Carbon Stock Estimation in Green Areas Using Transfer Learning Model With Drone and GEE Imagery

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***Abstract*— Measuring the carbon store in green spaces accurately is crucial for managing ecosystems and reducing the effects of climate change. In order to estimate carbon stock using high-resolution UAV (drone) images and satellite imagery from Google Earth Engine (GEE), this study presents a Convolutional Neural Network (CNN) technique improved with transfer learning. 8,762 GEE photos, 2,072 UAV images, and 10,834 mixed images from various Indonesian plot regions make up the collection. VGG19, ResNet50, MobileNet, and InceptionV3 were among the transfer learning models that were compared to a baseline CNN model. With a coefficient of determination (R^2) of 0.4011, MobileNet outperformed the baseline CNN by a wide margin for the drone dataset. VGG19 performed exceptionally well on the GEE dataset, with an R^2 of 0.7325 as opposed to the baseline CNN's R^2 of 0.6191. In the mixed dataset, VGG19 outperformed the baseline CNN with an R^2 of 0.7529, outperforming it by 0.6192. Even while all models had high Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values, transfer learning models continuously improved prediction accuracy over the baseline. The integration of diverse data sources and advanced machine learning techniques demonstrates the potential for scalable and precise carbon stock estimation. Future work will expand the dataset and optimize model parameters to further improve robustness and accuracy.**

Keywords*— *Carbon Stock Estimation, Convolutional Neural Networks, Transfer Learning, UAV Imagery, Google Earth Engine

I. INTRODUCTION

Green spaces are essential for preserving the equilibrium of ecosystems because they regulate pollution, regulate biogeochemical cycles, and supply food supplies. The absorption and storage of CO_2 in the atmosphere is one of green space's primary functions [1]. The CO_2 that is absorbed and stored in green spaces is referred to as carbon stock. Because they show that the land is efficient at absorbing CO_2 from the atmosphere, one of the factors causing global warming, green spaces with high carbon stocks are essential for reducing the effects of climate change [2]. We can determine how well green spaces store carbon in the ecosystem by measuring carbon stock.

Measuring carbon stocks is crucial for managing natural resources and reducing the effects of climate change. The ability of green spaces to absorb and store CO_2 from the atmosphere can be ascertained by monitoring carbon stock, which is a crucial step in lowering CO_2 concentrations and combating global warming. Additionally, this data aids in identifying carbon-absorbing regions that might be enlarged or safeguarded. Furthermore, by using the land's capacity to store carbon, we may plan conservation and sustainable land use, which improves the effectiveness of natural resource management [3].

In the traditional method of calculating carbon stocks, vegetative biomass, such as tree height, diameter, and species type, is directly measured in the field [4]. Then, using allometric equations, biomass is computed and the amount of carbon stored is estimated. This approach is accurate, but it is inefficient since it necessitates a huge investment of time, money, and specialized knowledge in data collecting and analysis, which makes it challenging to use on a wide scale or for long-term monitoring. Machine learning advancement is required for carbon stock estimating jobs in order to get beyond the drawbacks of conventional approaches and produce estimates that are faster and more accurate.

Google Earth Engine (GEE), which offers access to a sizable collection of satellite imagery with worldwide coverage, is one of the most widely used remote sensing tools for estimating carbon stocks. GEE has been widely used to track changes in plant cover and land use over time and gives researchers access to datasets from multiple satellites, including Landsat and MODIS [5]. Large-scale monitoring is facilitated by this method, particularly in areas where direct field measurements are impractical. However, satellite imagery's accuracy in estimating carbon stocks at finer scales may be limited by its relatively coarse spatial resolution, particularly in locations with complex topography or dense vegetation.

On the other hand, UAVs (drones) have gained popularity in carbon stock estimation due to their ability to capture high-resolution imagery at a local scale. For precise carbon stock estimation, drones can offer comprehensive data on tree biomass, canopy height, and vegetation structure [6]. By obtaining high-resolution imagery that enables accurate measurements of tree height and canopy volume, studies have shown how useful drones are for estimating carbon stocks, especially in wooded environments [7]. While drones offer superior spatial resolution, they come with their own set of challenges, including higher operational costs and limited spatial coverage compared to satellite imagery.

Given the advantages and limitations of both GEE and drone imagery, machine learning techniques, particularly Convolutional Neural Networks (CNNs), have shown great potential in carbon stock estimation using satellite and drone datasets. Many studies have demonstrated the effectiveness of machine learning in satellite data analysis for various applications, including carbon stock estimation through regression. For instance, research by [8] used machine learning with a Convolutional Neural Network (CNN)-based architecture for carbon stock estimation with a dataset of images taken by unmanned aerial vehicles (drones). The results showed that the CNN-based model successfully estimated carbon stock, although not very accurately, with a coefficient of determination (R^2) of 0.711 and a Root Mean Squared Error (RMSE) of 26.08 kg. Despite these promising results, drone data is often limited in terms of coverage and is more expensive compared to satellite-based methods like GEE, making it impractical for large-scale monitoring.

On the other hand, GEE provides the benefit of worldwide coverage through satellite imaging, which makes it a perfect instrument for estimating carbon stocks on a big scale. GEE offers a platform for processing big datasets over long periods of time and integrates data from multiple satellite sources, such as MODIS and Landsat. GEE has been employed in a number of studies to estimate carbon stocks, showing promise for large-scale carbon storage and vegetation dynamics monitoring. Despite the difficulties with coarse resolution and cloud cover, a study by [9] that estimated carbon stocks in forests using GEE data and CNNs managed to obtain an R^2 value of 0.82. A drawback in densely vegetated areas is that GEE's satellite imagery's reduced spatial resolution makes it more difficult to capture finer-scale vegetation characteristics.

The accuracy of CNN-based models is frequently constrained by the quantity of labeled data available and the difficulty of the task, even though both drone and GEE imaging provide insightful information about carbon stock estimation. By using pre-trained models to enhance performance on particular tasks, transfer learning has become a viable way to overcome these difficulties, especially in situations with little data. By fine-tuning its learnt characteristics, a model trained on a large, broad dataset can adapt to a smaller, more specialized dataset through transfer learning. In remote sensing jobs, where labeled datasets can be hard to come by and acquiring high-quality training data for particular locations might be resource-intensive, this method has proven especially helpful.

For example, [10] applied transfer learning to an image regression task where they used a CNN pre-trained on ImageNet and fine-tuned it on a smaller dataset of depth estimation images. According to their findings, transfer learning significantly increased regression accuracy, with the model's error decreasing by more than 20% when compared to training from scratch. In a similar vein, [11] used transfer learning in a regression task to predict depth maps from monocular images, where they fine-tuned a pre-trained CNN to estimate depth with high accuracy. Their model performed far better than conventional techniques, showing how transfer learning might enhance regression tasks, particularly when dealing with intricate image data.

Although the application of transfer learning for carbon stock estimation using satellite imagery, especially in regression tasks, is still relatively underexplored [12], its potential to improve model performance is significant. Similar remote sensing and image regression tasks have already seen impressive success with transfer learning, which has been shown to improve accuracy, decrease data dependency, and speed up model convergence. Thus, it is not only pertinent but also essential to advance the area to investigate the application of transfer learning in the context of carbon stock estimation, especially when dealing with satellite and drone datasets.

This study proposes a method to improve the accuracy and efficiency of carbon stock estimation by leveraging transfer learning with primary data that integrates field-collected carbon stock measurements, drone imagery, and GEE satellite data. By combining these diverse data sources with transfer learning techniques, the proposed approach aims to develop more robust, scalable, and accurate models for carbon stock assessment. In addition to offering useful insights for environmental monitoring and climate change mitigation methods, this approach is anticipated to facilitate more efficient, data-driven decision-making in environmental conservation and natural resource management.

II. Proposed Method

A. Overview of the Proposed Carbon Estimation Method

The proposed method uses satellite imagery and remote sensing data from drones to estimate carbon stock using a baseline CNN model. In addition to investigating how transfer learning enhances model performance, the study seeks to ascertain which image source drone or GEE-based satellite data offers superior carbon stock predictions.

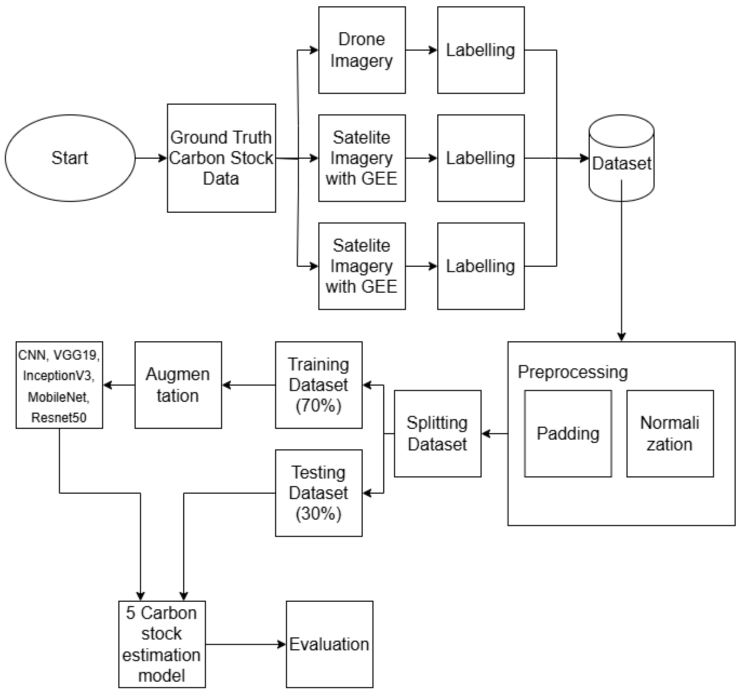

Fig. 1. Carbon stock estimation method flow process

The process begun with gathering ground truth data of carbon stock from plots scattered in Indonesia. Then getting high-resolution drone images and medium-resolution global data from GEE. Preprocessing procedures for these photos include resizing, normalizing, and using data augmentation methods including brightness, scale, and rotation. In order to increase model resilience under a variety of circumstances, these procedures guarantee that the images are appropriate for modeling and improve dataset variability.

CNN is then used to automatically extract features from the images. CNNs excel in image-based tasks by detecting spatial hierarchies in the data. Here, CNN focuses on features pertinent to carbon stock estimation. However, training a