Measuring Forest Biodiversity on the Ground and in the Air: Comparing Biodiversity Estimates from Ground Based Surveys and Areal Imagery

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Introduction

- Ecosystems are experiencing losses in biodiversity due to anthropogenic actives such as logging, agriculture, and urbanization
- Biodiversity has been shown in some communities to help support the productivity and the stability of the ecosystem
- The way in which biodiversity is quantified depends on the research topic. Most studies focus on estimating species richness, but biodiversity can also be characterized through the diversity of functional traits, phylogenetics, and structure.
- Estimating biodiversity through field surveys is difficult as they can be costly and time consuming and many areas of interest are inaccessible
- Some studies have shown that remote sensing can be used to estimate biodiversity with coarse spatial resolutions and over large areas, but few have looked at estimating biodiversity on small plot levels and fine spatial scales

Objectives

1. Look at the different ways in which biodiversity can be quantified and test the similarity between the metrics.

1. Test the potential of estimating the different metrics of biodiversity from fine spatial resolution, hyperspectral imagery and Light Detecting and Ranging (LiDAR) data

Methods

Study Site

- Bartlett Experimental Forest (BEF)
  - Bartlett NH, USA (Figure 1)
- 1,052 hectare, northern-hardwood forest
- Contains 400+, evenly spaced 32m by 32m inventory plots
- Most recent publicly available species inventory was collected in 2001to 2003
- SpecTIR hyperspectral imagery collected in 2014
  - Spatial resolution = 5m
  - Spectral resolution = 400 to 2500nm; 360 bands
- 2014 LiDAR collected from the National Ecological Observatory Network (NEON)

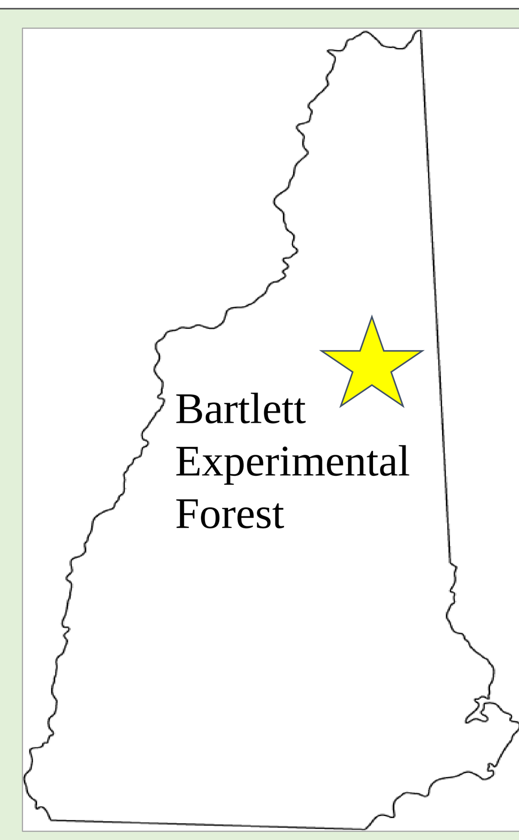


Figure 1: Approximate Location of Bartlett Experimental Forest in New Hampshire, USA

Biodiversity Indices

- Species Diversity
  - Shannon's Index (sp.shannon)
  - Richness (sp.richness)
  - Peilou J Evenness (sp.evenness)
- Functional Diversity
  - Richness (FRic)
  - Evenness (FEve)
  - Divergence (FDiv)
  - Dispersion (FDis)
  - Rao's Quadradic Entropy (RaoQ)
- Phylogenetic Diversity
  - Faith's PD (PD)
  - Variability (PSV)
  - Richness (PSR)
  - Evenness (PSE)
  - Clustering (PSC)
- Structural Diversity
  - Standard deviation (sd) of DBH (sd_dbh)
  - Stand density (StanDen)

Remote Sensing Analyses

- Hyperspectral
  - Entropy of spectra
  - Reflectance
  - Vegetation indices
  - Gray-Level Co-Occurrence Matrix (GLCM)
- LiDAR
  - Rumple
  - Shannon Index of height profile
  - Max and sd height

Colors represent groups made by the dendrogram in the next section

Relatedness of Biodiversity Indices

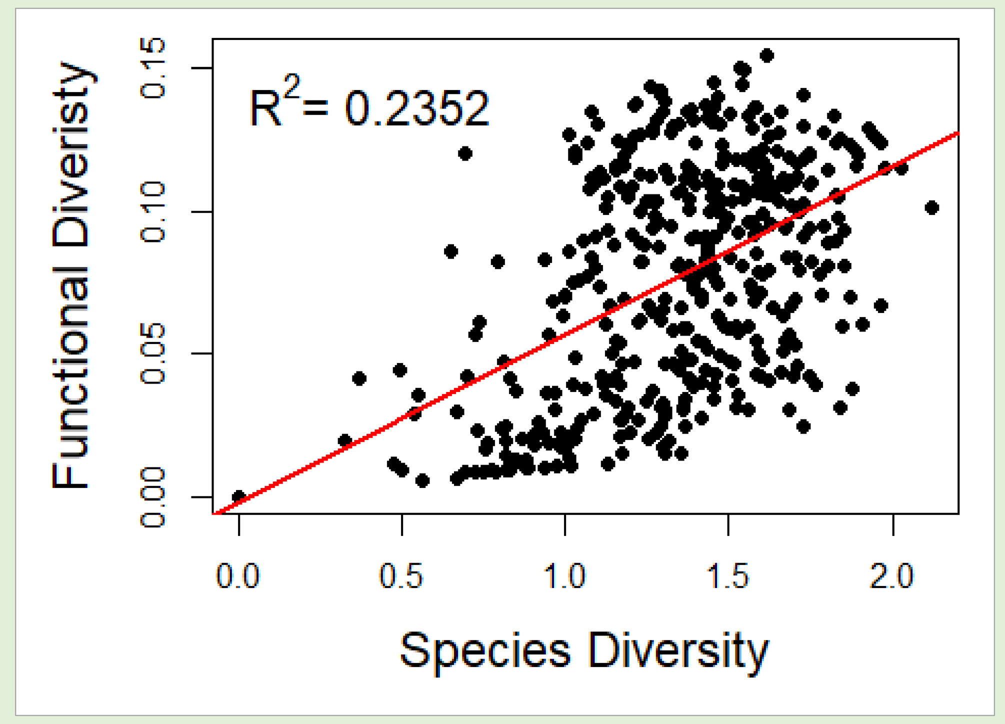
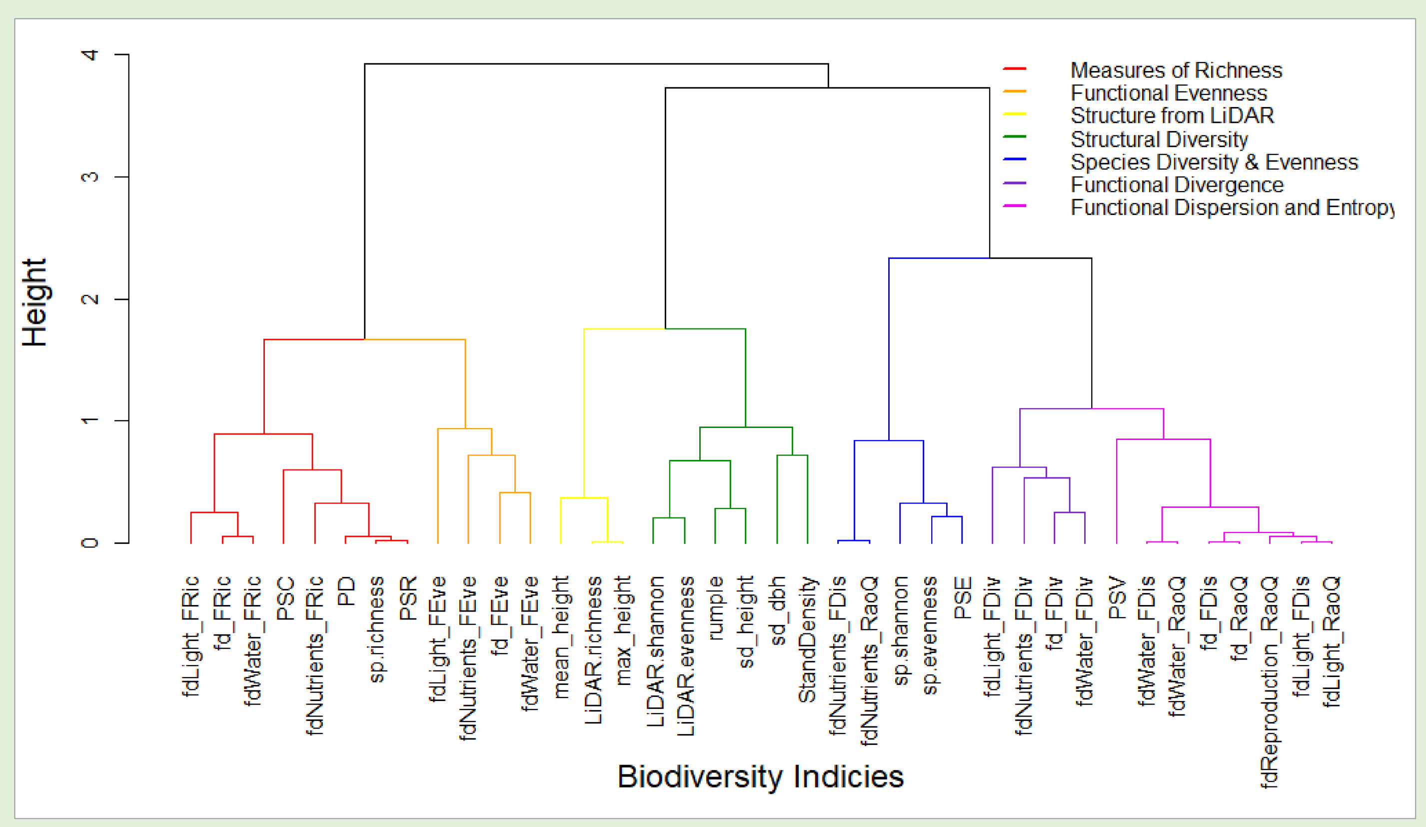


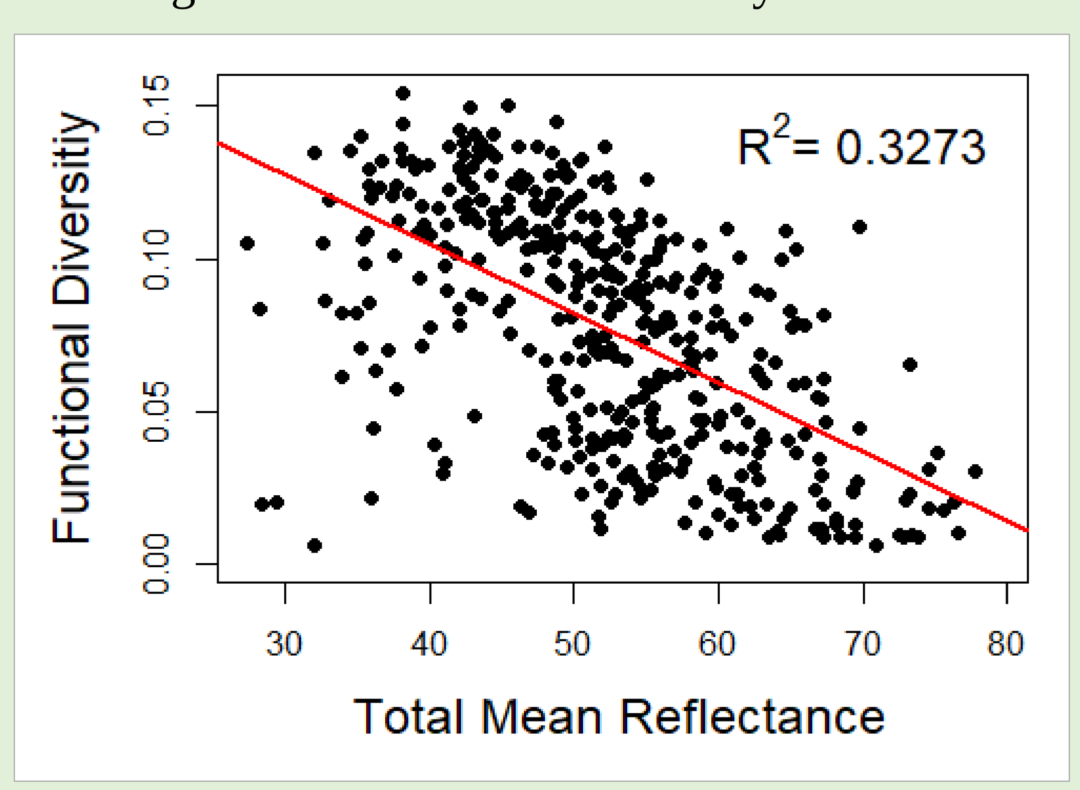
Figure 2 (left): An example simple linear regression between RaoQ's entropy index for functional diversity and Shannon's index for species diversity. Overall, relationships between biodiversity metrics were found to be weakly correlated.

Figure 3 (below): Since the biodiversity indices used to calculate the four main metrics of diversity were similar, indices were grouped together based on the strength of their correlations. From there, an index from each group was selected to represent the other indices in future analyses.



Estimating Biodiversity from Remote Sensing

Figure 4: Linear regressions were used to see how the biodiversity metrics could be estimated from the remote sensing analyses. All relationships were showed weak correlations, with the strongest correlation being between functional diversity and reflectance.



Relationships Compared at Larger Scales

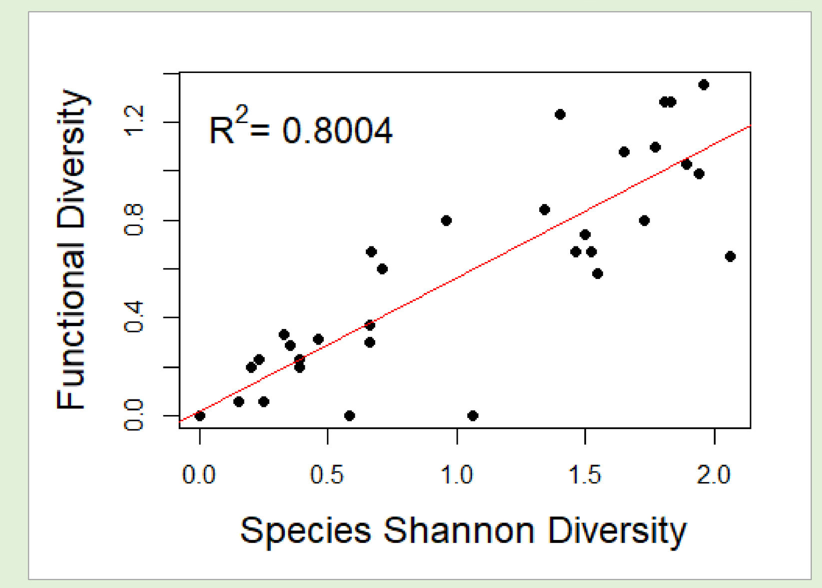


Figure 5: Linear regression between species and functional diversity across the United States using data from Fluxnet showing stronger relationships between metrics at broad scales.

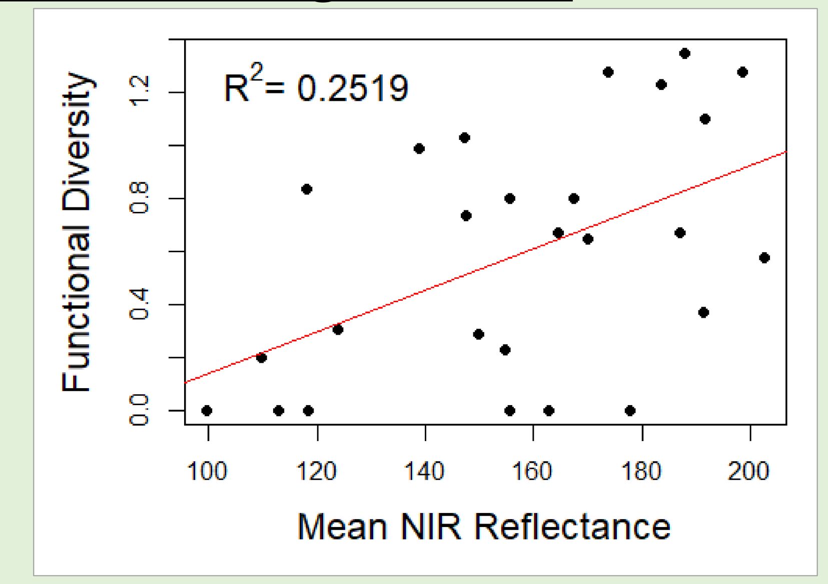
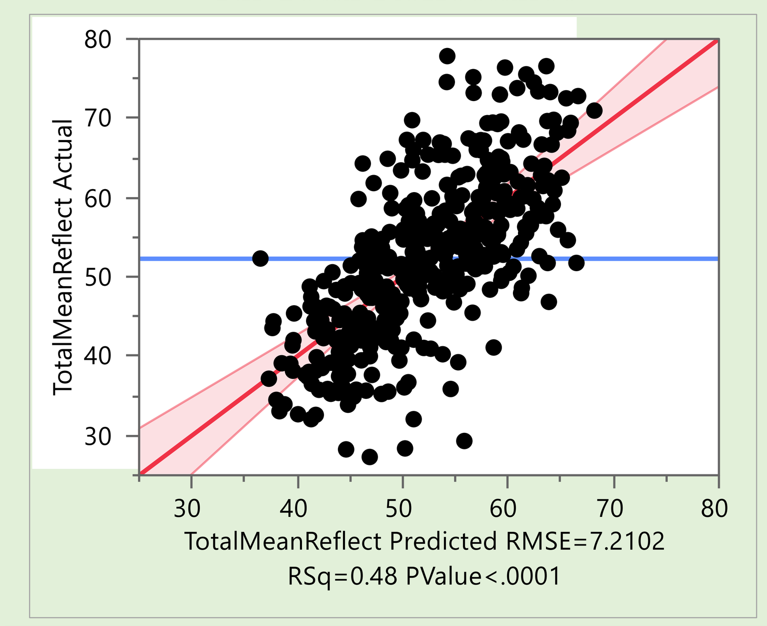


Figure 6: Linear regression between mean NIR reflectance from NAP and functional diversity showing similar strength relationships between biodiversity and remote sensing at broad scales.

Influence of Canopy Structure and Function

Select Biodiversity Indices with Total Reflectance

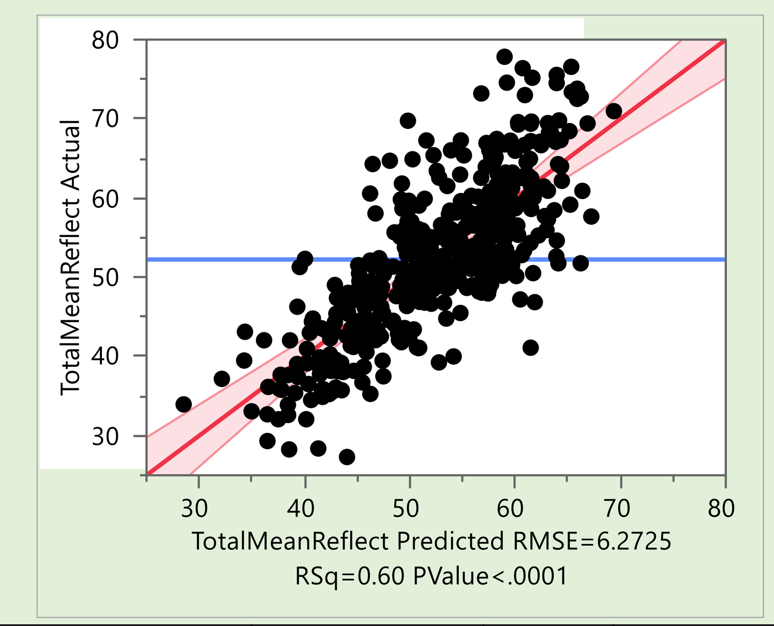


Source	Log Worth		PValue
StandDensity	8.301		0.0000
fd_RaoQ	7.564		0.0000
rumple	5.295		0.0000
PSV	3.578		0.0003
fd_FDiv	2.184		0.0065
mean_height	1.074		0.0843
fd_FEve	0.975		0.1059
sp.richness	0.698		0.2005
sp.shannon	0.638		0.2299

Figure 7: Standard least squares (SLS) analysis looking at the effect of the biodiversity metrics on reflectance.

Table 1: The effect summary of each for the biodiversity metrics showing each variable's effect on reflectance

Select Biodiversity Indices and % Broadleaf Cover with Total Reflectance



Source	Log Worth		PValue
%broadleaf	25.650		0.0000
StandDensity	4.067		0.0001
rumple	3.377		0.0004
sp.shannon	2.419		0.0038
PSV	0.984		0.1037
fd_FEve	0.643		0.2278
mean_height	0.474		0.3360
sp.richness	0.311		0.4891
fd_FDiv	0.218		0.6059
fd_RaoQ	0.085		0.8226

Figure 8: SLS analysis again but also accounting for the percent broadleaf coverage of the plots

Table 2: The effect summary of each for the biodiversity metrics

Takeaways

- Strength of relationships between biodiversity metrics improve as scale broadens.
- Estimates from remote sensing at fine and broad scales both show weak correlations.
- The influence of function and structure on reflectance suggests that both these variables are working together as drivers of reflectance
- The influence of broad leaf coverage is an example of potential outside influences that aren't accounted for when looking at diversity alone. Other influences looked at include management history and topography.

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