Disentangling linkages between satellite derived forest structure and productivity across a range of forest types and ecosystems.

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# Introduction

Biodiversity is the summation of variation in biological life, across genes, species, communities, and ecosystems. Currently, biodiversity is in decline, facing extinction rates above the background extinction rate (Thomas et al., 2004; Urban, 2015), and homogenization of communities at various scales (McGill et al., 2015). In response, the global biodiversity community is making efforts to assess and halt the degradation of biodiversity on earth. The Group for Earth Observation Biodiversity Observation Network has developed the Essential Biodiversity Variables (EBVs, Pereira et al., 2013), designed as an analog to the Essential Climate Variables framework (Bojinski et al., 2014). EBVs are designed to be global in scope, relevant to biodiversity information, feasible to utilize, and complementary to one another (Skidmore et al., 2021). There are six EBV classes, each of which correspond to a different facet of biodiversity including species populations, species traits, community composition, ecosystem structure, ecosystem function, and genetic composition (Pereira et al., 2013).

Satellite remote sensing has proven to be capable of measuring five of the six EBV classes, the exception being genetic composition, which requires in-situ observation and sampling (Skidmore et al., 2021). Species populations - and in turn community composition - can be assessed with very-high-resolution imagery to identify tree species at the tree-crown scale, however it is difficult and computationally expensive to extend these analyses to broader extents (Fassnacht et al., 2016; Graves et al., 2016) while species traits such as vegetation phenology have been observed at the single-tree scale using, for example, PlanetScope imagery and drone-based measurements (Wu et al., 2021). Coarser spatial measurements, such as those taken from satellites by the MODIS (Zhang et al., 2003), Landsat imaging systems(Fisher et al., 2006), or Sentinel (Darvishzadeh et al., 2019; Helfenstein et al., 2022) can monitor these functional processes at broader extents, corresponding to ecosystem function, but the coarse spatial resolution removes the ability to relate these traits to individual trees. Remote sensing data has been shown to be arguably the most effective at monitoring ecosystem structure and function at regional to global extents through the use of optical imagery (Cohen and Goward, 2004) and active sensors such as lidar and radar datasets (Lang et al., 2021; Lefsky et al., 2002; Neuenschwander and Pitts, 2019).

Notably, while remote sensing can provide information on the species-level EBVs, this information is typically acquired with an *ad-hoc* approach requiring high spatial and spectral resolution data (Skidmore et al., 2021). This data can often only be collected at small extents, rather than the global or regional scales required for biodiversity trend assessment (Valdez et al., 2023). The two landscape-level EBVs (ecosystem structure and function) are well suited to be examined at global or regional scales using moderate-resolution satellite imagery, such as those provided by the Landsat or Sentinel series of satellites (Skidmore et al., 2021).

Forest structural diversity has been linked to biodiversity at various scales (Bergen et al., 2009; Gao et al., 2014; Guo et al., 2017). Many metrics derived from lidar remote sensing have been used as local indicators of biodiversity, including simple metrics such as canopy cover and canopy height as well as derived metrics including vertical profiles, aboveground biomass (Lefsky et al., 1999). Other second order derived metrics such as canopy texture, height class distribution, edges, and patch metrics have also been used to examine habitat and biodiversity at landscape scales (Bergen et al., 2009). Increased structural complexity has been hypothesized to create additional niches, leading to increased species diversity (Bergen et al., 2009), which has been frequently demonstrated using avian species diversity metrics (Macarthur and Macarthur, 1961). For example: Herniman et al. (2020) used spectral and lidar derived forest structure data to model avian habitat suitability; Clawges et al. (2008) found that lidar derived forest structural attributes are capable of identifying habitat types associated with avian species in pine/aspen forests; Goetz et al. (2007) used canopy structural diversity to predict bird species richness, finding that canopy vertical distribution was the strongest predictor of species richness. Forest structural metrics have also been used to study biodiversity in other clades as well (Davies and Asner, 2014; Nelson et al., 2005).

With respect to ecosystem function, energy availability in an ecosystem has shown to be a predictor of species richness and abundances at various scales (Chase and Leibold, 2002; Coops et al., 2019; Radeloff et al., 2019; Razenkova et al., n.d.), and is measurable using satellite remote sensing via the use of various vegetation indices (Huete et al., 2002; Radeloff et al., 2019). Vegetation indices, which are indicative of photosynthetic activity, are commonly used as proxies of gross primary productivity (Huang et al., 2019). These vegetation indices have also been used to assess patterns in biodiversity at single time points (Bonn et al., 2004), and more recently, through yearly summaries of productivity (Radeloff et al., 2019). The relationship between energy availability and biodiversity occurs via various hypotheses, such as the available energy hypothesis, the environmental stress hypothesis, and the environmental stability hypothesis. These three hypotheses have in turn been linked to patterns of surface reflectance in remote sensing data (Radeloff et al., 2019). The Dynamic Habitat Indices (DHIs) have been shown to be well suited to assess these hypotheses. The cumulative DHI calculates the total amount of energy available in a given pixel over the course of a year. Cumulative DHI is strongly linked to the available energy hypothesis, which suggests that with greater available energy species richness will increase (Wright, 1983). The minimum DHI, which calculates the lowest productivity over the course of a year can be matched to the environmental stress hypothesis, which proposes that higher levels of minimum available energy will lead to higher species richness (Currie et al., 2004). Finally, the variation DHI, which calculates the coefficient of variance in a vegetation index through the course of a year, corresponds to the environmental stability hypothesis which states that lower energy variation throughout a year will lead to increased species richness (Williams and Middleton, 2008).

Within forested ecosystems, there are therefore many possible remotely sensed derived ecosystem structure and function metrics that can be assessed. Structural variables range in complexity from simple (canopy cover; canopy height), to more complex (elevation coefficient of variation; elevation standard deviation) to modelled (aboveground biomass; basal area), all of which can be assessed using lidar data (Coops et al., 2021). Data on ecosystem functionality ranges from phenology metrics (date of leaf on/leaf off; length of growing season) to functional traits (chlorophyll content; leaf area index) to productivity estimates (GPP; total available energy) (Pettorelli et al., 2018). Advances in satellite remote sensing processing have allowed 3D forest structure data to be imputed across wide spatial scales (Coops et al., 2021; Matasci et al., 2018) using data fusion approaches involving collected lidar data and optical/radar data. Other advances in image compositing have allowed yearly summaries of vegetation productivity to be calculated at regional to global scales, summarizing the yearly total, minimum, and variation in energy availability at similar spatial resolutions (Radeloff et al., 2019).

Linkages between forest structure and function have been examined within a remote sensine context for over 20 years Knyazikhin et al. (1998). While there is significant theoretical and empirical evidence for their relationship at single time points (within a single image) (Myneni and Williams, 1994), various relationship directions and shapes have been found between forest structure and function metrics (Ali, 2019). These relationships, their shapes, and their strengths have been attributed to multiple possible hypotheses and have been shown to vary based on environmental conditions (Ali, 2019). The relationship in particular between forest structural diversity metrics - which are now more accurately and comprehensively derived from lidar data - and temporal variation in functional metrics, specifically the metrics of ecosystem productivity via the DHI framework, have yet to be fully examined.

Understanding the complementarity between potential EBVs is an integral component of their creation (Skidmore et al., 2021). Structural equation modelling (SEM) and path analyses have been commonly used in ecology to assess the causal effects behind various hypotheses (Fan et al., 2016; Grace et al., 2010), including the relationship between forest structure, functioning, and biodiversity (Ali, 2019). For example, SEM has commonly been used to assess the role of structural diversity of carbon storage as compared to species diversity (Ali et al., 2016; Zhang and Chen, 2015).

The overall goal of this paper is to characterize patterns of forest ecosystem structure and function and their interrelationships across a wide range of ecosystems encompassing significant environmental gradients. To do so, we synthesize data from moderate-scale remote-sensing derived metrics of structure, represented as both simple ALS metrics of canopy height and cover, as well as modeled forest structure variables including volume, and above ground biomass, with a remote sensing derived index on ecosystem function. Our first question is to examine how ecosystem structure and function vary across a large environmental gradient and then compare the simple and modeled representations of forest structure to different levels of ecosystem function. This question is important as it provides insights to the EBV community around redundancy in remote sensing metrics when describing structure and function on ecosystem and proposes a method to examine potential overlap when generating remote sensing EBV’s.

Our second question examines the independent and shared relationships of ecosystem structure height and cover, with modeled forest structure, on function. This provides insight into the choice of remote sensing attributes to use when developing EBV’s. Remote sensing datasets can comprise relatively unprocessed, observations, in this case ALS measures of height and cover which are retrieval from the raw 3D point cloud, vs modeled attributes, such as biomass and volume, which involve the use the statistical relationships to transform the observations into more refined data products. Assessing which of these two (or combination of the two) approaches has more or less redundancy with estimates of function provides insights into the choice of data used to build EBV’s. Lastly we examine how the primary and modeled structure attributes vary in their variance partitioning within key biomes across this large environmental range, examining to what extend ecosystem type impacts these interrelationships and thus the applicability of these results globally.

# Methods

## Study Area

British Columbia is the westernmost province of Canada, and is home to a variety of terrestrial ecosystems (Pojar et al., 1987). Approximately 64% of the province is forested (BC Ministry of Forests, 2003). There is a large amount of ecosystem variation in the province, with large climate and topographic gradients. The Biogeoclimatic Ecosystem Classification (BEC) system identifies 16 zones based on the dominant tree species and the ecosystems general climate. These zones can be further split into subzones, variants, and phases based on microclimate, precipitation, and topography (Pojar et al., 1987). To examine trends across the large environmental gradients, we group the BEC zones into five broad biomes, specifically, the south interior, northern, montane, alpine, and coastal groups similar to Hamann and Wang (2006).

{insert figure showing ecosystems of interest} need to remake figure showing ecosystems, highlighting that bunchgrass and alpine zones are not included

{table showing elevations and climate ranges for each included bec zone}

## Data

### Forest Structure

We utilize a suite of forest structural diversity variables (canopy height, canopy cover, Lorey’s height, overstory cover, basal area, aboveground biomass, gross stem volume, mean elevation, elevation standard deviation, and structural complexity [coefficient of variation in elevation returns]). This dataset is created at a 30 m spatial resolution according to Matasci et al. (2018). In brief, the method utilizes a set of lidar collections and field plots across Canada, and imputes the remaining pixels using a random forest k-Nearest Neighbour approach. Detailed information on the creation of this dataset can be found in Matasci et al. (2018).

### Dynamic Habitat Indices

The Dynamic Habitat Indices are a set of satellite remote sensing derived productivity variables that summarize the cumulative amount of available energy, the minimum available energy, and the variation in available energy throughout a given year (Radeloff et al., 2019). The DHIs have previously been produced at a global extent using MODIS imagery (Radeloff et al., 2019), however, recent studies have examined how these indices can be constructed at a finer spatial resolution using multi-annual Landsat imagery.

The DHIs were calculated according to {RAZENKOVA LANDSAT DHI PAPER IN PRESS} for all of terrestrial British Columbia. In brief, they utilized Google Earth Engine (Gorelick et al., 2017) to obtain all valid Landsat pixels for a given study area by filtering out low quality pixels, then calculated the NDVI for each pixel. They use the median NDVI value for each month across the ten year time span (2011-2020) to calculate the sum, minimum, and coefficient of variation in NDVI values. More detailed information can be found in {Razenkova In Press}.

## Sampling

We conducted model based sampling across the fifteen forest dominated ecosystems found within British Columbia [BC figure reference, I have not made this figure yet]. Samples were randomly selected within BEC zones of interest alongside multiple criteria. Each sampled pixel had to have a forested land cover class (coniferous, deciduous, mixed-wood, or wetland-treed), and be surrounded by the same land cover class. Additionally, each pixel had to have a coefficient of variation less than 0.5 in the Lorey’s height and canopy cover forest structural metrics. A maximum of 3000 samples were sampled in each BEC zone. All variables were natural-log transformed and standardized. Variables containing zeros were natural-log plus one transformed.

## Analysis

### General Trends in Forest Structure and Ecosystem Variables

General statistics were computed to characterize British Columbia-wide variables of ecosystem structure and function. To do so, the primary and modeled forest structure attributes and the three DHI components were compared with ANOVAs.

### Partial Redundancy and Variable Partitioning:

Partial redundancy analysis and variable partitioning was used to relate the primary and modeled forest structure variables to ecosystem structure, to assess the inter-relationships on forest ecosystem function across the broad environment range. Redundancy analysis has widely been used in community ecology where environmental variables of interest are compared to species composition, and when the effect of space for example is assessed as a third covariate, in an approach known as partial redundancy analysis. While RDA is common in the ecological literature, this represents one of the first times this technique has been applied to assess redundancy in proposed essential biodiversity variables. Redundancy analysis utilizes multiple regression in that it models the effect of an explanatory matrix on a response matrix; with the key difference being the use of a response matrix rather than a single response variable. The first step is a multiple regression where each of the variables in the response and explanatory matrices are regressed resulting in a matrix of fitted values. PCA is then used in the second step to reduce dimensionality through eigenvectors and to allow the strength of relationships between assessed, taking into account the number of explanatory variables. Partial Redundancy Analysis (PRA) allows the use of additional explanatory variables, or co-variates. This is useful, as it allow the assessment of the effect of one set of variables on another while taking into account variations due to other third set that are not the focus of the study. The output is similar to standard RDA except it is also possible to examine how much variation is explained in the primary variables of interest, and the co-variates alone, and then when combined together. This variance partitioning is then shown typically through a Venn diagram, in which the percentage of explained variance by each explanatory data set is reported.

## Software

The processing for this paper was done in R version 4.2.2 (R Core Team, 2022). We used *sgsR* (Goodbody et al., 2023) for sampling, *terra* (Hijmans, 2023) for raster analyses, *sf* for vector analyses (Pebesma, 2022), and *vegan* (Oksanen et al., 2022) for redundancy analysis and variance partitioning.

Focal analyses were conducted in R and Python, and the sampling was conducted across a masked suitability raster for each BEC zone using the *sgsR* R package version 1.3.4 (Goodbody et al., 2023).

All code associated with this analysis is available at https://github.com/emuise/code-structProdSem.

# Results

## Path Analysis

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| Figure 1: Proportion of strongest signficant forest structural predictors of yearly productivity metrics in models based on canopy cover vs canopy height. |

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| Figure 2: Bar plot of strongest predictors in path analysis for each BEC zone and predicted DHI variable. |

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| Figure 3: Map of strongest structural attribute predictor strength on yearly productivity metrics by BEC zone for the two proposed models. If there are no significant predictors, shown in dark grey |

## Exploratory Structural Equation Modelling

I also want to run exploratory SEM with and without the DHI’s to see what grouping it goes in. MinDHI has been breaking because some zones only have 0 as mindhi (makes sense, they are in the alpine).

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| Figure 4: Groups of latent variables with loadings greater than or equal to 0.5 for each BEC zone. Loadings were determined using exploratory factor analysis with up to four latent variables, and selecting the number of possible latent variables with the lowest AIC. All forest structure variables were potentially included as indicators in each latent variable. |

Exploratory factor analysis shows three groups of latent variables ([Figure 4](#fig-esem-latent)). We assigned the groups to latent variables indicating canopy cover / biomass metrics, canopy height / biomass metrics, and structural complexity metrics. Indicators to latent variable groups by examining anchors for each latent variable. The anchors were calculated by choosing the indicator variable with the largest difference between the maximum value in a given loading compared to to said indicators loadings in all other latent variables.

Both the Ponderosa Pine (PP) and Sub-boreal Pine – Spruce zones have one latent variable. Coastal Western Hemlock (CWH), Engelmann Spurce – Subalpine Fir (ESSF), and Montane Spruce (MS) are the only zones to have structural complexity based latent variables. CWH is the only zone to include elevation standard deviation in the structural complexity latent variable.

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| Figure 5: Groups of latent variables with loadings greater than or equal to 0.5 for each BEC zone, including the DHIs. Loadings were determined using exploratory factor analysis with up to five latent variables, and selecting the number of possible latent variables with the lowest AIC. All forest structure variables were potentially included as indicators in each latent variable. |

Exploratory factor analysis shows three groups of latent variables. We assigned these groups to attributes based on the indicator variables in each latent variable, indicating canopy cover, height and biomass, and structural complexity. When including the DHIs in this EFA, it is rare that they are included with latent variables with large loadings. The cumulative DHI is an indicator for the canopy cover latent varible in the IDF (Interior Douglas-fir) and MS (Montane Spruce) BEC zones. The DHIs are not included in any other latent variable, indicating that they compose different information than the forest structural variables.

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| Figure 6: Boxplots of latent variable loadings across BEC zones as determined by exploratory factor analysis. Red dashed lines show latent variable indicator cutoff before being used as starting values for the SEM models. |

[Figure 6](#fig-latent-boxplots) shows boxplots of latent variable loadings from forest structure indicator variables. A maximum of three valid latent variables were identified across the sixteen BEC zones. We assigned indicators variables to latent variable groups by examining the anchoring variables for each latent variable. The anchoring variables were calculated by choosing the indicator variable with the largest difference between the maximum value in a given loading compared to said indicators loadings in all other latent variables. The only DHI variable that was included in the latent variables after subsetting the latent variables to only include strong loadings was the Cumulative DHI in the canopy cover latent variable.

I need to actually make the DAGs and plot the parameters, but I haven’t gotten there yet. I’ll plot the global one to show what it looks like, then aggregate it in some way - probably similar to the path analysis. I also may include the variable partitioning that Meg talked about in the email if I can get it working.

# Discussion

# Conclusion

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