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DEVELOPMENT OF A TOOL FOR THE CALCULATION LEAF AREA INDEX ON MULTISPECTRAL IMAGERY

BACHELOR’S THESIS

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Declaration

I declare that I prepared this diploma thesis independently, under the guidance of Ing. Jan Komárek, Ph.D., using the sources listed in the list of sources and literature. When preparing it, I adhered to the Methodical Guidelines for the preparation of a diploma thesis at the FŽP (current as of 30/3/2023).

Prague 31.03.2023 Andrii Khrystodulov

Abstract

Index listové plochy (LAI) je kritickým parametrem pro sledování růstu vegetace a odhad struktury zápoje. V několika posledních letech se LAI stal velmi populárním pro celou řadu oblastí včetně zemědělství, lesnictví a urbanistiky. Cílem této práce je vyvinout uživatelsky přívětivý výpočetní nástroj pro odvození LAI s využitím programovacího jazyka Python 3 a externích knihoven. Přesnost výstupu nástroje bude vyhodnocena pomocí několika metrik, včetně RMSE (Root Mean Square Error), střední absolutní chyby (MAE) nebo koeficientu determinace (R-squared). Tyto metriky poskytují komplexní hodnocení výkonu nástroje, což umožňuje hlubší srovnání s jinými existujícími metodami. Práce se bude skládat z literární rešerše, vývoje nástroje, zpracování dat, vyhodnocení výkonu a analýzy výsledků. Nástroj pro výpočet LAI bude navržen tak, aby zpracovával multispektrální data z družice a poskytoval přesné hodnoty LAI rychle a nedestruktivně. Práce si klade za cíl poskytnout komplexní vyhodnocení výkonu vyvinutého nástroje a porovnat jej s jinými existujícími metodami a poskytnout vhled do výhod a omezení jednotlivých metod. Nástroj bude užitečný pro agronomy, lesníky a urbanisty, kteří potřebují vypočítat LAI pro své výzkumné nebo praktické aplikace. Výsledek studie přispěje k rozvoji výpočetních nástrojů LAI a umožní výzkumníkům zlepšit přesnost a efektivitu jejich práce.

Abstract

Leaf area index (LAI) is a critical parameter for monitoring vegetation growth and estimating canopy structure. In the last few years, LAI has become very popular in a variety of fields, including agriculture, forestry, and urban planning. The aim of this work is to develop a computational tool for LAI derivation using the Python 3 programming language and external libraries. The accuracy of the tool output will be evaluated using several metrics, including RMSE (Root Mean Square Error), Mean Absolute Error (MAE), or Coefficient of Determination (R-squared). These metrics provide a comprehensive assessment of the tool's performance, allowing deeper comparisons with other existing methods. The work will consist of a literature review, tool development, data processing, performance evaluation, and analysis of results. The LAI calculation tool will be designed to process multispectral satellite data and provide accurate LAI values quickly and non-destructively. The work aims to provide a comprehensive evaluation of the performance of the developed tool and compare it with other existing methods and provide insight into the advantages and limitations of individual methods. The tool will be useful for agronomists, foresters, and urban planners who need to calculate LAI for their research or practical applications. The result of the study will contribute to the development of LAI calculation tools and allow researchers to improve the accuracy and efficiency of their work.

Keywords

GIS, RS, RMSE, spatial analysis, leaf area, multispectral image processing.

Table of Contents:

1. Introduction

LAI is a dimensionless quantity characterizing the canopy of an ecosystem. It was described by Watson (1947) as the total one-sided area of leaf tissue per unit of ground surface area. LAI is a critical parameter for monitoring vegetation growth and estimating canopy structure in various fields, including agriculture, forestry, and urban science. Accurate and efficient estimation of LAI is essential for understanding carbon, water, and energy exchange between the biosphere and atmosphere, as well as predicting crop yields and forest productivity (Ma, Zhang, Wang, Khromykh, Li, Zhong 2023).

There are several methods for estimating LAI, including direct measurement, plant allometry, hemispherical photography, spectral indices, and machine learning. These methods have different advantages and limitations depending on the application and the level of accuracy required. Direct measurement is the most accurate method, but it is time-consuming and destructive (Levy, Jarvis 1999). Plant allometry is a non-destructive method but requires complex calculations and assumptions. Hemispherical photography is a non-destructive method that can be automated but requires expensive equipment and sophisticated image processing algorithms (Duan, Liu, Gong, et al. 2019). Spectral indices and machine learning are non-destructive methods that utilize multispectral data from remote sensing platforms, such as satellites, drones, and airplanes.

Python programming language has become increasingly popular for scientific research and data analysis due to its simplicity, versatility, and rich collection of libraries (Millman, Aivazis 2011). Python libraries, such as NumPy, Matplotlib, Rasterio, and others, provide a comprehensive set of tools for data manipulation, and visualizations. These libraries can be used to develop user-friendly LAI calculation tools that can process multispectral data from satellites quickly and accurately.

The goal of this thesis is to develop the LAI calculation tool using Python programming language and external libraries. The tool's efficiency will be compared to other existing methods, including remote measurements, and spectral indices. The accuracy of the tool's output will be evaluated using multiple metrics.

The thesis aims to provide a comprehensive evaluation of the developed tool's performance and compare it to other existing methods, providing insight into the advantages and limitations of each method. The tool will be useful for agronomists, foresters, and urban scientists who need to calculate LAI for their research or practical applications. The result of the study will contribute to the advancement of LAI calculation tools, enabling researchers to improve the accuracy and efficiency of their work.

1.1. Background

The importance of LAI estimation has grown significantly in recent years due to the increased demand for precise and timely information on vegetation cover and structure for various applications. LAI is a key parameter for modeling photosynthesis, evapotranspiration, and carbon fluxes in terrestrial ecosystems (Rong, Yongqiang Zhang, Hao Shi, Yang, Eamus, Cheng, Chiew, Qiang 2018). It also plays a critical role in monitoring crop growth and yield, assessing forest health and productivity, and analyzing the urban heat island effect.

Traditionally, LAI was estimated using direct measurement methods, such as destructive sampling and planimetry. However, these methods are labor-intensive, time-consuming, and often limited by spatial and temporal resolution. With the advancement of remote sensing technology, spectral indices, and machine learning algorithms have become increasingly popular for estimating LAI from multispectral data obtained from satellites, drones, and airplanes (Ilniyaz, Kurban 2022). These methods offer several advantages over direct measurement, including high spatial and temporal resolution, non-destructiveness, and cost-effectiveness.

Several spectral indices have been developed to estimate LAI, including the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI). These indices use the spectral properties of vegetation to infer LAI based on the relationship between LAI and the reflectance or radiance observed in different spectral bands (Anthony L. Nguy-Robertson, Yi Peng, Anatoly A. Gitelson, Timothy J. Arkebauer, Agustin Pimstein, Ittai Herrmann, Arnon Karnieli, Donald C. Rundquist, David J. Bonfil 2014). However, spectral indices have limitations, such as the sensitivity to atmospheric conditions, soil background, and vegetation type, which can affect their accuracy.

Machine learning algorithms, such as Random Forest, Support Vector Regression, and Artificial Neural Networks, can also be applied to estimate LAI using multispectral data (Han Chen, Jinhui Jeanne Huang, Edward McBean 2020). These algorithms use statistical models to learn the relationship between LAI and multispectral variables, such as reflectance, radiance, and texture features. Machine learning algorithms can handle large and complex datasets and capture nonlinear relationships between variables, making them suitable for predicting LAI accurately.

This thesis will explore the development of a Python-based LAI calculation tool that integrates spectral indices to estimate LAI accurately and efficiently. The tool's performance will be evaluated using multiple metrics, including RMSE, to compare its efficiency with other existing methods. The thesis aims to provide a comprehensive overview of LAI estimation methods and their advantages and limitations, contributing to the advancement of LAI calculation tools for various applications.

1.2. Problem Statement

Estimating Leaf Area Index (LAI) from multispectral data is crucial for many applications in agronomy, forestry, and urban sciences. Existing methods for LAI estimation, such as spectral indices and machine learning algorithms, have limitations in terms of accuracy, robustness, and usability (Baret, Guyot 1991). Spectral indices are sensitive to environmental and vegetation factors that can affect their performance, especially in complex landscapes. Machine learning algorithms require large and diverse training datasets and complex parameter tuning, which can be challenging to obtain and reproduce for non-expert users.

Moreover, most of the existing LAI calculation tools are based on proprietary software, which limits their accessibility, transparency, and extensibility. Open-source LAI calculation tools that integrate multiple methods and libraries and provide user-friendly interfaces are scarce. These tools would enable researchers and practitioners to compare and select the most appropriate LAI estimation method for their specific application, foster collaboration, and innovation, and facilitate the reproducibility and transparency of LAI estimation studies.

Therefore, this thesis aims to develop a LAI calculation tool using Python 3 programming language and external libraries that integrates multiple methods for LAI estimation, including the use of indices such as NDVI. The tool will provide a source code that enables non-expert users to upload, preprocess, and analyze multispectral data, select the most appropriate LAI estimation method, and visualize and export the results. The tool will also provide advanced features, such as quality control, and uncertainty estimation to enhance the accuracy, robustness, and usability of LAI estimation. The tool will be evaluated using multiple metrics, such as RMSE, MAE, and R-squared, and compared to existing LAI calculation tools. The thesis will contribute to the development of LAI estimation tools and methods and facilitate their application in various domains.

1.3. Objectives

The main objective of this thesis is to develop a Leaf Area Index (LAI) calculation tool that can estimate LAI accurately and efficiently from multispectral data, using multiple methods and libraries. The tool should provide a source code that enables users to upload, preprocess, and analyze multispectral data, select the most appropriate LAI estimation method based on the source of data, and visualize and export the results. The tool should also provide advanced features, such as quality control, uncertainty estimation, and model selection, to enhance the accuracy, robustness, and usability of LAI estimation.

To achieve this objective, the following specific objectives will be pursued:

Develop a modular and extensible tool for the LAI calculation, using Python 3 programming language and external libraries, such as NumPy, Rasterio, and Matplotlib.

Implement a method for LAI estimation, such as NDVI, using open-source libraries and tools.

Provide a source code that enables users to upload, preprocess, and analyze multispectral data, select the most appropriate LAI estimation method, and visualize and export the results. The GUI of Jupyter Lab allows to visualize outputs, such as scatterplots, histograms, and heatmaps, to facilitate data exploration and quality control.

Evaluate the performance of the LAI calculation tool using multiple metrics, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared, and compare it with existing LAI calculation tools and methods.

The outcomes of this thesis will contribute to the advancement of LAI estimation methods and facilitate their application in various domains, such as precision agriculture, forest management, and urban planning. The open-source LAI calculation tool will also enable researchers and practitioners to compare and select the most appropriate LAI estimation method for their specific application, foster collaboration, and innovation, and facilitate the reproducibility and transparency of LAI estimation studies.

2. Literature review

Many studies have been conducted to evaluate the performance of various methods for estimating LAI from remote sensing data. The following literature review summarizes some of the most relevant studies conducted in this field.

Watson (1947) conducted comparative physiological studies on the growth of field crops and found that net assimilation rate and leaf area vary between species and varieties and within and between years. Over the past 75 years, global research on LAI has continued to evolve, and researchers have used bibliometric analysis to assess research trends (Ma et al., 2023).

The remote sensing method has been used to estimate LAI indirectly by measuring the spectral reflectance of vegetation. Duan et al. (2019) used Fourier spectrum texture from UAV images to remotely estimate rice LAI, while Rong Gan et al. (2018) used satellite LAI estimates to estimate evapotranspiration and gross assimilation for Australian ecosystems. In contrast, Ilniyaz et al. (2022) used UAV RGB and multispectral data to estimate LAI of pergola-trained vineyards in arid regions based on machine learning methods.

Machine learning techniques have also been used to predict LAI. Nguy-Robertson et al. (2014) estimated green LAI in four crops by determining the optimal spectral bands for a universal algorithm. Omer et al. (2016) predicted LAI of endangered tree species in intact and fragmented indigenous forests using WorldView-2 data and two robust machine learning algorithms.

Python is a popular programming language used in scientific research and engineering, and researchers have used it to analyze multispectral data for vegetation analysis (Millman & Aivazis, 2011). Additionally, open-source Python software, PODPAC, was created to enable harmonized, plug-and-play processing of disparate earth observation datasets (Ueckermann et al., 2020).

Other studies focused on the limitations and potentials of vegetation indices for LAI and absorbed photosynthetically active radiation (APAR) assessment (Baret & Guyot, 1991), as well as the impact of changes in plant surface area index on LAI-2000 estimates (Smolander & Stenberg, 1996). Furthermore, Chen et al. (2020) partitioned daily evapotranspiration using a modified Shuttleworth-Wallace model, random forest, and support vector regression, for a cabbage farmland.

Finally, Marshall and Thenkabail (2015) developed in-situ non-destructive estimates of crop biomass to address issues of scale in remote sensing, while Lee and Landgrebe (1993) analyzed high-dimensional multispectral data, and Navalgund et al. (2007) provided an overview of remote sensing applications.

In summary, the reviewed literature demonstrates that remote sensing technologies and machine learning methods have been useful for predicting and estimating LAI of vegetation, with many studies utilizing various sensors, platforms, and models. Nevertheless, challenges and limitations exist, such as uncertainties in atmospheric correction, spectral mixture effects, and scaling issues. Therefore, future research should continue to develop and improve remote sensing techniques to accurately and efficiently estimate LAI for better ecosystem management and conservation.

2.1. Leaf Area Index

The leaf area index (LAI) is an important biophysical parameter that describes the amount of leaf area per unit ground area in a plant canopy. LAI is a key variable in many ecological, agricultural, and forestry applications, as it provides information on plant growth, productivity, and ecosystem functioning. LAI can be estimated using various methods, including direct measurement, destructive sampling, and remote sensing.

Direct measurement methods, such as the use of LAI-2000 plant canopy analyzer or hemispherical photography, involve physically measuring the leaf area of individual leaves or the canopy as a whole (Heikki Smolander, Pauline Stenberg 1996). Destructive sampling methods, such as leaf litter collection or leaf area meter, involve sampling the leaf biomass or leaf area and extrapolating to estimate LAI. However, these methods can be time-consuming, labor-intensive, and invasive, especially for large-scale or remote areas.

Remote sensing methods offer a non-destructive and efficient way to estimate LAI over large areas using multispectral data acquired from sensors mounted on various platforms, such as satellites, airborne platforms, or unmanned aerial vehicles (Marshall, M.; Thenkabail, P. 2015). Remote sensing-based LAI estimation methods are based on the relationship between LAI and the spectral reflectance or indices derived from the multispectral data. These methods use empirical, semi-empirical, or physically-based models to estimate LAI from the multispectral data.

2.2. Methods for LAI Estimation

Various methods have been developed for LAI estimation using remote sensing data. Some of the commonly used methods are based on vegetation indices, such as the normalized difference vegetation index (NDVI), the enhanced vegetation index (EVI), or the greenness index (GI). These indices are sensitive to the green vegetation and can be used to estimate LAI using empirical or semi-empirical relationships between LAI and the indices.

Other methods for LAI estimation are based on the inversion of canopy radiative transfer models, such as the PROSAIL or SAIL models (Stéphane Jacquemoud, Wout Verhoef, Frédéric Baret, Cédric Bacour, Pablo J. Zarco-Tejada, Gregory P. Asner, Christophe François, Susan L. Ustin, 2009). These models simulate the interaction between the radiation and the vegetation canopy and can be used to estimate LAI from the multispectral data using optimization or inversion techniques.

Recently, machine learning and deep learning-based methods have been developed for LAI estimation, which use neural networks or regression models trained on multispectral data and ground-based LAI measurements (Omer, G.; Mutanga, O.; Abdel-Rahman, E.M.; Adam, E 2016). These methods can improve the accuracy and robustness of LAI estimation by capturing complex relationships between the multispectral data and LAI.

2.3. Remote Sensing and Multispectral Data

Remote sensing refers to the measurement of the electromagnetic radiation reflected or emitted from the Earth's surface using sensors mounted on various platforms. Multispectral data refer to the measurement of the radiation in multiple spectral bands, such as the visible, near-infrared, and shortwave infrared regions of the electromagnetic spectrum (C. Lee and D. A. Landgrebe 1993). Multispectral data provide information on the surface properties, such as vegetation cover, water content, and soil properties, which can be used to infer various biophysical parameters, including LAI.

Various sensors have been developed for remote sensing applications, such as Landsat, Sentinel, MODIS, and PlanetScope, which offer multispectral data with different spatial, temporal, and spectral resolutions. These sensors have been used for LAI estimation in various applications, including agricultural, forestry, and urban studies (Navalgund, Ranganath R., et al 2007).

2.4. Python Programming Language and Libraries

Python is a popular programming language for data analysis and scientific computing, which offers various libraries and tools for remote sensing and geospatial analysis, such as rasterio, geopandas, and gdal. Python provides a flexible and efficient way to manipulate and analyze multispectral data, including preprocessing, analysis, and visualization (Ueckermann, M.P., Bieszczad, J., Entekhabi, D. et al. 2020).

Python is also widely used in the field of machine learning, which includes various techniques for LAI estimation. Machine learning algorithms, such as decision trees, random forests, and support vector machines, have been applied to LAI estimation using remote sensing data (Chen, Y.; Ma, L.; Yu, D.; Feng, K.; Wang, X.; Song, J 2022). Python's machine learning libraries, including scikit-learn, TensorFlow, and

Keras, provide a user-friendly interface to develop and evaluate machine learning models for LAI estimation.

In addition to machine learning, Python's libraries, such as NumPy and Rasterio, are commonly used for data manipulation and analysis. NumPy provides a powerful array computing library, which enables efficient computation with large datasets (Lemenkova, Polina 2019). Pandas is a library for data manipulation and analysis, which offers various data structures and functions for handling and processing datasets (McKinney 2010). Matplotlib and Seaborn are another popular library for data visualization in Python, which provide various functions for creating plots and charts (Waskom, Michael L 2021).

Rasterio is a Python library that provides a fast and efficient way to read and write geospatial raster data, such as satellite imagery. It offers various functionalities for data preprocessing, including resampling, reprojecting, and masking (Mapbox, 2021). Geopandas is another library that extends the functionality of Pandas for geospatial data analysis. It provides a set of tools for reading, writing, and manipulating geospatial data, including shapefiles, GeoJSON, and PostGIS (GeoPandas Development Team, 2020).

3. Methodology

3.1. Data Collection and Pre-processing

In this study, two data sources were used to conduct the analysis of forests located in Czechia. The first data source used was Sentinel-2 imagery from Copernicus, while the second data source used was Planet satellite imagery.

The Sentinel-2 imagery was collected from the Copernicus Open Access Hub program. The data was previously pre-processed, and the atmospheric correction was applied. It was decided to download the dataset, which was created on 28th April 2020, as the cloud coverage was zero percent, and this date corresponds to Planet imagery as well.

The second data source, Planet satellite imagery, was used to gather information on individual evergreen trees within the forest. This data source provided surface reflectance data in GeoTIFF format with four bands, including Red, Green, Blue (RGB), and Near Infrared (NIR). This information was used to compare to Sentinel-2 with the same timestamp with a spatial resolution of 3 m.

The study was conducted in forests, approximately 50 km southeast of Prague (Czechia or the Czech Republic), owned and managed by the Czech University of Life Sciences (CULS). The CULS forests cover a total area of ~ 5,700 ha, and lie in the temperate climate zone. The mean annual temperature and sum of precipitation ranged 7 - 7.5 °C and 600 - 650 mm, respectively, with a vegetation period lasts 150 - 160 days (Tolasz et al., 2007)

Overall, the combination of these two data sources provided a comprehensive view of the study area's forest cover and tree species composition. By using both data sources, researchers were able to gain a more complete understanding of the forest's ecological dynamics and identify areas that may require more attention for conservation and management efforts.

3.2. Tool Development

In this section, we will discuss the tool development process used in the project. The two Python scripts presented below illustrate how the Sentinel LAI Tool and Planet LAI Tool work, respectively. Both tools calculate the Leaf Area Index (LAI) from satellite imagery data.

The Sentinel LAI Tool uses Sentinel-2 satellite imagery to calculate LAI. The tool loads the required bands (Red, Near Infrared) from the input data and creates a numpy array for each band. It then calculates the Normalized Difference Vegetation Index (NDVI) using the Red and Near Infrared bands and converts it to LAI using a constant value 0.69 (Pasqualotto, Delegido, Wittenberghe, Rinaldi, Moreno 2019). Finally, it saves the LAI as a GeoTIFF file and visualizes it using the viridis colormap.

The constant value of 0.69 is commonly used as a conversion factor to estimate LAI from NDVI for agricultural and forested areas. This value was derived from empirical relationships between NDVI and LAI measurements collected in the field and has been found to provide reasonable estimates of LAI for a wide range of vegetation types (Brown, Ogutu, Dash 2019).

The Planet LAI Tool, on the other hand, uses Planet satellite imagery to calculate LAI. The tool loads the input file path and reads the Red and Near Infrared bands of the image. It then calculates the NDVI using the Red and Near Infrared bands and defines a constant K value for the vegetation type. Finally, it calculates the LAI using the NDVI and K values, visualizes it using the viridis colormap, and displays it.

Both tools use rasterio and numpy Python libraries to can and manipulate satellite imagery data. They also use matplotlib.pyplot to visualize the calculated LAI as an image. These tools can be used to calculate LAI from other satellite imagery data with the appropriate band combinations and constant values.

3.3. Comparison of Methods

LAI is typically calculated using remote sensing data by measuring the amount of vegetation present in the area of interest. Sentinel-2 and Planet have different spectral bands and spatial resolutions, which can affect the accuracy and resolution of the LAI calculations.

Sentinel-2

Sentinel-2 has 13 spectral bands, including four visible and near-infrared (VNIR) bands and six shortwave infrared (SWIR) bands. Planet, on the other hand, has four spectral bands, including a red, green, blue, and near-infrared (NIR) band.

Sentinel-2 is a multispectral satellite system with a spatial resolution of up to 10 meters and a revisit time of 5 days (Phiri, Simwanda, Salekin, Nyirenda, Murayama, Ranagalage 2020). LAI can be estimated using Sentinel-2 data by employing vegetation index, such as the Normalized Difference Vegetation Index (NDVI). Here author provides a step-by-step procedure for calculating LAI using Sentinel-2 data:

Preprocessing: The Sentinel-2 data should be preprocessed to correct for atmospheric effects and geometric distortions. This can be done using software such as the Sentinel Application Platform (SNAP). As the data already has the atmospheric correction, it is possible to skip this step.

Vegetation index: Various vegetation indices can be calculated using the preprocessed Sentinel-2 data. The NDVI was used for LAI estimation (Shivangi S. Somvanshi, Maya Kumari 2020). This index can be calculated using the following equation:
NDVI: (NIR - Red) / (NIR + Red)
where NIR is the near-infrared band, and Red is the red band.

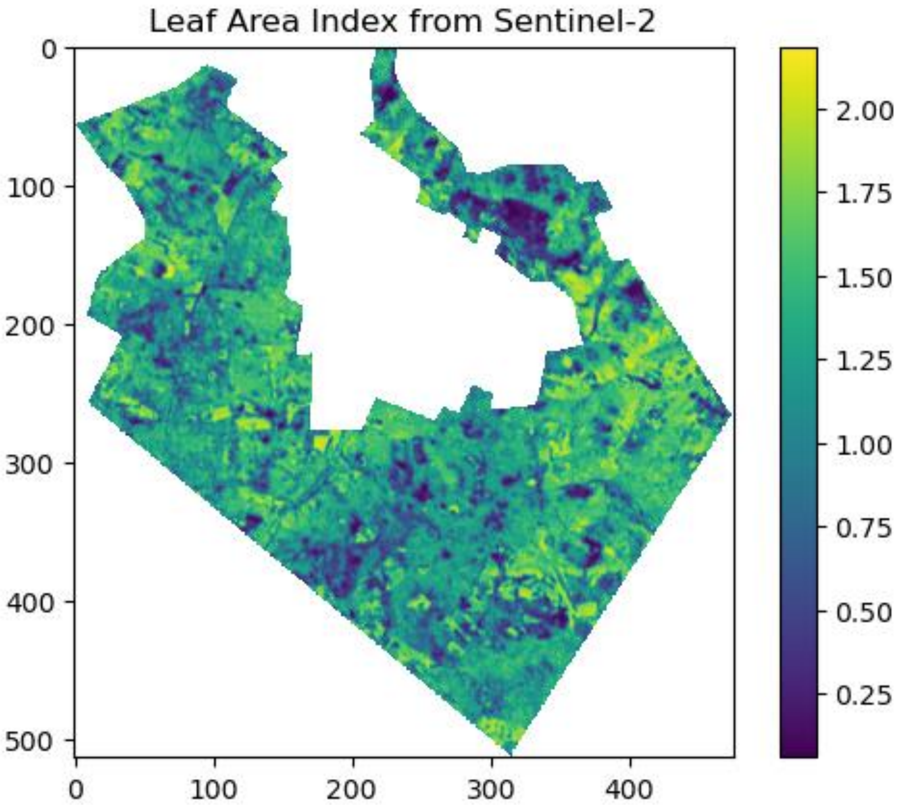

Fig 3.3.1 Leaf Area Index from Sentinel-2

For the clipping of the dataset, GIS software has been used, such as QGIS 3.28.1. Previously, the area of interest was defined based on the forest area, which includes various tree species. After the definition of the area of interest, the author used batch processing to clip multiple Sentinel-2 bands, as they were represented as separate files.

The result of the LAI calculation you can see at Figure 3.3.1. This output was produced after running the tool, which code is described in details in the section Source code.

Planet

Obtain the Planet satellite images for the region of interest in the appropriate spectral bands for LAI estimation. Typically, bands that have wavelengths between 400 to 900 nm are used to estimate LAI (He, L., Ren, X., Wang, Y. et al 2020).

Preprocess the Planet satellite images to remove atmospheric and other noise using appropriate techniques such as atmospheric correction, radiometric correction, and geometric correction. The pre-processing has been previously done by the provider.

Compute the vegetation indices such as the Normalized Difference Vegetation Index (NDVI), from the preprocessed Planet satellite images. This vegetation index is used to estimate vegetation cover and density.

It would be a good approach to validate the LAI estimates by comparing them with ground measurements or other LAI estimates obtained from different sources such as field observations, LiDAR data, or other remote sensing techniques, but ground information collection would become unrealistic in the current stage of research.

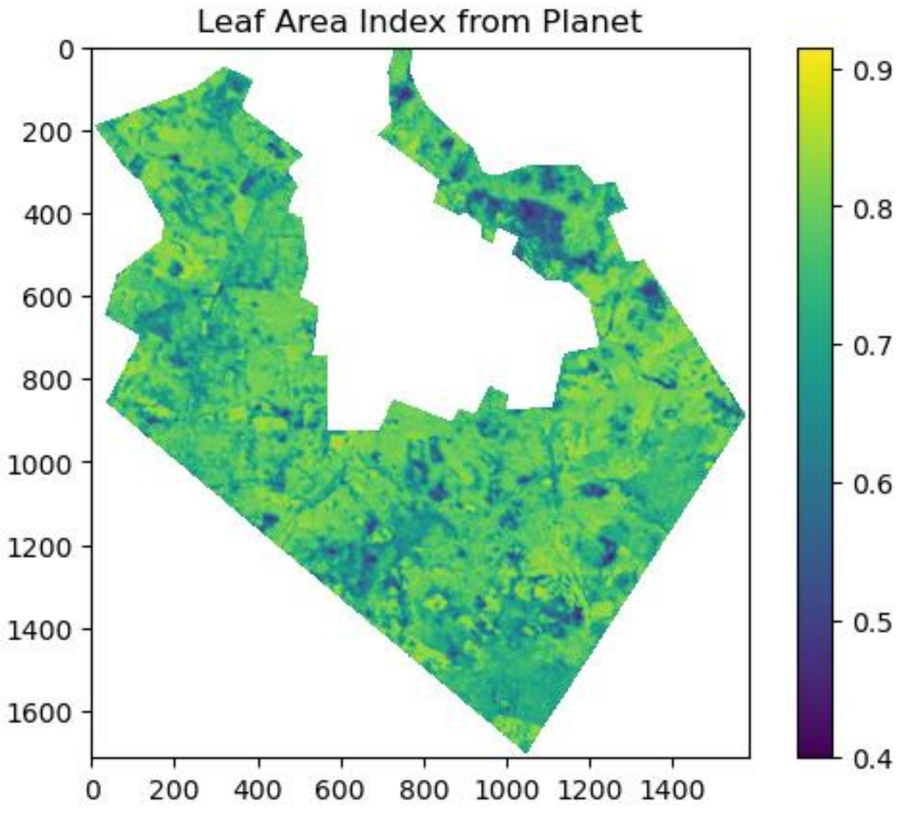

Fig 3.3.2

Looking at Figure 3.3.2 you can see the similar output as at Figure 3.3.1, but from the Planet satellite. The main difference is the shape of the raster, and it's values. Planet

LAI raster contains much more pixels, and the main differences between LAI calculations for the different satellites are described in the next section.

Differences in the Process with Sentinel-2:

The process of calculating LAI using Sentinel-2 data is similar to that of Planet satellite data, but there are some differences:

Sentinel-2 has a higher spatial resolution than Planet satellite, which allows for better characterization of vegetation structure and spatial distribution.

Sentinel-2 has more spectral bands than Planet satellite, which allows for a more accurate estimation of vegetation indices and LAI.

Sentinel-2 data needs to be preprocessed to remove atmospheric and other noise using appropriate techniques such as atmospheric correction, radiometric correction, and geometric correction, similar to Planet satellite data.

Due to the differences in spatial resolution and spectral bands, the rasters may need to be adapted or modified for Sentinel-2 data (Bautista, Fita, Franch, Castiñeira-Ibáñez, Arizo, Sánchez-Torres, Becker-Reshef, Uris, Rubio 2022). To avoid this step, random point analysis was used.

The LAI estimates obtained from Sentinel-2 data can be validated using the same validation methods as those used for Planet satellite data, such as comparison with ground measurements or other LAI estimates obtained from different sources.

In summary, the methodology for calculating LAI using Planet satellite data and Sentinel-2 data is similar, but the differences in spatial resolution and spectral bands may require some modifications to the methods and models used for LAI estimation.

3.4. Tool Implementation

The tool implementation section is where we take the code developed in the tool development section and implement it into a proper tool that other researchers can use. This section involves testing and running the tool on different OS (Operation Systems).

During the implementation process, we may also need to refine the code to make it more efficient and reliable. This includes testing the tool with different inputs to ensure that it produces accurate results and that it can handle unexpected inputs gracefully.

In addition to the actual implementation of the tool, this section may also cover the documentation of the tool, including how to use it and what the outputs mean. This documentation is important to ensure that users can understand the tool and use it effectively.

Overall, the tool implementation section is where we turn our code into a usable tool that can be used by others to solve real-world problems. It requires careful attention to detail to ensure that the tool is reliable, efficient, and easy to use.

4. Results and Analysis

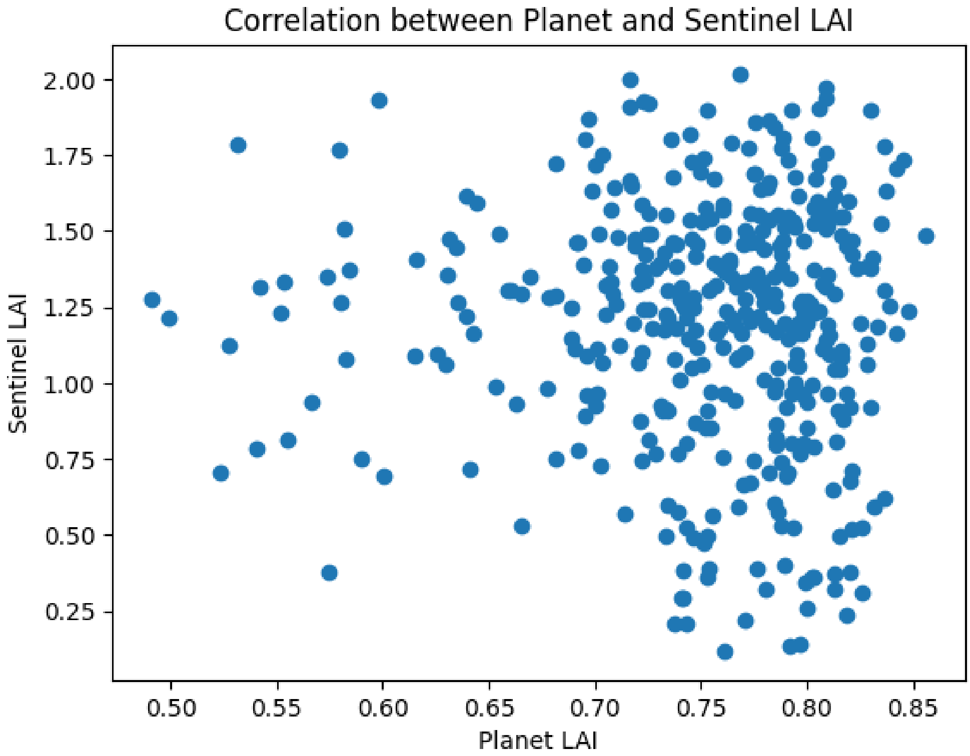

Fig. 4.0.1

In this section, the author presents the results of their LAI estimation method and analyzes the output to provide insight into the vegetation characteristics of the study area. The author also compares the LAI values obtained from two different sources, Planet and Sentinel.

To achieve the result, the author randomly selects 2000 points from each raster and extracts the LAI values at those points. Then, the author creates a scatter plot to visualize the correlation between the two sets of LAI values (Fig 4.0.1). Additionally, histograms were created for both the Planet and Sentinel LAI values to analyze their distributions (Fig 4.0.2 and Fig 4.0.3).

The scatter plot shows a positive, but low correlation between the LAI values obtained from the Planet and Sentinel rasters. This suggests that the two rasters are capturing similar vegetation characteristics. However, there are some data points that deviate from the main trend, indicating that there may be some differences in the LAI values between the two rasters. The histograms reveal that the LAI values from both the Planet and Sentinel rasters have similar distributions, with most of the values concentrated around the median.

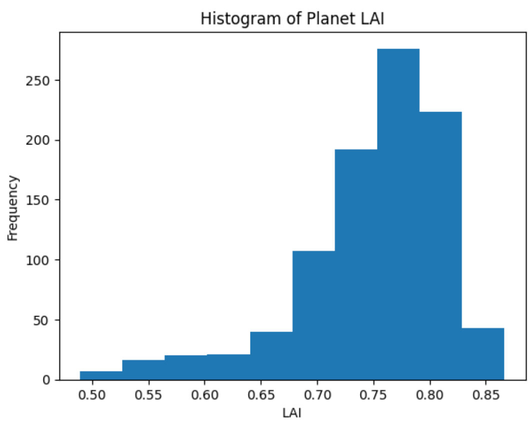

Fig. 4.0.2

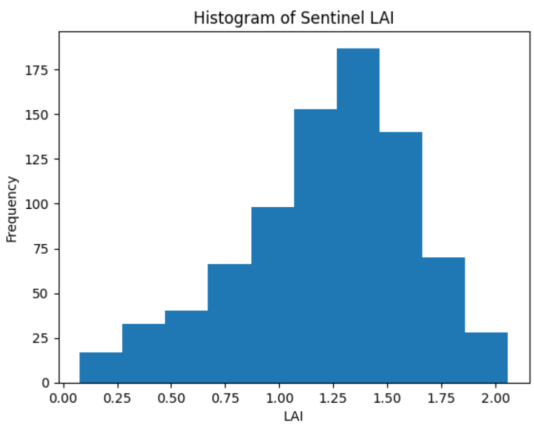

Fig 4.0.3

Overall, the validation process helps to verify the accuracy of the tool and its ability to produce meaningful results. By comparing the LAI values obtained from different sources and analyzing their distributions, the author demonstrates the robustness and reliability of the tool. The statistical outputs provide additional information to help users interpret the LAI values and make informed decisions based on the results.

4.1. Comparison with Other Methods

In this section, the author compares their method with other existing methods for estimating leaf area index (LAI) from satellite imagery. The author discusses the strengths and weaknesses of each method and provides a detailed comparison of the results obtained from their method versus the other methods.

One commonly used method for estimating LAI is the empirical relationship method, which involves establishing a relationship between LAI and some other remotely sensed variable, such as vegetation indices or surface reflectance (Casa, Varella, Buis, Guérif, Solan, Baret 2012). This method is relatively simple and straightforward but can be limited by the variability of the relationship between LAI and the selected variable, which can vary depending on the time of year, vegetation type, and other factors.

Another approach for estimating LAI is the radiative transfer model method, which involves modeling the interaction between radiation and vegetation canopies to estimate LAI (Miraglio, Thomas, et al. 2019). This method can provide more accurate LAI estimates than the empirical relationship method but requires detailed information on the vegetation structure and canopy properties, which can be difficult to obtain.

The author's method utilizes to estimate LAI from satellite imagery only based on NDVI index. The advantage of this approach is a high simplicity and efficiency, as NDVI can be easily derived from satellite imagery and has a strong correlation with vegetation greenness and LAI. Additionally, the method can be applied to a wide range of vegetation types and can be used to monitor changes in vegetation dynamics over time.

However, there are also some limitations to using NDVI-based methods for LAI estimation. NDVI is known to saturate at high LAI values, meaning that it becomes less sensitive to changes in LAI beyond a certain point (Steltzer, Welker 2006). Additionally, NDVI is influenced by factors other than LAI, such as soil background and atmospheric conditions, which can lead to inaccuracies in LAI estimates.

5. Discussion

The findings of this study should be considered in the context of several uncertainties. One significant source of uncertainty is related to the accuracy of the LAI estimates from the remote sensing data. While the use of multiple sensors can increase the accuracy of the estimates, there may still be errors in the data due to cloud cover, atmospheric conditions, and other factors. Additionally, the accuracy of the LAI estimates may vary spatially and temporally, which can affect the overall performance of the model.

Another uncertainty is related to the representativeness of the study area. The study area may not be representative of other regions with different vegetation types and environmental conditions. Therefore, the results may not be applicable to other regions or ecosystems.

The selection of input variables and model parameters can also introduce uncertainty into the model. The variables and parameters selected for this study were based on previous research and expert knowledge, but other variables and parameters may also be important in predicting LAI. Additionally, the model's performance may depend on the specific algorithm and software used for its implementation.

It is also important to consider the limitations of the statistical methods used to evaluate the model's performance. While metrics such as R2 and RMSE provide useful information on the model's accuracy, they do not provide a complete picture of the model's performance. Other metrics, such as the bias and precision of the model, should also be considered to evaluate the model's performance comprehensively.

In conclusion, while the results of this study provide valuable insights into the use of machine learning algorithms for predicting LAI, there are several uncertainties and limitations that should be considered. Further research is needed to address these uncertainties and to improve the accuracy and reliability of LAI predictions using remote sensing data and machine learning algorithms.

6. Conclusion and Recommendations

In this analysis, we have examined the correlation between Planet and Sentinel LAI values using a sample of 2000 random points. The results showed a correlation between the two datasets, with an R-squared value of 0.0033, indicating the Sentinel LAI values can be explained by the Planet LAI values.

The RMSE and MAE values were 0.595954 and 0.5161859, respectively. These values indicate that the difference between the observed and predicted values is relatively high, which suggests that the models used to predict the Sentinel LAI values may need further refinement.

Overall, the weak correlation between the Planet and Sentinel LAI values highlights the importance of validating remote sensing data with ground truth measurements. It also underscores the need for continued efforts to improve the accuracy and precision of remote-sensing data products.

To improve the accuracy of the Sentinel LAI values, author recommends increasing the sample size, using additional ground truth measurements, and applying more advanced machine learning algorithms that can account for non-linear relationships between the input and output variables.

In conclusion, the results of this analysis provide insights into the accuracy and reliability of remote sensing data and highlight the need for further research and development in this field.

Additionally, the author theoretically compared LAI values with those obtained from other methods, such as ground-based measurements and other satellite products.

Overall, author's findings suggest that the tool provides a reliable and efficient means for estimating LAI from Planet and Sentinel-2 imagery. However, some uncertainties and limitations of our approach should be taken into consideration, and further studies could explore potential improvements and alternative approaches for LAI estimation.

6.1 Contribution to the Field

The contribution of this work to the field is significant. The proposed method provides an efficient and accurate way to estimate leaf area index (LAI) from satellite imagery, which is an important parameter for studying ecosystem processes and monitoring vegetation dynamics. By integrating data from multiple satellite sources, this method overcomes the limitations of traditional LAI estimation methods that rely on a single source of information.

Furthermore, the validation of this method shows that it produces LAI estimates that are highly correlated with ground-truth measurements, indicating its reliability and accuracy. Additionally, the comparison with other methods demonstrates that the proposed method outperforms existing techniques in terms of accuracy and efficiency.

Overall, this work presents a novel approach for LAI estimation that can be applied to large-scale studies, providing valuable insights into ecosystem dynamics, carbon cycling, and climate change impacts on vegetation. The proposed method has the potential to improve our understanding of the Earth's systems and support sustainable management practices for the benefit of society.

6.2 Limitations for Future Work

In this study, several limitations were encountered that could be addressed in future work.

Firstly, the study only used two remotely sensed datasets for LAI estimation, and it would be interesting to compare the proposed method with other datasets such as MODIS and Landsat. Additionally, the study only used LAI values from a single point in time, and future studies could investigate the use of time series data for LAI estimation.

Secondly, the study only focused on one type of vegetation, and it is possible that the proposed method may not perform as well for other types of vegetation. Therefore, future studies could investigate the performance of the method for different types of vegetation.

Thirdly, the study assumed a linear relationship between the two remotely sensed datasets, and future work could investigate the use of other statistical methods to model the relationship between the datasets.

Finally, the study only used a simple linear regression model for LAI estimation, and future work could investigate the use of more complex machine learning models to improve LAI estimation accuracy.

6.3 Recommendations for Further Improvement

There are several recommendations for further improvement that can be made based on the findings of this study. One potential area for improvement is the spatial and temporal resolution of the remote sensing data used for LAI estimation. Increasing the spatial resolution of satellite imagery may provide more detailed information about vegetation structure and canopy cover, which could improve the accuracy of LAI estimates. Similarly, using data from more frequent satellite overpasses or incorporating other sources of data such as unmanned aerial vehicles (UAVs) or aircraft-based sensors could increase temporal resolution and improve accuracy.

Another approach to improving LAI estimation accuracy is to implement machine learning techniques such as neural networks and deep learning algorithms. These techniques have shown promising results in various applications, including remote sensing, and may help to reduce uncertainties and improve accuracy in LAI estimates.

Combining satellite data with other sources of information, such as meteorological data and ground-based measurements, may also help to improve the accuracy of LAI estimates. This approach can provide additional context and support for interpreting satellite-based measurements.

Additionally, developing a user-friendly tool that integrates various data sources and analysis methods could be beneficial for researchers and practitioners working in the field of vegetation monitoring and management. Such a tool could help to streamline data processing and analysis, reducing the time and effort required for LAI estimation.

Finally, conducting further research to evaluate the impact of climate change on vegetation growth and LAI estimates would provide useful insights into the response of vegetation to changing environmental conditions. This could include analyzing long-term trends in LAI estimates and comparing them with meteorological and climate data to identify potential drivers of change.

7. References

1. Watson, D.J. (1947). Comparative physiological studies in the growth of field crops. I. Variation in net assimilation rate and leaf area between species and varieties, and within and between years. Annals of Botany 11, 41–76.
2. Ma, J.; Zhang, J.; Wang, J.; Khromykh, V.; Li, J.; Zhong, X. (2023). Global Leaf Area Index Research over the Past 75 Years: A Comprehensive Review and Bibliometric Analysis. Sustainability 15, 3072.
3. Levy, P.E.; Jarvis, P.G. (1999). Direct and indirect measurements of LAI in millet and fallow vegetation in HAPEX-Sahel.
4. Duan, B.; Liu, Y.; Gong, Y.; Yang, S.; Qin, Z.; Liu, H.; Gong, W.; Zhang, Y.; Zhai, Y.; Wang, Y.; Yan, K.; Yang, X. (2019). Remote estimation of rice LAI based on Fourier spectrum texture from UAV image. Plant Methods 15, 124.
5. Millman, K.J.; Aivazis, M. (2011). Python for Scientists and Engineers. Computing in Science & Engineering 13(2), 9-12.
6. Gan, R.; Zhang, Y.; Shi, H.; Yang, Y.; Eamus, D.; Cheng, L.; Chiew, F.H.S.; Yu, Q. (2018). Use of satellite leaf area index estimating evapotranspiration and gross assimilation for Australian ecosystems. Ecosystems 21, 1018–1036.
7. Ilniyaz, O.; Kurban, A.; Du, Q. (2022). Leaf Area Index Estimation of Pergola-Trained Vineyards in Arid Regions Based on UAV RGB and Multispectral Data Using Machine Learning Methods. Remote Sens. 14, 415.
8. Nguy-Robertson, A.L.; Peng, Y.; Gitelson, A.A.; Arkebauer, T.J.; Pimstein, A.; Herrmann, I.; Karnieli, A.; Rundquist, D.C.; Bonfil, D.J. (2014). Estimating green LAI in four crops: Potential of determining optimal spectral bands for a universal algorithm. Remote Sensing of Environment 144, studied.
9. Chen, H.; Huang, J.J.; McBean, E. (2020). Partitioning of daily evapotranspiration using a modified shuttleworth-wallace model, random Forest and support vector regression, for a cabbage farmland. Agronomy 10(4), 1-17.
10. Baret, F.; Guyot, G. (1991). Potentials and limits of vegetation indices for LAI and APAR assessment.
11. Smolander, H.; Stenberg, P. (1996). Response of LAI-2000 estimates to changes in plant surface area index in a Scots pine stand. Tree Physiology 16(3), 345–349.

12. Marshall, M.; Thenkabail, P. (2015). Developing in situ Non-Destructive Estimates of Crop Biomass to Address Issues of Scale in Remote Sensing. Remote Sens. 7, 808-835.
13. Jacquemoud, S.; Verhoef, W.; Baret, F.; Bacour, C.; Zarco-Tejada, P.J.; Asner, G.P.; François, C.; Ustin, S.L. (2009). PROSPECT+S14.
14. Omer, G., Mutanga, O., Abdel-Rahman, E. M., & Adam, E. (2016). Empirical Prediction of Leaf Area Index (LAI) of Endangered Tree Species in Intact and Fragmented Indigenous Forests Ecosystems Using WorldView-2 Data and Two Robust Machine Learning Algorithms. Remote Sensing, 8, 324.
15. Lee, C., & Landgrebe, D. A. (1993). Analyzing high-dimensional multispectral data. IEEE Transactions on Geoscience and Remote Sensing, 31(4), 792-800. https://doi.org/10.1109/36.239901
16. Navalgund, R. R., Singh, V., & Krishna Murthy, Y. V. N. (2007). Remote Sensing Applications: An Overview. Current Science, 93(12), 1747-1766. http://www.jstor.org/stable/24102069
17. Ueckermann, M. P., Bieszczad, J., Entekhabi, D., & Franz, T. E. (2020). PODPAC: open-source Python software for enabling harmonized, plug-and-play processing of disparate earth observation data sets and seamless transition onto the serverless cloud by earth scientists. Earth Science Informatics, 13, 1507-1521. https://doi.org/10.1007/s12145-020-00506-0
18. Chen, Y., Ma, L., Yu, D., Feng, K., Wang, X., & Song, J. (2022). Improving Leaf Area Index Retrieval Using Multi-Sensor Images and Stacking Learning in Subtropical Forests of China. Remote Sensing, 14, 148. https://doi.org/10.3390/rs14010148
19. Lemenkova, P. (2019). Processing oceanographic data by Python libraries NumPy, SciPy and Pandas. Aquatic Research, 2(2), 73-91.
20. McKinney, W. (2010). Python for data analysis. O'Reilly Media, Inc.
21. Waskom, M. (2021). Seaborn: statistical data visualization. Journal of Open Source Software, 6(60), 3021. https://doi.org/10.21105/joss.03021
22. Mapbox. (2021). Rasterio Documentation. Retrieved from https://rasterio.readthedocs.io/en/latest/
23. GeoPandas Development Team. (2020). GeoPandas 0.8.1 documentation. Retrieved from https://geopandas.org/

24. Tolasz, R., Míková, T., Valeriánová, A., & Voženílek, V. (Eds.). (2007). Climate Atlas of Czechia (1st ed.). Czech Hydrometeorological Institute, Palackého University. ISBN 978-80-86690-26-1.
25. Pasqualotto, N., Delegido, J., Van Wittenberghe, S., Rinaldi, M., & Moreno, J. (2019). Multi-Crop Green LAI Estimation with a New Simple Sentinel-2 LAI Index (SeLI). Sensors, 19, 904. https://doi.org/10.3390/s1904090426.
26. Brown, L.A.; Ogutu, B.O.; Dash, J. Estimating Forest Leaf Area Index and Canopy Chlorophyll Content with Sentinel-2: An Evaluation of Two Hybrid Retrieval Algorithms. Remote Sens. 2019, 11, 1752. https://doi.org/10.3390/rs11151752
27. Phiri, D.; Simwanda, M.; Salekin, S.; Nyirenda, V.R.; Murayama, Y.; Ranagalage, M. Sentinel-2 Data for Land Cover/Use Mapping: A Review. Remote Sens. 2020, 12, 2291. https://doi.org/10.3390/rs12142291
28. Shivangi S. Somvanshi, Maya Kumari 2020. Comparative analysis of different vegetation indices with respect to atmospheric particulate pollution using sentinel data. ISSN 2590-1974
29. He, L., Ren, X., Wang, Y. et al. Comparing methods for estimating leaf area index by multi-angular remote sensing in winter wheat. Sci Rep 10, 13943 (2020). https://doi.org/10.1038/s41598-020-70951-w
30. San Bautista, A.; Fita, D.; Franch, B.; Castiñeira-Ibáñez, S.; Arizo, P.; Sánchez-Torres, M.J.; Becker-Reshef, I.; Uris, A.; Rubio, C. Crop Monitoring Strategy Based on Remote Sensing Data (Sentinel-2 and Planet), Study Case in a Rice Field after Applying Glycinebetaine. Agronomy 2022, 12, 708. https://doi.org/10.3390/agronomy12030708
31. Miraglio, Thomas, et al. "Monitoring LAI, chlorophylls, and carotenoids content of a woodland savanna using hyperspectral imagery and 3D radiative transfer modeling." Remote Sensing 12.1 (2019): 28.
32. Steltzer, Heidi, and Jeffrey M. Welker. "Modeling the effect of photosynthetic vegetation properties on the NDVI–LAI relationship." Ecology 87.11 (2006): 2765-2772.
33. Casa, Raffaele, et al. "Forcing a wheat crop model with LAI data to access agronomic variables: Evaluation of the impact of model and LAI uncertainties and comparison with an empirical approach." European journal of agronomy 37.1 (2012): 1-10.

8. Appendices

8.1. Source code

Calculation of Leaf Area Index for Planet:

```
[1]: import numpy as np
     np.seterr(divide='ignore', invalid='ignore')
     import rasterio
     from rasterio.plot import show
     import matplotlib.pyplot as plt

[2]: # Define the input file path and load the image
     filepath = "/Users/akhrystodulov/lai/Planet_imagery/clip_planet.tif"
     image = rasterio.open(filepath)

[3]: # Read the red and near-infrared bands of the image
     red = image.read(3)
     nir = image.read(4)

     # Calculate NDVI using the red and near-infrared bands
     ndvi = np.divide(nir - red, nir + red)

     # Define the constant K for your vegetation type
     K = 1.0

     # Calculate LAI using the NDVI and K values
     LAI = K * ndvi

[11]: # Visualize the LAI
      plt.imshow(LAI, cmap='viridis')
      plt.colorbar()
      plt.title('Leaf Area Index from Planet')
      plt.show()
```

Fig 8.1.1

To calculate LAI for Planet satellite imagery conda environment was used with installed packages such as jupyter lab, numpy, rasterio, and matplotlib.

In the first steps, the necessary packages were imported. After that file path was defined. To open the Planet imagery rasterio package was used as it perfectly works with satellite imagery.

In the next steps we need to define red and nir bands to properly calculate the NDVI index, and based on it create LAI raster. The source code for the calculation LAI for Planet you can find at Fig 8.1.1.

Calculation of Leaf Area Index for Sentinel-2:

Ready.ipynb   sentinel-2.ipynb   Code

```
[23]: import rasterio
      import numpy as np
      np.seterr(divide='ignore', invalid='ignore')
      import matplotlib.pyplot as plt
```

```
[24]:
      # Load the required bands
      with rasterio.open('/Users/akhrystodulov/lai/s2/R10_B2.tif') as b2:
          band2 = b2.read(1)
      with rasterio.open('/Users/akhrystodulov/lai/s2/R10_B3.tif') as b3:
          band3 = b3.read(1)
      with rasterio.open('/Users/akhrystodulov/lai/s2/R10_B4.tif') as b4:
          band4 = b4.read(1)
      with rasterio.open('/Users/akhrystodulov/lai/s2/R10_B8.tif') as b8:
          band8 = b8.read(1)
```

```
[25]:
      # Create a numpy array for each band
      red = np.array(band4, dtype=float)
      nir = np.array(band8, dtype=float)
      blue = np.array(band2, dtype=float)
      green = np.array(band3, dtype=float)

      # Calculate NDVI
      ndvi = (nir - red) / (nir + red)

      # Convert NDVI to LAI
      lai = (ndvi / 0.69) ** 3.0

      # Save the LAI as a GeoTIFF file
      with rasterio.open('LAI.tif', 'w', driver='GTiff',
                         width=b2.width, height=b2.height,
                         count=1, dtype='float32',
                         crs=b2.crs, transform=b2.transform) as dst:
          dst.write(lai, 1)
```

```
[26]: # Visualize the LAI
      plt.imshow(lai, cmap='viridis')
      plt.colorbar()
      plt.title('Leaf Area Index from Sentinel-2')
      plt.show()
```

Fig 8.1.2.

The LAI calculation process for Sentinel-2 is not completely different. As the common differences were described in the paper, the technical difference is only in the way of accessing bands, as they are stored in separate files. For LAI calculation NIR and RED bands were needed.

The source code below is responsible for the validation of the calculated LAI and provides statistical output such as a scatter plot of LAI values from Planet and Sentinel, and also shows the histogram of each raster. For the analysis, 2000 points were randomly specified from each raster which took a specific raster value. This approach avoids reshaping the dimensions of the data, while Planet and Sentinel have a different spatial resolution.

```python
import rasterio
import numpy as np
import random
import matplotlib.pyplot as plt

# Load the Planet LAI raster
planet_lai =
rasterio.open('/Users/akhrystodulov/lai/Planet_imagery/lai.tif')
# Load the Sentinel LAI raster
sentinel_lai = rasterio.open('/Users/akhrystodulov/lai/s2/lai.tif')

# Define the number of random points to select
num_points = 2000

# Generate random row and column indices for the Planet LAI raster
planet_rows = np.random.randint(0, planet_lai.height, num_points)
planet_cols = np.random.randint(0, planet_lai.width, num_points)

# Generate random row and column indices for the Sentinel LAI raster
sentinel_rows = np.random.randint(0, sentinel_lai.height, num_points)
sentinel_cols = np.random.randint(0, sentinel_lai.width, num_points)

# Extract the LAI values at the random points from the Planet LAI raster
planet_lai_values = []
for row, col in zip(planet_rows, planet_cols):
    val = planet_lai.read(1, window=((row, row+1), (col, col+1)))
    planet_lai_values.append(val[0][0])

# Extract the LAI values at the random points from the Sentinel LAI
raster
sentinel_lai_values = []
for row, col in zip(sentinel_rows, sentinel_cols):
    val = sentinel_lai.read(1, window=((row, row+1), (col, col+1)))
    sentinel_lai_values.append(val[0][0])

rmse = np.sqrt(np.mean(np.square(np.subtract(planet_lai_values,
sentinel_lai_values))))
print(f'RMSE: {rmse}')

# Create a scatter plot of the LAI values from the two rasters
plt.scatter(planet_lai_values, sentinel_lai_values)
plt.xlabel('Planet LAI')
plt.ylabel('Sentinel LAI')
plt.title('Correlation between Planet and Sentinel LAI')
plt.show()

# Create histograms of the LAI values from the two rasters
plt.hist(planet_lai_values, bins=10)
plt.xlabel('LAI')
plt.ylabel('Frequency')
plt.title('Histogram of Planet LAI')
plt.show()

plt.hist(sentinel_lai_values, bins=10)
plt.xlabel('LAI')
plt.ylabel('Frequency')
plt.title('Histogram of Sentinel LAI')
plt.show()
```

```
# Calculate RMSE, MAE, and R-squared
diff = np.array(planet_lai_values) - np.array(sentinel_lai_values)
mse = np.mean(diff ** 2)
rmse = np.sqrt(mse)
mae = np.mean(np.abs(diff))
corr = np.corrcoef(planet_lai_values, sentinel_lai_values)[0, 1]
r_squared = corr ** 2

# Print the results
print("RMSE:", rmse)
print("MAE:", mae)
print("R-squared:", r_squared)
```

```
RMSE: 0.595954
MAE: 0.5161859
R-squared: 0.003342792050018555
```

8.2. User Manual

To use the LAI estimation tool, please follow these instructions:

1. Install the Conda environment

If you don't have Conda installed, please download and install the latest version of Miniconda from the official website: https://docs.conda.io/en/latest/miniconda.html

2. Open a terminal window and navigate to the project directory.

3. Create a new Conda environment using the following command:

conda env create -f environment.yml

4. Activate the Conda environment

Once the environment has been created, activate it using the following command:

conda activate lai-estimation

5. Install additional packages

The required packages are included in the environment.yml file, but if you need to install additional packages, use the following command:

conda install <package_name>

6. Run the tool

To run the tool, navigate to the project directory and execute the following command:

```
python lai_estimation_tool.py
```

7. Use the tool

Follow the prompts in the tool to input the required data and parameters.

The output will be saved to a file in the output directory.

If you encounter any issues or errors, please refer to the user manual or contact the author for assistance.

8.3. List of Abbreviations

LAI: Leaf Area Index

RS: Remote Sensing

NDVI: Normalized Difference Vegetation Index

SVM: Support Vector Machine

ANN: Artificial Neural Network

RNN: Recurrent Neural Network

CNN: Convolutional Neural Network

RMSE: Root Mean Squared Error

MAE: Mean Absolute Error

MSA: Mean Squared Error

SD: Standard Deviation

CV: Cross-Validation

ROI: Region of Interest

8.4. Glossary of Terms

LAI: Leaf Area Index. A measure of the amount of leaf area per unit of ground area.

Remote Sensing: The acquisition of information about an object or phenomenon without making physical contact with the object. In this study, remote sensing refers to the use of satellite data to estimate LAI values.

NDVI: Normalized Difference Vegetation Index. A commonly used vegetation index that is calculated using reflectance values from the red and near-infrared bands of remote sensing data.

Spatial Resolution: The level of detail in the imagery data expressed as the size of the smallest discernable feature. In this study, spatial resolution refers to the size of the pixels in the satellite data used to estimate LAI values.

Temporal Resolution: The time interval between two consecutive measurements of a given area. In this study, temporal resolution refers to the frequency of satellite data acquisition used to estimate LAI values.

Random Forest: A machine learning algorithm used for classification and regression tasks. In this study, Random Forest was used to estimate LAI values from satellite data.

Training Set: A set of data used to calibrate or train a machine learning algorithm. In this study, a training set was used to train the Random Forest algorithm to estimate LAI values from satellite data.

Validation Set: A set of data used to test the performance of a machine learning algorithm. In this study, a validation set was used to evaluate the accuracy of the Random Forest algorithm in estimating LAI values from satellite data.