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LAI calculation for Landsat, Hyperion, Sentinel using Time Series Analysis

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Abstract: Precision crop agriculture is an innovative approachthat utilizes information technology to effectively manage crop variability through observation, measurement, and responsiveactions. This paper focuses on the observation aspect of precisioncrop agriculture, specifically exploring the analysis of leaf areain agricultural land. Leaf Area Analysis is a technique employed to determine the total leaf area within a given ground area. It relies on the Leaf Area Index (LAI), a biophysical parameter thatquantifies leaf area per unit of ground area. LAI is crucial in assessing vegetation processes like photosynthesis, transpiration, and energy balance. In this study, LAI is calculated usinga statistical approach based on the dimensionless NormalizedDifference Vegetation Index (NDVI), which compares visible and near-infrared reflectance of vegetation cover. The paper utilizes satellite data from Sentinel, Hyperion EO-1, and Landsat, consisting of various bands, with a specific focus on the red and near-infrared bands which have been taken from Earthexplorer for seasonal duration. The statistical approach employed for LAIcalculation proves to be suitable for the Sentinel dataset dueto its simplicity and effectiveness. Additionally, determining the percentage of vegetation cover is an important aspect of crop observation, providing insights into the greenness and growth variability across different regions and agricultural seasons within a defined timeframe. The proposed methodology verifies the increase in LAI from crop sown season to harvesting season and then decreases. Using various dataset over the same landarea cross-verifies and confirms the LAI pattern change over the area..

Keywords: *NDVI, LAI, Hyperion EO-1, Sentinel, Landsat*

1. Introduction

This Precision agriculture, also referred to as smart farming, is a science that integrates information technology with tra- ditional farming practices to enhance agricultural efficiency, productivity, and sustainability. With the increasing demand for food production, simply growing crops is no longer suffi- cient. Therefore, the integration of information technology in agriculture is crucial to achieving efficient crop growth with minimal input and maximum output.

One significant aspect of precision agriculture is leaf area analysis, which involves studying the total leaf area in cultivated land. By analysing the leaf area, valuable insights can be obtained about the health and overall condition ofthe agricultural land, as well as the growth patterns of crops over time. Leaf Area Index (LAI), a dimensionless biophysical variable, is commonly used to quantify the extent of leaf areaper unit area of ground, in a canopy.

In recent years, advances in information technology, specif- ically in the field of machine learning, have facilitated the development of techniques for analysing leaf areas. Various machine learning models, such as clustering, have been appliedto calculate the percentage of vegetation cover in agricultural lands. Additionally, the use of remote sensing data from satellite images, like the Sentinel-2 dataset [1], has proven to be of high value for LAI calculations, as it provides comprehensive and accurate information about agricultural lands. By using LAI values obtained from satellite images, researchers can monitor and assess the structure of ecosystems,predict changes in crop patterns due to factors such as floods and seasonal variations, and analyse the percentage of vegetation cover in a given area. With the help of statistical techniques of machine learning, like support vector regression, neural networks, and random forest models, LAI calculations can be accurately and efficiently obtained.

The research paper focuses on the utilization of information technology and statistical approaches to calculate LAI and analyse the growth patterns of major crops in different regions. The study involves the collection of satellite images from the Sentinel-2, Hyperion [2], and Landsat [3] datasets for specific areas and months, and the verification of crop types through time series models. By comparing LAI values and vegetation cover using clustering techniques, the research aims to providea scientific understanding of how crops' growth patterns are influenced by various factors such as seasonal changes and natural disasters.

The goal is to gain insights into the growth patterns of crops and understand how they are affected by

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different factors, ultimately contributing to the advancement of smart farming practices. This is achieved through the verification of crop types using time series models plotted from images captured in regions such as Ambatpalle and Chinchori bore. The time series models provide a visual representation of the changesin crop growth attributed to different factors.

The remaining paper is organized as follows:

Section II provides a brief review of relevant works on calculation of LAI.

Section III provides the details of datasets, parameter setting and other information of the experimental study.

Section IV provides the summary of the proposed study.

2. Literature Study

In [4], Bayesian networks were applied on satellite images of dry and wet seasons provided by Landsat 7, for inferring Leaf Area Index (LAI) of tropical dry forest. Bayesian Networks are mainly used for calculating LAI. The Naive Bayesian classifier consists of a set of random variables with directional links connecting them representing a conditional relationship. The advantages include that Bayesian networks exploit specific probabilistic relationships amongst variables. The reliability and robustness of variables depends on how good the learning data is and the pre-distribution of methods of estimation. Bayesian Networks have been ascertained as more optimal when compared to neural networks with estimations of network weights defining the characteristics of hidden units and classifications that are approximate. However, there is no standard or specific method for constructing a network from data and a process of selecting a prior

In [5], the main objective was to assess the robustness and sensitivity of LAI-VIs RE model when compared to Sentinel-2, WorldView-2 (WV-2) and Unmanned Aerial Vehicle (UAV) multispectral imagery for assessing mangrove LAI. The algorithm used here is a generic estimation model modified from Beer's law which was used for the estimation of mangrove LAI. The results of this algorithm showed that estimation accuracy was highest for WV-2 images, followed by Hyperion Eo-1 images. When compared to the generic estimation model of WV-2, the Hyperion Eo-1 multispectral imagery, NDVI, and NDVI RE1 exhibited better performance for estimation of mangrove LAI. However, LAI-NDVI RE2 based on UAV multispectral imagery was found to be highly unsuitable for retrieval of mangrove LAI the method was found to be inaccurate to take extinction coefficient as a unique constant value in various mangrove forests.

In [6], the work presented is a novel algorithm for global retrieval of Leaf Area Index (LAI) with a Bidirectional Reflectance Distribution Function (BRDF). The algorithm used a physically based Geometrical Optical (GO) model for simulating interaction of incoming solar radiation with vegetated surface for generating parameters that are required for LAI. The advantages are that it is computationally highly efficient without sacrificing the accuracy of LAI retrieval. It is now feasible to produce global LAI images at 1-km resolution on a personal computer. However, the complication here is that the kernel coefficients depend on LAI to be retrieved and a fundamental problem in integration of BRDF with LAI algorithm is the equations describing the dependence between BRDF and LAI are functional relationships.

In [7], an LAI model with an inversion approach applied on multitemporal optical data was assessed, on an agricultural region with different types of crops across varying crop seasons. Results exhibited strong relationship when in-situ LAI measurements of mid-July were compared, but with a little bias. Temporal variation in LAI of analyzed fields shows consistency with crop phenological stages of most types of crops. However, performance of techniques of model inversion will additionally depend on satellite data used. Inversion techniques using uneven resolution data with a supposition of spatially homogeneous pixels, will induce bias into LAI.

In [8], an updated algorithm for retrieving Leaf Area Index (LAI) from satellite imagery of Moderate Resolution Imaging Spectroradiometer (MODIS) is discussed. The distinct features of this algorithm are: i) improved spatial resolution when compared with corresponding standard MODIS product ii) tuning of the model to spectral characteristics of mountain grasslands. The advantage of this algorithm is that the model has an RMSE accuracy of 1.68. This model provides an option for exploiting satellite data with moderate-resolution, for further studies on accurately monitoring mountain environments at a regional scale. But, a misalignment exists between estimated and measured temporal trajectories. This can lead to constant deviations in scatter plots when applied on certain sample data.

In [9], spectral information of Hyperion Eo-1MSI satellite images for retrieving LAI was accessed overa mixed forest ecosystem which is located in northwest of Greece. The algorithm uses a parametrically specified Gaussian process for implementation of regression problems to ascertain the relationships between on-field biophysical LAI measurements and spectral data. The advantage of this algorithm is the fact that the GPR algorithm finds an appropriate covariance amongst observations. The GPR algorithm uses a kernel method approach providing advantages like conditional and statistical information for a predicted variable. However, the robustness of the model could be increased further by additional sampling efforts.

Our proposed methodology uses K-means clustering for image segmentation.

3. Design and Methodology

3.1 *Existing calculation for NDVI*

A dimensionless index called Normalized Difference Vegetation Index (NDVI) distinguishes between vegetation cover of visible and near-infrared reflectance. This index is used for estimating density of green area of a land.

$$NDVI = (NIR. RED) / (NIR + RED)$$

3.2 *Existing calculation for LAI*

Leaf Area Index (LAI) is a dimensionless biophysical variable used to quantify vegetation leaf area per unit. It is the ratio of one-sided leaf area per unit ground area and calculated as

$$LAI = (leafarea / groundarea)$$

But, for the available data set it is calculated as

$$LAI = \sum_{n=0} n$$

where n is NDVI value is calculated for each pixel of the image. The calculation of LAI is directly related to green leaves in a plant and how dense they are compared to the ground and landarea present. After the NDVI value is calculated for each pixel, take the summation of it and divide it by the ground area. Thisground area is obtained by multiplying the dimensions of the image.

3.3 Our proposed methodology: K-means Algorithm

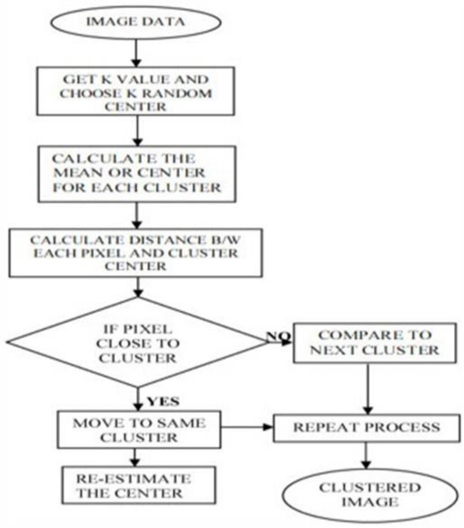

Fig 1: Flow indicating methodology

Fig 1 gives us a complete overview of how the clustering algorithms work for calculating the percentage of vegetation cover. Clustering is being used to get the percent of vegetationcover in the total ground area. For a satellite image, we needto get four clusters. The first cluster marks all the green areas, the second cluster marks just the ground area, the third cluster will mark all the water bodies and the fourth cluster will mark the dense green areas which include forests. K- Means clustering picks out a centroid and groups all the pixelsconsidering Euclidean distances. The pixels are classified into four clusters based on how near the pixel is to the random centroid pixel picked. When all the pixels are classified the area of the clusters is calculated to give us an estimate ofthe percent of vegetation cover. This can be plotted to get a more clear idea. Method of K-Means from OpenCV is used. The clustering algorithm is applied in HSV(Hue Saturation value) space and not in RGB space. We provide different initial centroids for the algorithm to proceed and also the stopping criteria for the process to end. After the stopping criteria is reached, the iteration stops to label the parts of the images. Once the clustered image is obtained, bar graphs are plotted for the percentage of vegetation cover for the three region datasets. Verification is the understanding of which label is assigned to which color for each pixel. For every image, the labels keep changing as the initial centroids taken are random.We verify the green clusters by calculating the average NDVI value for all the clusters and picking only those clusters whichhave NDVI greater than 0.1.

3.4 Datasets

The statistical algorithm employed in this research utilizes the Hyperion EO-1 dataset, which is a high-resolution hyperspectral imaging mission. Managed and operated by NASA’s Goddard Space Flight Center (GSFC), the EO-1 spacecraft was part of NASA’s New Millennium Program (NMP) and served as a technology demonstration mission. Launched in November 2000 with an initial planned operationduration of 1.5 years, the mission aimed to test advancedsatellite and instrument technologies for potential integration into future missions. Recognizing its significant contributions,NASA granted extensions to the mission until its final decommissioning in March 2017.

Landsat 8 was successfully launched on February 11, 2013, from Vandenberg Air Force Base in California, using an Atlas-V 401 rocket provided by United Launch Alliance, LLC, along with the extended payload fairing (EPF). The satellite payload of Landsat 8 consists of two key scientific instruments—the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Together, these sensors offer seasonal coverage of the Earth’s landmass at a spatial resolution of 30 meters for visible, near-infrared, and shortwave infrared data, 100 meters for thermal data, and 15 meters for panchromatic data.

Sentinel-2 dataset is used for the statistical algorithm. Sentinel-2 is a high-resolution, multispectral imaging mission with a 5-day revisit frequency. This mission was developed within the Copernicus program with two satellites phased at 180 degrees to each other. It was launched by the European Space Agency. The Hyperion

Eo-1, Sentinel, and Landsat dataset is collected from Google Earth Explorer. A combination of datasets is used for the project of Sentinel 2A and 2B. The has been filtered according to various attributes like cloud cover, resolution, and orbit number. The dataset is acquired usinga library in Python called GDAL. The Geospatial Data Abstraction Library (GDAL) is a software library for reading and writing raster and vector geospatial data. Pre-processing the data involves taking each image and converting it into an array of pixels and extracting the required bands(near-infrared, infrared, red, green, blue) from the image. These steps are done using gdal and rasterio libraries in Python.

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S.no	State	District	Mandal	Village
1	Telangana	Mahbubnagar	Lingal	Ambatpalle
2	Maharashtra	Buldhana	Mehkar	Chincholi Bore

Fig 2: Satellite Imagery - Ambatpalle

Label	Satellite	Samples	Dates (yyyy-mm-dd)
1	Hyperion EO-1	12	2009-06-17, 2009-12-12, 2010-03-25, 2010-05-18, 2011-05-07, 2012-02-09 2012-02-19, 2012-06-08, 2012-12-11, 2013-04-24, 2017-03-06, 2017-03-11.
2	Sentinel-2	12	2018-03-19, 2018-04-13, 2018-04-18, 2018-04-23 2018-05-28, 2018-06-02 2018-06-12, 2018-07-07 2018-09-30, 2018-10-05 2018-10-25, 2018-11-19
3	Landsat	6	2018-01-10, 2018-03-22, 2018-07-05, 2018-10-25, 2018-11-10, 2018-12-10

(a) Number of images used

Fig 2: Satellite Imagery – Chincholi Bore

Label	Satellite	Samples	Dates (yyyy-mm-dd)
1	Hyperion EO-1	6	2015-04-17, 2015-06-20, 2015-07-17, 2015-08-05, 2015-09-12, 2015-12-10.
2	Sentinel-2	12	2018-02-02, 2018-03-29, 2018-05-28, 2018-06-13, 2018-07-07, 2018-10-15, 2018-11-09, 2018-11-19, 2018-11-24, 2018-12-09, 2018-12-14, 2018-12-19.
3	Landsat	6	2015-04-17, 2015-06-20, 2015-07-15, 2015-08-16, 2015-09-17, 2015-12-13.

(b) Number of Images used

1) *Ambatpalle:* Ambatpalle is a Village in Lingal Mandal in Mahbubnagar District of Telangana State, India. It belongs to Telangana region. It is located 82 KM

towards South from ICT head quarters Mahabubnagar and 8 KM from Lingal.

2) Chincholi Bore: Chincholi Bore is a Village in Mehkara in Buldhana District of Maharashtra State, India. Itgs to Vidarbha region . It belongs to Amravati Division . located 69 KM towards South from District head quartersana. 14 KM from Mehkar. 473 KM from State capital.

4. Results

4.1 Analysis

1) Time Series: The time series plots for Ambatpalle and Chincholi Bore have been plotted specifically using Hyperion EO-1 to understand the Leaf area trend in the regions.

Ambatpalle The plot depicts the lowest in the months of June and July which is the sowing season and gradually reaches the highest peak in the months of October and November which is the harvesting season.

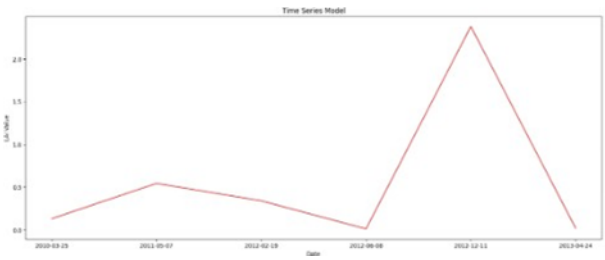

Fig. 4: Ambatpalle

Chincholi Bore The plot depicts the highest peak during the harvesting season in the month of October and gradually decreases. The lowest is found during the months of March and February when the crop is sown.

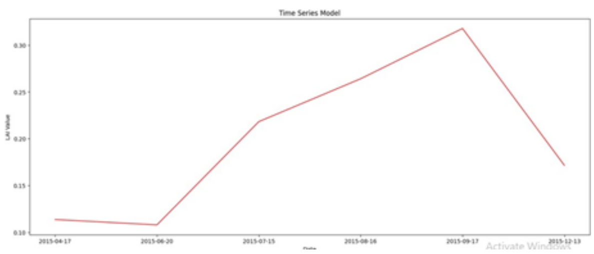

Fig. 5: Chincholi Bore

4.2 Comparison between Satellite Images

It has been beneficial to extend the application of the statistical algorithm to other satellite datasets, such as Landsat or Sentinel, in order to validate and compare the LAI results across different platforms and sensors. This cross-validation has enhanced our understanding of LAI estimation and has verified the calculation of LAI by statistical methods and by other satellites.

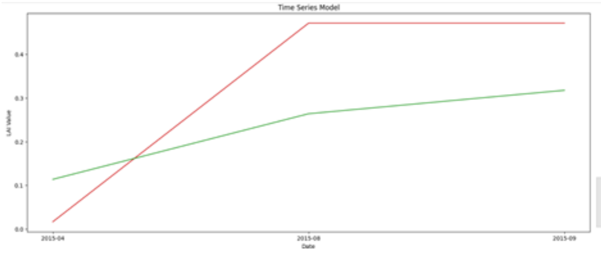

Fig. 6: Hyperion and Landsat

5. CONCLUSIONS AND FUTURE DIRECTIONS

The statistical algorithm employed for calculating Leaf Area Index (LAI) using the Normalized Difference VegetationIndex (NDVI) has demonstrated its effectiveness and simplicity when applied to the Hyperion Eo-1 dataset.

This algorithm can be readily applied to various agricultural regions in India, including the Chincholi Bore and Ambatpalleregions. The analysis conducted in these regions has indicated favorable crop health over the years. Comparing the results obtained from different satellites further validates the accuracyand correctness of the LAI calculations, with minor variations observed due to differences in sensor characteristics amongthe satellites. Some potential future directions and scope for further research include:

Integration of machine learning techniques: Incorporating machine learning techniques, such as deep learning or ensemble methods, into the LAI calculation process can potentially enhance accuracy and prediction capabilities. Exploring the use of advanced models can help uncover complex relationships and patterns within the data.

Assessment of LAI variations with climate change: Investigating how LAI values and crop health are influenced by climate change factors, such as temperature, precipitation, and carbon dioxide levels, can contribute to understanding the impact of changing environmental conditions on agricultural productivity. This analysis can assist in developing adaptation strategies for sustainable farming practices.

Integration of ground-based measurements: Integrating ground-based measurements of LAI with satellite-based analysis can provide a more comprehensive assessment of crop health and vegetation dynamics. Combining remote sensing data with field observations and ground truthing can improve the accuracy of LAI calculations and enhance the understanding of regional and local variations.

Evaluation of LAI in different crop types: Extending the analysis to include various crop types and their response to different environmental factors can offer insights into specific agricultural systems. Comparing LAI values and crop health across different crops can help optimize farming practices and inform decision-making for specific crop managementstrategies.

Development of decision support systems: Utilizing the LAIcalculation results and integrating them into decision support systems can assist farmers and agricultural stakeholders in making informed decisions regarding irrigation scheduling, fertilization, pest management, and overall crop health monitoring. This can contribute to increased efficiency, reduced costs, and improved sustainability in agricultural operations.

Exploration of multi-sensor fusion techniques: Investigatingthe fusion of data from multiple sensors, such as hyperspectraland multispectral imagery, can enhance the accuracy and resolution of LAI calculations. Integrating data from different sensors can provide a more comprehensive and detailed assessment of vegetation properties and improve the understanding of crop dynamics.

By pursuing these future research directions, the scientific community can further advance the field of LAI estimation, improve agricultural monitoring practices, and contribute to the development of sustainable farming systems.

6. Abbreviations

The following abbreviations are used in this manuscript:

Normalized Difference Vegetation Index (NDVI)

Leaf Area Index (LAI) Earth

Observing-1 (EO-1) Short-Wave

Infrared (SWIR)

Visible and Near Infrared (VNIR)

Near Infrared (NIR)

7. Acknowledgements

We would like to express our gratitude to Vasavi College of Engineering(Autonomous) for providing us with the deep learning server with which we were able to complete this work.

We would also extend our thanks to Dr. Raghavendra Kune for the support and guidance he extended towards completion of this work.

8. References and Footnotes

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We would like to express our gratitude to Vasavi College of Engineering(Autonomous) for providing us with the deep learning server with which we were able to complete this work.

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