

1           **Cumulative and individual impacts of the human  
2           footprint on similarity to high ecological integrity  
3           reference states.**

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11 **Abstract**

12 Natural forests with high ecological integrity have natural or near natural ecosystem  
 13 structure, function, and composition, and are home to large amounts of terrestrial  
 14 biodiversity and provide integral ecosystem services. Anthropogenic pressures such  
 15 as climate change, overexploitation, and invasive species are leading to the degrada-  
 16 tion or loss of high integrity forests. Due to this, it is important to be able to locate  
 17 and assess the quality of forests stands across wide swaths of land. Remote sens-  
 18 ing is rapidly providing more and more data capable of making these assessments,  
 19 such as wall to wall metrics of forest structure and productivity. In this paper, we  
 20 demonstrate a method to assess similarity to known high quality reference states  
 21 using coarsened exact matching and the sigma dissimilarity metric. Using this dis-  
 22 similitude metric, we can assess how far, in structural and functional space, every  
 23 forest stand across Vancouver Island is to a comparable forest found in the oldest  
 24 and largest protected area on the island, Strathcona Provincial Park. We further  
 25 assess how cumulative and individual anthropogenic pressures are influencing ecolog-  
 26 ical dissimilarity. We found that cumulative anthropogenic pressures influence the  
 27 vertical layering of forests (canopy height and structural complexity), but do not in-  
 28 fluence forest energy availability or energy seasonality. Further individual pressures  
 29 increase dissimilarity for the majority of forest structural attributes, and population  
 30 density reduces similarity to highly seasonal forests. Our results demonstrate that  
 31 applying strict matching procedures and the sigma dissimilarity metric can be used  
 32 to assess ecosystem similarity, which could be especially useful when working with  
 33 the location of rare ecosystems under large amounts of anthropogenic pressure. Fur-  
 34 ther, we demonstrate that vertical forest structural attributes strongly related to  
 35 biodiversity via niche availability and resource partitioning are influenced negatively  
 36 by anthropogenic pressures.

37 **1 Introduction**

38 A global biodiversity crisis is currently underway, driven by anthropogenic changes  
 39 to natural habitats (Dirzo and Raven, 2003). Pressures such as climate change,  
 40 overexploitation, and invasive species are leading to species extinctions (Thomas et  
 41 al., 2004; Urban, 2015) and the homogenization of biological communities (McGill  
 42 et al., 2015). The Kunming-Montreal Global Biodiversity Framework (GBF) was  
 43 adopted in December 2022 with the goal of restoring and safeguarding global biodi-  
 44 versity (Convention on Biological Diversity, 2023). Targets within this framework  
 45 include restoring 30% of all degraded ecosystems, protecting 30% of the Earth's ter-  
 46 restrial, inland water, and marine areas, and achieving no loss of high biodiversity  
 47 importance areas, including high ecological integrity ecosystems (Convention on  
 48 Biological Diversity, 2023). In the terrestrial environment, forest biomes have been  
 49 shown to harbour the largest amount of biodiversity (Cardinale et al., 2012; Myers,  
 50 1988; Pimm and Raven, 2000), and provide key ecosystem services (Thompson et  
 51 al., 2009). To provide these services, it is integral that these forest ecosystems are  
 52 in good ecological condition, as represented by natural or near-natural levels of for-  
 53 est structure, function, and composition, often referred to as having high ecological  
 54 integrity (Marín et al., 2021).

55 While understanding forest condition is a key aspect of understanding biodiversity  
 56 and the provision of ecosystem services due to their inherent linkages (Cardinale et  
 57 al., 2012; Marín et al., 2021), it is challenging to obtain suitable field-derived data  
 58 across extensive land areas due to the significant financial and temporal costs asso-  
 59 ciated with large-scale field campaigns. Remote sensing data, however, can provide  
 60 a efficient and cost-effective alternative to field data, offering access to new spatially  
 61 explicit and comprehensive datasets that can be linked to ecological condition, with  
 62 additional metrics being proposed at a rapid pace (Pereira et al., 2013; Radeloff et  
 63 al., 2024; Skidmore et al., 2021). Advances in lidar technologies and modelling meth-

ods are enabling the generation of wall-to-wall estimates of forest stand structure for across entire countries (Becker et al., 2023; Matasci et al., 2018a; Matasci et al., 2018b), which serve as a more detailed indicator of ecosystem structure than the often previously used landscape fragmentation metrics (Andrew et al., 2012). Productivity metrics have been employed as a proxy for ecosystem function for many years (Pettorelli et al., 2018, 2005), with new Landsat-derived datasets providing integrative annual estimates of energy availability at a 30 m spatial resolution (Radeloff et al., 2024; Radeloff et al., 2019; Razenkova et al., n.d.). Remote sensing is quickly providing access to a vast array of datasets suitable for monitoring the various facets of biodiversity and ecological condition (Noss, 1990; Pereira et al., 2013; Skidmore et al., 2021). The integration of these datasets with information pertaining to the location of known high-ecological-integrity forests enables researchers and managers to identify high-quality forest reference states across entire jurisdictions, even in the presence of anthropogenic pressures.

Ecological reference states represent baseline conditions of ecosystems, serving as a benchmark for assessing ecological health and guiding restoration efforts (Nielsen et al., 2007). The application of counterfactual thinking, which entails considering the potential state of an ecosystem in the absence of anthropogenic pressures (Ferraro, 2009) can be instrumental for mapping high-integrity forests. Approaches such as coarsened exact matching (Iacus et al., 2012), can be used to facilitate comparisons between forest stands and their hypothetical reference states. These methods account for confounding environmental variables, thereby ensuring that all forests are compared to an appropriate reference state. Identifying a suitable reference state can be difficult, however there are methods which can be used to approximate high-integrity reference conditions. Historical reference states can be used when an ecosystem has a large depth of temporal data to compare to, however, it is not always guaranteed that an ecosystem can be restored to these historical norms due to changing climates (Balaguer et al., 2014; McNellie et al., 2020). Other proposed methods for delineating baseline conditions include protected areas (Arcese and Sinclair, 1997), and empirical estimates of the reference state generated by modelling outcomes (oftentimes species abundances and occurrence) in the absence of anthropogenic disturbance (Nielsen et al., 2007).

Protected areas, specifically designed for biodiversity conservation, are frequently faced with lower levels anthropogenic pressure as a result of biases in their placement (Joppa and Pfaff, 2009; Muise et al., 2022). In forested ecosystems, over time this leads to undisturbed high-integrity forests remaining within protected areas due to their natural disturbance regimes and a lack of anthropogenic pressures (Brumelis et al., 2011). These high-integrity forests, situated within protected areas, can serve as effective ecological baselines (Arcese and Sinclair, 1997). When suitably matched to unprotected areas, they can be used as a reference state to assess the differences between all forests and their high-integrity counterparts (Ferraro, 2009). Further, protected areas and undisturbed ecosystems such as intact forest landscapes have been shown to have increased structural densities when compared to other ecosystems (Li et al., 2023; Muise et al., 2022).

Anthropogenic pressure such as increased road densities (Nielsen et al., 2007), harvesting and fossil fuel exploration activities leading to edge effects (Bourgoin et al., 2024; Harfoot et al., 2018), and other human-induced disturbances (Liira et al., 2007) have been shown to influence forest structure. Novel datasets such as the Forest Structural Condition Index have been developed which integrate both structure and anthropogenic pressure into an index which identifies ecosystems of high conservation value, with high structural complexity and low anthropogenic pressure (Hansen et al., 2019). The impacts of anthropocentric pressure on forest functioning and energy availability is less frequently assessed. Hedwall et al. (2019) assessed plant community shifts under anthropogenic pressures in the boreal forests

of Sweden, and hypothesized that changed communities may affect forest functioning. Grantham et al. (2020) used forest extent and arrangement, alongside pressure datasets, to assess ecosystem integrity, with expectations that high-integrity ecosystems will retain high levels of ecosystem functioning. However, to our knowledge, direct impacts of anthropogenic pressures on forest ecosystem function have not been assessed at a landscape scale.

We proposed a novel, data-driven, approach to identify high-integrity forests based on various satellite-derived metrics of ecosystem condition, and calculate the degree of structural and functional similarity for unprotected areas to high-integrity forests found on Vancouver Island, British Columbia, Canada. We use a strict matching approach to ensure ecological similarity, and choose the highest 10% of metric values across variables that are known to be correlated with ecological condition and biodiversity. We then calculate ecological similarity using sigma dissimilarity (Mahony et al., 2017) alongside human footprint layers developed by Hirsh-Pearson et al. (2022) to assess the influence of anthropogenic pressure of ecological integrity by cumulative and individual pressures. Further, we compare the similarity metrics between ecological structure and function to identify linkages between ecological similarity of forest structure and forest functioning, while accounting for the presence of anthropogenic pressures.

## 2 Methods

### 2.1 Study Area

We focus on the forested areas of Vancouver Island, British Columbia, Canada. Vancouver island has approximately 31285 km<sup>2</sup> of land area, of which 79.5% is forested. The dominant forest species on Vancouver Island are Douglas-fir (*Pseudotsuga menziesii*), western red cedar (*Thuja plicata*), western hemlock (*Tsuga heterophylla*), yellow cedar (*Chamaecyparis nootkatensis*), and Sitka spruce (*Picea sitchensis*) (Burns, 1990). British Columbia generally has a temperate maritime climate, with mild, wet winters, and cool, dry summers. There are four ecosystems on Vancouver Island as defined by British Columbia's biogeoclimatic ecosystem classification (BEC) framework (Pojar et al., 1987), Coastal Western Hemlock (CWH), Mountain Hemlock (MH), Coastal Douglas Fir (CDF), and Coastal Mountain-heather Alpine (CMA), which are broadly delineated based on soil, climate, and elevation. Forestry is an important industry on Vancouver Island, while fires are historically rare and low severity (Daniels and Gray, 2006).

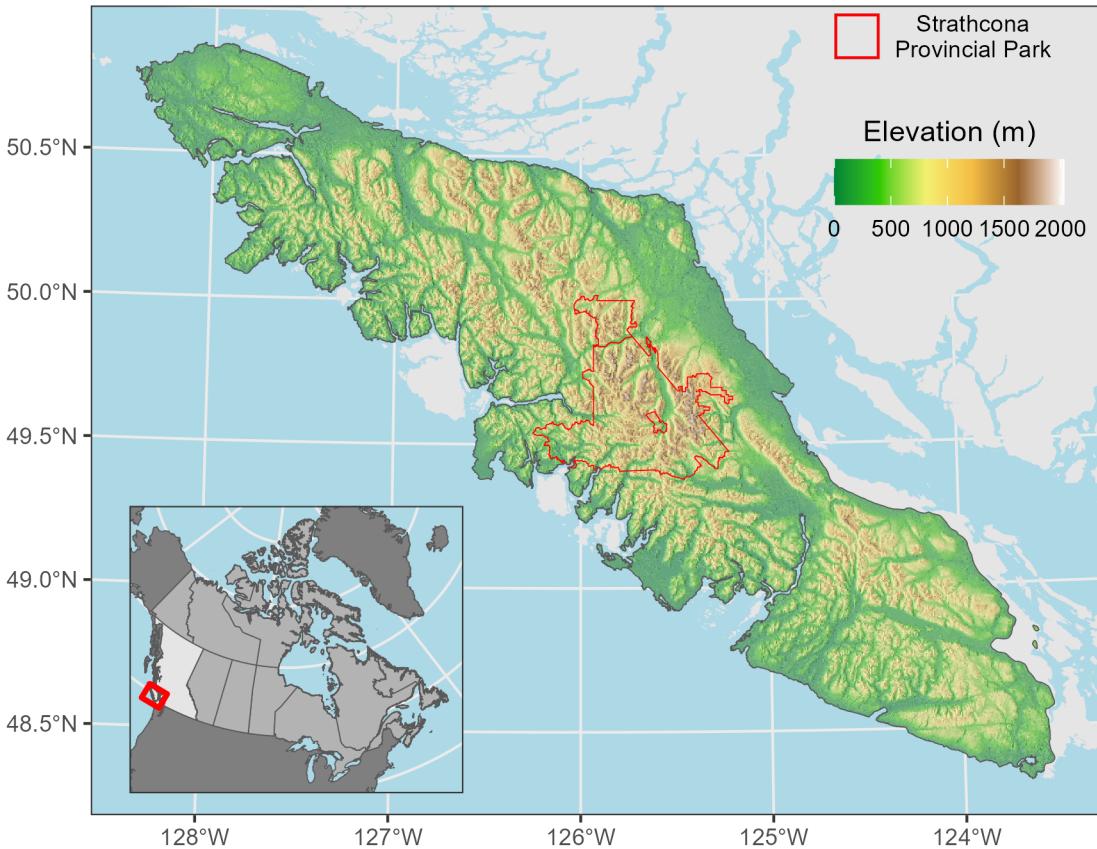


Figure 1: Study area on Vancouver Island, British Columbia, Canada, including the location of Strathcona Provincial Park.

## 152 2.2 Data

### 153 2.2.1 Reference State

154 We defined our reference state as the forested area of Strathcona Park. We chose  
 155 Strathcona Park as a temporal and protected area reference state, as the oldest and  
 156 largest ( $2480 \text{ km}^2$ ) protected area in British Columbia. Strathcona Park was estab-  
 157 lished in 1911, and 80% of the park is preserved as wilderness area and designated  
 158 as Nature Conservancy Areas under the *Park Act* ("Park Act," n.d.). The park con-  
 159 tains three BEC zones, CWH, MH, and CMA, but does not include CDF, which  
 160 is only found in the southern portion of the island. Due to this, we do not include  
 161 CDF in our analysis.

**2.2.2 Forest Structure**

Wall-to-wall, 30 m forest structure metrics (canopy height, canopy cover, structural complexity, and aboveground biomass) were generated by Matasci et al. (2018a) for 2015 across the forested landscape of British Columbia. This data was generated by using a random forest-kNN approach, imputing airborne laser scanning derived forest structural attributes across the entirety of Canada using Landsat-derived best-available-pixel (BAP) composites (Hermosilla et al., 2016; White et al., 2014) and topographic information (Matasci et al., 2018a; Matasci et al., 2018b). The BAP composites were derived by selecting optical observations from the Landsat archive (including Landsat-5 Thematic Mapper, Landsat-7 Enhanced Thematic Mapper Plus, and Landsat-8 Operational Land Imager imagery) over the course of the growing season, considering atmospheric effects (haze, clouds, cloud shadows) and distance from the desired composite date (in this case, August 31st). Details on the pixel scoring method can be found in White et al. (2014). The BAP composites were further refined by using a spectral trend analysis on the normalized burn ratio to remove noise, and missing pixels are infilled using temporally-interpolated values. This procedure results in gap-free, surface-reflectance image composites (Hermosilla et al., 2015), which are used as the primary dataset to impute forest structural attributes (Matasci et al., 2018a; Matasci et al., 2018b).

**2.2.3 Forest Function**

For our forest ecosystem function dataset, we calculated the Dynamic Habitat Indices (Radeloff et al., 2019) using Landsat data on Google Earth Engine (Gorelick et al., 2017), following the methodology of Razenkova et al. (n.d.). Briefly, we created a synthetic year of NDVI composites using all available Landsat imagery from 2011-2020 (centred on 2015). We used the Landsat QA band derived from the fmask algorithm (Zhu and Woodcock, 2012) to filter out erroneous pixels, such as clouds and cloud shadows. Monthly NDVI values were calculated by taking the median of each month's NDVI observations, ignoring the year the image was acquired. This allows us to generate the DHIs at spatial resolution of 30 m, while accounting for the lower temporal resolution of the Landsat series when compared to the more commonly used MODIS satellites (Razenkova et al., n.d.). The DHIs are calculated as the sum (Cumulative DHI), minimum (Minimum DHI), and coefficient of variation (Variation DHI) of these monthly observations. The three DHIs have been shown to be indicative of biodiversity over a range of scales (Radeloff et al., 2019; Razenkova et al., 2022) and extents (Coops et al., 2019, 2009) for a variety of clades (Michaud et al., 2014; Suttidate et al., 2021). In this study, we focus on the Cumulative and Variation DHIs, as the minimum DHI is consistently 0 due to the presence of snow.

**2.2.4 Anthropogenic Pressures**

We use the Canadian Human Footprint as developed by Hirsh-Pearson et al. (2022). The Canadian Human Footprint is an additive pressure map generated by summing the 12 different anthropogenic pressures (built environments, crop land, pasture land, population density, nighttime lights, railways, roads, navigable waterways, dams and associated reservoirs, mining activity, oil and gas, and forestry), which ranges from zero to 55 for any cell across Canada. This cumulative dataset is also distributed with Canada-wide individual pressure values (Hirsh-Pearson et al., n.d.). Here, we focus on the overall cumulative pressure map and four individual pressures: population density, built environments, roads, and forestry. We selected these pressures as they do not exclude the forested land cover, as pasture land, crop land, and marine access do.

**2.2.5 Covariates**

In our matching procedure (see Section 2.3) we use two core datasets as our matching covariates. Firstly, we use a 30 m digital elevation model and derived slope dataset from the Advanced Spaceborne Thermal Emission and Reflection Radiome-

ter (ASTER) Version 2 GDEM product (Tachikawa et al., 2011). We also match on four climate variables; mean annual precipitation (MAP), mean annual temperature (MAT), mean warmest month temperature (MWMT), and mean coldest month temperature (MCMT) calculated from 1990-2020 climate normals using the ClimateNA software package at a 1 km spatial resolution, and downsampled to 30 m using cubic spline resampling in the **terra** (version 1.7-71) R package (Hijmans, 2024) in R (R Core Team, 2024 version 4.4.1). A visualization of one of each input dataset can be found in Figure Figure 2.

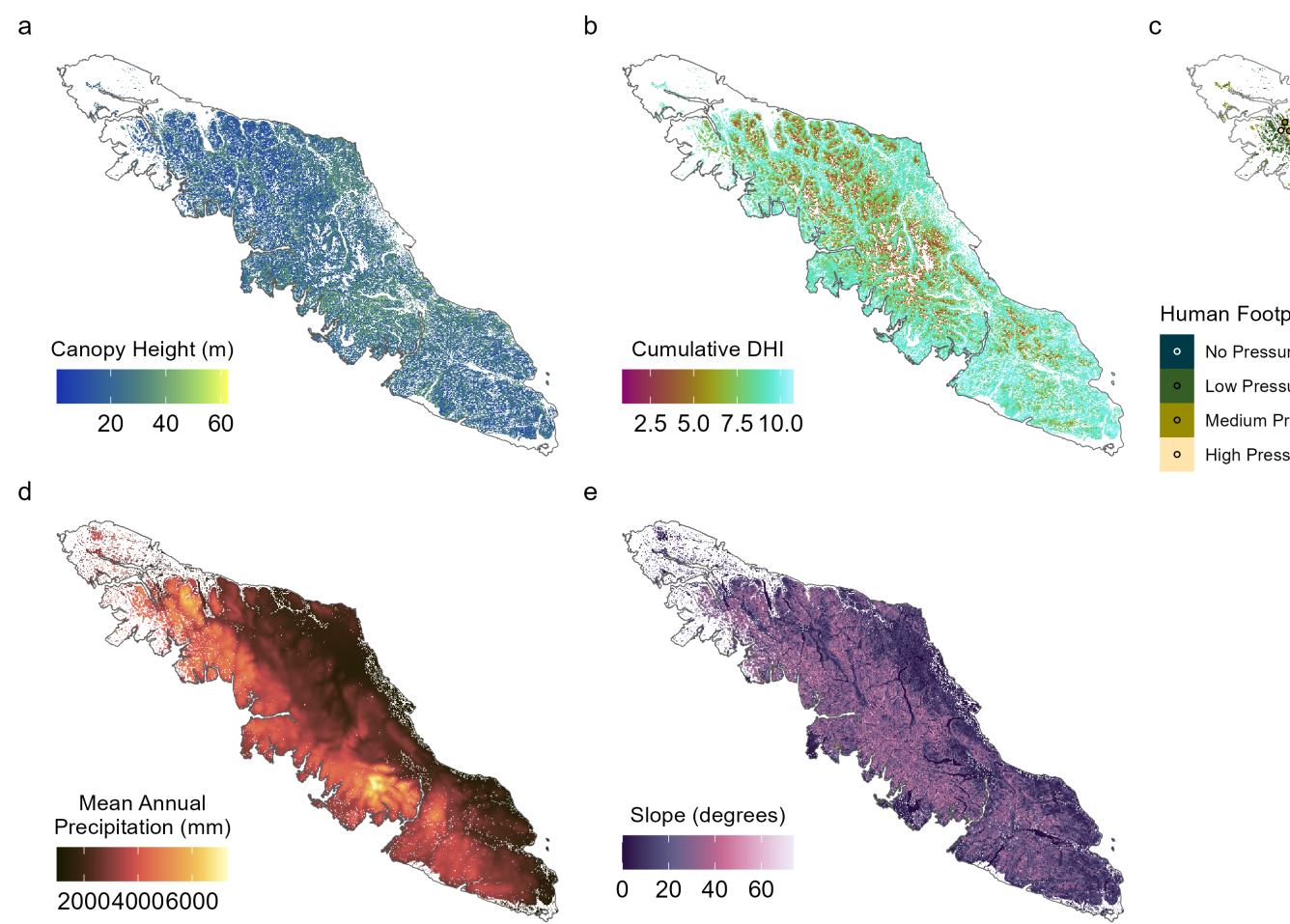


Figure 2: Visualization of the input datasets used in the study. Panel C shows the human footprint and the location of the samples used for our analysis.

### 223 2.3 Calculating similarity

224 We calculate the sigma dissimilarity (Mahony et al., 2017) of forested pixels across  
 225 British Columbia by using an expanded coarsened exact matching (CEM) technique  
 226 , Figure 3. This methodology enables us to evaluate the degree of similarity between  
 227 all forested pixels in the province and natural forests, while accounting for potential  
 228 confounding variables such as climate and topography. The CEM technique  
 229 creates comparable groups of observations among covariates by initially coarsening  
 230 the covariates. In this instance, all six covariates were coarsened into five quintiles  
 231 hereafter referred to as bins. CEM then performs exact matching on the bins, with  
 232 each pixel matched to a climatically and topographically similar group of pixels  
 233 within Strathcona Park, hereafter referred to as strata. In the case where there is  
 234 not enough matched pixels found in Strathcona Park, we calculate the nearest neighbours  
 235 in bin space for all strata, and sample up to 1000 pixels while minimizing the  
 236 nearest neighbour distance. If the nearest neighbour distance is on average above  
 237 two, we do not consider that strata in our analysis.

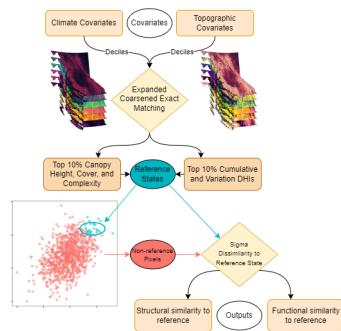


Figure 3: Conceptual flow diagram of the study.

238 Following the matching procedure, we identify data driven reference states in both  
 239 structural and functional attributes by selecting the top 10% of protected obser-  
 240 vations for each structural (canopy height, cover, and structural complexity) and  
 241 functional (cumulative and variation DHIs) attribute, separately. We then deter-  
 242 mine the similarity of all pixels, in both structural and functional attributes, to the  
 243 reference states by calculating the sigma dissimilarity metric. Sigma dissimilarity  
 244 standardizes the Mahalanobian distance (Mahalanobis, 1936) by rescaling it into  
 245 percentiles of the chi distribution (Mahony et al., 2017). This effectively accounts for  
 246 the effect of dimensionality when creating a multivariate similarity metric (Mahony  
 247 et al., 2017). We calculate sigma dissimilarity for every strata with a suitable refer-  
 248 ence state, comparing all forested pixels to the top 10% of each attribute for that  
 249 reference state.

### 250 2.4 Sampling

251 We reclassify the Canadian Human Footprint (Hirsh-Pearson et al., n.d.; Hirsh-  
 252 Pearson et al., 2022) into categorical data following Hirsh-Pearson et al. (2022) and  
 253 Arias-Patino et al. (2024) : a value of zero has no anthropogenic pressure, zero to  
 254 four has low anthropogenic pressure, four to eight has medium anthropogenic pres-  
 255 sure, and > eight has high anthropogenic pressure. To assess the cumulative impact  
 256 of anthropogenic pressure on ecological similarity, we implement stratified sam-  
 257 pling on all suitable strata, sampling 100 samples from each anthropogenic pressure  
 258 class. For our individual pressures, we follow the same reclassification steps on each  
 259 pressure layer, and sample an additional hundred samples for each pressure class.  
 260 Sampling was performed using the **sgsR** (version 1.4.5) R package (Goodbody et

261 al., 2023) with the Quiennec method (Quiennec et al., 2021). Geospatial data pro-  
 262 cessing was performed using the **terra** (version 1.7-78) (Hijmans, 2024) **sf** (version  
 263 1.0-16) (Pebesma, 2018; Pebesma and Bivand, 2023) and **tidyterra** (version 0.6.1)  
 264 (Hernangómez, 2023a, 2023b) R packages.

## 265 2.5 Analysis

266 We used a one-way analysis of variance (ANOVA) with a critical value of 0.05 to  
 267 identify differences in the mean similarity values across cumulative anthropogenic  
 268 pressure classes. We account for family-wise error rate for our ANOVAs using the  
 269 Holm-Bonferroni method, only continuing the analysis for similarity variables with  
 270 significant ANOVAs at the adjusted critical value. As ANOVAs only identify if there  
 271 is a difference in means, but does not identify which means are different, we used  
 272 a Tukey HSD post-hoc test to identify which means are different from the control  
 273 group (no anthropogenic pressure), which also controls for the family-wise error rate.

274 We follow the same protocol to identify the difference in means for each anthro-  
 275 pogenic pressure of interest (roads, population density, forestry, and built envi-  
 276 ronment). We compare each pressure to the same ‘no pressure’ values sampled in  
 277 the cumulative pressure analysis. All statistical analysis were conducted using the  
 278 **rstatix** (version 0.7.2) R package (Kassambara, 2023).

## 279 3 Results

280 Our sigma dissimilarity processing workflow resulted in six island wide maps of  
 281 structural and functional similarity to the reference state found in Strathcona  
 282 Provincial Park (Figure 4). We display three selected subsets of Vancouver Island  
 283 to demonstrate variation in similarity and the anthropogenic footprint layers. Subset  
 284 A shows a region near Lake Cowichan where harvesting is a common anthropogenic  
 285 pressure (Figure 4 A). Subset B shows a protected area near Campbell River with  
 286 high population density (Figure 4 B). Subset C shows a region with generally low  
 287 anthropogenic pressure (Figure 4 C). We see more variation in the similarity to high  
 288 aboveground biomass and functional reference states, while the similarity to canopy  
 289 cover, canopy height, and structural complexity is often lower across Vancouver  
 290 Island.

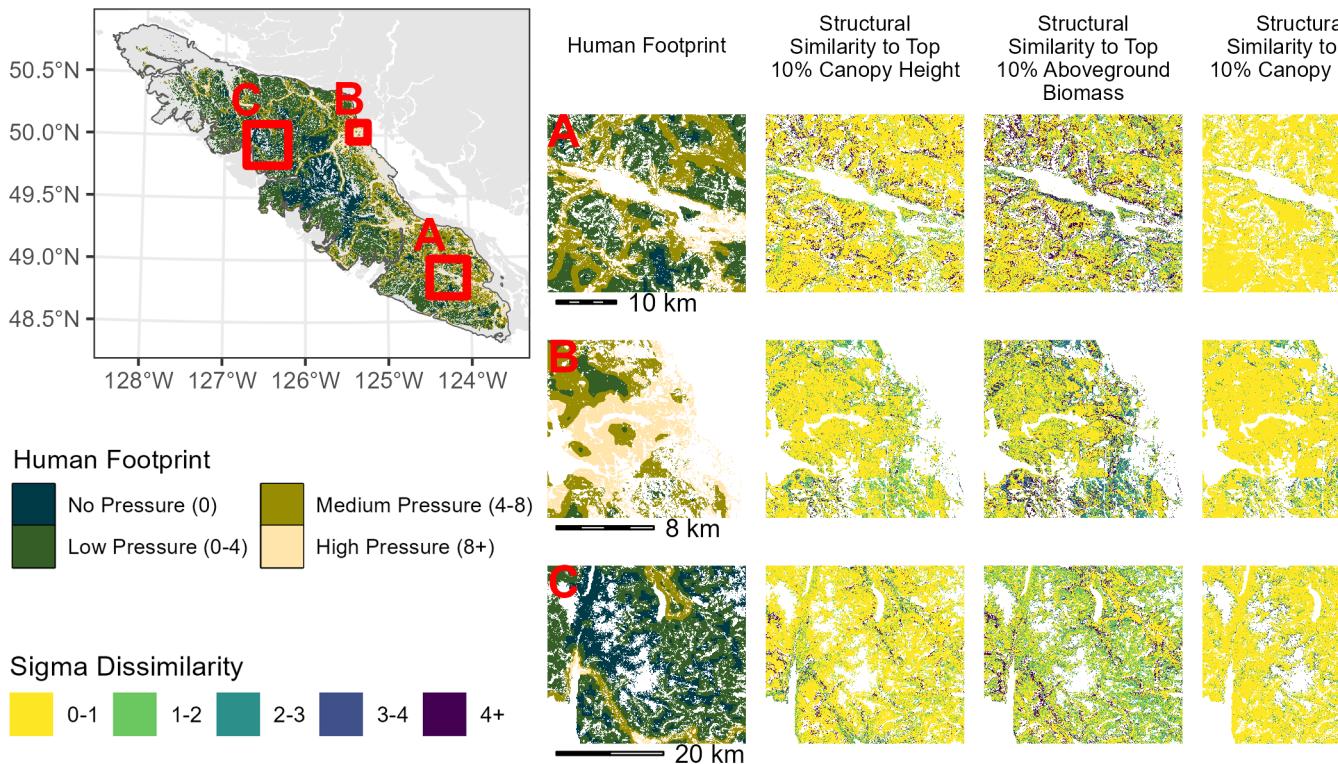


Figure 4: Regional details of the human footprint and sigma dissimilarity across the sites on Vancouver Island. Subset A show Cowichan Lake, a heavily harvested region. Subset B shows Elk Falls Provincial Park, just outside Campbell River, a region with high population density. Subset C shows a region with generally low anthropogenic pressure.

We found that similarity to high structural complexity (Anova:  $p = 0.007$ ) and tall canopy height (Anova:  $p = 0.003$ ) reference states was influenced by medium to high levels of cumulative anthropogenic pressure (Figure 5). Similarity to high biomass (Anova:  $p = 0.142$ ) and canopy cover (Anova:  $p = 0.855$ ) regions were not significantly influenced by cumulative anthropogenic pressures. Neither of the productivity metrics were influenced by cumulative anthropogenic pressures.

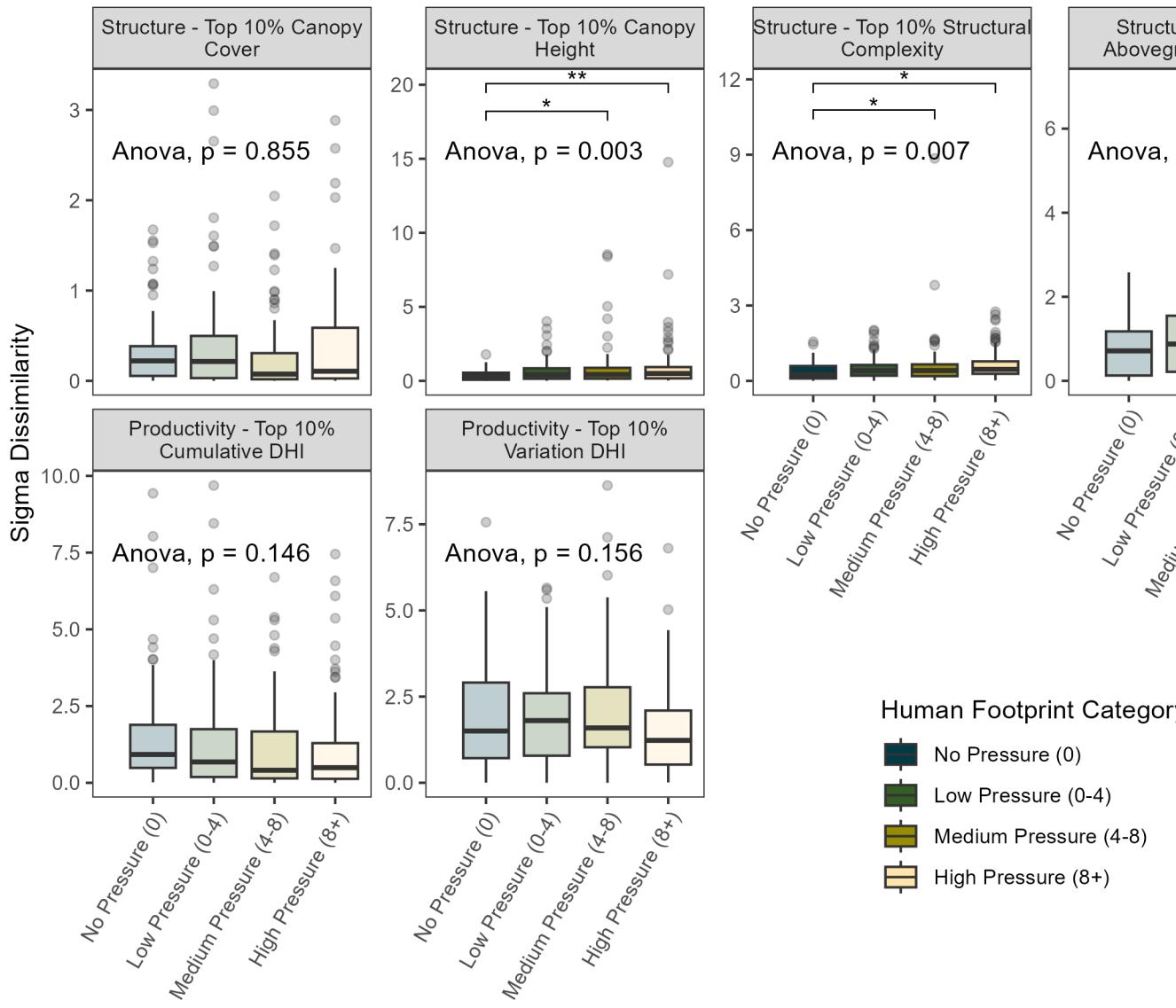


Figure 5: Boxplots of sigma similarity to the reference state in Strathcona Provincial Park by cumulative human footprint category. Anova p-values corrected using the Holm-Bonferroni method. \* indicates a Tukey HSD p-value  $< 0.05$ . \*\* indicates a Tukey HSD p-value  $< 0.01$ .

Increases in all individual anthropogenic pressures led to increased dissimilarity when compared to most structural reference states (Figure 6). Increases in pressures from roads and built environment did not increase or reduce similarity to structural reference states with high canopy cover. Medium and high pressures from population density and forestry/harvesting increased dissimilarity to all structural reference states. Anthropogenic pressures generally did not influence the similarity to reference states based on productivity metrics, however, increases in pressures from population density decreased dissimilarity to ecosystems with high variation in energy availability.

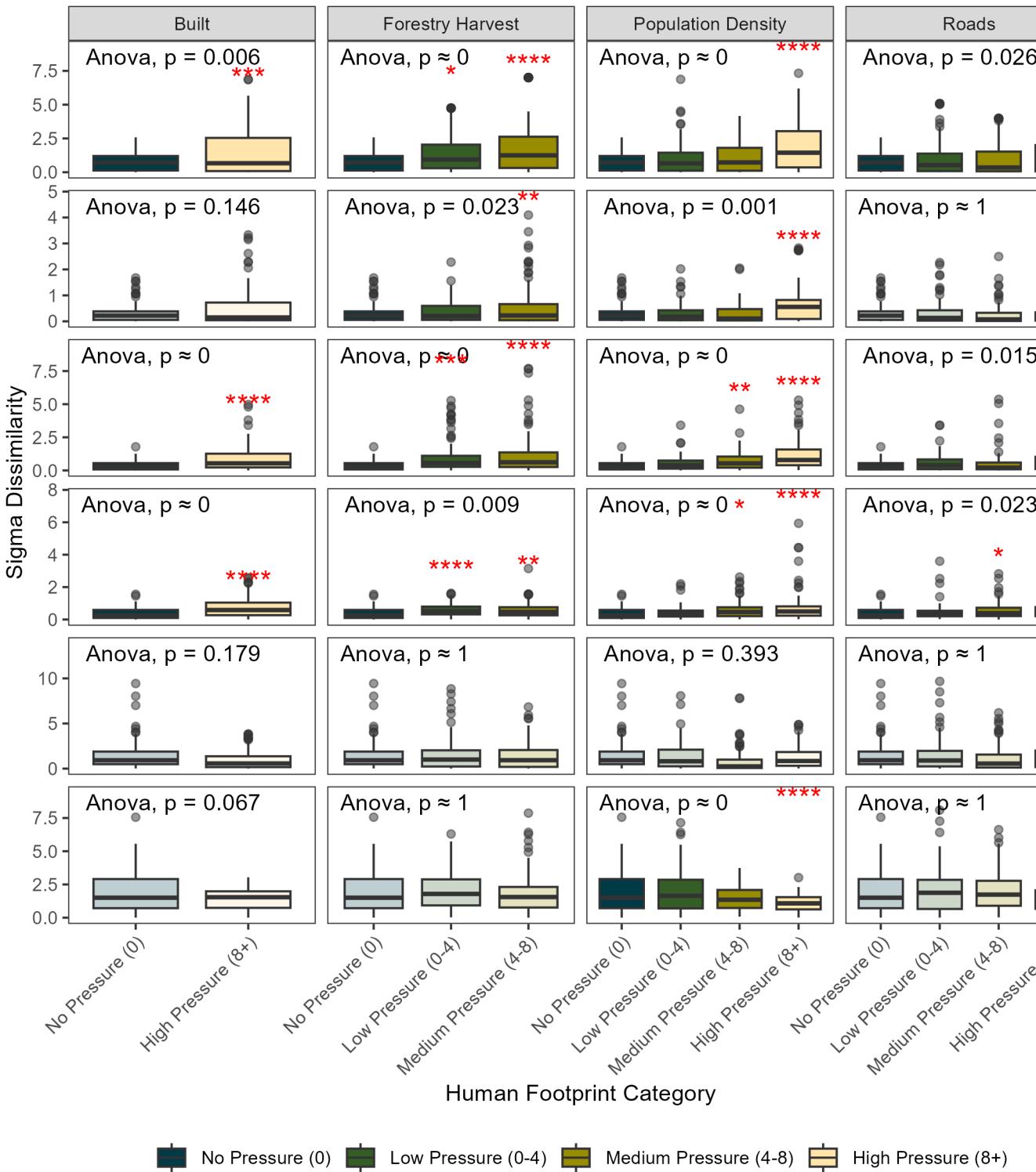


Figure 6: Boxplots of sigma similarity to the reference state in Strathcona Provincial Park by individual anthropogenic pressures. Anova p-values corrected using the Holm-Bonferroni method. \* indicates a Tukey HSD p-value < 0.05. \*\* indicates a Tukey HSD p-value < 0.01. \*\*\* indicates a Tukey HSD p-value < 0.001. \*\*\*\* indicates a Tukey HSD p-value < 0.0001.

306 **4 Discussion**

307 In this paper, we use medium-resolution remote sensing metrics of ecosystem struc-  
 308 ture and function to assess similarity to high-integrity forests across Vancouver  
 309 Island, British Columbia. We validate our approach by assessing the influence of  
 310 the human footprint on these reference states, finding that ecosystem structure in  
 311 the form of forest structural attributes is influenced by increased anthropogenic  
 312 pressures on a cumulative and individual level (Figure 5; Figure 6). Forest ecosys-  
 313 tem function, as represented by the DHIs, is generally not significantly influenced  
 314 by anthropogenic pressures, although population density increased similarity to  
 315 ecosystems with high variation in energy availability (Figure 6).

316 We find that similarity to high structural complexity forests, which are often high  
 317 in biodiversity due to increased niche availability (Macarthur and Macarthur, 1961;  
 318 Walter et al., 2021), is impacted by medium to high levels of anthropogenic pres-  
 319 sures. Structural similarity to tall forests is also impacted by medium to high levels  
 320 of anthropogenic pressure, while productivity metrics were not influenced by cumula-  
 321 tive anthropogenic pressures in this region (Figure 5). In tropical forests, Bourgoin  
 322 et al. (2024) found that anthropogenic forest degradation influenced aboveground  
 323 biomass and canopy height, however, they focus on edge effects, fire, and selective  
 324 logging, rather than cumulative and individual anthropogenic pressures. Li et al.  
 325 (2023) also found a global impact of anthropogenic pressures on forest structural  
 326 density, however, they do not explore which facets of anthropogenic pressure are the  
 327 strongest driver of forest degradation. Hansen et al. (2020) integrate forest struc-  
 328 ture and anthropogenic pressure into the forest structural integrity index to identify  
 329 forest stands of high ecological value (high structural quality; low anthropogenic  
 330 footprint). We further this research by assessing individual pressures on a multivari-  
 331 ate metric of structural similarity to a high-quality reference state (Figure 6).

332 It is possible that we did not find a relationship between cumulative anthropogenic  
 333 pressures and canopy cover/aboveground biomass as these forest structural at-  
 334 tributes are typically high on Vancouver Island due to the regions mild climate and  
 335 suitability for forest growth (Waring et al., 2006). Conversely, we did find a rela-  
 336 tionship between the vertical layering (canopy height and structural complexity) of trees  
 337 and anthropogenic pressures (Figure 5). This is especially relevant as structurally  
 338 complex forests are crucial for harbouring biodiversity and providing ecosystem func-  
 339 tions and services. The lack of a relationship between canopy cover/aboveground  
 340 biomass and the cumulative human footprint is potentially due to replanting efforts  
 341 from the forestry industry following harvest, which are required in British Columbia  
 342 and often lead to single species, single aged stands (Lieffers et al., 2020). Stands of  
 343 this configuration are unlikely to be found in our reference state, Strathcona Provin-  
 344 cial Park, as it has been a protected area for over 100 years, thus leading to higher  
 345 dissimilarity values.

346 Anthropogenic effects on forest function and energy availability have rarely been  
 347 examined. Here, we also examine how anthropogenic pressures influence similarity  
 348 to high available energy and high energy variation forests, both hypothesized to in-  
 349 dicate high levels of biodiversity in a number of guilds and clades (Radeloff et al.,  
 350 2019; Razenkova et al., 2022). We do not find a strong influence of cumulative an-  
 351 thropogenic pressure on our forest functioning metrics, however, we did find that  
 352 similarity to forest stands with high annual energy variability was increased in high  
 353 population density areas (Figure 6). This increase in similarity in high density areas  
 354 is potentially driven by ornamental trees and the bias for North American urban  
 355 forests to be primarily deciduous trees (Clapp et al., 2014; Roman et al., 2018),  
 356 which would have a stronger variation DHI component due to annual leaf senescence  
 357 and green-up.

358 Further, the calculation of the DHIs is dependent on using a vegetation index or  
 359 productivity estimate, in our case NDVI. Vegetation indices have been shown to sat-  
 360 urate at high levels of canopy cover and leaf area index (Huete et al., 2002; Huete et  
 361 al., 1997), which are common on Vancouver Island, and comparisons of unprotected  
 362 areas to the highest 10% cover in reference states shows no significant difference  
 363 (Figure 5). Recent research has shown that seasonality, here represented as the Vari-  
 364 ation DHI, drives functional diversity in avian assemblages, however, these results  
 365 also strongly varied by region (Keyser et al., 2024). It is possible that examining  
 366 anthropogenic pressure impacts in regions with more variation in canopy cover  
 367 may lead to differing results depending on the amount of total variation present in  
 368 canopy cover, which would in turn influence seasonality and energy availability.

369 Assessing individual pressure influences on the environment is also relevant to ques-  
 370 tions of how cumulative anthropogenic pressure maps are calculate. There is cur-  
 371 rently a debate between additive and antagonistic anthropogenic pressure mapping  
 372 methods, as there is little information on mechanistic interactions between pressures  
 373 (Arias-Patino et al., 2024). We assess individual pressures on structural and func-  
 374 tional similarity in forests across Vancouver Island, Canada, an advancement upon  
 375 the current standard of using a single value of cumulative anthropogenic pressure  
 376 (Bourgoin et al., 2024; Li et al., 2023). Similar methods could be used to examine  
 377 mechanistic pressure interactions across large scales.

378 We apply the Sigma Dissimilarity metric developed by Mahony et al. (2017) to de-  
 379 termine similarity to high-integrity ecosystems, and use a matching approach to  
 380 account for environmental covariates. This method accounts for the multidimes-  
 381 sionality of the structure and function datasets, and standardizes them so they are  
 382 comparable. This is especially relevant in our case as we use four forest structural  
 383 attributes and two forest function metrics. These methods are similar to other simi-  
 384 larity metrics commonly applied in remote sensing for multivariate similarity such as  
 385 spectral similarity (Schweiger et al., 2018), and phenospectral similarity (Osei Darko  
 386 et al., 2024).

387 While we are limited in number of structural variables due to the imputation of the  
 388 lidar-derived dataset across the study area (Matasci et al., 2018a; Matasci et al.,  
 389 2018b), future studies could directly use raw lidar datasets to create a multitude of  
 390 metrics, and apply the sigma similarity method to those. This could capture addi-  
 391 tional facets of similarity which are missed when using a Canada-wide dataset with  
 392 limited forest structural attributes at 30 m. New spaceborne lidar missions such as  
 393 GEDI (Dubayah et al., 2020) and IceSAT-II (Neumann et al., 2019) are also pro-  
 394 viding estimates of forest structure across the globe. However, these satellites are  
 395 sample based missions, and do not provide wall-to-wall coverage (Duncanson et al.,  
 396 2021).

397 We assess multiple definitions of high quality forest across a large region using a  
 398 data-driven approach. Often, it is common for reference states to be unavailable  
 399 due to a lack of data on regions of high ecological integrity, especially across large  
 400 regions (McNellie et al., 2020). We attempt to circumvent this by using a large,  
 401 long-established protected area (Strathcona Provincial Park; Figure 1), and a match-  
 402 ing technique that preserves ecological similarity between reference states and their  
 403 counterparts. The long-established, large protected area ensures that little anthro-  
 404 pogenic pressures or modification have been made to the landscape, while also guar-  
 405 anteeing that the reference state is attainable for a given topography and climate  
 406 (Corlett, 2016; Hobbs et al., 2014) due to contemporary nature of the reference  
 407 state. Our matching technique (coarsened exact matching, combined with an kNN  
 408 approach when no exact match is available) allows us to generate reference states  
 409 in a near wall-to-wall fashion, which ensures similarity between reference state and  
 410 compared pixels.

Our techniques move beyond traditional impact evaluation techniques (Ferraro, 2009) commonly used in protected area effectiveness assessments by allowing spatial reconstruction of conservation outcomes, and generating a multivariate, rather than univariate, assessment of similarity to high ecological integrity forests. While our methods in this paper use a data-driven approach to derive reference states, if an individual or organization is interested in a specific species or ecosystem, and has known locations of high quality ecosystems associated with that species or ecosystem, these methods can be applied to assess similarity to those high quality ecosystems across large regions.

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## 6 Ethics

The authors declare no conflicts of interest.

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