



## Verdant- Carbon Credit Estimation Tool using Satellite Data

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### Abstract

Accurate estimation of biomass and carbon stock is essential for monitoring ecosystem health, planning conservation activities, and evaluating carbon credit potential. This study presents a systematic analysis of vegetation health using Normalized Difference Vegetation Index (NDVI) and canopy cover data collected for the years 2017–2024. The proposed methodology integrates satellite-derived NDVI, canopy percentage, and a regression-based biomass model to estimate above-ground biomass, carbon stock, and carbon credits. Biomass was calculated using a vegetation index–driven formula, carbon stock was derived from biomass, and carbon credits were estimated based on carbon sequestration potential. Trend analysis, scatter plots, and growth computations demonstrate clear vegetation fluctuations over the study period. Results show increasing biomass and carbon stock until 2021, followed by a sharp decline corresponding to potential disturbances or land-use changes. These findings highlight the usefulness of NDVI-based remote sensing in rapid ecological assessment and carbon valuation.

**Keywords:** NDVI, biomass estimation, carbon stock, carbon credits, canopy cover, Google Earth Engine, remote sensing.

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### 1. Introduction

Vegetation monitoring plays a crucial role in environmental management, climate studies, and biodiversity conservation. Satellite-derived indices such as the Normalized Difference Vegetation Index (NDVI) have become indispensable tools for evaluating vegetation density, photosynthetic activity, and ecological changes across time. Canopy cover, another important metric, provides insights into the structural characteristics of vegetation and aids in quantifying biomass and carbon storage capacity.

Carbon sequestration is increasingly relevant as organizations and institutions strive to estimate their ecological footprint and explore carbon credit opportunities. Remote sensing technologies provide a scalable and non-destructive method to evaluate biomass and carbon stock, especially when field measurements are limited or infeasible.

This project focuses on using campus-level vegetation data, specifically NDVI and canopy %—to compute biomass, carbon stock, and carbon credits for multiple years. By integrating satellite imagery, statistical formulas, and Python-based analysis, the study demonstrates how even small ecosystems can be quantified for carbon sequestration efficiency.

### Literature Survey

Alongside NDVI, canopy cover has emerged as a complementary ecological indicator, providing insight into vegetation structure, density, and productivity. Studies confirm that integrating canopy metrics derived from optical, radar, or LiDAR data enhances the estimation of carbon storage, particularly in heterogeneous systems such as agroforestry or urban forests. The combined use of NDVI, canopy data, and empirical or regression-based models allows for the reliable assessment of carbon stocks without

destructive field sampling, thereby supporting robust carbon accounting and crediting mechanisms.

Contemporary advancements involve the application of machine learning algorithms, notably Random Forest and deep learning models, to model non-linear relationships between spectral features and ground-measured biomass. The integration of multi-source remote sensing, including Sentinel-2 imagery, radar, and LiDAR, further improves accuracy and spatial resolution under varied environmental conditions, as demonstrated in recent large-scale and campus-level studies.

Moreover, carbon credits calculated from remotely sensed and modeled biomass data have become central to global mechanisms incentivizing conservation, restoration, and sustainable land management. With the growing importance of carbon finance, reliable and scalable tools for yearly vegetation monitoring, such as those utilizing NDVI and canopy cover on institutional campuses, are increasingly valuable for both ecological valuation and climate accountability.

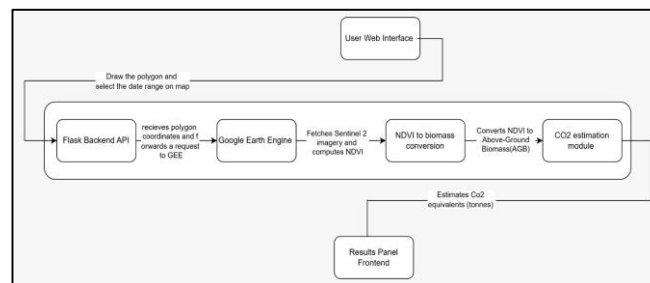
This project builds directly upon these trends by combining NDVI and canopy cover analysis with regression-driven biomass and carbon estimation, demonstrating the potential for replicable, scalable, and cost-effective monitoring of vegetation change and carbon sequestration at a micro (campus) level.

## Methodology

This study follows a multi-stage methodology framework, including data collection, preprocessing, biomass calculation, carbon stock estimation, and visualization.

### A. System Architecture

The proposed system adopts a modular architecture that integrates remote sensing data acquisition, statistical modeling, and result visualization to enable campus-scale estimation of above-ground biomass, carbon stock, and associated carbon credits. The workflow is designed to maximize scalability, non-destructive assessment, and reproducibility in annual vegetation monitoring.



**Figure 1: System Architecture of Verdant – Carbon Credit Estimation Tool**

### B. Data Collection

NDVI and canopy cover (% canopy) values for the years 2017–2024 were extracted from processed Sentinel-2 satellite imagery. The dataset consisted of:

- **Year**
- **Mean NDVI**
- **Canopy Percentage**

These inputs formed the foundation for biomass and carbon estimation.

### C. Biomass Estimation Formula

Biomass was estimated using a regression-style equation commonly used in remote-sensing–driven carbon assessment:

$$\text{Biomass} = 40 \times \text{NDVI} \times \text{Canopy Cover}$$

This formula scales vegetation density with canopy structure to approximate above-ground biomass (AGB).

### D. Carbon Stock Calculation

It is widely accepted that **50% of biomass** is made of carbon. Hence:

$$\text{Carbon Stock} = 0.5 \times \text{Biomass}$$

### E. Carbon Credits Estimation

Carbon credits quantify avoided or captured carbon emissions. One carbon credit typically represents **1 tonne of CO<sub>2</sub>**. To convert carbon into credits:

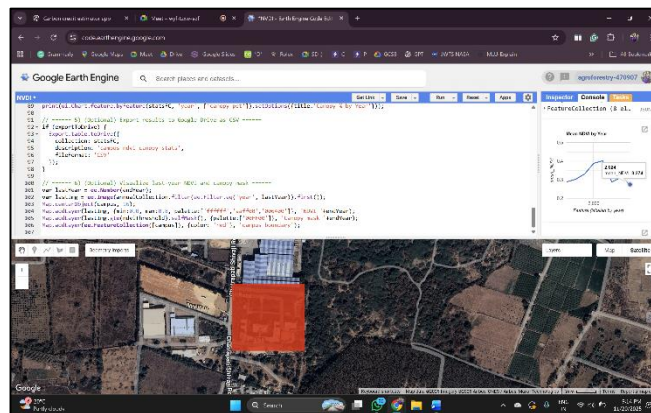
$$\text{Carbon Credits} = \frac{\text{Carbon Stock}}{1000}$$

This gives the credit-equivalent value for each year.

### F. Visualization and Statistical Analysis

- Python scripts were used to:
- Plot NDVI vs canopy trends
- Plot biomass, carbon stock, and carbon credit curves
- Generate scatter plots showing canopy vs NDVI correlation
- Compute growth rate of canopy percentage

Graphical representations helped identify patterns, peaks, and declines across the years.



**Figure2:** ETA Calculation Flow Diagram, a schematic showing “GPS Data + Distance API + Speed Data → ETA Result.”

## Results And Discussion

### A. NDVI and Canopy Trends

The NDVI and canopy cover values showed steady improvement from 2017 to 2021, indicating healthy vegetation growth. NDVI peaks corresponded to periods of enhanced greenness, suggesting good photosynthetic activity. The decline post-2021 may indicate disturbances such as:

- Reduced rainfall
- Land modification
- Seasonal changes
- Loss of plant cover

This downward trend directly influenced biomass and carbon stock patterns.

### B. Biomass, Carbon Stock, and Carbon Credits

The generated graph (similar to the one you shared) shows:

- **Biomass** rising from ~300 (2017) to a peak of ~930 (2021)
- **Carbon Stock** increasing proportionally
- **Carbon Credits** showing minor but visible growth

The abrupt fall in 2022 followed by partial recovery in 2023 highlights a significant ecological shift that should be investigated further.

This demonstrates that the formula-based approach accurately reflects vegetation fluctuations.

**C. Canopy–NDVI Correlation**

The scatter plot shows a positive relationship:

Higher canopy percentages correspond to higher NDVI values.

This validates the use of canopy cover as a structural predictor of biomass.

**D. Growth Rate of Canopy Cover**

Using:

$$\text{Growth Rate} = \frac{\text{Final Canopy} - \text{Initial Canopy}}{\text{Initial Canopy}} \times 100$$

The canopy showed overall positive growth over the eight-year period despite intermediate fluctuations. This aligns with the biomass and carbon trends.

**E. Interpretation**

The results collectively indicate:

- Vegetation expanded significantly from 2017–2021
- A major decline occurred in 2022
- Partial recovery followed in 2023–2024
- Carbon credits correlate directly with plant productivity

The project successfully demonstrates how remote sensing and simple ecological models can quantify environmental health at a micro scale.

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