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# BIOMASS ESTIMATION USING MACHINE LEARNING IN GOOGLE EARTH ENGINE PLATFORM

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***Abstract*— Earth Observation (EO) data, such as high resolution satellite imaginary or LIDAR has become one primary source for forestry, Agriculture and others. Biomass release in the environment is harmful to living beings and the atmosphere, contributing to air pollution and climate change. Biomass can be used as renewable energy, providing heat, electricity, and biofuels while reducing reliance on fossil fuels and lowering greenhouse gas emissions, thus promoting sustainability. Machine learning techniques are employed to estimate biomass, addressing challenges associated with traditional methods. However, Managing and analysing the large amount of globally or locally available EO data remains a great challenge. The Google Earth Engine (GEE) which leverages Machine Learning Services to provide powerful capabilities on the management and rapid analysis of various types of EO data, has appeared as an inestimable tool to address this challenge. By leveraging state-of-the-art technology, the project seeks to develop innovative approaches for estimating biomass levels, contributing to the advancement of sustainable energy solution. Traditional methos for estimating aboveground biomass (AGB) are field Measurements, Allometric Equations, Ground Surveys, Destructive Sampling, Field Spectroscopy and etc.***

## *I. INTRODUCTION*

***Biomass estimation plays a critical role in environmental management and sustainability efforts. Traditional methods, such as field measurements, have been the historical cornerstone for biomass estimation. However, these approaches are often limited by labor-intensive procedures and restricted spatial coverage (e.g., Huynh et al., 2020). Additionally, conventional methods based on allometric equations derived from destructive sampling can be regionally specific and have high prediction errors (e.g., Moradi et al., 2020). LiDAR technology, while offering advantages, also faces challenges in terms of cost and data processing complexity (Xu et al., 2021).***

***To address these limitations and enhance the accuracy and scalability of biomass estimation, advanced techniques like machine learning and remote sensing have emerged as promising alternatives. In this study, we leverage the power of Google Earth Engine (GEE), a cloud-based platform that facilitates the efficient collection and analysis of vast satellite imagery datasets (Gorelick et al., 2017). GEE's capabilities allow us to overcome the spatial constraints associated with traditional field measurements and extract valuable insights into forest biomass dynamics.***

***The methodology is to utilization of Sentinel-2 imagery, renowned for its high spatial resolution (10 to 20 meters) and spectral capabilities well-suited for capturing detailed information about forest ecosystems (Mueller-Jung et al., 2021, Sentinel-2 Product Guide). This imagery selection makes it an optimal choice for biomass estimation in our research.***

*Furthermore, A suite of machine learning models are employed to perform biomass mapping with high accuracy and efficiency. These models include Random Forest, Decision Tree and Support Vector Machine. Each of these models offers unique strengths in handling complex spatial and spectral data, enabling us to effectively capture the intricate relationships between satellite imagery and biomass distribution in forested areas.*

*By integrating cutting-edge remote sensing techniques, powerful machine learning algorithms, and the vast capabilities of Google Earth Engine, this research delves into the potential for a new era in biomass estimation.*

## *II. RELATED WORK*

### *2.1. Biomass Estimation*

*Biomass estimation, the quantification of the total amount of organic matter within a living organism or ecosystem, plays a crucial role in various environmental applications. Accurate biomass assessments are essential for:*

- *Biodiversity conservation: Biomass data helps evaluate habitat suitability for different species and monitor changes in ecosystem health, aiding in conservation efforts.*

- *Carbon sequestration: Forests act as carbon sinks, storing atmospheric carbon in biomass. Accurate biomass estimates are critical for assessing carbon stocks and monitoring their changes over time to understand global carbon cycles and climate change mitigation strategies (Körner et al., 2003; Mäkelä & Satja-Eriksson, 2001).*

- *Sustainable forest management: Biomass information is vital for sustainable forest management practices, allowing for informed decisions about logging quotas, regeneration strategies, and monitoring forest health.*

*Therefore, developing accurate and efficient methods for biomass estimation is crucial for environmental monitoring and sustainable resource management.*

### *2.2. Traditional Methods of Biomass Estimation*

*Traditional methods of biomass estimation rely on various approaches, each with its limitations:*

- *Field measurements: This involves destructive or non-destructive sampling techniques to measure tree height, diameter, and other physical characteristics. While providing accurate data for individual trees, field measurements are time-consuming, labor-intensive, and often limited in spatial coverage (McRoberts et al., 2010).*

- *Allometric equations: These equations relate easily measurable tree parameters (e.g., diameter at breast height) to aboveground biomass. However, allometric equations are often species-specific and may not be accurate for diverse ecosystems (Chave et al., 2005).*

- *Wood Density Approach: The wood density approach estimates biomass based on the density of wood, typically measured as mass per unit volume. This method provides a direct measure of biomass and can be particularly useful in forests where wood density varies across species and ecosystems.*

*It Relies on accurate wood density values, which may vary within species and across regions. May not capture the biomass of non-woody components like leaves or branches (Nogueira et al.,2007).*

### *2.3. Advancements in Remote Sensing and Machine Learning*

*Recent advancements in remote sensing technology and machine learning offer promising solutions for overcoming the limitations of traditional methods:*

- *High-resolution satellite imagery: Satellites like Landsat and Sentinel-2 provide high-resolution multispectral data, capturing detailed information about the Earth's surface.*

- *LiDAR (Light Detection and Ranging): LiDAR systems emit laser pulses and measure the reflected light to create detailed 3D point clouds of the terrain and vegetation. LiDAR data provides valuable information about vegetation structure, which can be used for biomass estimation (Lefsky et al., 2002).*

- *Machine learning algorithms: Machine learning algorithms can analyze vast amounts of remote sensing data to identify complex patterns and relationships between spectral features, LiDAR data, and biomass. This allows for more accurate and efficient biomass estimation across large areas (Neighmour et al., 2012).*

*The integration of high-resolution remote sensing data and powerful machine learning techniques paves the way for large-scale, accurate biomass estimation, crucial for environmental monitoring and management.*

### *2.4. Previous Studies on Biomass Estimation*

*Numerous studies have demonstrated the effectiveness of machine learning models for biomass estimation in various ecosystems:*

- *Bhandari et al. (2019) employed Random Forest (RF) regression using LiDAR data and achieved high accuracy in estimating aboveground biomass in a tropical forest ecosystem.*

- *Xu et al. (2020) utilized Support Vector Regression (SVR) with multispectral satellite imagery and LiDAR data to estimate biomass in a subtropical forest, achieving good results.*

- *Li et al. (2021) explored the use of deep learning models, specifically Convolutional Neural Networks (CNNs), for biomass estimation using high-resolution satellite imagery and found them to be effective in capturing spatial patterns within the data.*

*These studies highlight the potential of machine learning for accurate and scalable biomass estimation across diverse forest types. However, there is a need for further research on applying these techniques to specific regions with unique ecological characteristics.*

## *III. PROPOSED METHODOLOGY*

*Biomass estimation plays a critical role in environmental monitoring and management. However, traditional field-based approaches, while historically important, are hindered by several limitations:*

*Labor Intensity: Field measurements can be time-consuming and require significant manpower, making large-scale assessments difficult and expensive.*

*Limited Spatial Coverage: Traditional methods are often restricted to specific sampling plots, limiting their ability to capture the full spatial variability of biomass across vast landscapes.*

*Destructive Sampling: Conventional allometric equations often rely on destructive sampling techniques, which can damage ecosystems and are not suitable for long-term monitoring.*

*Regional Specificity: Allometric equations developed in one region may not be accurate when applied to other areas with different forest types or environmental conditions.*

*This research focuses on overcoming these challenges by leveraging the potential of:*

*1. Machine Learning: Machine learning algorithms can analyze vast amounts of satellite imagery data and identify complex relationships between spectral features and biomass distribution.*

*2. Google Earth Engine (GEE): GEE is a cloud-based platform that provides access to a vast collection of satellite imagery datasets and powerful processing capabilities, facilitating large-scale and efficient analysis.*

*3. High-Resolution Satellite Imagery: Sentinel-2 imagery offers detailed spatial resolution (10-20 meters) and spectral information, allowing for the extraction of valuable insights on forest structure and biomass content.*

*By combining these elements, this research aims to develop a scalable and accurate method for biomass estimation using machine learning and GEE. This approach has the potential to:*

- *Reduce reliance on labor-intensive field measurements.*

- *Provide spatially comprehensive biomass maps across large landscapes.*

- *Promote sustainable forest management practices through non-destructive monitoring.*

- *Improve the accuracy and generalizability of biomass estimation models.*

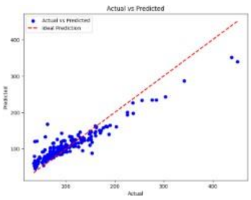
- *Explore the advantages of using Earth Engine's vast repository of satellite imagery and geospatial data.*

## *IV. RESULTS AND DISCUSSION*

*Random Forest:*

*The Random Forest model achieves a MSE of 663.93, indicating the average squared difference between predicted and actual biomass values. The MAE of 18.48 signifies the average absolute difference between predicted and actual values. RMSE at 25.77 represents the standard deviation of prediction errors. The high $R^2$ value of 0.8315 indicates that approximately 83.15% of the variance in biomass is explained by the model features.*

```
Mean Squared Error (MSE): 663.9286287729128
Mean Absolute Error (MAE): 18.48489456402548
Root Mean Squared Error (RMSE): 25.766812545848833
R-squared (R2): 0.8314572186796048
```




***Support Vector Machine (SVM):***

***The SVM model yields an MSE of 862.59, MAE of 17.42, RMSE of 29.37, and R² of 0.7810. These metrics indicate the model's performance in predicting biomass distribution, with R² suggesting that approximately 78.10% of the variance in biomass is explained by the model features.***

```
Mean Squared Error (MSE): 862.5877121272767
Mean Absolute Error (MAE): 17.419806297581584
Root Mean Squared Error (RMSE): 29.369843583636545
R-squared (R2): 0.7810262642184485
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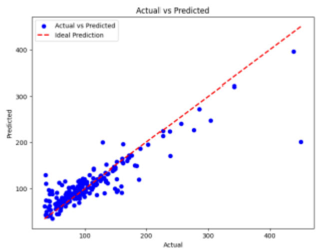
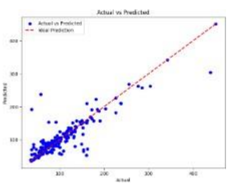



***Decision Tree:***

***The Decision Tree model achieves an MSE of 852.84, MAE of 15.43, RMSE of 29.20, and R² of 0.7835, demonstrating its effectiveness in predicting biomass distribution.***

```
Mean Squared Error (MSE): 852.8386851975885
Mean Absolute Error (MAE): 15.433327056402726
Root Mean Squared Error (RMSE): 29.203401945622506
R-squared (R2): 0.7835011207658065
```




**RESULT COMPARISON TABLE**

| Metric | Random Forest (Bold) | SVM | Decision Tree |
|---|---|---|---|
| MSE | 663.93 mg²/ha | 862.59 mg²/ha | 852.84 mg²/ha |
| MAE | 18.48 tons/ha | 17.42 tons/ha | 15.43 tons/ha |
| RMSE | 25.77 tons/ha | 29.37 tons/ha | 29.20 tons/ha |
| R² | **0.8315** | 0.7810 | 0.7835 |

## *DISCUSSION*

***The results are given in above states the performance of models, the table above show the result comparison of each model. Upon comparing various machine learning models for biomass estimation in forested areas, including Random Forest, Support Vector Machine (SVM) and Decision Tree, it was observed that Random Forest and Decision Tree models exhibit relatively lower error metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), indicating better accuracy in predicting biomass distribution. Specifically, Random Forest achieved an MSE of 663.93, an MAE of 18.48, an RMSE of 25.77, and an R² of 0.8315. However, among these models, Random Forest stands out as the most suitable choice due to its superior accuracy and robustness. SVM, despite their capabilities, show slightly higher error metrics and/or computational complexity, making them less preferable for this task. For instance, SVM yielded an MSE of 862.59, an MAE of 17.42, an RMSE of 29.37, and an R² of 0.7810. Decision Tree, while competitive, is not selected primarily due to its tendency to overfit and lack of scalability. Random Forest's ability to capture complex relationships while mitigating overfitting, along with its simplicity, interpretability, and scalability, makes it the preferred model for biomass estimation in forested areas, providing valuable insights for environmental management and sustainability efforts. Other models may lack the robustness, interpretability, or computational efficiency of Random Forest, rendering them less suitable for this specific task.***

## *V. CONCLUSION*

***In conclusion, this Research / Project addresses the critical need for innovative approaches to biomass estimation in environmental monitoring and***

*management, overcoming the limitations of traditional field-based methods. Traditional approaches suffer from labor intensity, limited spatial coverage, destructive sampling, and regional specificity. However, through the integration of machine learning techniques, Google Earth Engine (GEE), and high-resolution satellite imagery, particularly Sentinel-2 data, this study offers promising solutions to these challenges.*

*By using machine learning algorithms and GEE's capabilities, this research aims to develop a scalable and accurate method for biomass estimation, reducing reliance on labor-intensive field measurements and providing spatially comprehensive biomass maps across large landscapes. Moreover, the approach promotes sustainable forest management practices through non-destructive monitoring and improves the accuracy and generalizability of biomass estimation models.*

*Furthermore, the results obtained from various machine learning models, including Random Forest ($R^2$: 0.8315), Support Vector Machine (SVM) ($R^2$: 0.7810), demonstrate the effectiveness of these approaches in overcoming the limitations of traditional methods.*

*Moreover this research offers a comprehensive solution to biomass estimation challenges, providing accurate, scalable, and sustainable methods for environmental monitoring and management. By addressing the shortcomings of traditional models and leveraging advanced technologies, this study contributes to the advancement of biomass estimation methodologies and supports informed decision-making for ecosystem conservation and management.*

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