Bedding Orientation Impact Analysis and Tree Row Detection in Pine Plantations: Insights from Lidar, Remote Sensing, and Machine Learning

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Bedding Orientation Impact on Wetness Index, and Pine Growth

Introduction

Bedding direction in pine plantations, usually based on operational efficiency, can affect drainage, especially during seasonal floods in the southeastern US coastal plain. This may hinder growth and require more phosphorus fertilization. The study explores how bedding orientation relative to elevational gradients impacts these factors.

Objectives

- This study examines how bedding orientation relative to elevational gradients influences the wetness index (NDWI) and vegetation index (NDVI), potentially impacting seasonal flooding responses
- The study further evaluates the statistical relevance of average NDVI and NDWI values in forest plots from 1986 to 2018, considering the varying orientations of these plots

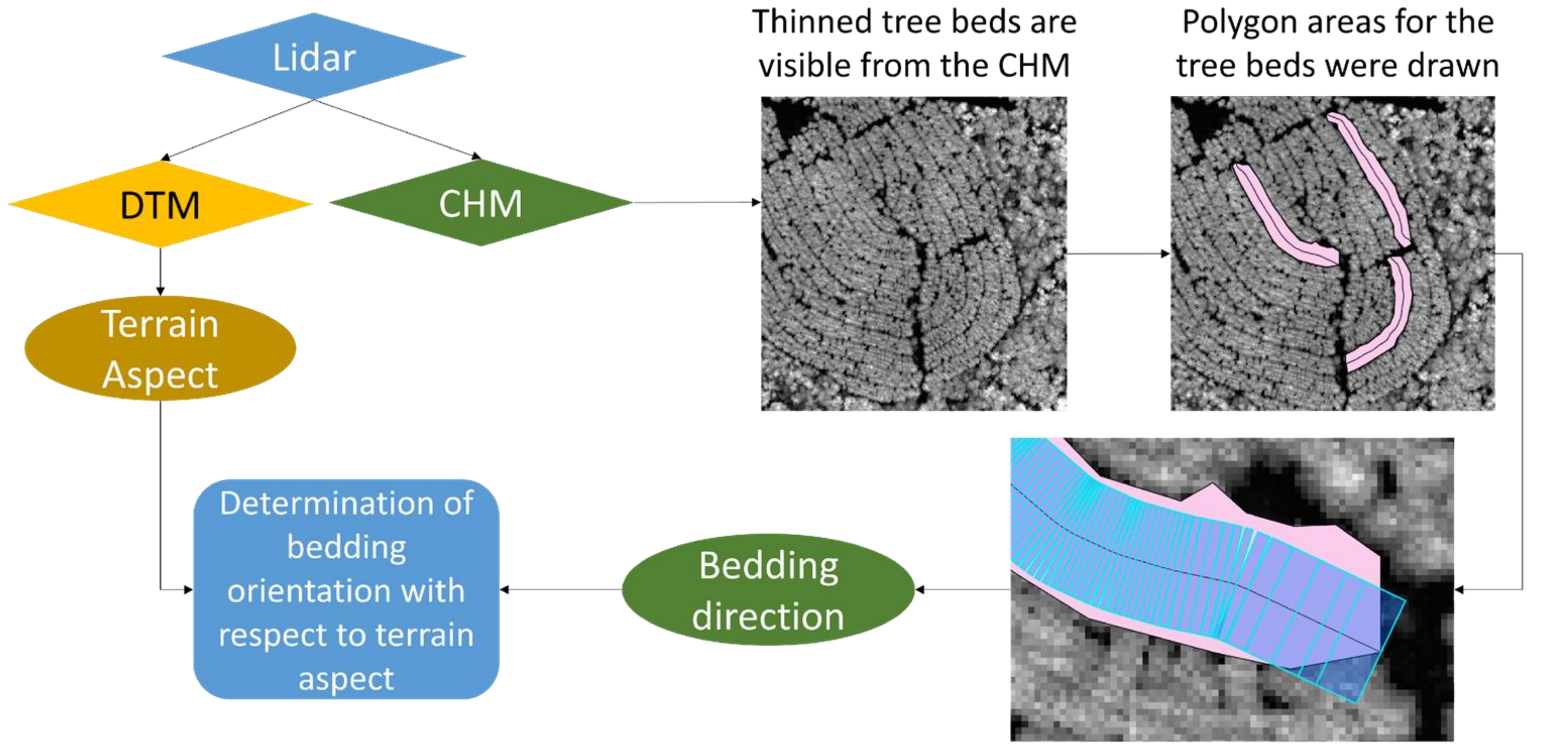
Methods

This section consists of 2 parts. The first one is identifying the tree beds and determining their orientation compared to the elevation gradient. The second one is extracting NDVI and NDWI values from Google Earth Engine (GEE).

We ran a mixed model ANOVA analysis to check whether the annual mean of NDVI and NDWI values of beds with different orientations have any significant differences.

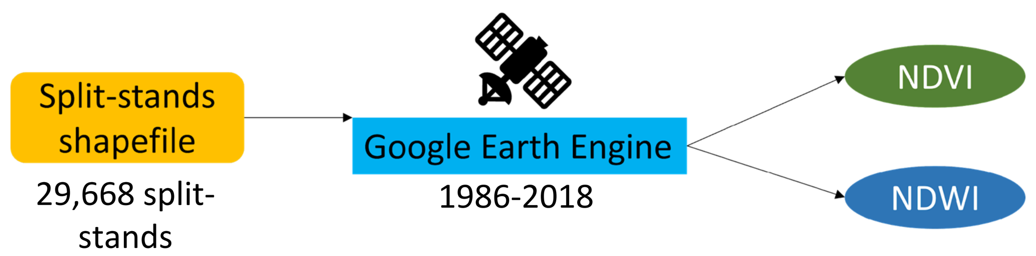
Study Area

Tree orientation determination



DTM = Digital Terrain Model
CHM = Canopy Height Model

NDVI & NDWI Time-series analysis

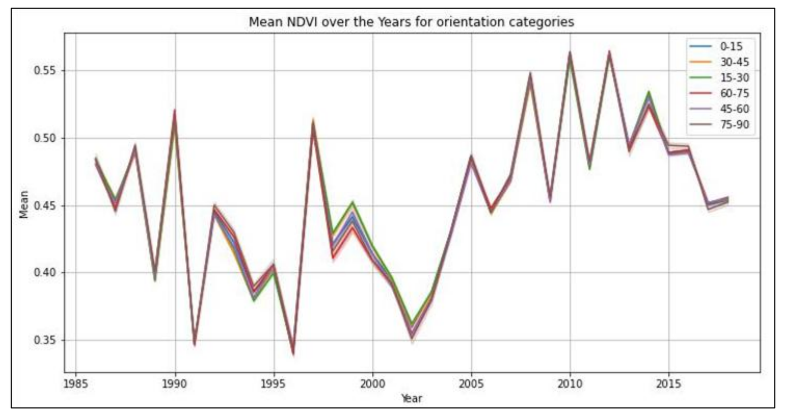


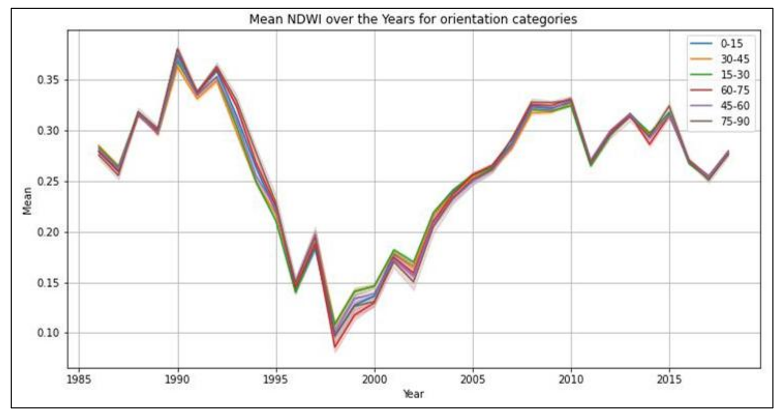
Data Sources

Landsat 7 C 1 T 1 32-Day NDVI Composite
Landsat 5 TM C 1 T 1 32-Day NDVI Composite
Landsat 5 TM C 1 T 1 32-Day NDWI Composite
Landsat 7 C 1 T 1 32-Day NDWI Composite

Using the split-stand shapefile annual NDVI and NDWI were extracted from GEE. The orientation angles were categorized at 15-degree intervals.

Results





The NDVI and NDWI trend for orientation categories show changes over time (1986-2018). However, the difference among the categories is not clear from these charts

Mixed-model ANOVA Results

NDVI

	Sum Sq	Mean Sq	NumDF	DenDF	F value	Pr(>F)	
Category	0.024	0.005	5	890817	0.9592	0.4413	
Year	260.96	260.96	1	890940	52128.4	<2e-16	***
Category :Year	0.024	0.005	5	890958	0.957	0.4427	

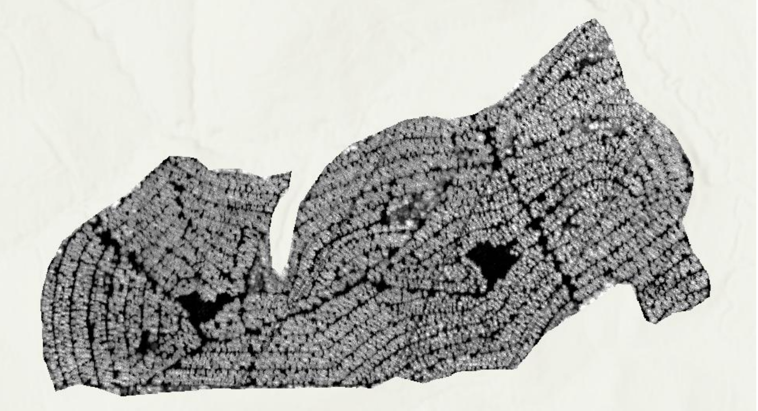
NDWI

	Sum Sq	Mean Sq	NumDF	DenDF	F value	Pr(>F)	
Category	0.1012	0.0202	5	865207	1.9032	0.09017	.
Year	8.3097	8.3097	1	875780	781.50	< 2e-16	***
Category :Year	0.1005	0.0201	5	874974	1.8902	0.09237	.

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

For both NDVI and NDWI, the annual variation of the mean values shows a significant difference ($F_{1, 875780} = 781.4979$, $p < .001$). However, for NDWI, the Category ($F_{5, 865207} = 1.9032$, $p = .05$) and the interaction between Category and Year ($F_{5, 874974} = 1.8902$, $p = .05$) shows significant difference.

We looked deeper into the fixed effects results of NDWI where we found that the mean NDWI values of orientation **category 30-45** (p=0.05) and **its interaction with Year** (p=0.05) are significantly different from other categories.



CHM of the clipped area shows thinned bed area where thinning tracks can be identified (black areas)

Identified treetops from CHM using *ForestTools* package in R

Density-based Spatial Clustering Algorithm (DBSCAN) was applied to the treetops point data to identify arbitrarily shaped clusters. In the context of detecting tree rows, the algorithm was used to group together points that belong to the same tree row based on their spatial proximity. The algorithm requires two parameters: the minimum number of points required to form a dense region (minPts) and the maximum distance between two points for them to be considered in the same neighborhood (eps).

The figure shows one of the identified clusters using the DBSCAN algorithm in a blue highlight. As seen in the image, the trees that are segregated by the thinning line are clustered together. However, it's still not detecting rows. Adjusting the parameters here might be helpful in retrieving more accurate results.

Tree Row Detection in Pine Plantations

Remote sensing tools and data science can optimize plantation forest management in the southeastern US, where current timber thinning decisions are arbitrary. Using LiDAR and machine learning, we're developing an automated method to improve thinning practices, aiming to increase yields and meet global wood demand.

Background

Bedding orientation relative to elevational gradients affects wetness and growth index. We manually identified beds and explored automatic tree row detection using Canopy Height Models (CHM) from airborne lidar data.
Tree row detection is crucial for forest thinning, a common treatment in plantations affecting growth (Albaugh et al. 2017). The southeastern US houses 15 million hectares of southern yellow pine plantations, with 500 thousand hectares thinned annually (Wear and Greis 2012). Given the arbitrary nature of thinning decisions, our goal is to create a LiDAR and machine learning tool to optimize these choices.

Objective

To design and implement a LiDAR and machine learning-based tool to optimize thinning decisions in forest plantations

Methods & Results

The first step was to identify the treetops as point data from the CHM. The same dataset for the previous work was used here. The total area was clipped down to a smaller area where the thinning operation was already conducted.

Using the clipped CHM, the treetops were identified using *ForestTools* package in R. The package uses a *variable window filter* and *marker-controlled segmentation algorithm* to detect individual trees from rasterized CHM. 5,626 trees were identified from the operation along with their heights.

Future Work

While we have some progress for the two projects, for more precision and validity, we need to conduct more experiments.

Directions for Elevational Impact on Bedding Orientation, Wetness Index, and Pine Growth

- Evaluate the current methodology across various bedding areas to determine the consistency and validity of the obtained results.
- Investigate additional variables, including stand age, planted species, initial fertilization, and planting density, to assess their potential influence on the wetness index and pine growth in conjunction with the bedding orientation.

Directions for Tree Row Detection

- Implement the Hough Transformation to evaluate the detection of tree row lines.
- Utilize the voxelization technique for individual tree identification, and employ both the DBSCAN algorithm and Hough Transformation to assess the accuracy of tree row line detection.
- In this scenario, it could also be beneficial to explore the use of Deep Learning methods for pattern recognition.

Conclusions

Determining the optimal orientation for Pine tree beds could be significantly beneficial, given its potential to impact millions of hectares of Pine plantations. This could enhance the drainage capacity during seasonal flood events and promote plant growth, thereby contributing to the overall productivity and sustainability of these plantations.

Conversely, developing a methodology for tree row identification could facilitate the precise detection of rows that require thinning. By employing an individual tree extraction method, we can identify those tree rows that are underperforming and potentially inhibiting the growth of surrounding trees. These can then be selectively thinned, potentially enhancing the efficiency and effectiveness of field foresters' work.

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