

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

Evan R. Muise^{a,*}, Nicholas C. Coops^a, Txomin Hermosilla^b, A. Cole Burton^a, Margaret E. Andrew^c, Stephen S. Ban^d

^a*University of British Columbia, Forest Resources Management, 2424 Main Mall, Vancouver, BC, Canada, V6T 1Z4*
^b*Natural Resources Canada, Canada Forest Service (Pacific Forestry Centre), 506 Burnside Rd W, Victoria, BC, Canada, V8Z 1M5*

^c*Murdoch University, Environmental and Conservation Sciences and Harry Butler Institute, Murdoch, WA, Australia, 6150*
^d*Ministry of Environment and Climate Change Strategy, BC Parks, 525 Superior Street, Victoria, BC, Canada, V8V 1T7*

Abstract

[insert abstract here - nicholas ignore the formatting on the authors for now, i can output to pdf and have it formatted nicely for submission]

Keywords: structural equation modelling, remote sensing, landsat, forest structure, forest productivity, dynamic habitat indices

1. 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 Bio-

diversity 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 corresponding to a different facet of biodiversity, including, genetic composition, species populations, species traits, community composition, ecosystem structure, and ecosystem function (Pereira et al., 2013). Fernández et al. (2020) divides the six classes into two approaches, with one focusing on species biodiversity, and the other focusing on ecosystem diversity. Remote sensing has proven to be capable of measuring five of the six classes, with the exception being genetic composition, which requires in-situ

*Corresponding author

Email addresses: evan.muise@student.ubc.ca (Evan R. Muise), nicholas.coops@ubc.ca (Nicholas C. Coops), txomin.hermosillagomez@NRCan-RNCan.gc.ca (Txomin Hermosilla), cole.burton@ubc.ca (A. Cole Burton), M.Andrew@murdoch.edu.au (Margaret E. Andrew), Stephen.Ban@gov.bc.ca (Stephen S. Ban)

observation and samples (Skidmore et al., 2021). Notably, while remote sensing can provide information on the remaining two species EBV classes, this information is typically acquired with an *ad hoc* approach requiring high spatial and spectral resolution data. This data can often only be collected at local extents, rather than the global or regional scales required for biodiversity trend assessment (Valdez et al., 2023). Community composition falls into a similar dilemma, requiring species population information which necessitates high resolution spatial data.

The remaining two classes, ecosystem structure and function, are incredibly well suited to be examined at global or regional scales using mid-resolution satellite imagery, such as that provided by the Landsat series of satellites. Advances in satellite remote sensing processing have allowed 3d forest structure data to be imputed across wide spatial scales (Matasci et al., 2018; Coops et al., 2021) 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 energy totals, minimums, and variations (Radeloff et al., 2019). These datasets correspond quite well with the EBV classes ecosystem structure (forest structural diversity metrics), and ecosystem function (forest productivity metrics).

Forest structural diversity has been linked to biodiversity at various scales (Guo et al., 2017; Bergen et al., 2009; Gao et al., 2014). Increased structural complexity is hypothesized to create addi-

tional niches, leading to increased species diversity (Bergen et al., 2009). The relationship between forest structure and biodiversity is commonly assessed using avian species diversity metrics (MacArthur and MacArthur, 1961; Goetz et al., 2007), however, other clades (and habitats), have also been used (Davies and Asner, 2014; Nelson et al., 2005). Many metrics derived from lidar remote sensing have been used as local indicators of biodiversity, including canopy cover, canopy height, vertical profiles, and aboveground biomass, while other 2nd order derived metrics such as canopy texture, height class distribution, edges, and patch metrics have been used to examine habitat and biodiversity at landscape scales (Bergen et al., 2009).

The dynamic habitat indices (DHIs) are indicators of productivity calculated by summarizing vegetation indices over the course of one (or multiple) years (Radeloff et al., 2019). These indices have been related to multiple facets of biodiversity at a range of scales, including species occurrence and abundance (Razenkova et al., 2020), alpha (Radeloff et al., 2019) and beta diversity (Andrew et al., 2012). Hypotheses behind the biodiversity productivity relationships have been established, including the species-energy hypothesis, the environmental stress hypothesis, and the environmental stability hypothesis (Coops et al., 2019). 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).

Some vegetation structure metrics are simpler, and more accurate, to calculate than others (Coops et al., 2021). These basic metrics, such as canopy height and canopy cover, can then be used to estimate additional structure metrics, such as basal area or total biomass. Canopy height and cover are commonly used as indicators of vertical and horizontal variation, respectively. Recently, more attention has been paid to internal structural complexity metrics, which can be more difficult and time consuming to generate (Coops et al., 2021; Ma et al., 2022), but have been shown to have stronger linkages with biodiversity (Guo et al., 2017), and productivity (Ali, 2019).

Linkages between forest structure and productivity (namely, vegetation indices) have been examined for nearly 20 years (Huete et al., 2002, Knyazikhin et al. (1998); Myneni and Williams, 1994). 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 productivity 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 between forest structural diversity metrics and annual productivity summaries has yet to be fully examined, including the DHIs.

Understanding the complementarity between potential EBVs is an integral component of their creation (Skidmore et al., 2021). Biodiversity has been shown to be linked to both forest structure (Guo et al., 2017; Gao et al., 2014), and productivity (Radeloff et al., 2019) at a range of scales. Research has highlighted that the relationship between productivity and biodiversity is reciprocal (Worm and Duffy, 2003), making productivity a suitable biodiversity indicator. In forested ecosystems, stand structural attributes have also been shown to influence productivity, with a range of responses dependent on environmental conditions (Ali, 2019).

Structural equation modelling 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). In this paper we seek to untangle the relationship between two EBVs: forest structure diversity metrics and yearly summaries of forest productivity. To accomplish this, we assess this relationship using path analysis to assess the direct and indirect (as mediated by more complex forest structural diversity metrics) effects of commonly collected forest structural metrics (canopy

height and canopy cover) on yearly productivity summaries. Further, we use exploratory structural equation modelling (ESEM) to identify the latent variables driving the productivity metrics. We run this analysis both globally, and stratified by the forested ecosystems of British Columbia, Canada, and compare models using AIC scores and global fit measures across the ecosystems. The results from this study will assess the linkages and complementarity between two biodiversity indicators.

2. Methods

2.1. 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](#)).

{insert figure showing ecosystems of interest} need to remake figure showing ecosystems, highlighting that bunchgrass isn't included

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

2.2. Data

2.2.1. NTEMS

2.2.2. 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.

2.3. 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. These focal analyses were pre-processed in R and Python, and randomly sampled across a masked suitability raster for each BEC zone using the *sgsR* R package version 1.3.4 ([Goodbody et al., 2023](#)). A maximum of 3000 samples were taken from each BEC zone.

[note to ncc; I've stopped doing this sampling step as Meg said she didn't feel it was necessary]

The imputation method used to generate the forest structure layers leads to many duplicated values as there are a limited number of samples to predict from (Matasci et al., 2018). A discussion of imputation approaches to large area lidar attribute modelling can be found in Coops et al. (2021). To account for duplicated input values in our modelling we averaged the endogenous variables within each ecosystem for each uniquely imputed set of forest attributes, forest type, and ecosystem. Due to variations in ecosystem size, differing numbers of samples were generated for each ecosystem. To account for this during model comparison, each ecosystem and land cover sample set was downsampled to the minimum number of samples for a single BEC zone (in this case, 170). For the forest type models, we attempted to select equal numbers of observations from each BEC zone. However, some forest types are rarely found in certain zones. To account for this, if an equal number of samples from each BEC zone were not available, the entire sample from that zone was taken. The amount of samples taken from other zones was then increased in order to collect a total number equal to the minimum number of samples in a single BEC zones (170). To meet the normality assumptions of path analysis, all variables were natural-log transformed and standardized, as per Grace et al. (2016). Variables containing zeros were natural-log plus one transformed.

2.4. Analysis

2.4.1. Path Analysis

To determine the relationships between simple lidar derived forest structural attributes, complex/derived forest structural attributes, and forest productivity, we used path analysis to analyze two causal models (Figure 1). To determine primary drivers of the three DHIs, we will summarize the predictors across ecosystems by counting the strongest predictor in each BEC zone. This will determine if the primary driver for each facet of the DHI is simple or complex, and allow us to assess ecosystem differences.

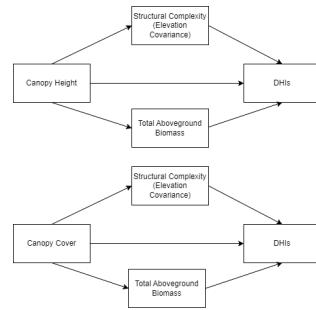


Figure 1: Proposed path diagrams

2.4.2. Exploratory Structural Equation Modelling

Secondly, we will use exploratory structural equation modelling (Marsh et al., 2020; Asparouhov and Muthén, 2009) to identify latent forest structural variables within the data, and use these latent variables to predict the dynamic habitat indices. Exploratory structural equation modelling is a combination of exploratory factor analysis (EFA) and structural equation modelling, which relaxes the strict requirement of zero cross-loadings in confirmatory factor analysis and allows for less strict measurement models to be used. ESEM is used when it is known that there is a latent structure to

the data, but the specific indicator variables have not yet been determined.

One advantage of ESEM is that it can create varying numbers of latent variables. For our analysis, we first ran exploratory factor analysis on all forest structural attributes both globally and by BEC zone with between 1-4 potential latent variables. We chose the most parsimonious EFA model with the lowest AIC scores for each ecosystem, leading to varying numbers of latent variables. We then determined the anchoring indicator 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 said indicators loadings in all other latent variables. Each anchor variable was then assigned to a named group (Canopy Cover, Height and Biomass, and Structural Complexity).

Following the EFA, we used structural equation modelling, with latent variables loadings determined by the EFA. We also filtered the loadings to be greater than or equal to 0.5, allowing us to examine the number and composition of latent variables found in each ecosystem. Following this, we predicted the DHIs in a single SEM with covariances between the DHIs. If a forest structural attribute did not end up in a latent variable, it was included in the structural equation model as a DHI predictor, without a latent variable as a mediator.

Fig. (x): Proportion of strongest significant predictors in models based on canopy cover vs canopy height

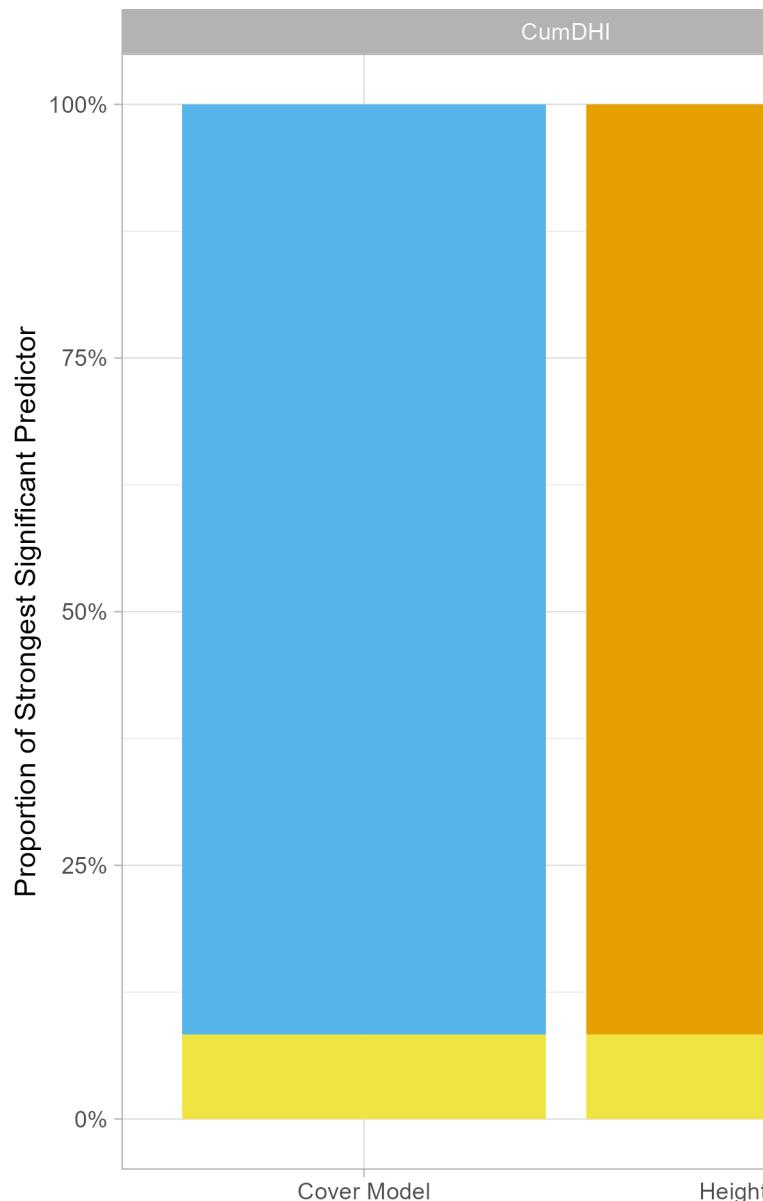
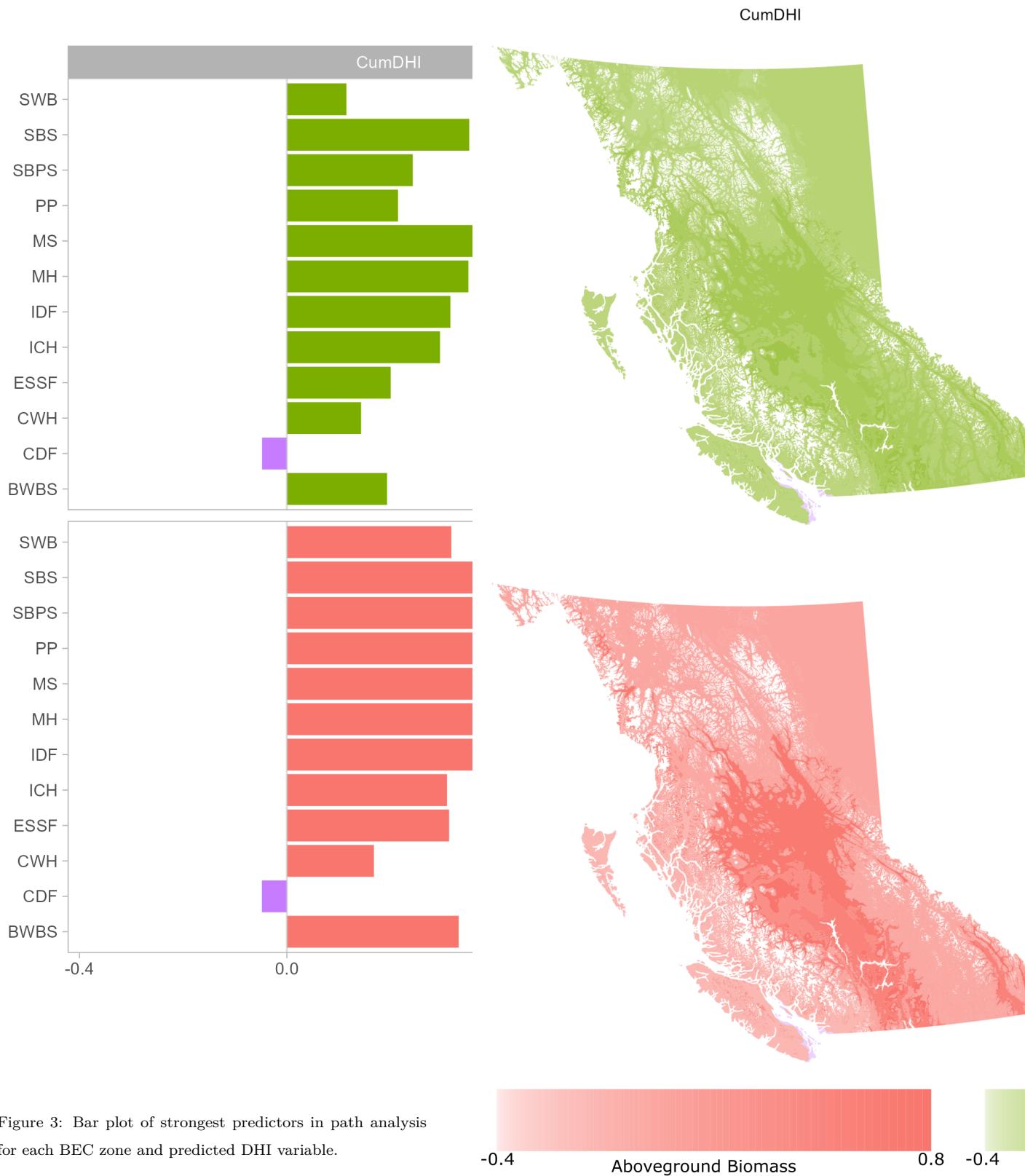


Figure 2: Proportion of strongest significant forest structural predictors of yearly productivity metrics in models based on canopy cover vs canopy height.



3. Results

3.1. Path Analysis

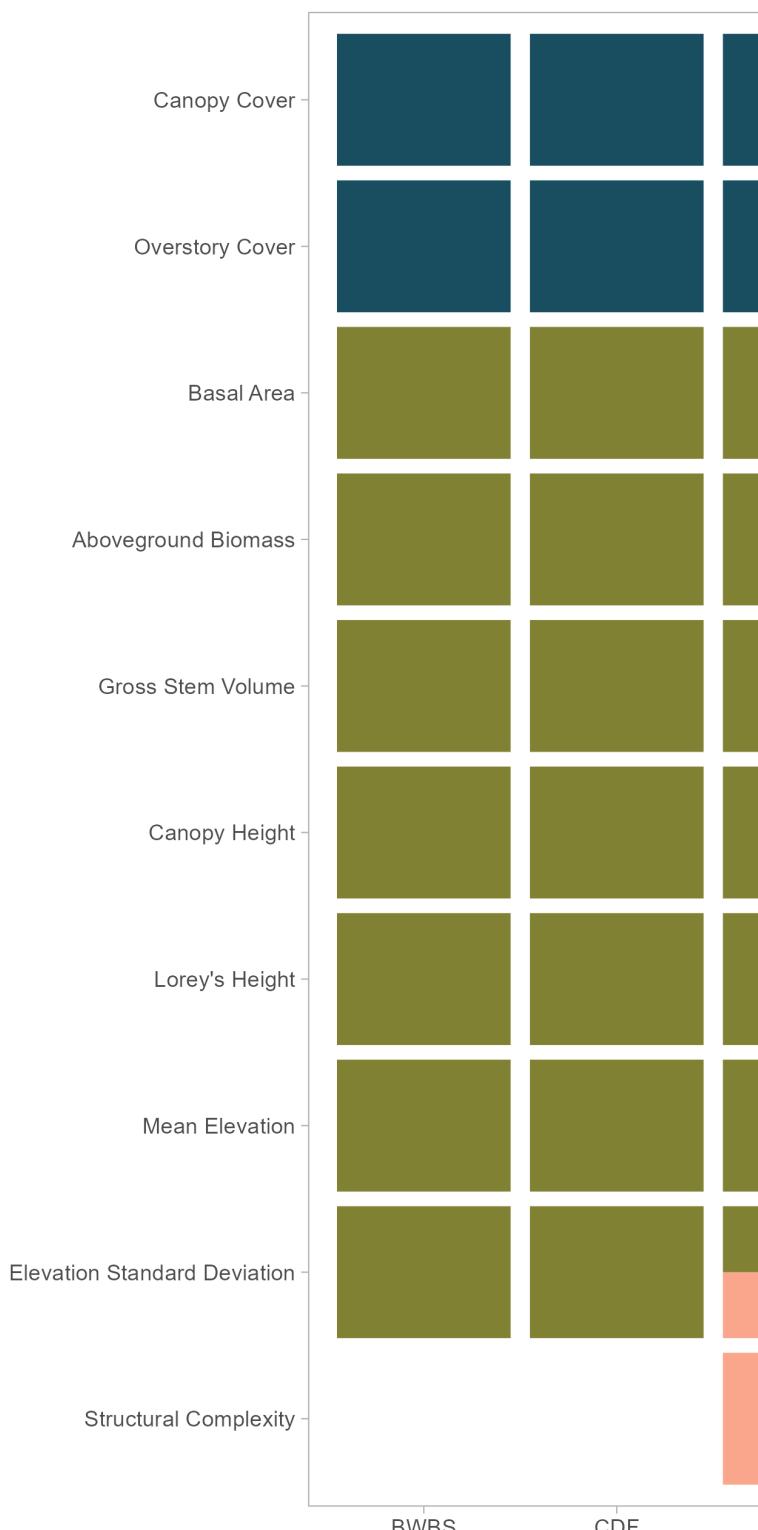
3.2. Exploratory Structural Equation Modelling

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).

Exploratory factor analysis shows three groups of latent variables (Figure 5). 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 Spruce – 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.

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



8 Figure 5: 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.



Figure 6: 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.

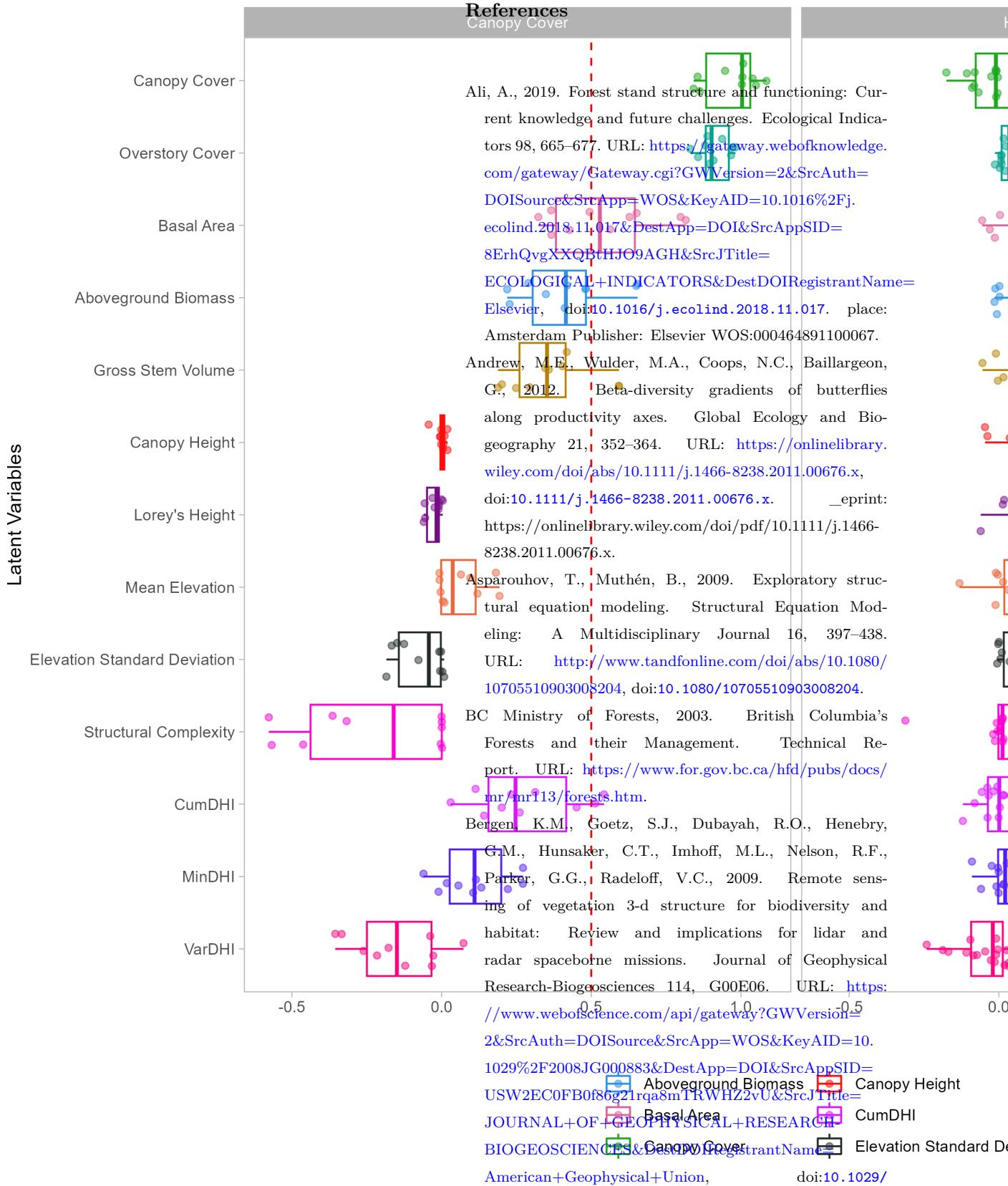


Figure 7: Boxplots of latent variable loadings across BEC zones as determined by exploratory factor analysis. Red dashed lines show latent variable indicator cutoff before being used as starting values for the SEM models.

- 2008JG000883. place: Washington Publisher: Amer Geophysical Union WOS:000273047000001.
- Bojinski, S., Verstraete, M., Peterson, T.C., Richter, C., Simmons, A., Zemp, M., 2014. The concept of essential climate variables in support of climate research, applications, and policy. *Bulletin of the American Meteorological Society* 95, 1431–1443. URL: <https://journals.ametsoc.org/view/journals/bams/95/9/bams-d-13-00047.1.xml>, doi:10.1175/BAMS-D-13-00047.1.
- Coops, N.C., Bolton, D.K., Hobi, M.L., Radeloff, V.C., 2019. Untangling multiple species richness hypothesis globally using remote sensing habitat indices. *ECOLOGICAL INDICATORS* 107. doi:10.1016/j.ecolind.2019.105567. tex.article-number: 105567 tex.eissn: 1872-7034 tex.orcid-numbers: Radeloff, Volker C/0000-0001-9004-221X Hobi, Martina/0000-0003-3537-9738 tex.researcherid-numbers: Radeloff, Volker C/B-6124-2016 tex.unique-id: WOS:000490757500029.
- Coops, N.C., Tompalski, P., Goodbody, T.R.H., Queinnec, M., Luther, J.E., Bolton, D.K., White, J.C., Wulder, M.A., van Lier, O.R., Hermosilla, T., 2021. Modelling lidar-derived estimates of forest attributes over space and time: A review of approaches and future trends. *Remote Sensing of Environment* 260, 112477. URL: <https://www.sciencedirect.com/science/article/pii/S0034425721001954>, doi:10.1016/j.rse.2021.112477.
- Currie, D.J., Mittelbach, G.G., Cornell, H.V., Field, R., Guégan, J.F., Hawkins, B.A., Kaufman, D.M., Kerr, J.T., Oberdorff, T., O'Brien, E., Turner, J.R.G., 2004. Predictions and tests of climate-based hypotheses of broad-scale variation in taxonomic richness. *Ecology Letters* 7, 1121–1134. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1461-0248.2004.00671.x>. _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1461-0248.2004.00671.x>.
- Davies, A.B., Asner, G.P., 2014. Advances in animal ecology from 3d-lidar ecosystem mapping. *Trends in Ecology & Evolution* 29, 681–691. URL: <https://www.webofscience.com/api/gateway?GWVersion=2&SrcAuth=DOISource&SrcApp=WOS&KeyAID=10.1016%2Fj.tree.2014.10.005&DestApp=DOI&SrcAppSID=USW2EC0FB0f86g21rqa8mTRWHZ2vU&SrcJTitle=TRENDS+IN+ECOLOGY+%26+EVOLUTION&DestDOIRegistrantName=Elsevier>, doi:10.1016/j.tree.2014.10.005.
- Fan, Y., Chen, J., Shirkey, G., John, R., Wu, S.R., Park, H., Shao, C., 2016. Applications of structural equation modeling (sem) in ecological studies: an updated review. *Ecological Processes* 5, 19. URL: <https://doi.org/10.1186/s13717-016-0063-3>, doi:10.1186/s13717-016-0063-3.
- Fernández, N., Ferrier, S., Navarro, L.M., Pereira, H.M., 2020. Essential Biodiversity Variables: Integrating In-Situ Observations and Remote Sensing Through Modeling. Springer International Publishing, Cham. chapter 18. pp. 485–501. URL: https://doi.org/10.1007/978-3-030-33157-3_18, doi:10.1007/978-3-030-33157-3_18.
- Gao, T., Hedblom, M., Emilsson, T., Nielsen, A.B., 2014. The role of forest stand structure as biodiversity indicator. *Forest Ecology and Management* 330, 82–93. URL: <https://www.sciencedirect.com/science/article/pii/S0378112714004241>, doi:10.1016/j.foreco.2014.07.007.
- Goetz, S., Steinberg, D., Dubayah, R., Blair, B., 2007. Laser remote sensing of canopy habitat heterogeneity as a predictor of bird species richness in an eastern temperate forest, usa. *Remote Sensing of Environment* 108, 254–263. doi:10.1016/j.rse.2006.11.016.
- Goodbody, T.R.H., Coops, N.C., Queinnec, M., White, J.C., Tompalski, P., Hudak, A.T., Auty, D., Valbuena, R., LeBoeuf, A., Sinclair, I., McCartney, G., Prieur, J.F., Woods, M.E., 2023. sgsr: a structurally guided sampling toolbox for lidar-based forest inventories. *Forestry: An International Journal of Forest Research*, cpac055URL: <https://doi.org/10.1093/forestry/cpac055>, doi:10.1093/forestry/cpac055.
- Grace, J.B., Anderson, T.M., Olff, H., Scheiner, S.M., 2010. On the specification of structural equation models for ecological systems. *Ecological Monographs* 80, 67–87. URL: <http://doi.wiley.com/10.1890/09-0464.1>, doi:10.1890/09-0464.1.
- Grace, J.B., Anderson, T.M., Seabloom, E.W., Borer, E.T., Adler, P.B., Harpole, W.S., Hautier, Y., Hillebrand, H., Lind, E.M., Pärtel, M., Bakker, J.D., Buck-

- ley, Y.M., Crawley, M.J., Damschen, E.I., Davies, K.F., Fay, P.A., Firn, J., Gruner, D.S., Hector, A., Knops, J.M.H., MacDougall, A.S., Melbourne, B.A., Morgan, J.W., Orrock, J.L., Prober, S.M., Smith, M.D., 2016. Integrative modelling reveals mechanisms linking productivity and plant species richness. *Nature* 529, 390–393. URL: <https://www.nature.com/articles/nature16524>, doi:10.1038/nature16524. number: 7586 Publisher: Nature Publishing Group.
- Guo, X., Coops, N.C., Tompalski, P., Nielsen, S.E., Bater, C.W., John Stadt, J., 2017. Regional mapping of vegetation structure for biodiversity monitoring using airborne lidar data. *Ecological Informatics* 38, 50–61. URL: <https://www.sciencedirect.com/science/article/pii/S1574954116300905>, doi:10.1016/j.ecoinf.2017.01.005.
- Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the modis vegetation indices. *Remote Sensing of Environment* 83, 195–213. URL: <https://gateway.webofknowledge.com/gateway/Gateway.cgi?GWVersion=2&SrcAuth=DOISource&SrcApp=WOS&KeyAID=10.1016%2FS0034-4257%2802%2900096-2&DestApp=DOI&SrcAppSID=6ABQuYtmtvvjzqEmPms&SrcJTitle=REMOTE+SENSING+OF+ENVIRONMENT&DestDOIRegistrantName=Elsevier>, doi:10.1016/S0034-4257(02)00096-2. place: New York Publisher: Elsevier Science Inc WOS:000179160200014.
- Knyazikhin, Y., Martonchik, J.V., Myneni, R.B., Diner, D.J., Running, S.W., 1998. Synergistic algorithm for estimating vegetation canopy leaf area index and fraction of absorbed photosynthetically active radiation from modis and misr data. *Journal of Geophysical Research: Atmospheres* 103, 32257–32275. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1029/98JD02462>, doi:10.1029/98JD02462. _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/98JD02462>.
- Ma, Q., Su, Y., Hu, T., Jiang, L., Mi, X., Lin, L., Cao, M., Wang, X., Lin, F., Wang, B., Sun, Z., Wu, J., Ma, K., Guo, Q., 2022. The coordinated impact of forest internal structural complexity and tree species diversity on forest productivity across forest biomes. *Funda-*mental Research URL: <https://www.sciencedirect.com/science/article/pii/S2667325822004162>, doi:10.1016/j.fmre.2022.10.005.
- MacArthur, R., MacArthur, J., 1961. On bird species-diversity. *Ecology* 42, 594–598. URL: <https://www.webofscience.com/api/gateway?GWVersion=2&SrcAuth=DOISource&SrcApp=WOS&KeyAID=10.2307%2F1932254&DestApp=DOI&SrcAppSID=USW2EC0FB0f86g21rqa8mTRWHZ2vU&SrcJTitle=ECOLOGY&DestDOIRegistrantName=JSTOR>, doi:10.2307/1932254.
- Marsh, H.W., Guo, J., Dicke, T., Parker, P.D., Craven, R.G., 2020. Confirmatory factor analysis (cfa), exploratory structural equation modeling (esem), and set-esem: Optimal balance between goodness of fit and parsimony. *Multivariate Behavioral Research* 55, 102–119. URL: <https://www.tandfonline.com/doi/full/10.1080/00273171.2019.1602503>, doi:10.1080/00273171.2019.1602503.
- Matasci, G., Hermosilla, T., Wulder, M.A., White, J.C., Coops, N.C., Hobart, G.W., Bolton, D.K., Tompalski, P., Bater, C.W., 2018. Three decades of forest structural dynamics over canada's forested ecosystems using landsat time-series and lidar plots. *Remote Sensing of Environment* 216, 697–714. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0034425718303572>, doi:10.1016/j.rse.2018.07.024.
- McGill, B.J., Dornelas, M., Gotelli, N.J., Magurran, A.E., 2015. Fifteen forms of biodiversity trend in the anthropocene. *Trends in Ecology & Evolution* 30, 104–113. URL: <https://www.sciencedirect.com/science/article/pii/S0169534714002456>, doi:10.1016/j.tree.2014.11.006.
- Myneni, R.B., Williams, D.L., 1994. On the relationship between fapar and ndvi. *Remote Sensing of Environment* 49, 200–211. URL: <https://www.sciencedirect.com/science/article/pii/0034425794900167>, doi:10.1016/0034-4257(94)90016-7.
- Nelson, R., Keller, C., Ratnaswamy, M., 2005. Locating and estimating the extent of delmarva fox squirrel habitat using an airborne lidar profiler. *Remote Sensing of Environment* 96, 292–301. URL: <https://www.webofscience.com/api/gateway?GWVersion=2&SrcAuth=DOISource&SrcApp=WOS&KeyAID=10.1016/j.rse.2005.03.001>.

- 2&SrcAuth=DOISource&SrcApp=WOS&KeyAID=10.1016%2Fj.rse.2005.02.012&DestApp=DOI&SrcAppSID=USW2EC0FB0f86g21rqa8mTRWHZ2vU&SrcJTitle=REMOTE+SENSING+OF+ENVIRONMENT&DestDOIRegistrantName=Elsevier, doi:[10.1016/j.rse.2005.02.012](https://doi.org/10.1016/j.rse.2005.02.012).
- Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, R.J., Bruford, M.W., Brummitt, N., Butchart, S.H.M., Cardoso, A.C., Coops, N.C., Dulloo, E., Faith, D.P., Freyhof, J., Gregory, R.D., Heip, C., Hoft, R., Hurtt, G., Jetz, W., Karp, D.S., McGeoch, M.A., Obura, D., Onoda, Y., Pettorelli, N., Reyers, B., Sayre, R., Scharlemann, J.P.W., Stuart, S.N., Turak, E., Walpole, M., Wegmann, M., 2013. Essential biodiversity variables. *Science* 339, 277–278. URL: <https://www.sciencemag.org/lookup/doi/10.1126/science.1229931>, doi:[10.1126/science.1229931](https://doi.org/10.1126/science.1229931).
- Pojar, J., Klinka, K., Meidinger, D., 1987. Biogeoclimatic ecosystem classification in british columbia. *Forest Ecology and Management* 22, 119–154. URL: <https://linkinghub.elsevier.com/retrieve/pii/0378112787901009>, doi:[10.1016/0378-1127\(87\)90100-9](https://doi.org/10.1016/0378-1127(87)90100-9).
- Radeloff, V.C., Dubinin, M., Coops, N.C., Allen, A.M., Brooks, T.M., Clayton, M.K., Costa, G.C., Graham, C.H., Helmers, D.P., Ives, A.R., Kolesov, D., Pidgeon, A.M., Rapacciulo, G., Razenkova, E., Suttidate, N., Young, B.E., Zhu, L., Hobi, M.L., 2019. The dynamic habitat indices (dhis) from modis and global biodiversity. *Remote Sensing of Environment* 222, 204–214. URL: <https://www.sciencedirect.com/science/article/pii/S0034425718305625>, doi:[10.1016/j.rse.2018.12.009](https://doi.org/10.1016/j.rse.2018.12.009).
- Razenkova, E., Radeloff, V.C., Dubinin, M., Bragina, E.V., Allen, A.M., Clayton, M.K., Pidgeon, A.M., Baskin, L.M., Coops, N.C., Hobi, M.L., 2020. Vegetation productivity summarized by the dynamic habitat indices explains broad-scale patterns of moose abundance across russia. *Scientific Reports* 10, 836. URL: <https://www.nature.com/articles/s41598-019-57308-8>, doi:[10.1038/s41598-019-57308-8](https://doi.org/10.1038/s41598-019-57308-8). number: 1 Publisher: Nature Publishing Group.
- Skidmore, A.K., Coops, N.C., Neinavaz, E., Ali, A., Schaepman, M.E., Paganini, M., Kissling, W.D., Vihervaara, P., Darvishzadeh, R., Feilhauer, H., Fernandez, M., Fernández, N., Gorelick, N., Geijzendorffer, I., Heiden, U., Heurich, M., Hoborn, D., Holzwarth, S., Muller-Karger, F.E., Van De Kerchove, R., Lausch, A., Leitão, P.J., Lock, M.C., Mücher, C.A., O'Connor, B., Rocchini, D., Turner, W., Vis, J.K., Wang, T., Wegmann, M., Wingate, V., 2021. Priority list of biodiversity metrics to observe from space. *Nature Ecology & Evolution* URL: <http://www.nature.com/articles/s41559-021-01451-x>, doi:[10.1038/s41559-021-01451-x](https://doi.org/10.1038/s41559-021-01451-x).
- Thomas, C.D., Cameron, A., Green, R.E., Bakkenes, M., Beaumont, L.J., Collingham, Y.C., Erasmus, B.F.N., de Siqueira, M.F., Grainger, A., Hannah, L., Hughes, L., Huntley, B., van Jaarsveld, A.S., Midgley, G.F., Miles, L., Ortega-Huerta, M.A., Peterson, A.T., Phillips, O.L., Williams, S.E., 2004. Extinction risk from climate change. *Nature* 427, 5.
- Urban, M.C., 2015. Accelerating extinction risk from climate change. *Science* 348, 571–573. URL: <https://www.science.org/doi/10.1126/science.aaa4984>, doi:[10.1126/science.aaa4984](https://doi.org/10.1126/science.aaa4984).
- Valdez, J.W., Callaghan, C.T., Junker, J., Purvis, A., Hill, S.L.L., Pereira, H.M., 2023. The undetectability of global biodiversity trends using local species richness. *Ecography* 2023, e06604. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1111/ecog.06604>, doi:[10.1111/ecog.06604](https://doi.org/10.1111/ecog.06604). _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecog.06604>.
- Williams, S.E., Middleton, J., 2008. Climatic seasonality, resource bottlenecks, and abundance of rainforest birds: implications for global climate change. *Diversity and Distributions* 14, 69–77. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1472-4642.2007.00418.x>, doi:[10.1111/j.1472-4642.2007.00418.x](https://doi.org/10.1111/j.1472-4642.2007.00418.x). _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1472-4642.2007.00418.x>.
- Worm, B., Duffy, J.E., 2003. Biodiversity, productivity and stability in real food webs. *Trends in Ecology & Evolution* 18, 628–632. URL: <https://www.sciencedirect.com/science/article/pii/S0169534703002799>, doi:[10.1016/j.tree.2003.09.003](https://doi.org/10.1016/j.tree.2003.09.003).
- Wright, D.H., 1983. Species-energy theory: An extension of species-area theory. *Oikos* 41, 496–506. URL: <https://doi.org/10.2307/3545110>.

[//www.jstor.org/stable/3544109](http://www.jstor.org/stable/3544109), doi:10.2307/3544109.

publisher: [Nordic Society Oikos, Wiley].