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 classes, with 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). Species traits such as phenology have been on a single-tree scale using PlanetScope imagery and drone-based measurements (Wu et al., 2021). Coarser measurements, such as those taken by the MODIS (Zhang et al., 2003), Landsat (Fisher et al., 2006), or Sentinel (Darvishzadeh et al., 2019; Helfenstein et al., 2022) series of satellites can monitor these functional processes at larger 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 effective at monitoring ecosystem structure at regional to global extents through the use of optical imagery (Cohen and Goward, 2004) and lidar 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).

Energy availability in an ecosystem has also been 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 is proposed to function through 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).

Biodiversity has been shown to be linked to both forest structure (Gao et al., 2014; Guo et al., 2017), 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. Within a forest environment, there are many possible 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).

In forested ecosystems, stand structural attributes have also been shown to influence productivity, with a range of responses dependent on environmental conditions (Ali, 2019). Linkages between forest structure and productivity (namely, vegetation indices) have been examined for nearly 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 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). 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).

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 using a sample of wall-to-wall forest structure and productivity data across the province of British Columbia, and stratified by the forested ecosystems of British Columbia, Canada, which has some of the largest environmental gradients on the planet. We compare models using AIC scores and global fit measures across the ecosystems (Pojar et al., 1987). The results from this study will assess the linkages and complementarity between two commonly used biodiversity indicators.

# 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).

{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. To meet the normality assumptions of structural equation modelling, all variables were natural-log transformed and standardized, as per Grace et al. (2016). Variables containing zeros were natural-log plus one transformed.

## Analysis

### 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](#fig-pathdag)). 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.

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| Figure 1: Proposed path diagrams. |

### Exploratory Structural Equation Modelling

Secondly, we will use exploratory structural equation modelling (Asparouhov and Muthén, 2009; Marsh et al., 2020) 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 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.

## 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 *lavaan* (Rosseel, 2012) for path analysis and structural equation modelling.

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 2: 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 3: Bar plot of strongest predictors in path analysis for each BEC zone and predicted DHI variable. |

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| Figure 4: 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 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. |

Exploratory factor analysis shows three groups of latent variables ([Figure 5](#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 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. |

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 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. |

[Figure 7](#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

# References

Ali, A., 2019. Forest stand structure and functioning: Current knowledge and future challenges. Ecological Indicators 98, 665–677. <https://doi.org/10.1016/j.ecolind.2018.11.017>

Ali, A., Yan, E.-R., Chen, H.Y.H., Chang, S.X., Zhao, Y.-T., Yang, X.-D., Xu, M.-S., 2016. Stand structural diversity rather than species diversity enhancesaboveground carbon storage in secondary subtropical forests in Eastern China. Biogeosciences 13, 4627–4635. <https://doi.org/10.5194/bg-13-4627-2016>

Asparouhov, T., Muthén, B., 2009. Exploratory Structural Equation Modeling. Structural Equation Modeling: A Multidisciplinary Journal 16, 397–438. <https://doi.org/10.1080/10705510903008204>

BC Ministry of Forests, 2003. [British columbia’s forests and their management](https://www.for.gov.bc.ca/hfd/pubs/docs/mr/mr113/forests.htm).

Bergen, K.M., Goetz, S.J., Dubayah, R.O., Henebry, G.M., Hunsaker, C.T., Imhoff, M.L., Nelson, R.F., Parker, G.G., Radeloff, V.C., 2009. Remote sensing of vegetation 3-d structure for biodiversity and habitat: Review and implications for lidar and radar spaceborne missions. Journal of Geophysical Research-Biogeosciences 114, G00E06. <https://doi.org/10.1029/2008JG000883>

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. <https://doi.org/10.1175/BAMS-D-13-00047.1>

Bonn, A., Storch, D., Gaston, K.J., 2004. Structure of the speciesenergy relationship. Proceedings of the Royal Society of London. Series B: Biological Sciences 271, 1685–1691. <https://doi.org/10.1098/rspb.2004.2745>

Chase, J.M., Leibold, M.A., 2002. Spatial scale dictates the productivitybiodiversity relationship. Nature 416, 427–430. <https://doi.org/10.1038/416427a>

Clawges, R., Vierling, K., Vierling, L., Rowell, E., 2008. The use of airborne lidar to assess avian species diversity, density, and occurrence in a pine/aspen forest. Remote Sensing of Environment 112, 2064–2073. <https://doi.org/10.1016/j.rse.2007.08.023>

Cohen, W.B., Goward, S.N., 2004. Landsat’s role in ecological applications of remote sensing. Bioscience 54, 535–545. <https://doi.org/10.1641/0006-3568(2004)054[0535:LRIEAO]2.0.CO;2>

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. <https://doi.org/10.1016/j.ecolind.2019.105567>

Coops, N.C., Tompalski, P., Goodbody, T.R.H., Queinnec, M., Luther, J.E., Bolton, D.K., White, J.C., Wulder, M.A., Lier, O.R. van, 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. <https://doi.org/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. <https://doi.org/10.1111/j.1461-0248.2004.00671.x>

Darvishzadeh, R., Skidmore, A., Abdullah, H., Cherenet, E., Ali, A., Wang, T., Nieuwenhuis, W., Heurich, M., Vrieling, A., O’Connor, B., Paganini, M., 2019. Mapping leaf chlorophyll content from sentinel-2 and RapidEye data in spruce stands using the invertible forest reflectance model. International Journal of Applied Earth Observation and Geoinformation 79, 58–70. <https://doi.org/10.1016/j.jag.2019.03.003>

Davies, A.B., Asner, G.P., 2014. Advances in animal ecology from 3D-LiDAR ecosystem mapping. Trends in Ecology & Evolution 29, 681–691. <https://doi.org/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. <https://doi.org/10.1186/s13717-016-0063-3>

Fassnacht, F.E., Latifi, H., Sterenczak, K., Modzelewska, A., Lefsky, M., Waser, L.T., Straub, C., Ghosh, A., 2016. Review of studies on tree species classification from remotely sensed data. Remote Sensing of Environment 186, 64–87. <https://doi.org/10.1016/j.rse.2016.08.013>

Fisher, J.I., Mustard, J.F., Vadeboncoeur, M.A., 2006. Green leaf phenology at landsat resolution: Scaling from the field to the satellite. Remote Sensing of Environment 100, 265–279. <https://doi.org/10.1016/j.rse.2005.10.022>

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. <https://doi.org/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. <https://doi.org/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 cpac055. <https://doi.org/10.1093/forestry/cpac055>

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, Big Remotely Sensed Data: tools, applications and experiences 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>

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. <https://doi.org/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., Buckley, 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. <https://doi.org/10.1038/nature16524>

Graves, S.J., Asner, G.P., Martin, R.E., Anderson, C.B., Colgan, M.S., Kalantari, L., Bohlman, S.A., 2016. Tree Species Abundance Predictions in a Tropical Agricultural Landscape with a Supervised Classification Model and Imbalanced Data. Remote Sensing 8, 161. <https://doi.org/10.3390/rs8020161>

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. <https://doi.org/10.1016/j.ecoinf.2017.01.005>

Helfenstein, I.S., Schneider, F.D., Schaepman, M.E., Morsdorf, F., 2022. Assessing biodiversity from space: Impact of spatial and spectral resolution on trait-based functional diversity. Remote Sensing of Environment 275, 113024. <https://doi.org/10.1016/j.rse.2022.113024>

Herniman, S., Coops, N.C., Martin, K., Thomas, P., Luther, J.E., Lier, O.R. van, 2020. Modelling avian habitat suitability in boreal forest using structural and spectral remote sensing data. Remote Sensing Applications: Society and Environment 19, 100344. <https://doi.org/10.1016/j.rsase.2020.100344>

Hijmans, R.J., 2023. [Terra: Spatial data analysis](https://rspatial.org/terra/).

Huang, X., Xiao, J., Ma, M., 2019. Evaluating the Performance of Satellite-Derived Vegetation Indices for Estimating Gross Primary Productivity Using FLUXNET Observations across the Globe. Remote Sensing 11, 1823. <https://doi.org/10.3390/rs11151823>

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. <https://doi.org/10.1016/S0034-4257(02)00096-2>

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. <https://doi.org/10.1029/98JD02462>

Lang, N., Kalischek, N., Armston, J., Schindler, K., Dubayah, R., Wegner, J.D., 2021. [Global canopy height estimation with GEDI LIDAR waveforms and Bayesian deep learning](http://arxiv.org/abs/2103.03975). arXiv:2103.03975 [physics].

Lefsky, M.A., Cohen, W.B., Acker, S.A., Parker, G.G., Spies, T.A., Harding, D., 1999. Lidar remote sensing of the canopy structure and biophysical properties of douglas-fir western hemlock forests. Remote Sensing of Environment 70, 339–361. <https://doi.org/10.1016/S0034-4257(99)00052-8>

Lefsky, M.A., Cohen, W.B., Parker, G.G., Harding, D.J., 2002. Lidar remote sensing for ecosystem studies. Bioscience 52, 19–30. <https://doi.org/10.1641/0006-3568(2002)052[0019:LRSFES]2.0.CO;2>

Macarthur, R., Macarthur, J., 1961. On bird species-diversity. Ecology 42, 594–598. <https://doi.org/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. <https://doi.org/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, 697714. <https://doi.org/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. <https://doi.org/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. <https://doi.org/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. <https://doi.org/10.1016/j.rse.2005.02.012>

Neuenschwander, A., Pitts, K., 2019. The ATL08 land and vegetation product for the ICESat-2 Mission. Remote Sensing of Environment 221, 247–259. <https://doi.org/10.1016/j.rse.2018.11.005>

Pebesma, E., 2022. [Sf: Simple features for r](https://CRAN.R-project.org/package=sf).

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. <https://doi.org/10.1126/science.1229931>

Pettorelli, N., Schulte to Bühne, H., Tulloch, A., Dubois, G., Macinnis-Ng, C., Queirós, A.M., Keith, D.A., Wegmann, M., Schrodt, F., Stellmes, M., Sonnenschein, R., Geller, G.N., Roy, S., Somers, B., Murray, N., Bland, L., Geijzendorffer, I., Kerr, J.T., Broszeit, S., Leitão, P.J., Duncan, C., El Serafy, G., He, K.S., Blanchard, J.L., Lucas, R., Mairota, P., Webb, T.J., Nicholson, E., 2018. Satellite remote sensing of ecosystem functions: opportunities, challenges and way forward. Remote Sensing in Ecology and Conservation 4, 71–93. <https://doi.org/10.1002/rse2.59>

Pojar, J., Klinka, K., Meidinger, D.V., 1987. Biogeoclimatic ecosystem classification in British Columbia. Forest Ecology and Management 22, 119–154. <https://doi.org/10.1016/0378-1127(87)90100-9>

R Core Team, 2022. [R: A language and environment for statistical computing](https://www.R-project.org/). R Foundation for Statistical Computing, Vienna, Austria.

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., Rapacciuolo, 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. <https://doi.org/10.1016/j.rse.2018.12.009>

Razenkova, E., Dubinin, M., Pidgeon, A.M., Hobi, M.L., Zhu, L., Bragina, E.V., Allen, A.M., Clayton, M.K., Baskin, L.M., Coops, N.C., Radeloff, V.C., n.d. Abundance patterns of mammals across Russia explained by remotely sensed vegetation productivity and snow indices.

Rosseel, Y., 2012. lavaan: An R package for structural equation modeling. Journal of Statistical Software 48, 1–36. <https://doi.org/10.18637/jss.v048.i02>

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., Hobern, 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. <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., Siqueira, M.F. de, Grainger, A., Hannah, L., Hughes, L., Huntley, B., Jaarsveld, A.S. van, 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. <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. <https://doi.org/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. <https://doi.org/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. <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. <https://doi.org/10.2307/3544109>

Wu, S., Wang, J., Yan, Z., Song, G., Chen, Y., Ma, Q., Deng, M., Wu, Y., Zhao, Y., Guo, Z., Yuan, Z., Dai, G., Xu, X., Yang, X., Su, Y., Liu, L., Wu, J., 2021. Monitoring tree-crown scale autumn leaf phenology in a temperate forest with an integration of PlanetScope and drone remote sensing observations. ISPRS Journal of Photogrammetry and Remote Sensing 171, 36–48. <https://doi.org/10.1016/j.isprsjprs.2020.10.017>

Zhang, X.Y., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C.F., Gao, F., Reed, B.C., Huete, A., 2003. Monitoring vegetation phenology using MODIS. Remote Sensing of Environment 84, 471–475. <https://doi.org/10.1016/S0034-4257(02)00135-9>

Zhang, Y., Chen, H.Y.H., 2015. Individual size inequality links forest diversity and above-ground biomass. Journal of Ecology 103, 1245–1252. <https://doi.org/10.1111/1365-2745.12425>