Comparative Analysis of UAVSAR Polarimetric Decompositions for Wetland Aboveground Biomass Mapping Using Machine Learning Models

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Abstract

Wetlands play a vital role in carbon sequestration, biodiversity conservation, and water regulation, making their accurate monitoring essential for environmental management. Synthetic Aperture Radar (SAR) is particularly effective for assessing wetland ecosystems due to its ability to penetrate vegetation and capture biomass dynamics under various weather conditions. This study leverages UAVSAR quad-polarization data to estimate aboveground biomass (AGB) in the wetlands of southern Louisiana, USA, a region with diverse wetland types and significant ecological importance. A total of 103 features were extracted from UAVSAR data using various polarimetric decomposition methods, including Zhang, Huynen, Van Zyl, and others. Three machine learning models, including Support Vector Machine (SVM), Random Forest (RF), and Histogram-based Gradient Boosting (HGB) were employed to evaluate the effectiveness of these decompositions. Results indicated that the Zhang decomposition, combined with HGB, achieved the highest accuracy with an R^2 of 0.74 and an RMSE of 183.95 g m^{-2}, outperforming other decomposition methods and classifiers. Additionally, RF showed strong performance, while SVM consistently underperformed. These findings highlight the potential of UAVSAR-derived polarimetric features for wetland biomass estimation, demonstrating that targeted decomposition selection and advanced machine learning models can enhance accuracy. This study provides valuable insights for improving wetland monitoring and conservation efforts, supporting ecosystem management, and climate change mitigation strategies.

1. Introduction

Wetlands are among the most productive and ecologically significant ecosystems on Earth, playing a crucial role in maintaining biodiversity, regulating water quality, and providing habitat for a wide range of species (Banks et al., 2019; Hemati et al., 2023). Beyond their biodiversity value, wetlands also serve a critical function in global carbon cycles. Although wetlands are one of the largest natural emitters of methane, their ability to sequester carbon outweighs their emissions, making them essential for climate change mitigation (Kleinen et al., 2023; Hemati et al., 2024a). These ecosystems are substantial carbon sinks, sequestering large amounts of carbon dioxide through both plant growth and the accumulation of organic matter in waterlogged conditions (Cao and Tzortziou, 2021). This process, referred to as "blue carbon," is vital for mitigating climate change, as wetlands store more carbon per unit area than forests (Kuwae et al., 2022). As such, wetland degradation, particularly through drainage or land-use changes, results in the release of significant amounts of stored carbon, contributing to global warming (Mitsch et al., 2013; Hemati et al., 2022). Understanding the carbon storage potential of wetlands, particularly through accurate estimation of aboveground biomass (AGB), is therefore essential for the conservation and management of these ecosystems, as well as for broader efforts in carbon sequestration and climate change mitigation (Sun et al., 2021).

AGB is a key variable for understanding the carbon storage capacity of wetland ecosystems, as it represents the amount of carbon stored in the aboveground portion of the vegetation. Accurate mapping of AGB provides insights into the health and function of wetlands, enabling better management and conservation practices (Chen et al., 2022). Traditional methods for AGB estimation, such as field-based biomass sampling, are often labor-intensive, expensive, and spatially limited. Furthermore, these methods are not always feasible in remote or difficult-to-reach wetland areas. Remote sensing technologies offer a practical and scalable alternative for large-scale biomass mapping, allowing for the estimation of AGB over vast and inaccessible areas (Jensen et al., 2021). Among the various remote sensing technologies, Synthetic Aperture Radar (SAR) stands out due to its ability to operate under all weather conditions and penetrate through cloud cover, making it particularly suitable for wetland monitoring (Berninger et al., 2018; Hemati et al., 2024b).

SAR systems, unlike optical remote sensing, capture information based on the backscattered microwave radiation from the Earth's surface, which is influenced by surface roughness, moisture content, and vegetation structure (Berninger et al., 2018). These properties make SAR an ideal tool for monitoring wetland vegetation, which often consists of dense, waterlogged, and heterogeneous plant types such as marshes, swamps, and mangroves. Additionally, SAR data are less affected by environmental factors like cloud cover and varying illumination angles, which pose challenges for optical systems (Dabboor et al., 2015). Within the SAR domain, UAVSAR (Unmanned Aerial Vehicle Synthetic Aperture Radar) has emerged as a powerful tool for high-resolution mapping, offering both fine spatial and polarimetric capabilities (Akhavan et al., 2021). UAVSAR's ability to capture multiple polarization channels enables the extraction of detailed information about the scattering mechanisms of different vegetation types, which is crucial for estimating biomass in complex wetland environments (Moreau and Le Toan, 2003). Polarimetric SAR, which analyzes the radar signal's interaction with the Earth's surface across different polarization states (e.g., horizontal-vertical, vertical-horizontal), provides unique insights into the structural and dielectric properties of vegetation (Adeli et al., 2021). This method is particularly useful for distinguishing between various types of vegetation and estimating biophysical parameters such as biomass, moisture content, and leaf area index (Mohammadimanesh et al., 2019).

Polarimetric decompositions, which break down the radar backscatter into different scattering mechanisms, are crucial for improving biomass estimation accuracy. These decompositions offer a more detailed understanding of the interactions between the radar signal and the vegetation, allowing for more robust interpretations of biomass density in wetlands (Ferguson and Gunn, 2022). Several polarimetric decomposition methods have been developed to enhance the interpretation of SAR data for biomass estimation. These include the Freeman decomposition (Ballester-Berman and Lopez-Sanchez, 2010), which separates the scattering into surface, volume, and double-bounce components; the Yamaguchi decomposition (Yamaguchi et al., 2005), which identifies volume scattering, surface scattering, and a combination of both; and the Zhang decomposition (Zhang et al., 2008), which focuses on separating the scattering contributions from vegetation and soil. Each method has its strengths and limitations depending on the specific characteristics of the vegetation and the radar system used. For example, the Zhang and Huynen decompositions are particularly useful for wetlands with dense, waterlogged vegetation, as they can distinguish between different types of scattering mechanisms (Hong et al., 2015).

In recent years, machine learning models have been increasingly applied to SAR data to improve the accuracy of AGB estimation. These models can handle large, complex datasets and capture non-linear relationships between the SAR features and biomass (Lapini et al., 2020). By combining polarimetric decompositions with machine learning algorithms, researchers can extract meaningful patterns from SAR data, leading to more accurate and efficient biomass estimation (Adeli et al., 2021). The use of machine learning also allows for the identification of important features and the optimization of model parameters, further improving the reliability of biomass predictions. This study aims to compare several polarimetric decomposition methods using UAVSAR data for wetland biomass estimation in the Mississippi River Delta, Louisiana. By integrating these decomposition techniques with machine learning models, we seek to identify the most effective combinations for AGB estimation. The results of this study will contribute to the growing body of research on SAR-based wetland monitoring and provide valuable insights for ecosystem management, carbon sequestration efforts, and climate change mitigation strategies.

2. Study Area and Ground Data

The study area is located in the coastal wetlands of southern Louisiana, encompassing hydrologic units defined by the United States Geological Survey (USGS) at Level-4 classification. This region includes the Mississippi River Delta (MRD) and the Western Louisiana Delta (WLD), two critical wetland ecosystems in the United States (Olson and Suski, 2021). These deltas are essential for understanding the broader dynamics of coastal wetland systems and their role in carbon sequestration, flood regulation, and habitat provision (Jensen et al., 2021). Figure 1 shows the study area region, along with field data sampling sites and Pauli RGB (Maitra et al., 2012) images of the UAVSAR dataset.

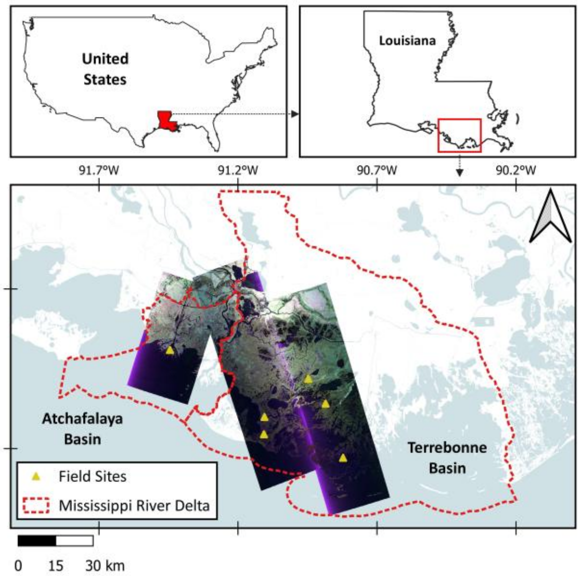

Figure 1. Study area region, UAVSAR Pauli RGB, and field sampling sites.

The Mississippi River Delta is a dynamic landscape shaped by both natural processes and human interventions. A key feature of this region is the presence of river diversions, such as the one implemented in the 1940s to control channel flow to Morgan City and reduce flooding risks. The WLD became subaerial in 1973 due to a previous river diversion and continues to receive sediment from river floods and organic matter production (Jensen, D.J. et al., 2022). This region is also affected by hurricanes, tidal freshwater species, and seasonal water level variations, making it a valuable area for studying sea-level rise and land loss. The study area spans the Atchafalaya and Terrebonne basins, each with distinct vegetation influenced by local hydrogeomorphic zones, including supratidal, intertidal, and subtidal areas (Castaneda et al., 2020). These basins receive approximately 30% of the Mississippi River’s water discharge, with the Atchafalaya River outlet contributing 10%, further shaping the dynamic hydrological processes.

The Delta-X mission, part of NASA’s Earth Venture Suborbital-3 project, provides critical data for monitoring the ecological health of the MRD and WLD. Over five years, Delta-X has collected airborne and in situ data to predict deltaic land loss or gain and assess wetland degradation impacts (Castañeda-Moya, E. and Solohin, E., 2022). This study will leverage Delta-X data to improve SAR-based biomass estimation, focusing on biomass dynamics. Field campaigns, conducted in spring (March 19 – April 2, 2021) and fall (August 19 – August 27, 2021), captured seasonal variations in vegetation, with 86 AGB samples collected in spring and 96 in fall (Castañeda-Moya, E. and Solohin, E., 2022). Samples were collected along transects perpendicular to the wetland boundary to capture various hydrogeomorphic zones spanning freshwater, brackish, and saline environments. Two sampling stations were established at 30-meter intervals, with vegetation structure assessed and AGB measured in duplicate 0.25 m² plots, positioned 5 meters apart. Plant material was clipped at soil level, transported to the lab, and analyzed, with biomass values reported in grams per square meter (g m^{-2}). The Delta-X ground-truth data play a crucial role in training and validating SAR-based biomass estimation models. By sampling AGB, necromass (AGN), and nutrient content (carbon, nitrogen, and phosphorus), the mission provides a comprehensive dataset for assessing wetland vegetation across hydrogeomorphic zones. This dataset supports evaluating different polarimetric decomposition methods and machine learning models for AGB estimation using UAVSAR data. The seasonal sampling approach ensures that models account for biomass variations, enhancing prediction accuracy throughout the year (Hemati et al., 2025).

3. Materials and Methods

3.1 UAVSAR Dataset

In this study, UAVSAR data were utilized to analyze the wetland AGB and assess hydrological processes within the study area. The data used in this research include UAVSAR Level 1 (L1) Single Look Complex (SLC) stack products collected during the Delta-X flight campaign in 2021 (Jones et al., 2022). These datasets were acquired over the Atchafalaya and Terrebonne Basins, located in the southern region of Louisiana, USA. The data were obtained during two distinct timeframes: from March 27 to April 18, 2021 (spring season) and from September 3 to September 13, 2021 (fall season). UAVSAR is a polarimetric L-band SAR flown on the NASA Gulfstream-III (C20) aircraft. It is designed for high-precision interferometry (InSAR) with a swath width of 22 km, an incidence angle ranging from 22° to 67°, and a spatial resolution of approximately 3 m (cross-track average) by 1 m (along-track). The radar operates at a frequency of 1217.5–1297.5 GHz, with an 80 MHz bandwidth, and employs quad-polarization modes (HH, HV, VH, and VV) to capture a variety of scattering mechanisms from the wetland surfaces.

A 3×3 Refined Lee filter was applied to the UAVSAR data to reduce speckle noise while preserving spatial details (Yommy et al., 2015). This approach maintained a balance between noise reduction and spatial resolution, allowing for accurate biomass estimation. The UAVSAR data acquisition system includes a Platform Precision Autopilot (PPA) to ensure the accuracy of flight track repeatability and antenna steering, enabling precise data collection during the airborne campaign. The instrument’s electronic steering capability and onboard monitoring software ensured that data were collected with minimal deviations from the planned flight paths, contributing to the high spatial and temporal accuracy of the resulting products. These high-resolution, multi-temporal UAVSAR data are critical for capturing subtle changes in the wetland landscape and for the evaluation of biomass dynamics in relation to hydrological changes within the study area. The UAVSAR data, along with in situ data, provide a comprehensive approach to understanding the ecological processes in the coastal wetlands of Louisiana.

3.2 Polarimetric Decompositions

The UAVSAR quad-polarization data used in this study were preprocessed using PolSARPro 6.0, specialized software for polarimetric SAR data processing. The preprocessing involved applying necessary corrections to the raw data, including calibration and georeferencing. Once the data were preprocessed, the C3 covariance matrix was extracted from the UAVSAR dataset, which provided the basis for the polarimetric decompositions. Several polarimetric decomposition methods were applied to the C3 covariance matrix, enabling the extraction of key features that characterize different scattering mechanisms. These decompositions allow for a more detailed analysis of the wetland's surface and vegetation structure, which is essential for biomass estimation and hydrological analysis. The binary outputs from the decompositions were then converted into GeoTIFF format for easier processing and further analysis. Polarimetric decompositions used in this study are listed in Table 1. All polarimetric decomposition features were extracted using default parameter settings with a 3×3 window size to ensure consistency in feature generation.

Decomposition Method	**Key Features**	**Number of features**
Aghababaee	Scattering matrix components	18
H/A/Alpha	Entropy (H), Anisotropy (A), Alpha (α)	4
Eigenvalue Set Parameters	Eigenvalue decomposition	15
Freeman	Surface, volume, double-bounce components	3
Diversity Indices	Scattering diversity	7
Zhang	Surface and volume scattering	6
Singh	Angular scattering characteristics	10
Touzi	Entropy and randomness	16
Van Zyl	Eigenvector analysis	3
Yamaguchi	Scattering types differentiation	4
Huynen	Polarization state and scattering parameters	3

Table 1. Decomposition methods were used in this study.

Each decomposition technique was chosen for its ability to reveal different physical characteristics of the wetland landscape, such as volume scattering (which is related to vegetation) and surface scattering (important for wetland surface analysis). The extracted features were integrated into machine learning models to improve biomass estimation modeling in the study area. By applying these polarimetric decomposition methods to the UAVSAR data, we were able to effectively characterize the wetland ecosystem's dynamics and estimate biomass more accurately. The conversion of the outputs into GeoTIFF format further facilitated the integration of these data into the analysis pipeline, enabling more efficient processing and visualization.

3.3 Machine Learning and Evaluation

To evaluate the effectiveness of different polarimetric SAR decompositions in estimating AGB in wetlands, we employed three machine learning models: Support Vector Machine (SVM), Random Forest (RF), and Histogram-based Gradient Boosting (HGB). These models were chosen to ensure that the comparison of decompositions was not biased toward a single machine learning algorithm while leveraging a variety of modeling techniques. SVM provides a kernel-based regression approach that can capture nonlinear relationships. The NuSVR variant of SVM was used to estimate aboveground biomass, offering a flexible approach to handle nonlinear relationships in the data. RF is an ensemble learning method that enhances predictive accuracy by aggregating multiple decision trees, and HGB offers an efficient gradient-boosting method that can handle complex interactions among features. By using these diverse models, we ensured a comprehensive analysis of how different polarimetric features contribute to biomass estimation.

To utilize the UAVSAR-derived features in AGB estimation, we initially included all 103 extracted features from various polarimetric decompositions and covariance matrix elements. However, this approach proved inefficient and did not yield the best results due to multiple factors. Many of the polarimetric decompositions describe similar scattering mechanisms but apply different mathematical formulations, leading to significant redundancy in the dataset. For example, the double-bounce scattering mechanism is represented in multiple decomposition methods, such as Freeman, Yamaguchi, and Van Zyl, each with slightly different parameterization. Using all of these features together introduces high collinearity without adding substantial new information, making feature selection critical for improving model performance. Additionally, the presence of irrelevant or redundant features can increase computational complexity and potentially degrade model accuracy. To address these challenges, we performed Principal Component Analysis (PCA) to determine the intrinsic dimensionality of the dataset and to identify the most significant components that capture the majority of the variance. PCA allowed us to reduce the dimensionality of the feature space while retaining the most informative components, improving computational efficiency, and reducing the risk of overfitting. Furthermore, we employed RF and Linear Regression (LR) to assess feature importance when all 103 features were included together. This provided insights into which decompositions contributed most significantly to AGB estimation, allowing us to refine our feature selection strategy.

Beyond feature importance analysis, we explored different subsets of features to systematically evaluate their impact on model accuracy and generalization. Various groupings of polarimetric decompositions were tested to understand their individual and combined contributions. For example, we tested models using only H/A/Alpha features, scattering-based decompositions, or eigenvalue-based parameters to assess their standalone performance. This iterative process enabled us to determine the optimal feature subset that balances accuracy, interpretability, and computational efficiency. The dataset was split into training (70%) and testing (30%) sets, ensuring a balanced representation of biomass values across different wetland types. Model performance was assessed using statistical metrics, including the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), to quantify prediction accuracy. To prevent overfitting and improve generalization, we optimized model hyperparameters through cross-validation, ensuring that the trained models could perform well on unseen data. By systematically evaluating the impact of different decomposition methods and feature selection strategies, we gained deeper insights into the most effective polarimetric features for wetland biomass estimation. This analysis not only improved the predictive accuracy of AGB models but also contributed to a better understanding of the role of SAR-based decomposition techniques in characterizing wetland vegetation structures. The findings from this study can guide future efforts in optimizing feature selection for biomass mapping using UAVSAR and other polarimetric SAR data.

4. Results and Discussions

In the analysis of UAVSAR-derived polarimetric decomposition features, PCA was applied to determine the intrinsic dimensionality of the dataset. The cumulative explained variance curve, as shown in Figure 2, illustrates how the variance in the data is distributed across different principal components. The results indicate that the first few components capture the majority of the variance, with the first 17 principal components explaining approximately 95% of the total variance. This suggests that although 103 features were initially extracted, a significant portion of the information is concentrated within a smaller subset of key features. This finding highlights the presence of redundancy in the dataset, as many polarimetric decompositions describe similar scattering mechanisms. By reducing the dimensionality while preserving most of the variance, PCA enables a more efficient representation of the data, which is crucial for improving the performance and interpretability of machine learning models. The identification of 17 principal components as the optimal feature subset provides a strong foundation for selecting relevant variables for biomass estimation while minimizing computational complexity and the risk of overfitting.

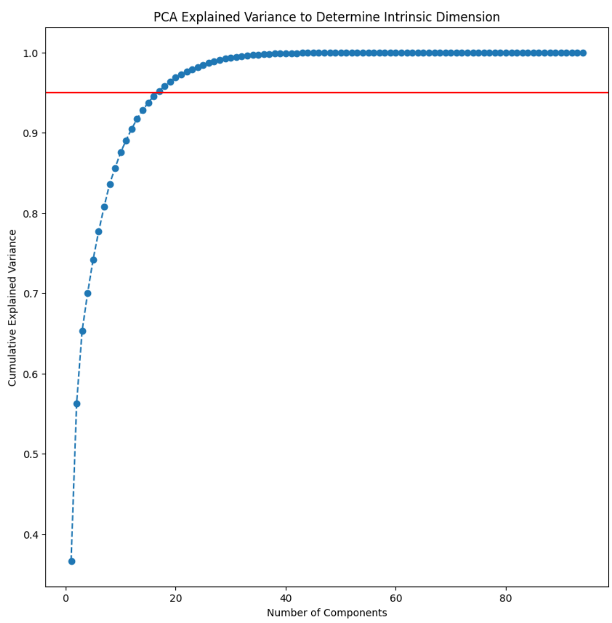

Figure 2. Cumulative explained variance based on the number of PCA components.

To determine the contribution of each decomposition method to AGB estimation, we analyzed feature importance using two approaches: RF importance scores and LR coefficients. The goal was to assess which decomposition techniques provided the most useful information for biomass prediction and to compare their relative influence across different modeling approaches. RF importance was calculated based on the mean decrease in impurity, which measures how much each feature contributes to reducing the variance in biomass estimation. Higher values indicate features that play a more significant role in model predictions. In contrast, LR coefficients represent the weight assigned to each feature in a linear model, reflecting its direct relationship with AGB. To ensure a fair comparison between these two approaches, we normalized both importance values and regression coefficients to a common scale and aggregated them by the decomposition method.

The results revealed distinct differences in feature importance across decomposition techniques. Eigenvalue set parameters exhibited the highest overall contribution in RF (61.95%), highlighting their strong influence in nonlinear regression models. Aghababaee decomposition also showed notable importance in both methods, with 11.34% in RF and the highest contribution (18.85%) in LR. The Touzi decomposition ranked third in overall importance, particularly in RF (14.30%), indicating its potential relevance in biomass estimation. Other decomposition methods, such as H/A/Alpha and diversity indices, demonstrated lower importance, suggesting that they contribute less unique information compared to dominant features. A graphical representation of these findings is shown in Figure 3, which presents a side-by-side comparison of the decomposition method's importance in RF and LR. Each method is represented by two bars, one for RF importance and another for LR coefficients, allowing for a direct visual assessment of their respective contributions. By integrating feature importance from different modeling perspectives, this analysis provides valuable insights into the role of polarimetric decompositions in biomass mapping. It also supports more informed feature selection, guiding future studies toward the most effective SAR-based predictors for wetland vegetation characterization.

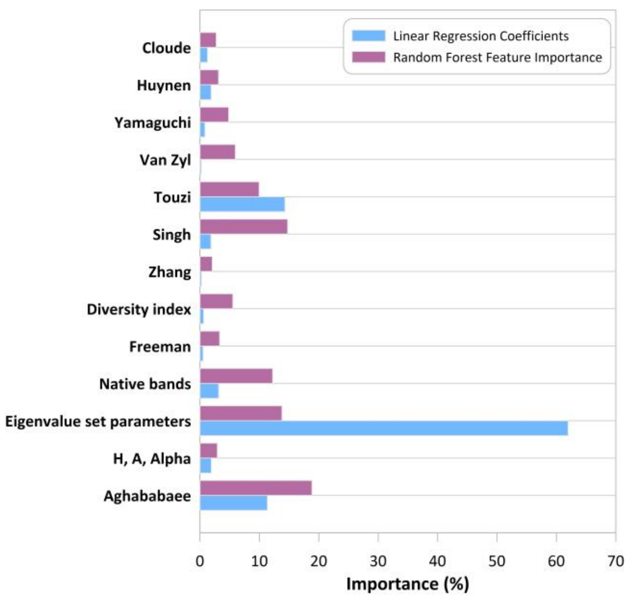

Figure 3. Aggregated feature importance of different decompositions.

To further understand the standalone performance of each decomposition method, we evaluated their predictive accuracy in biomass estimation when used individually alongside the original UAVSAR bands. This approach helped assess how well each decomposition method contributes to biomass estimation without the influence of other decompositions. We used three machine learning models, SVM, RF, and HGB, to ensure that the comparison of decompositions was not biased toward a single algorithm and to capture the strengths of different modeling approaches. Each decomposition method was tested separately by training the models on features derived from that specific decomposition along with the original SAR bands. The models were assessed using MAE, RMSE, and R^2. The results varied significantly across decomposition methods and machine learning models.

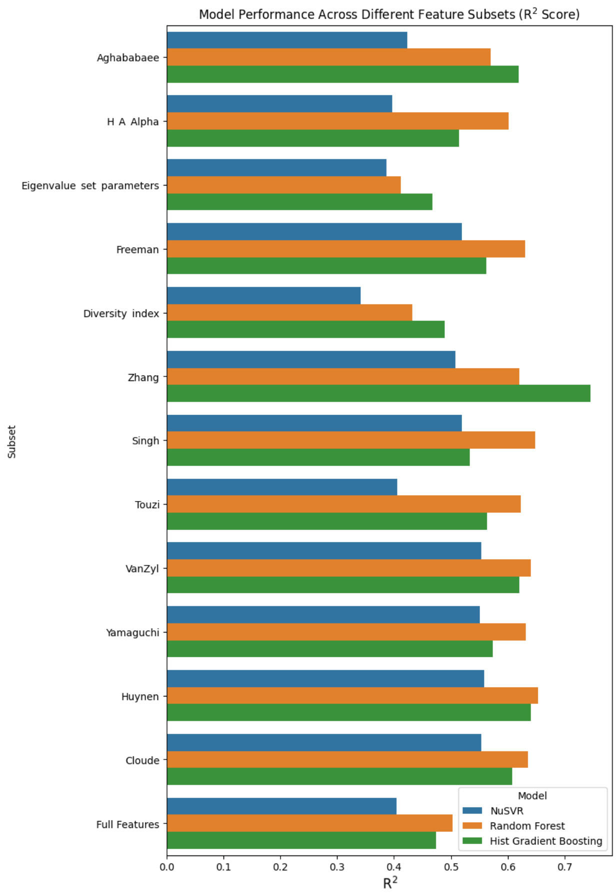

Figure 4. The R^2 score of different machine learning models using different decomposition methods.

The performance evaluation clearly indicates that the Zhang decomposition method provided the best overall results across all machine learning models. In particular, when combined with HGB, Zhang achieved an R^2 of 0.74, an RMSE of 183.95 g m^{-2}, and an MAE of 152.61 g m^{-2}, demonstrating its superior ability to capture the vital scattering characteristics that relate to AGB. Following Zhang, the Huynen and Van Zyl decompositions also showed promising performance, ranking next in terms of predictive accuracy. When comparing the machine learning classifiers, HGB generally delivered the highest average performance, closely followed by RF. In contrast, SVM consistently underperformed relative to the other two models, indicating that ensemble-based and boosting methods are better suited to handle the complex, nonlinear relationships inherent in the polarimetric features derived from UAVSAR data.

Interestingly, the full feature set, containing all decompositions, yielded the poorest accuracy, further reinforcing that using all features together is not the most effective approach. This highlights the importance of feature selection and using the decomposition methods for AGB estimations in wetlands. This result aligns with our earlier feature importance analysis, indicating that certain decomposition techniques contribute redundant or overlapping information. The findings suggest that specific decomposition methods, particularly Zhang, Huynen, and Van Zyl, are more informative for biomass estimation than others. The performance differences among models also highlight the importance of selecting an appropriate machine learning algorithm when working with SAR-derived features for vegetation mapping. These insights will help refine feature selection strategies and improve the efficiency of biomass estimation models.

5. Conclusions

This study demonstrated the effectiveness of polarimetric decomposition methods for estimating AGB in wetland ecosystems using UAVSAR data. Among the decompositions evaluated, the Zhang method exhibited the highest predictive performance when combined with HGB, achieving an R^2 of 0.74, an RMSE of 183.95 g m^{-2}, and an MAE of 152.61 g m^{-2}. Huynen and Van Zyl followed closely, indicating that these methods effectively capture critical scattering mechanisms relevant to biomass estimation. Conversely, the use of full resulted in one of the poorest performances, highlighting the necessity of targeted feature selection to mitigate redundancy. Comparisons among machine learning classifiers revealed that HGB consistently outperformed the other models, with RF showing competitive results, while SVM demonstrated notably lower performance across all decomposition methods. The superior outcomes achieved by ensemble-based and boosting techniques suggest that they are better equipped to handle the complexity and nonlinear relationships inherent in the polarimetric features derived from UAVSAR data. Additionally, the application of PCA helped reduce dimensionality and improve model efficiency by identifying the intrinsic structure of the dataset. These findings underline the potential of UAVSAR-derived polarimetric features for accurate AGB mapping in wetlands. By refining feature selection and leveraging robust machine learning methodologies, particularly HGB and RF, our approach promises more accurate and efficient biomass monitoring, thereby enhancing ecosystem management and supporting climate change mitigation strategies.

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References

Adeli, S., Salehi, B., Mahidanpari, M., Quackenbush, L.J., Chapman, B., 2021. Wetland Classification Using Simulated NISAR Data: a case study in Louisiana, in: 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS. Presented at the IGARSS 2021 - 2021 IEEE International Geoscience and Remote Sensing Symposium, IEEE, Brussels, Belgium, pp. 100–103. https://doi.org/10.1109/IGARSS47720.2021.9553878

Akhavan, Z., Hasanlou, M., Hosseini, M., McNairn, H., 2021. Decomposition-Based Soil Moisture Estimation Using UAVSAR Fully Polarimetric Images. Agronomy 11, 145. https://doi.org/10.3390/agronomy11010145

Ballester-Berman, J.D., Lopez-Sanchez, J.M., 2010. Applying the Freeman–Durden Decomposition Concept to Polarimetric SAR Interferometry. IEEE Transactions on Geoscience and Remote Sensing 48, 466–479. https://doi.org/10.1109/TGRS.2009.2024304

Banks, S., White, L., Behnamian, A., Chen, Z., Montpetit, B., Brisco, B., Pasher, J., Duffe, J., 2019. Wetland Classification with Multi-Angle/Temporal SAR Using Random Forests. Remote Sensing 11, 670. https://doi.org/10.3390/rs11060670

Berninger, A., Lohberger, S., Stängel, M., Siegert, F., 2018. SAR-Based Estimation of Above-Ground Biomass and Its Changes in Tropical Forests of Kalimantan Using L- and C-Band. Remote Sensing 10, 831. https://doi.org/10.3390/rs10060831

Cao, F., Tzortziou, M., 2021. Capturing dissolved organic carbon dynamics with Landsat-8 and Sentinel-2 in tidally influenced wetland–estuarine systems. Science of The Total Environment 777, 145910. https://doi.org/10.1016/j.scitotenv.2021.145910

Castaneda, E., Christensen, A.I., Simard, M., Bevington, A., Twilley, R., Mccall, A., 2020. Pre-Delta-X: Vegetation Species, Structure, Aboveground Biomass, MRD, LA, USA, 2015. https://doi.org/10.3334/ORNLDAAC/1805

Castañeda-Moya, E., Solohin, E., 2022. Delta-X: Aboveground Biomass and Necromass across Wetlands, MRD, Louisiana, 2021. https://doi.org/10.3334/ORNLDAAC/2000

Chen, C., Ma, Y., Ren, G., Wang, J., 2022. Aboveground biomass of salt-marsh vegetation in coastal wetlands: Sample expansion of in situ hyperspectral and Sentinel-2 data using a generative adversarial network. Remote Sensing of Environment 270, 112885. https://doi.org/10.1016/j.rse.2021.112885

Dabboor, M., White, L., Brisco, B., Charbonneau, F., 2015. Change Detection with Compact Polarimetric SAR for Monitoring Wetlands. Canadian Journal of Remote Sensing 41, 408–417. https://doi.org/10.1080/07038992.2015.1104634

Ferguson, J.E., Gunn, G.E., 2022. Polarimetric decomposition of microwave-band freshwater ice SAR data: Review, analysis, and future directions. Remote Sensing of Environment 280, 113176. https://doi.org/10.1016/j.rse.2022.113176

Hemati, M., Mahdianpari, M., Hasanlou, M., Mohammadimanesh, F., 2022. Iranian Wetland Hydroperiod Change Detection Using an Unsupervised Method on 20 Years of Landsat Data Within the Google Earth Engine, in: IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium. Presented at the IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, IEEE, Kuala Lumpur, Malaysia, pp. 6209–6212. https://doi.org/10.1109/IGARSS46834.2022.9884716

Hemati, M., Mahdianpari, M., Nassar, R., Shiri, H., Mohammadimanesh, F., 2024a. Urban methane emission monitoring across North America using TROPOMI data: an analytical inversion approach. Sci Rep 14, 9041. https://doi.org/10.1038/s41598-024-58995-8

Hemati, M., Mahdianpari, M., Shiri, H., Mohammadimanesh, F., 2024b. Integrating SAR and Optical Data for Aboveground Biomass Estimation of Coastal

Wetlands Using Machine Learning: Multi-Scale Approach. Remote Sensing 16, 831. https://doi.org/10.3390/rs16050831

Hemati, M., Mahdianpari, M., Shiri, H., Mohammadimanesh, F., 2023. Comprehensive Landsat-Based Analysis of Long-Term Surface Water Dynamics over Wetlands and Waterbodies in North America. Canadian Journal of Remote Sensing 50, 2293058. https://doi.org/10.1080/07038992.2023.2293058

Hemati, M., Mahdianpari, M., Shiri, H., Mohammadimanesh, F., Salehi, B., Wu, J., 2025. Advancing wetland aboveground biomass mapping: Insights from high-resolution PlanetScope data in the Mississippi River Delta. Remote Sensing Applications: Society and Environment 38, 101604. https://doi.org/10.1016/j.rsase.2025.101604

Hong, S.-H., Kim, H.-O., Wdowinski, S., Feliciano, E., 2015. Evaluation of Polarimetric SAR Decomposition for Classifying Wetland Vegetation Types. Remote Sensing 7, 8563–8585. https://doi.org/10.3390/rs70708563

Jensen, D., Cavanaugh, K.C., Simard, M., Christensen, A., Rovai, A., Twilley, R., 2021. Aboveground biomass distributions and vegetation composition changes in Louisiana's Wax Lake Delta. Estuarine, Coastal and Shelf Science 250, 107139. https://doi.org/10.1016/j.ecss.2020.107139

Jensen, D.J., Castañeda-Moya, E., Solohin, E., Rovai, A., Thompson, D.R., Simard, M., 2022. Delta-X: Herbaceous Aboveground Biomass from AVIRIS-NG, MRD, Louisiana, USA, 2021 0 MB. https://doi.org/10.3334/ORNLDAAC/2107

Jones, C., Simard, M., Lou, Y., Oliver-Cabrera, T., 2022. Delta-X: UAVSAR L1 Single Look Complex (SLC) Stack Products, MRD, Louisiana, 2021. https://doi.org/10.3334/ORNLDAAC/1984

Kleinen, T., Gromov, S., Steil, B., Brovkin, V., 2023. Atmospheric methane since the last glacial maximum was driven by wetland sources. Clim. Past 19, 1081–1099. https://doi.org/10.5194/cp-19-1081-2023

Kuwae, T., Watanabe, A., Yoshihara, S., Suehiro, F., Sugimura, Y., 2022. Implementation of blue carbon offset crediting for seagrass meadows, macroalgal beds, and macroalgae farming in Japan. Marine Policy 138, 104996. https://doi.org/10.1016/j.marpol.2022.104996

Lapini, A., Pettinato, S., Santi, E., Paloscia, S., Fontanelli, G., Garzelli, A., 2020. Comparison of Machine Learning Methods Applied to SAR Images for Forest Classification in Mediterranean Areas. Remote Sensing 12, 369. https://doi.org/10.3390/rs12030369

Maitra, S., Gartley, M.G., Kerekes, J.P., 2012. Relation between degree of polarization and Pauli color coded image to characterize scattering mechanisms, in: Polarization: Measurement, Analysis, and Remote Sensing X. Presented at the Polarization: Measurement, Analysis, and Remote Sensing X, SPIE, pp. 128–136. https://doi.org/10.1117/12.918486

Mitsch, W.J., Bernal, B., Nahlik, A.M., Mander, Ü., Zhang, L., Anderson, C.J., Jørgensen, S.E., Brix, H., 2013. Wetlands, carbon, and climate change. Landscape Ecol 28, 583–597. https://doi.org/10.1007/s10980-012-9758-8

Mohammadimanesh, F., Salehi, B., Mahdianpari, M., Brisco, B., Gill, E., 2019. Full and Simulated Compact Polarimetry SAR Responses to Canadian Wetlands: Separability Analysis and Classification. Remote Sensing 11, 516. https://doi.org/10.3390/rs11050516

Moreau, S., Le Toan, T., 2003. Biomass quantification of Andean wetland forages using ERS satellite SAR data for optimizing livestock management. Remote Sensing of Environment 84, 477–492. https://doi.org/10.1016/S0034-4257(02)00111-6

Olson, K.R., Suski, C.D., 2021. Mississippi River Delta: Land Subsidence and Coastal Erosion. Open Journal of Soil Science 11, 139. https://doi.org/10.4236/ojss.2021.113008

Sun, S., Wang, Y., Song, Z., Chen, C., Zhang, Y., Chen, X., Chen, W., Yuan, W., Wu, X., Ran, X., Wang, Y., Li, Q., Wu, L., 2021. Modelling aboveground biomass carbon stock of the bohai rim coastal wetlands by integrating remote sensing, terrain, and climate data. Remote Sensing 13. https://doi.org/10.3390/rs13214321

Yamaguchi, Y., Moriyama, T., Ishido, M., Yamada, H., 2005. Four-component scattering model for polarimetric SAR image decomposition. IEEE Transactions on Geoscience and Remote Sensing 43, 1699–1706. https://doi.org/10.1109/TGRS.2005.852084

Yommy, A.S., Liu, R., Wu, Shuang, 2015. SAR Image Despeckling Using Refined Lee Filter, in: 2015 7th International Conference on Intelligent Human-Machine Systems and Cybernetics. Presented at the 2015 7th International Conference on Intelligent Human-Machine Systems and Cybernetics, pp. 260–265. https://doi.org/10.1109/IHMSC.2015.236

Zhang, L., Zou, B., Cai, H., Zhang, Y., 2008. Multiple-Component Scattering Model for Polarimetric SAR Image Decomposition. IEEE Geoscience and Remote Sensing Letters 5, 603–607. https://doi.org/10.1109/LGRS.2008.2000795