

Southern Indiana Ecological Conservation II

Mapping Foliage Height Diversity and Canopy Closure Trends to Inform Oak and Hickory restoration and Inform Public Outreach

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Abstract: The Central Hardwood Forest, nestled in the Midwestern United States, encompasses approximately 65,000 square miles. Oak and hickory trees are keystone species in Central Hardwood ecosystems, as they support a wide diversity of organisms, like songbirds and insects, by providing food, shelter, and habitat. This ecosystem is currently undergoing mesophication. Let the Sunshine In-Indiana is a public/private partnership looking to address mesophication through active forest management to preserve native ecosystems but need public support to do so. Let the Sunshine In-Indiana partnered with DEVELOP to identify areas undergoing mesophication to inform restoration and to characterize tree canopy closure trends in Southern Indiana for public outreach and education. DEVELOP used NASA Earth observation data, such as Landsat 5 Thematic Mapper, Landsat 8 Operational Land Imager, and the International Space Station’s Global Ecosystem Dynamic Investigation data to help the partners address these objectives. While our tested methods and data indicated no statistically predictive relationship, they can help inform future research efforts to determine adequate metrics to identify forest mesophication and conserve native oak-hickory ecosystems.

Key Terms: forest restoration, Landsat, GEDI, Indiana, Central Hardwood Forest, suitability, oak-hickory forest, mesophication, foliage height diversity, tree canopy

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1. Introduction

The Central Hardwood region of southern Indiana is a long-established ecosystem, where oak (*Quercus*, spp.) and hickory (*Carya*, spp.) trees serve as keystone species (Brooke et al., 2023). Oak-hickory forests historically spanned from 27 to 32 million acres, dominating the region, and supporting balanced ecosystem processes. Many native songbird species are adapted to survive in oak-hickory forest ecosystems, which provide critical habitat and food supply (Outcalt & Pursell, 2022). Open-canopy forests allow for sunlight to reach the understory of the forest, providing drier conditions that support oak-hickory regeneration (Nowacki & Abrams, 2008). Historically, oak-hickory forests were maintained through prescribed burns to support open-canopy ecosystems (Brooke et al., 2023).

Following European settlement in Indiana, fire suppression practices became widespread, resulting in historically open-canopied oak-hickory forests declining by ~99% (Central Hardwoods Joint Venture, 2015). This triggered an ecological shift in overstory forest species composition known as mesophication, where fire-tolerant oak-hickory trees are being replaced with shade tolerant mesophytic trees such as maple (*Acer*, spp.) and birch (*Betula*, spp.), resulting in closed canopy forests. Closed canopy forests reduce the amount of sunlight that reaches the understory, creating a positive feedback cycle in which ideal habitat conditions for mesophytic species are supported and oak tree regeneration is reduced (Nowacki & Abrams, 2008). Mesophication disrupts natural ecosystem balance, negatively impacting oak-hickory forest dependent songbirds, leading to bird population decline (Outcalt & Pursell, 2022; Brooke et al., 2023).

In response to the mesophication in Indiana, a team of experts dedicated to maintaining healthy, sustainable oak-hickory ecosystems in the Central Hardwood region formed Let the Sunshine In – Indiana. This coalition consists of stakeholders from the American Bird Conservancy, the Central Hardwoods Joint Venture, the Indiana Department of Natural Resources, Division of Forestry, and the United States Department of Agriculture Forest Service for Hoosier National Forest. Let the Sunshine In-Indiana's goals are multipronged—not only do they want to use remote sensing to inform Indiana forest management practices, but they also want to focus on communication, outreach and education, and science-based implementation of oak-hickory forest restoration.

Within the Central Hardwood region, Let the Sunshine In-Indiana identified approximately 1,000 square miles of forest stewardship clusters, also known as areas of active restoration and management (Figure 1). Current forest management practices utilized by the partners within the forest stewardship clusters include prescribed burns, midstory trimming, and invasive species control. Increasing public awareness on the benefits of fire for forest management in oak-hickory ecosystems would strengthen restoration through the support of the public. These forest stewardship clusters account for a small portion of southern Indiana, and an even smaller portion of the Central Hardwood Forest. The project study area determined by the partners (Figure 1) spans 11,905 square miles across 30 counties in southern Indiana.

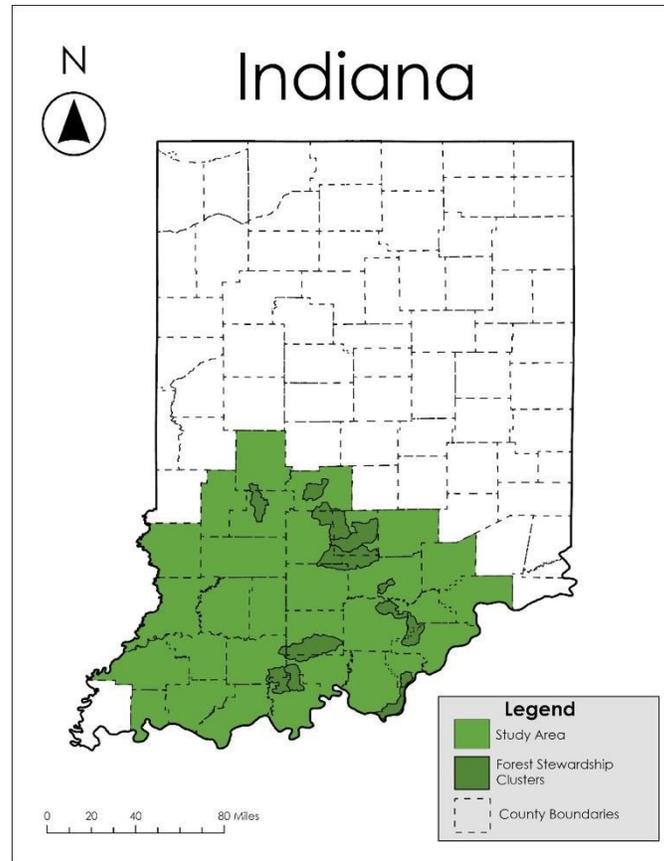


Figure 1. Map depicting the geographic extent of the study area within the state of Indiana. The lower portion in green is our specific study region for this research, while the dashed lines represent county boundaries in the state of Indiana to provide perspective on the large geographic extent this project employs. The dark green polygons within the study areas are forest stewardship clusters, regions where the partners are currently conducting active forest management.

Previous research includes publications on the encroachment of mesophytic vegetation into oak-hickory forests resulting in two primary shifts in forest structure: reduced canopy openness and greater foliage height diversity (Palus et al., 2018; Alexander et al., 2021). Palus et al. (2018) studied a forest undergoing mesophication in southern Ohio, across a 22-year study period, suggesting the need for a long-term, comprehensive study of the forest floor and canopy closure trends to better understand changes in species composition. Incorporating satellite-based remote sensing methods has shown to be an effective tool for observing these changes at landscape scales. Landsat and the International Space Station’s (ISS) Global Ecosystem Dynamic Investigation (GEDI) data products have been employed to characterize forest structure and estimate aboveground biomass, providing valuable insights into forest conditions (Potapov et al., 2021; Xu et al., 2023).

Building off previous studies, we utilized geospatial data acquired from several satellite sensors in NASA’s Earth observing fleet. We acquired data from Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI), as well as GEDI. We utilized data from these sensors to address the following objectives: 1) map canopy and foliage height diversity to evaluate levels of mesophication to identify areas suitable for restoration, and 2) show canopy closure trends over a 38-year period in southern Indiana for public outreach. To address our first objective regarding canopy and foliage height structure, we utilized GEDI’s Foliage Height Diversity product from June through September 2019 – 2024 to best capture forest structure in southern Indiana. The FHD metric, calculated by normalizing the vertical foliage profile by the total plant

area index, highlights the variation in overstory forest foliage height (United States Geological Survey, n.d.). FHD can be used to evaluate levels of mesophication by identifying areas of canopy closure with greater foliage height diversity (Palus et al., 2018). To produce Tree Canopy Cover change maps, we utilized data from the National Land Classification Database (NLCD) from 2011 to 2021 to identify changes in the tree canopy over a decade.

This is the second term of a Southern Indiana Ecological Conservation DEVELOP project with Let the Sunshine In-Indiana. The first iteration produced oak-hickory restoration suitability maps using landform, slope, aspect, NLCD canopy cover, and Soil Survey Geographic Database (SSURGO) soil type data. When creating green vegetation fraction change maps (1984 – 2023) using the Normalized Difference Vegetation Index (NDVI), the first term’s maps assigned NDVI no data pixels a value of zero, rather than Not a Number (NaN). This miscalculation inaccurately depicted temporally composited NDVI values, especially for historical NDVI baselines. For example, the first term’s historical NDVI was created using a mean three-year composite approach that unfortunately used 0 values (from no-data areas) in the derivation of mean NDVI.

This second term built on the work from the previous term by incorporating LiDAR-derived canopy structure and canopy height diversity data from GEDI to assess potential deciduous forests currently undergoing mesophication. To provide a historically accurate NDVI baseline, this team utilized max NDVI temporal compositing, as well as ten-year composites rather than three-year. We used max NDVI rather than mean to more accurately capture greenest NDVI pixel in this study region.

2. Methodology

2.1 Data Acquisition

To develop the canopy cover and foliage height diversity map deliverable, we collected Landsat and GEDI data, as well as a digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM; Table 1). Instead of manually downloading data from Collection 2 Level 2 Landsat 5 TM and Landsat 8 OLI, we received cloud-free composites from Google Earth Engine for each year capturing peak vegetation biomass for the date range of June to September for the years of 1986, 1995, 2005, 2015, and 2024. It is important to note we used the year 1986 rather than 1985 due to better cloud-free data availability. Creating composites from Google Earth Engine resolved various issues such as radiometric and phenological differences across Landsat scenes, seamline anomalies when mosaicking scenes from different months, and cloud cover when we attempted to download these data manually. These composites were based on a pixel-by-pixel NDVI maximum value for each year covering our study area and this included red and near-infrared (NIR) spectral bands for deriving other vegetation indices.

Table 1

Earth observations used in this study

Platform & Sensor	Data Product	Dates	Spatial Resolution	Mode of Acquisition
ISS GEDI	Level 2B Canopy Cover and Vertical Profile	June through September 2019 – 2024	25 meters	Earthdata Search
Landsat 5 TM	Surface Reflectance	June through September 1986, 1995, 2005	30 meters	Google Earth Engine
Landsat 8 OLI	Surface Reflectance	June through September 2015 and 2024	30 meters	Google Earth Engine
SRTM	Digital Elevation Model	February 11 – 22, 2000	30 meters	USGS EarthExplorer

With Landsat data collected, we next gathered global Level 2B GEDI Canopy Cover and Vertical Profile products as .H5 files from NASA Earthdata Search. These data were downloaded for July to September of 2019 – 2024 that included all available beams and coverage paths intersecting the designated study area. It is important to note that the option to subset these data by our study area was not available; therefore, we had to download all GEDI’s global paths, amounting to a dataset that exceeded 100 gigabytes prior to additional processing. We also acquired SRTM 1 Arc-Second DEM data from USGS EarthExplorer. Several tiles were downloaded as GeoTIFFs to cover the entirety of the study area. Additionally, we obtained percent tree canopy cover from the NLCD for the Continental United States for the years of 2011, 2015, and 2021. These datasets were downloaded from the Multi Resolution Land Consortium website, which contains all of the NLCD datasets available for download.

2.2 Data Processing

We used ArcGIS Pro 3.4.2 to clip the Landsat mosaics to our study area using the ‘Extract by Mask’ tool and computed several vegetation indices using ‘Raster Calculator’ (Equation 1; Equation 2; Equation 3). These indices include NDVI (Rouse et al., 1974), Enhanced Vegetation Index 2 (EVI2; Jiang et al., 2008), and Near Infrared Reflectance of Vegetation (NIRv; Badgley et al., 2017). These vegetation indices were used as inputs with both regression models, one to estimate canopy cover values and the other to estimate FHD values. All these spectral indices used the red and NIR bands as inputs.

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

$$NIRv = \frac{NIR - Red}{NIR + Red} \times NIR \quad (2)$$

$$EVI2 = 2.5 \times \frac{NIR - Red}{(NIR + (2.4 \times Red) + 1)} \quad (3)$$

With the vegetation indices calculated, we then quantified elevation to use within our FHD regression model. We used the ‘Slope’ and ‘Aspect’ tools in ArcGIS Pro to calculate terrain slope and aspect from the SRTM DEM data, which had a spatial resolution of 30 meters (Figure 2). The ‘Extract Multi Values to Points’ tool was then used on the NDVI, EVI2, NIRv, DEM, slope, and aspect rasters to add them to a singular table, along with the fhd_normal metric, representative of the foliage height diversity index, from the GEDI Level 2B dataset.

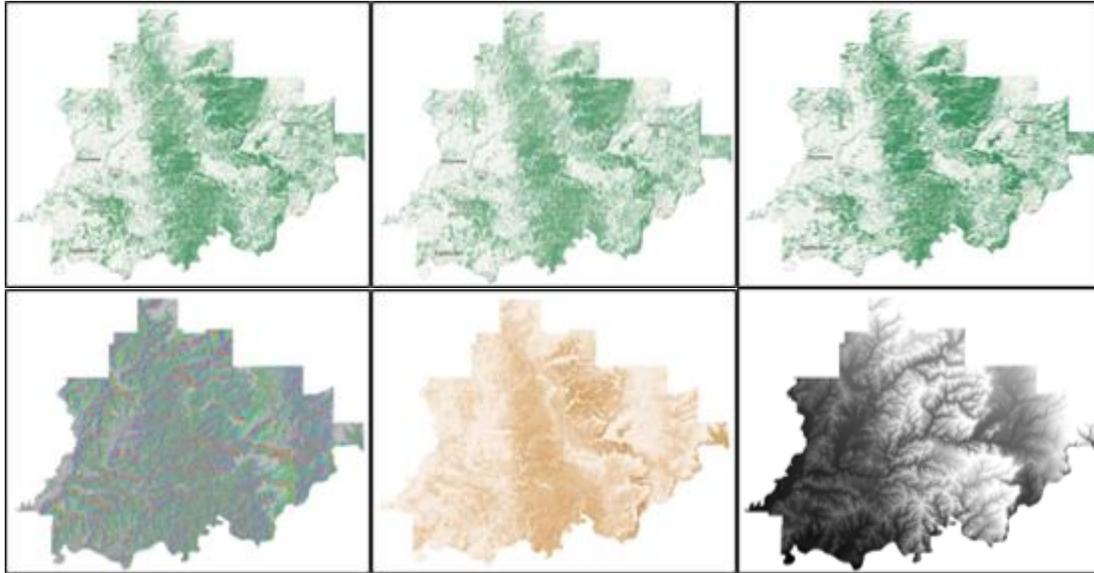


Figure 2. Vegetation indices computed from 2024 Landsat 8 OLI mosaicked imagery (top) and surface elevation metrics, generated from 2000 USGS SRTM data (bottom) used to predict FHD. In left to right row order, these inputs are EVI2, NIRv, NDVI, Aspect, Slope, and DEM.

To quantify tree canopy cover values, we downloaded geospatial data layers from the NLCD pertaining to land cover classification and tree canopy cover and clipped them to our study area after being uploaded into ArcGIS Pro as raster layers. We then clipped each layer by a mask derived with only pixel values that correspond to forested areas in accordance with the land cover classification dataset’s symbology (Multi Resolution Land Consortium, n.d.). These values for forests are as follows: 41 (deciduous forest), 42 (evergreen forest), 43 (mixed forest), and 90 (woody wetlands). After creating a mask of these pixel values for each year of NLCD data downloaded, we made all other values equal to “No Data” and removed them from our Landsat indices. This processing method ensured the indices and raster layers we included into our regression models only stored data for forest-associated pixels, thus cleaning the data to remove all other land classes and covers. Following the removal of non-forest pixels, we utilized ‘Raster Calculator’ to subtract the 2021 tree canopy cover raster layer from the 2011 tree canopy cover layer to observe changes in the tree canopy between 2011 and 2021.

To filter the raw GEDI data retrieved from Earthdata Search, we used the GEDI Subsetter, a Python-based application provided on the NASA GitHub webpage (NASA, 2025). The raw GEDI Level 2B data, as well as the shapefile of our area of interest, were required inputs. For the optional arguments, we selected all the full-power beams available: BEAM0101, BEAM0110, BEAM1000, BEAM1011. The full-power beams were selected because they penetrate denser canopies at 99% effectiveness (GEDI Ecosystem Lidar, 2025). The output of the tool was GEDI data subsetted by our beams and area of interest into the form of GeoJSON files. Using ArcGIS Pro, we merged the newly generated GEDI files into one feature class.

2.3 Data Analysis

To test for a predictive relationship and fulfil our project objectives, we utilized a random forest regression model, a regression tree technique combining bootstrap aggregation and the randomization of predictors to assess predictive accuracy (Rigatti, 2017). We trained two random forest regression models using the ‘randomForest’ package in R 4.3.3 to model two potential indicators of mesophication: tree canopy cover and FHD. The tree canopy cover model was constructed exclusively using spectral indices (NDVI, EVI2, and NIRv), while FHD included these spectral indices as well as surface elevation metrics (DEM, slope, and aspect). Training and testing data were generated for each model via random sampling in ArcGIS Pro. We used 11,980 points for training and 5,125 points for testing the tree canopy cover model. The FHD model

was trained using 200,564 points and tested using 85,957 points. We used 400 and 180 classification trees for the tree canopy cover and FHD models, respectively. The model accuracy was evaluated by computing the root mean squared error (RMSE) between model predictions and reference data.

3. Results

3.1 Analysis of Results

The results of this regression show that no significant relationship was observed between predicted and observed FHD values (Figure 5), indicating the model was ineffective for modeling FHD within the study period using spectral indices and surface elevation metrics as input data. Figure 6 displays the outcome of the regression, testing for a predictive relationship between vegetation indices for a given year, and the NLCD percent tree canopy cover data layer for the year. Figure 6 displays the relationship between the two datasets. The R-squared value was 0.09, indicating little to no predictive relationship between the two inputs. Figure 7 depicts the percent tree canopy cover change map from 2011 to 2021. Most pixel values fall in the relatively narrow -5% to 0% range, with more incremental increases and decreases seen in the inset map. Changes picked up mostly regarded low percentages, inferably due to the geographic extent of the study area (~12,000 square miles) as well as the reduced study period, going from 38 years to 10 years.

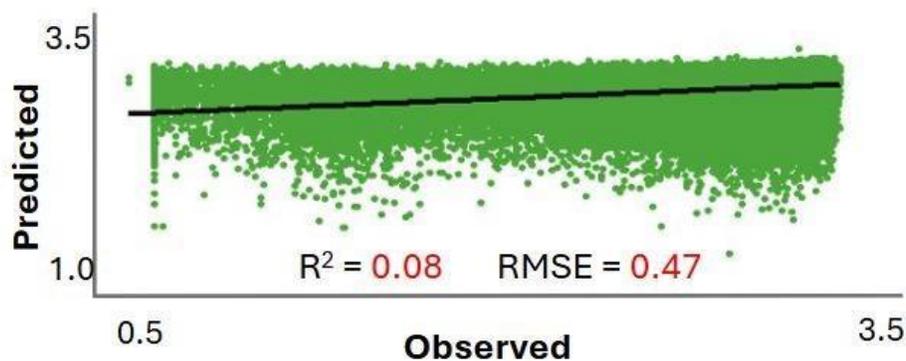


Figure 5. Comparison of FHD regression model predictions (“Predicted”) on the y-axis to reference FHD values from GEDI Level 2B (“Observed”) on the x-axis.

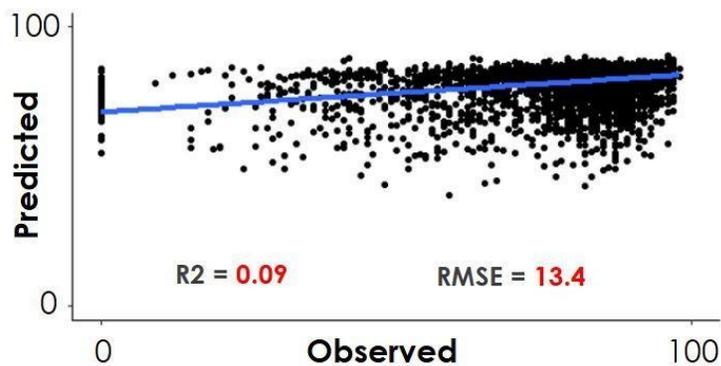


Figure 6. Performance of the random forest regression model for tree canopy cover values. On the y-axis are the tree canopy cover values predicted by our model, compared to reference data on the x-axis showing tree canopy values extracted from the NLCD. These results were calculated using vegetation indices from Landsat 8 OLI 2015 imagery and NLCD tree canopy cover data for 2015.

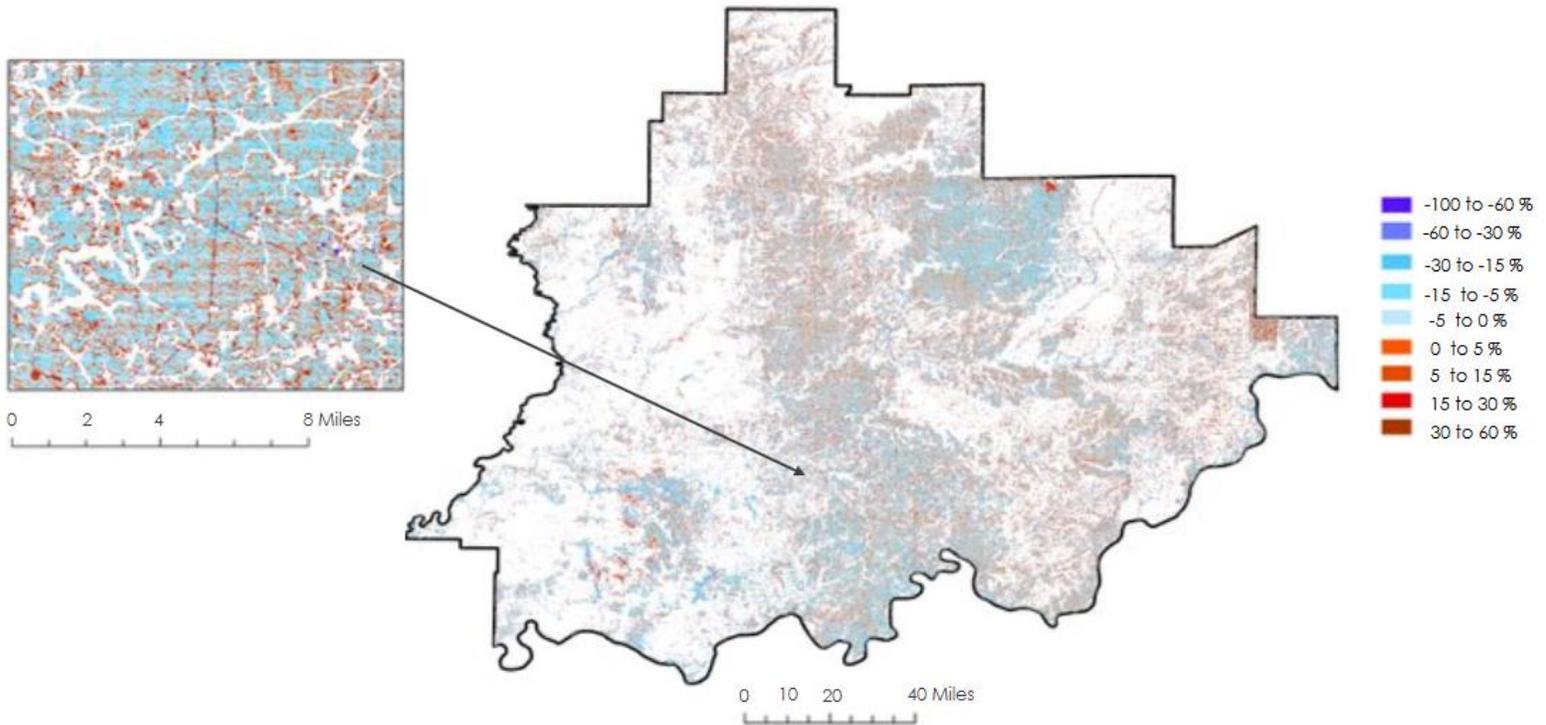


Figure 7. Percent tree canopy cover change from 2011 to 2021 within the study area. Increases are depicted in red, with decreases in blue. White pixels denote non-forested regions and were excluded from analysis. This map was configured using NLCD data from the given years.

3.2 Errors & Uncertainties

Several limitations hindered our team's outcomes. From downloading to preprocessing, multiple errors and uncertainties occurred in efforts to download and import GEDI data into GIS software. The process of downloading GEDI Level 2B data from NASA Earthdata was unclear, due to the complex Earthdata Search's graphical user interface. Additionally, the built-in subsetting tool was not functioning as expected. This necessitated over 100 gigabytes of unfiltered files to be downloaded overnight and subsetting in a subsequent processing phase. Once downloaded, there were additional roadblocks. GEDI's initial format, H5, was incompatible for most programs that we tried. Overall, GEDI data was not application-ready for use in a GIS package, based on the hurdles we encountered in downloading and preprocessing more basic GEDI data.

Additionally, the Landsat imagery utilized to compute spectral indices had "noise" artifacts in the data (e.g., from unmasked cloud shadows that can occur with the greenness pixel method in deriving Landsat temporal composites). The noise in the Landsat imagery caused several challenges. The large geographic extent of our study area (~12,000 square miles) required us to manually download five Landsat tiles for each year, processing and stitching them together manually in ArcGIS Pro to create max-NDVI greenest pixel maps. We were unable to fully automate this NDVI temporal compositing process in ArcGIS Pro, leading to us spending a lot of time computing these indices. Ultimately, this method was not employed for calculating

max-NDVI or greenest pixel, as doing the process manually introduced some user error, and we could not locate five Landsat tiles for each month that had less than 10% cloud cover as inputs. After spending several weeks attempting to refine these methods, one of our science advisors provided alternative Landsat-based max-NDVI composites for June through September for 1986, 1995, 2005, 2015, and 2024. These composites were computed using Landsat data within Google Earth Engine, which allowed for quicker return of the composited images truly representing max-NDVI, removing uncertainty of doing so manually in ArcGIS Pro. Alternative NDVIs were also derived by considering Landsat scenes containing more cloud cover than 10 percent. The mosaics acquired through our science advisor were used to calculate the following vegetation indices: NIRv and EVI2. We used these indices, as the Landsat composite images obtained from Google Earth Engine were provided with only the red and NIR bands, therefore we only could compute indices based on those two bands. Other spectral indices comparing the NIR and red could be tried to determine if improved results could be achieved. Additional spectral bands of Landsat temporally composited data could be acquired from Google Earth Engine to compute other spectral indices that use NIR and SWIR bands like the Normalized Burn Ratio, Normalized Difference Moisture Index, and Tasseled Cap Wetness that could be used to improve efforts to extract wall to wall region-wide maps of tree canopy cover and height. Other temporal compositing methods (e.g., median or medoid methods) could be tried to possibly reduce noise artifacts in Landsat temporal composites. Results may also improve by using Landsat data that is of the same data collection year as the GEDI data. Other GEDI data processing and analysis methods may possibly be useful for improving statistical relationships between the GEDI and Landsat data in terms of estimating forest canopy cover and tree height diversity.

4. Conclusions

4.1 Interpretation of Results

Results from the regression equation between vegetation indices and NLCD tree canopy cover data for 2015 did not yield a sufficiently high predictive relationship for accurately estimating tree canopy cover values back to 1986. These results were intended to be used to create a 38-year tree canopy cover trend map for our partners for public outreach and education, particularly to show the public that tree canopy closure is leading to mesophication in the Central Hardwood Forest. Due to the resulting model having a weak predictive relationship with NLCD data, our team pivoted to decreasing the study years to use available NLCD tree canopy cover data for the years of 2011 and 2021, to produce a viable tree canopy cover change product for the partners. NDVI, EVI2, NIRv, DEM, aspect, and slope do not show strong explanatory power for estimating FHD according to the regression model. This indicates that the chosen vegetation indices and GEDI's FHD product do not produce a predictive statistical relationship in our study and thus, cannot accurately identify locations in the study area undergoing mesophication.

We also ran into significant limitations regarding the useability of GEDI data. Challenges in acquisition and accessibility made it difficult to manipulate this data within software (e.g., ArcGIS Pro software), hindering our main analysis outcomes and resulting in setbacks and limited time to do the final processing. We had initially planned to process and analyze the GEDI data in ArcGIS Pro, but we resorted to processing the data in Python and analyzing it in R.

4.2 Feasibility and Partner Implementation

We determined that our methods were infeasible for reliably modeling tree canopy cover and foliage height diversity to identify mesophication trends. As such, our end products were of limited use to our project partners. Issues with model accuracy, data accessibility, automation of image processing, and technological/licensing constraints presented obstacles throughout the term. Our partner's management efforts may be better informed by incorporating additional indices in these methods to model forest structure, exploring the utility of preexisting application-ready data products, and reducing the area of interest for future studies. Indices such as Leaf Area Index and Normalized Burn Ratio may help to more accurately identify mesophication trends in the models outlined in this study. Moreover, partner could utilize premade datasets depicting forest structure, like the University of Maryland's Global Land Analysis (GLAD), alongside GEDI

Level 2A or Level 4A data products to determine if needed information on mesophication can be obtained with other GEDI or comparable Lidar (e.g., from ICESat) related datasets. As discussed in Potapov et al. (2021), incorporating Landsat, GEDI, and GLAD data products on forest height could strengthen regression results and quantify canopy values effectively, using GLAD products for training data alongside GEDI to effectively quantify forest height change over relevant timescales. Lastly, processing data at multiple time steps across the nearly 12,000 square mile study area was time consuming and computationally intensive. Therefore, reducing the spatial extent of the study area would help mitigate these issues while also potentially making it feasible to include more localized, higher-resolution data products such as airborne imagery or Lidar.

Overall, the methods and data we explored in this project to generate tree cover and height diversity maps were not sufficient for characterizing tree canopy closure trends and identifying areas of southern Indiana's Central Hardwood Forest undergoing mesophication. However, leveraging pre-existing mapping products and alternative workflows may enhance the future projects on the feasibility of using remote sensing to assess forest mesophication. Utilizing preexisting tree canopy cover and forest height map products may benefit our partners in the short-term, as well as exploring other remote sensing data types that may better inform management of native oak-hickory ecosystems.

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6. Glossary

DEM – Digital Elevation Model

Earth observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time

EVI2 – Enhanced Vegetation Index 2

Forest Stewardship Clusters – areas of active restoration and management within the Central Hardwood region identified by Let the Sunshine In-Indiana

GLAD – Global Land Analysis & Discovery

GEDI – Global Ecosystem Dynamic Investigation

ISS – International Space Station

Mesophication – an ecological shift in overstory forest species composition where fire-tolerant species are replaced with shade tolerant

NDVI – Normalized Difference Vegetation Index
NIRv – Near Infrared Reflectance of Vegetation
NLCD – National Land Classification Database
OLI – Operational Land Imager
SRTM – Shuttle Radar Topography Mission
TM – Thematic Mapper
USGS – United States Geological Survey

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