitzky-Golay filter, which fits adjacent data points with gradually lower level polynomials using linear least squares, resulting in a smoothed temporal sequence of NDVI observations (Jönsson & Eklundh, 2004). In past research, using the MODIS sensor, the DHI was developed using observations of the fPAR intercepted by vegetation, which is a key metric of vegetation production ranging from zero (on barren land) to one (for dense cover) (Knyazikhin, Kranigk, Myneni, Panfyrov, & Gravenhorst, 1998). The MODIS fPAR approach uses multiple spectral bands, a number of which are not available on the AVHRR sensor, restricting our capacity to derive fPAR directly from the AVHRR reflectance. As an alternative, we derived fPAR using a 2005 land cover-dependent linear scaling of NDVI to fPAR, following the methodology of Los, Collatz, Sellers, Malmstrom, Pollack, DeFries, Bounoua, Parris, Tucker, & Dazlich (2000) using the North American Land Cover 2005 database (www.cec.org), which was assumed to be constant throughout the AVHRR time series.

To limit our analysis to vegetated areas and enhance predictive modeling results, we utilized a baseline thematic mapping (BTM) land cover classification (BC Ministry of Sustainable Resource Management, 2001) to mask highly disturbed landscapes, such as agriculture and urban land cover types, and removed them from the analysis. Results are therefore only applicable to natural environments with no long term anthropogenic impacts. Areas identified by the BTM as water, urban, mining, and agriculture have been excluded from the analysis.

Regression Trees

Regression trees are a robust technique for ecological prediction illuminating interactions between predictor variables, modeling non-linear relationships, and excluding insignificant variables (Carpenter, Gillison, & Winter, 1993; Iverson & Prasad, 1998; Berry, Mackey, & Brown, 2002; Thuiller, 2003; Rounsevell, Ewert, Reginster, Leemans, & Carter, 2005; Prasad, Iverson, & Liaw, 2006). Using the “rpart” R statistical software package (Therneau & Atkinson, 1997) individual trees were built for each of the six distinct ecological regions of British Columbia. Regression trees were built on observed relationships between DHI and climate from 1987–2007. Model rules, from the observed relationships, were then applied to data representing future climate scenarios (2041 to 2070).

To understand how we built regression trees for each of the three productivity characteristics, it is helpful to clarify how input data were organized. Climate and fPAR metrics were partitioned into the six ecological regions. Within the regions, all data were represented at the spatial unit of the ecodistrict. For each of the 12 explanatory variables representing climate (Table 1) and three fPAR variables (cumulative greenness, coefficient of variation, and minimum cover) representing productivity, 21 annual average values (1987-2007) were linked to each spatial unit, generating a temporal distribution of climate and productivity values for individual ecodistricts. Regression tree rules were generated for the full temporal range of observed productivity values using the same temporal range of climate data.

The regression tree method applied thresholds to the explanatory variables, generating a ‘tree’ of recursive binary splits. The aim of the regression tree was to identify covariate splits that maximize the homogeneity of the predicted productivity classes, based on an analysis of variance (Prasad , Iverson, & Liaw, 2006). The hierarchy of variables used in each split, or the closer the tree branch to the base of the tree, implied the importance of each variable in the accurate prediction of productivity.

To improve the stability of the trees we ensured the ecological regions represented similar ecological and productivity processes as to reduce the effects of extreme values on the binary splits. We also assessed the independence of predictors prior to modeling. While methods such as random forest are considered robust for prediction across large datasets, when predictor collinearity and over fitting occur the “black box” approach to variable selection and thresholding make it difficult to interpret the impact of climate change on productivity. To assess the effectiveness of the regression trees a cross-validated error was calculated comparing predicted to observed productivity for the current climate conditions representing a coefficient of determination between 0 and 1.

RESULTS

Regression Trees:

The regression tree analysis using the actual climate annual averages from 1987–2007 against the DHI indicators resulted in 18 unique trees (three DHI indicators by six representative ecological regions) across British Columbia (Table 2). The most important climatic variables in describing the patterns of DHI included growing degree days, precipitation as snow, number of frost free days, evapotranspiration, and elevation. The models that produced the highest confidence occurred in the southern coastal regions of British Columbia, where clear productivity gradients are known to exist (Waring, 1969). In contrast, less productive environments in the north of British Columbia tended to have weaker relationships.

Cumulative greenness was the strongest performing DHI indicator followed by coefficient of variation (seasonality), and lastly, minimum cover. Trends in regression tree branches showed that northern regions such as the Boreal Cordillera and Taiga Plain resulted in models with a larger number of branches (18 to 30), while southern regions such as the Pacific Maritime had fewest (8 to 14). Patterns of future distributions of the DHI indicators, using the three climate scenarios (B1, A1, and A2) for 2065 are shown in Figure 2. Overall cumulative greenness across the province was predicted to increase in 2065; the coefficient of variation (an indicator of vegetation seasonality) was predicted to decrease almost universally except for the Boreal Cordillera and minimum cover was predicted to increase along the coast (Pacific Maritime) and Okanagan Caribou region. The mean change of the indicators between climate normal and future conditions by increasingly extreme climate scenarios is shown in Figure 3. Generally, as the climate scenarios became more extreme with respect to changes in atmospheric CO_2 and other anthropogenic drivers, the difference in DHI indicators between climate normal and 2065 conditions were forecast to also increase. Non-uniform responses in mean DHI were predicted, however, in some cases such as with cumulative greenness in the Okanagan Caribou and with the coefficient of variation in the Boreal Cordillera. Simultaneous display of all three DHI components for each climate scenarios enabled better interpretation of productivity regimes throughout the province (Figure 4).

Model Confidence:

Correlation analysis of the predicted DHI values using the historical long-term climate with the AVHRR-derived averaged DHI from 1987–2007 indicated good agreement (cumulative greenness, $R^2 = 0.92$, $p < 0.01$; coefficient of variation $R^2 = 0.89$, $p < 0.01$ and minimum cover $R^2 = 0.72$, $p < 0.01$) (Table 2).

Change in Indirect Indicators from Climate Normals Period to 2065:

Provincially, the mean change in the DHI indicators from present day to 2065 using the A1 scenario was greatest for minimum cover (+50.0%), followed by the coefficient of variation (-22.0%), and cumulative greenness (+11.0%). These changes are shown individually for each indicator in Figure 5 and summed (even weights for all 3 indicators) in Figure 6.

Cumulative Greenness:

Individual results for cumulative greenness using the A1 scenario showed an overall increase of 11.0%. The Pacific Maritime is predicted to have an overall increase in cumulative greenness of 17.8% (B1), 23.5% (A1), and 32.9% (A2). Increased productivity may be beneficial to generalist species that can survive and adapt to a variety of habitat types. The smallest change in cumulative greenness between scenarios was predicted for the dryer south central portion of the Okanagan Caribou region with 2.0% (B1), 1.0% (A1), and 0.0% (A2). Minimal change was predicted to occur in the lower elevation coastal and mid elevation interior regions. Some areas such as lowland valleys within the Okanagan Caribou and northeast corner of the Boreal Cordillera region were forecast to experience a reduction of up to 10% in overall productivity, principally due to increased temperatures. Overall the greatest difference in cumulative greenness was predicted for the mid to high elevation areas (500–1500m).

Coefficient of Variation

Over the province the mean in the DHI seasonality metric, coefficient of variation, was predicted to decrease 22.0% by 2065 under the A1 scenario. The coefficient of variation provides an indication of the variation within a year in the resource allocation of a site. Highly seasonal environments have large differences between summer and winter plant productivity. By 2065, DHI seasonality was projected to have the greatest decrease at higher elevations with the most change forecasted for edge forest environments like the Coast Mountains in the Pacific Maritime, low elevation Taiga Plain forests, Vancouver Island highlands (in the Pacific Maritime), the Mountain Cordillera and to a lesser extent the highland forests of the Kootenay region. Slight increases in coefficient of variation were projected in the Stikine forests, which are high elevation edge environments within the southern Taiga Plain region, and little change in the coefficient of variation was predicted in the southern lowlands that comprise most of the Okanagan Caribou, and in the Boreal Cordillera regions. The DHI seasonality metric showed considerable variation across scenarios. Trends between scenarios B1, A1, and A2 showed clusters of reduced coefficient of variation in the high elevation areas of the Pacific Maritime and increased coefficient of variation in the northeast. The Pacific Maritime region was projected to experience some of the greatest decreases in seasonality through the scenarios from 19.1% (B1), 25.8% (A1), and 35.2% (A2).

Minimum Cover

Provincially, the most substantial changes determined by our model were the minimum cover DHI metric. Minimum cover was projected to have a mean provincial increase of 50.0% by 2065 under an A1 scenario. Regions of greatest change were predicted to be the Pacific Maritime and interior mid to low elevations, which have higher and more consistent levels of productivity throughout the year. DHI minimum cover was forecast to change little in the northwest of British Columbia and in low (Coastal Vancouver Island) and high elevation areas (Rocky Mountains). Small patches of decreased minimum cover were predicted in the lower mainland, Haida Gwaii, and Vancouver Island areas of the Pacific Maritime. The Pacific Maritime was projected to have an increase of DHI minimum cover across climate change scenarios from 46.3% (B1), 64.4% (A1), and 89.4% (A2). The Kootenay region had the least amount of forecasted minimum cover with increases of 22.7% (B1), 28.5% (A1), and 35.6% (A2); these increases were predicted primarily for low-lying valleys, and although the regional mean increase may be lesser, the impact may be significant in low elevation landscapes.

DISCUSSION

The availability of contemporary climate and remote sensing data allowed us to model and then validate our predictions of the DHI under current climate conditions. The regression trees performed the poorest in the Boreal Cordillera region and best along the Pacific Maritime region, potentially due to strong climate-vegetation gradients in the south, compared to the northern parts of the province (Hamann & Wang, 2006). Despite these issues, complexity parameters, indicative of model success (Therneau & Atkinson, 1997), confirmed the models were reasonably strong and performed well.

Using three climate change scenarios we then predicted future DHI components in 2065. The results confirmed that each progressively extreme scenario (B1, A1, and A2) showed progressive shifts in the magnitude of change in each of the indicators, especially in the Pacific Maritime and Mountain Cordillera regions for all DHI indicators.

Generally the results indicated that overall provincial DHI seasonality, measured as coefficient of variation, will decrease and overall cumulative greenness and levels of minimum cover will increase. However, trends varied spatially. For instance, some parts of the Taiga Plain were forecast to have decreases in DHI seasonality, cumulative greenness, and minimum cover. The reduction in cumulative greenness by 2065 in the Okanagan grasslands (within the Okanagan Caribou) highlight the importance of using regional non-linear relationships between vegetation indicators and climate variables to ensure the unique interactions between the numerous landscapes of the province are modeled effectively and spatial variation in relationships identified.

The DHI coefficient of variation (or seasonality) was predicted to change substantially, but not uniformly, across British Columbia under climate change. Seasonality may be reduced the most in high-elevation, coastal habitats. Our models also indicated alterations may occur to vegetation along edge environments that are sensitive to climate change (Thuiller, 2007), which is especially evident in the high elevation areas (500–1500 m) of the Pacific Maritime. High elevation species are particularly vulnerable due to their slow growth, restricted viable habitat, and limited ability to adapt and migrate (Bakkenes, Alkemade, Ihle, Leemans, & Latour, 2002). Predicted increases in DHI minimum cover by 2065 could indicate that evergreen species may be more productive and could shift to higher latitudes and elevations (Coops, Wulder, Duro, Han, & Berry, 2008). Predicted increased year-round minimum cover suggests that that overall baseline productivity may escalate. Outcomes of this change would likely be increased productivity of forest habitats throughout the region and better growing conditions for generalist species to succeed in new habitats (Algar, Kharouba, Young, & Kerr, 2009). The resulting impacts to species due to increased minimum cover would be substantial. Since minimum cover indicates year round primary productivity, the projected increase would result in a more productive environment. The phenology of individual species would need to adapt to new climatological conditions and generalist primary productivity species would grow at a faster rate (Badeck, Bondeau, Bottcher, Doktor, Lucht, Schaber, & Sitch, 2004).

Mapping future scenarios for DHI indicators provides insights into how habitats will shift across British Columbia. Our understanding of the spatial changes aids our ability to properly prescribe best practices in conservation and management strategies (Lemieux & Scott, 2005; Gayton, 2008). Although our prediction method has some benefits, it also has some inherent limitations. Some researchers have argued that regression tree-based methods are too responsive to slight changes in climate (Iverson & Prasad, 1998; Guisan & Thuiller, 2005) and these types of climate-led predictions are over-simplified and do not incorporate sufficient ecological processes into the prediction (Hampe, 2004). Pearson and Dawson (2003) argued that the climate-determined models are validated by comparing simulated and actual species distributions and it is accepted that for macro (regional to global) studies a climate-deterministic approach would account for shifts (Hampe, 2004; Hamann & Wang, 2006; McKenney, Pedlar, Lawrence, Campbell & Hutchinson, 2007). Climate-determined regression trees have been used by other researchers (Franklin, 1995; Iverson & Prasad, 1998; Thuiller, 2003; Harrison, Berry, Butt, & New, 2006) to determine productivity shifts at the regional to global scale. Interpretation of our results should emphasize broad ecosystem shifts to in order to highlight the possible directionality of future spatial changes.

Cumulative greenness, seasonality, and minimum cover were all forecasted to change markedly by 2065. Some threatened species that currently occur in areas likely to undergo the most change are the burrowing owl (*Athene cunicularia*), Indra swallowtail (*Papilio indra*), three lobed daisy (*Erigeron trifidus*), Carolina draba (*Draba reptans*), and Lyall's mariposa lily (*Calochortus lyallii*), and poor pocket moss (*Fissidens pauperculus*) (Species at Risk British Columbia, 2012). Specialist species in high elevation environments were also indicated to be at higher risk. Given the anticipated changes to seasonality, it is likely that high elevation edge environments may continue to shift to higher elevations (Hebda, 1998). More productive habitats (as indicated by increases in minimum cover and cumulative greenness) can expand into the former seasonal habitats and are projected to move up mountain sides, and overall, forest ecosystems are projected to have greater vegetation productivity (Davis, Lawton, Shorrocks, & Jenkinson, 1998).

CONCLUSION

The results of our forecasting efforts provide a promising method to generate spatially explicit information of possible future shifts to vegetation productivity, which can be used to supplement direct sampling methods. The benefits of our methods are that they do not require direct sampling and therefore are an efficient and inexpensive method to monitor vegetation. Using productivity measures from enhanced remote sensing approaches to produce the DHI has provided an improved ecological landscape understanding at a broad spatial resolution. Utilizing climate information at 1 km spatial resolution in forecasting allowed for mapping of spatial variation in shifts of vegetation components due to climate change. Our methods can be repeated, enhanced, and updated regularly to give up-to-date information about the impacts to the terrestrial environment with complete and uniform coverage for large regions. Understanding the nature of possible spatial shifts in vegetation productivity is important for effectively planning for the future of protected areas, aiding conservation strategies, and properly managing natural resources. Our results provide detailed spatial information indicating the broad impact of climate change on vegetated landscapes. By understanding climate change impacts, decision makers can be better informed to properly adapt and mitigate these impacts.

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Tables

Table 1: Details the landscape, temperature, hybrid, and precipitation variables used in the regression tree process and their use in forecasting literature.

Regression tree explanatory variables

Explanatory Variable	Details	Reference
Mean annual temperature	Average annual temperature (^{o}C)	(Running & Nemani, 1988; Slayback, Pinzon, Los, & Tucker, 2003; Hamann & Wang, 2006; Latta, Hailemariam, & Barrett, 2009)
Temperature difference	Temperature difference between mean coldest and mean warmest months (^{o}C).	(Algar, Kharouba, Young, & Kerr 2009; Coops, Wulder, Iwanicka, 2009)
Growing degree days	Growing degree days greater than 5^{o}C	(Running & Nemani, 1988; Pearson, Dawson, Berry, & Harrison, 2002; Algar, Kharouba, Young, & Kerr, 2009)
Number of frost free days	Total number of frost free days (greater than 0 ^{o}C)	(Nigh, Ying, & Qian, 2004; Hamann & Wang, 2006)
Mean coldest month temperature	Average temperature of the coldest month (^{o}C)	(Running & Nemani, 1988; Pearson, Dawson, Berry, & Harrison, 2002; Algar, Kharouba, Young, & Kerr, 2009)
Julian date on which frost free period begins	Spring up date on which frost free period begins (temperatures greater than 0^{o}C)	(Monserud, Huang, & Yang, 2006)
Climate moisture deficit	Hargreaves climate moisture deficit; precipitation and temperature metric	(Carey, 1996; Hamann & Wang, 2006; Latta, Hailemariam, & Barrett, 2009)
Evapotranspiration	Hargreaves reference evapotranspiration; precipitation and temperature metric	(Currie, 1991; Hamann & Wang, 2006)
Mean summer precipitation	Mean annual summer (May to September precipitation (mm)	(Notaro, Liu, & William, 2006; Hamann & Wang, 2006)
Precipitation as snow	Average annual snowfall (mm)	(Running & Nemani, 1988; Pettorelli et al., 2005; Notaro, Liu, & William, 2006; Potter, Kumar, Klooster, & Nemani, 2007)
Mean annual precipitation	Average annual precipitation (mm)	(Running & Nemani, 1988; Slayback, Pinzon, Los, & Tucker 2003; Potter, Kumar, Klooster, & Nemani, 2007; Latta, Hailemariam, & Barrett, 2009)
Elevation	Landscape topography (m)	(Hamann & Wang, 2006; Daly, Halbleib, Smith, Gibson, Doggett, Taylor, Curtis, & Pasteris, 2008; Latta, Hailemariam, & Barrett, 2009)

Table 2. Regression tree dominant splits, complexity parameters, and coefficient of determination.

Regression Tree Dominant Splits, Complexity Parameters, and Coefficient of Determination

Region	Cumulative Greenness		Coefficient of Variation		Minimum Cover	
Pacific Maritime	Number of frost free days, growing degree days, mean annual temperature	0.668	Mean annual temperature and growing degree days	0.671	Number of frost free days, growing degree days, and precipitation as snow	0.514
Okaganan Caribou	Elevation, evapotranspiration	0.478	Precipitation as snow, evapotranspiration	0.680	Precipitation as snow, number of frost free days, date on which frost free period begins	0.509
Kootenay	Elevation, number of frost free days	0.616	Elevation and evapotranspiration	0.508	Elevation and evapotranspiration	0.487
Mountain Cordillera	Growing degree days, evapotranspiration, elevation	0.435	Growing degree days, precipitation as snow, and mean annual precipitation	0.453	Climate moisture deficit, precipitation as snow, and mean annual temperature	0.360
Boreal Plain	Seasonal temperature difference, Julian date on which frost free period begins	0.214	Precipitation as snow, Julian date on which frost free period begins	0.283	Precipitation as snow, julian date on which frost free period begins	0.413
Taiga Plain	Precipitation as snow, evapotranspiration	0.419	Precipitation as snow, mean summer precipitation	0.244	Precipitation as snow, evapotranspiration	0.063
Province	Number of frost free days, evapotranspiration, and precipitation as snow	0.459	Growing degree days and precipitation as snow	0.483	Growing degree days, precipitation as snow, and number of frost free days	0.411
Coefficient of Determination (R^2)	0.92		0.89		0.72	

Figure Legends

Figure 1: Study Area: British Columbia and the regional analysis borders.

Figure 2. DHI vegetation indicator results: present day and 2065 B1, A1, and A2 scenarios.

Figure 3. Regional and provincial percent change in DHI cumulative greenness, minimum cover, and coefficient of variation from present day to B1, A1, and A2 scenarios.

Figure 4. Composite DHI model results. Simultaneous display of the spatial distributions of the metrics uses a color gun technique where the red, green, and blue color bands each represent a different DHI component; consequently coefficient of variation is represented by red, cumulative greenness is characterized by green, and minimum cover, blue. The resulting image is a display of all three vegetation indicators to be observed at once resulting in a comprehensive view of the spatial shifts occurring to the habitat. Dark colored regions have little of all three DHI while light colored areas have high predicted levels of DHI. Furthermore, areas of definitive color with little mixing detail the dominant habitat indicator; for example, a region that is purely red denotes a highly variable habitat (high coefficient of variation). As indicators shift over time such as when seasonality decreases, other components such as cumulative greenness or minimum cover develop to fill into newly favorable habitats. Common DHI blending occurred with light blue, yellow, and darker colorations like purple or dark orange. The light blue regions represent the most productive habitats with high minimum cover, high cumulative greenness, and low seasonality found in coastal and low elevation habitats. Darker purple and orange colorations indicate low productivity, low seasonality, and low minimum cover. Present day through to scenarios B1, A1, and A2 indicate the greening of the province and decreases in seasonality. Observations of the composite DHI allow for more site specific analysis of change. Examples of typical climate-driven reactions are shown along the Coast Mountains of the Pacific Maritime where seasonality decreases and greenness increases. Sites alongside mountains in the Taiga Plain region have the opposite reaction to decreasing seasonality and decreases in all DHI variables are predicted in the future scenarios.

Figure 5. Change analysis for cumulative greenness, seasonality, and minimum cover from present day to 2065 using the A1 scenario.

Figure 6. Composite DHI change map comparing present day to the A1 scenario. Red areas highlight the greatest overall vegetation indicator change.

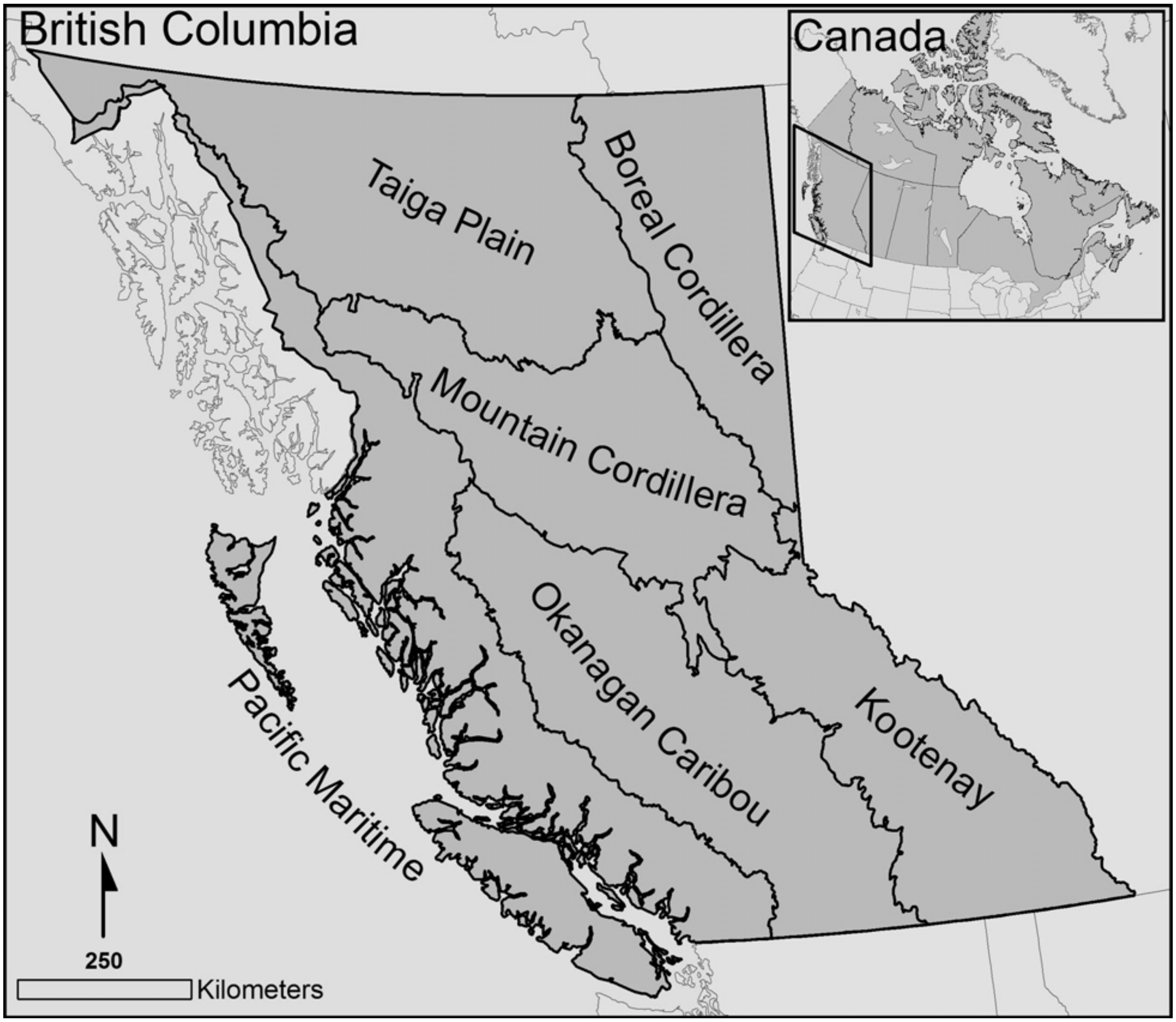
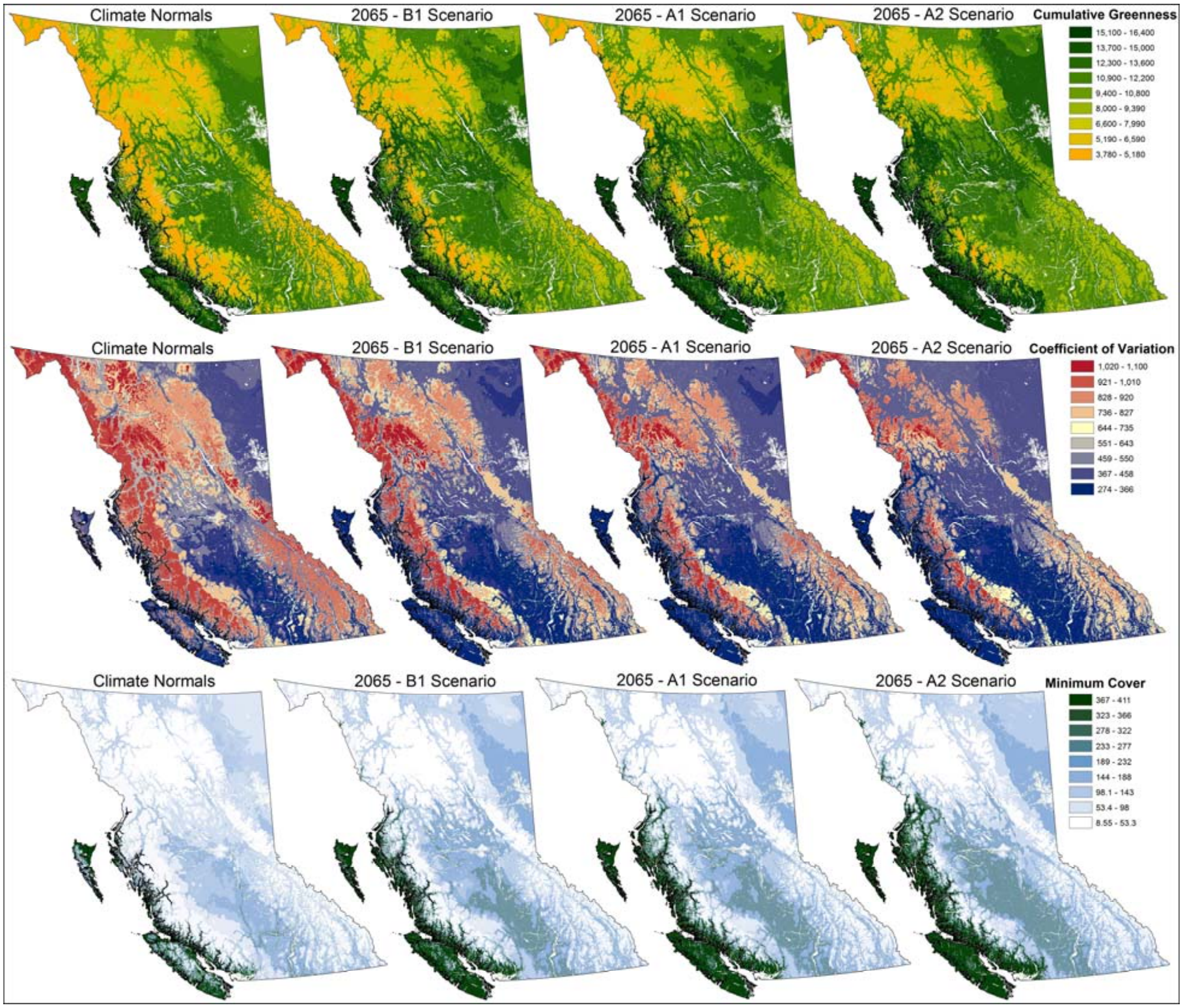

British Columbia
Canada
Taiga Plain
Boreal Cordillera
Mountain Cordillera
Okanagan Caribou
Kootenay
Pacific Maritime
N
250
Kilometers

Figure 1.



Climate Normals
2065 - B1 Scenario
2065 - A1 Scenario
2065 - A2 Scenario
Cumulative Greenness
15,100 - 16,400
13,700 - 15,000
12,300 - 13,600
10,900 - 12,200
9,400 - 10,800
8,000 - 9,390
6,600 - 7,990
5,190 - 6,590
3,780 - 5,180
Climate Normals
2065 - B1 Scenario
2065 - A1 Scenario
2065 - A2 Scenario
Coefficient of Variation
1,020 - 1,100
921 - 1,010
828 - 920
736 - 827
644 - 735
551 - 643
459 - 550
367 - 458
274 - 366
Climate Normals
2065 - B1 Scenario
2065 - A1 Scenario
2065 - A2 Scenario
Minimum Cover
367 - 411
323 - 366
278 - 322
233 - 277
189 - 232
144 - 188
98.1 - 143
53.4 - 98
8.55 - 53.3

Figure 2.

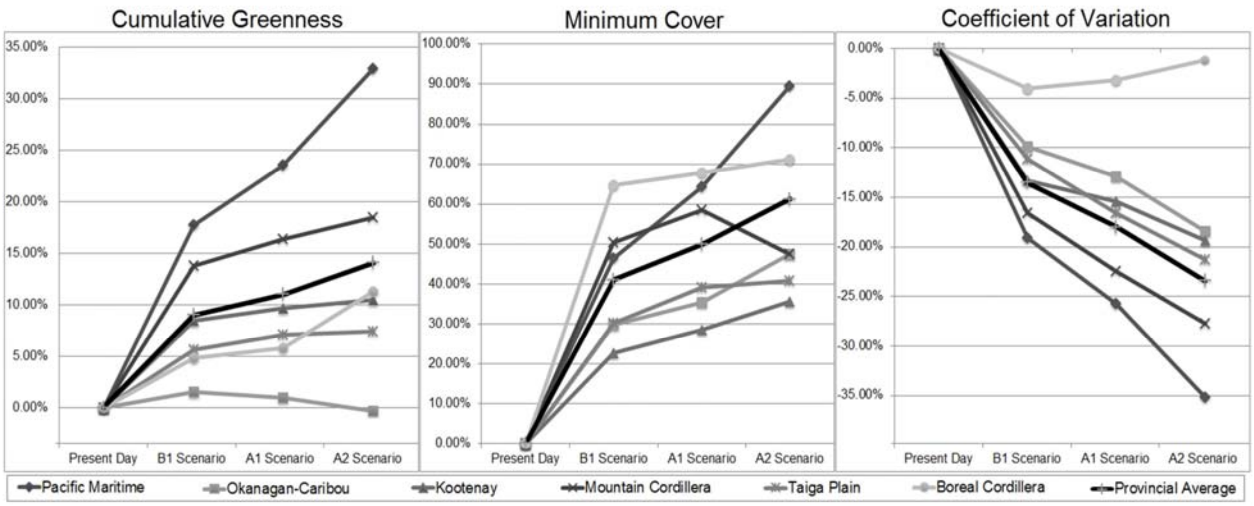

Cumulative Greenness
35.00%
30.00%
25.00%
20.00%
15.00%
10.00%
5.00%
0.00%
Present Day
B1 Scenario
A1 Scenario
A2 Scenario
Minimum Cover
100.00%
90.00%
80.00%
70.00%
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
Present Day
B1 Scenario
A1 Scenario
A2 Scenario
Coefficient of Variation
0.00%
-5.00%
-10.00%
-15.00%
-20.00%
-25.00%
-30.00%
-35.00%
Present Day
B1 Scenario
A1 Scenario
A2 Scenario
Pacific Maritime
Okanagan-Caribou
Kootenay
Mountain Cordillera
Taiga Plain
Boreal Cordillera
Provincial Average

Figure 3.

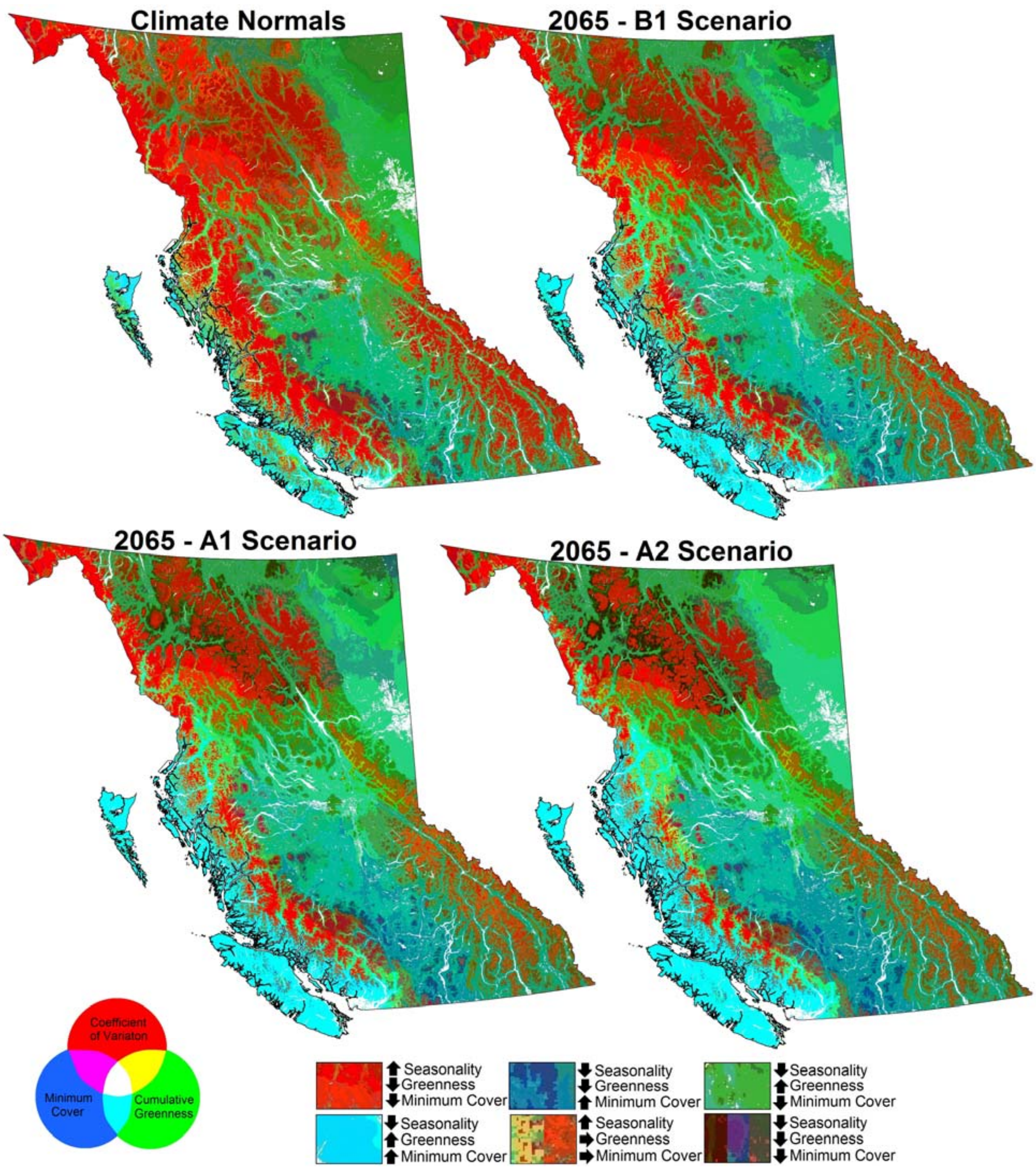

Climate Normals
2065 - B1 Scenario
2065 - A1 Scenario
2065 - A2 Scenario
Coefficient of Variaton
Minimum Cover
Cumulative Greenness
Seasonality
Greenness
Minimum Cover
Seasonality
Greenness
Minimum Cover
Seasonality
Greenness
Minimum Cover
Seasonality
Greenness
Minimum Cover
Seasonality
Greenness
Minimum Cover
Seasonality
Greenness
Minimum Cover

Figure 4.

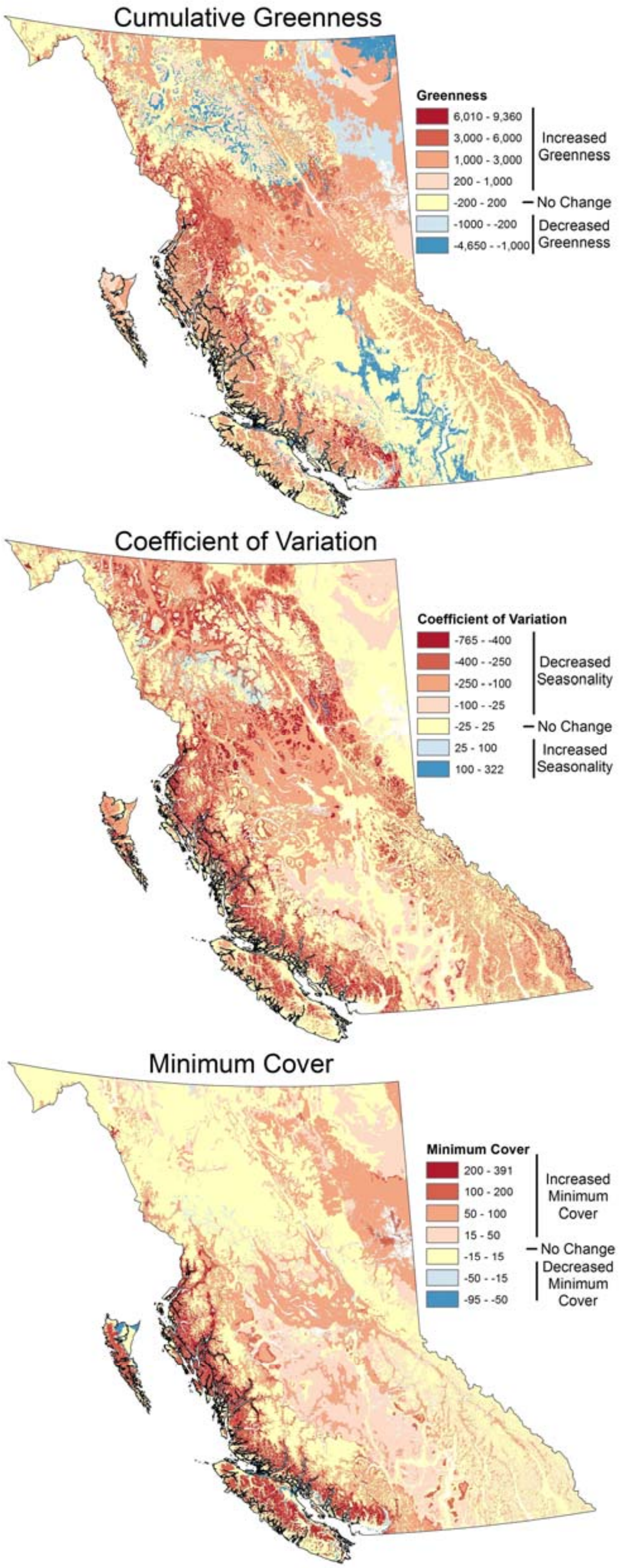

Cumulative Greenness
Greenness
6,010 - 9,360
3,000 - 6,000
1,000 - 3,000
200 - 1,000
-200 - 200
-1000 - -200
-4,650 - -1,000
Increased Greenness
No Change
Decreased Greenness
Coefficient of Variation
Coefficient of Variation
-765 - -400
-400 - -250
-250 - -100
-100 - -25
-25 - 25
25 - 100
100 - 322
Decreased Seasonality
No Change
Increased Seasonality
Minimum Cover
Minimum Cover
200 - 391
100 - 200
50 - 100
15 - 50
-15 - 15
-50 - -15
-95 - -50
Increased Minimum Cover
No Change
Decreased Minimum Cover

Figure5.

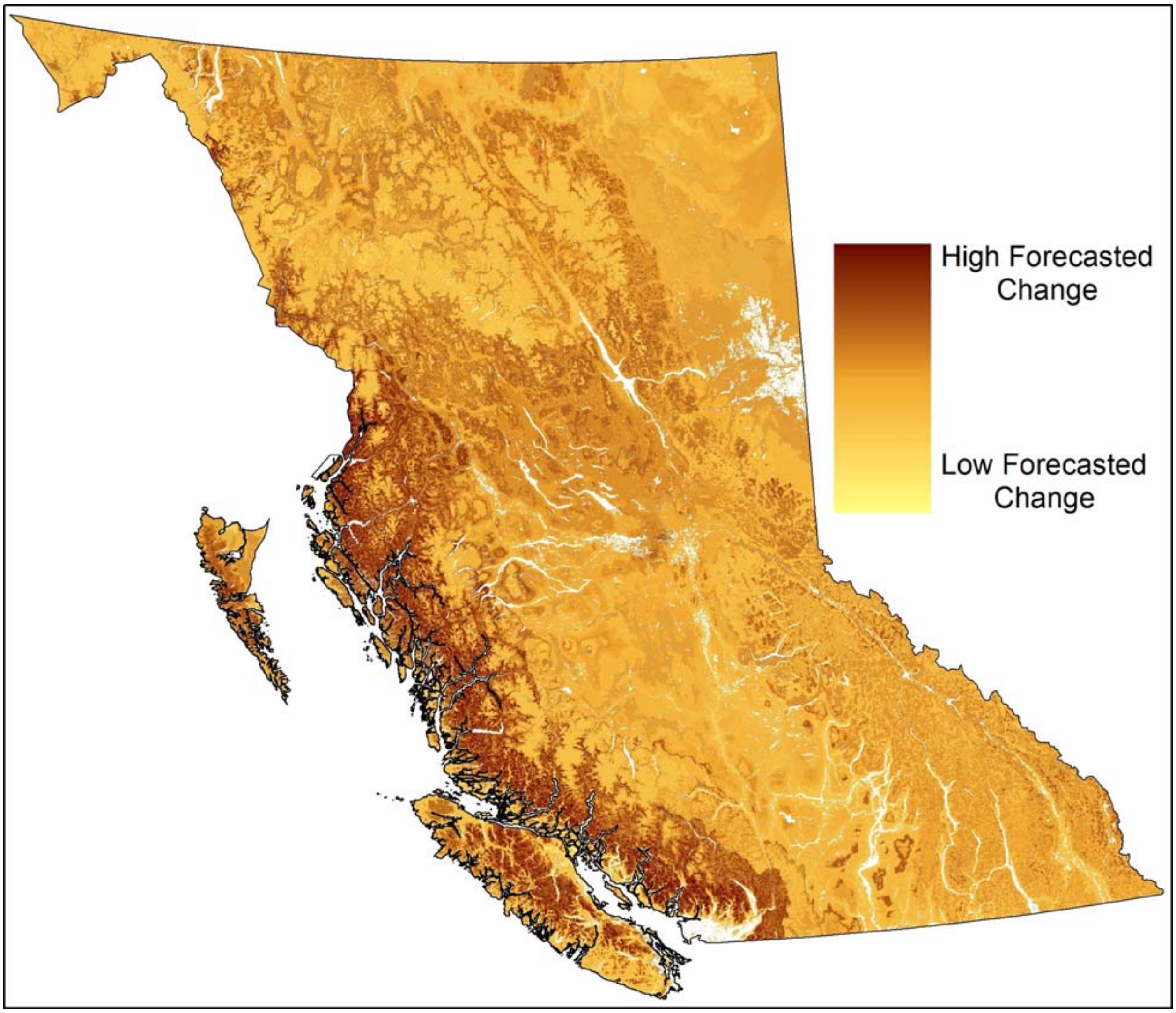


Figure 6.