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The Use of High-Resolution Satellite Imagery and Artificial Intelligence for Above-ground Biomass Modelling in the Mediterranean Region: A Review

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Abstract

The aim of this paper is to provide a comprehensive review, based on recently published papers and compare information regarding Above-ground biomass (AGB) modelling, data sources, methodology, and model accuracy. To fulfill the objectives of the INNO4CFIs project and as an output of this study, we propose utilizing high-resolution surface reflectance data acquired from commercial satellites for index and feature derivation. Integrating Digital Surface Models (DSM) and Digital Terrain Models (DTM) derived from Light Detection and Ranging (LiDAR), or Synthetic Aperture Radar (SAR) data, enhances the accuracy of biomass prediction. The Random forest (RF) model excels in incorporating multiple features, thus adeptly capturing sample characteristics.

Keywords: Above-ground Biomass; Satellite Imagery; Artificial Intelligence

Introduction

Climate change poses significant challenges to Mediterranean ecosystems, affecting environmental sustainability and socio-economic stability. The Intergovernmental Panel on Climate Change (IPCC, 2014) highlights the urgent need to address these issues, emphasizing the detrimental impact of emissions from various sources on the delicate ecological balance within the region (Giorgi, 2006).

Agroforestry to Mitigate Climate Change

In response to these challenges, agroforestry has emerged as a promising strategy to mitigate the effects of climate change through its multifaceted contributions to carbon sequestration, biodiversity conservation, and sustainable land management. Numerous scientific studies provide robust evidence supporting the efficacy of agroforestry in climate change mitigation. Agroforestry practices, as outlined by Nair et al. (2009), offer opportunities for carbon sequestration and the enhancement of ecosystem resilience. Additionally, agroforestry promotes biodiversity conservation by providing habitat and food resources for a diverse range of plant and animal species. Asner et al. (2014) demonstrated that agroforestry landscapes support higher levels of biodiversity compared to conventional agricultural systems, thereby contributing to ecosystem resilience in the face of climate change. According to Jose, (2009), agroforestry practices enhance soil fertility, reduce erosion, and provide additional income opportunities for farmers.

Remote Sensing and AI for Agroforestry AGB

To monitor the impact of agroforestry practices it becomes necessary to model and estimate the AGB. By quantifying the amount of biomass present in agroforestry systems, we can assess their productivity, carbon sequestration potential, and overall ecological health. This data allows us to evaluate the effectiveness of different agroforestry techniques in enhancing soil fertility, mitigating climate change, and promoting biodiversity.

Calculating agroforestry biomass using satellite imagery and Artificial Intelligence (AI) offers a sophisticated and accurate approach that has gained traction in recent years. Scientific literature provides compelling evidence supporting the effectiveness of this methodology.

Recent advancements in high-resolution remote sensing data and AI techniques have revolutionized biomass estimation (Asner et al., 2014). According to Ploton et al. (2017), Very high spatial resolution (VHSR) optical satellite imagery has demonstrated potential in estimating forest AGB by analyzing canopy texture. Research by Lu et al. (2019) and Fang et al. (2020) showcases the effectiveness of AI methodologies, such as convolutional neural networks (CNNs) and RF, in analyzing satellite imagery to predict biomass levels with high precision. These AI-based approaches leverage the wealth of information contained in satellite data to improve the reliability of emission calculations.

By leveraging these technologies, researchers aim to improve the accuracy and efficiency of biomass estimation, facilitating informed decision-making for sustainable resource management (Naidoo & Adam, 2011). However, accurately quantifying biomass in agroforestry systems remains a complex task (Montagnini & Nair, 2004), particularly in the Mediterranean climate, characterized by its unique environmental conditions (Giorgi, 2006).

Mediterranean Climate and Biodiversity

The Mediterranean climate supports a remarkable diversity of plant and animal species adapted to its unique environmental conditions. Research by Myers et al. (2000) highlights the Mediterranean Basin as one of the world's biodiversity hotspots, with a wealth of endemic species found in its diverse ecosystems. The combination of mild, wet winters and hot, dry summers creates a mosaic of habitats ranging from Mediterranean forests to shrublands and coastal ecosystems, fostering high levels of species richness and endemism.

Furthermore, the Mediterranean climate significantly influences ecosystem functioning and species interactions. Studies such as Ojeda et al. (2010) demonstrate the role of seasonal rainfall patterns in shaping plant community composition and structure. Variations in precipitation regimes, including droughts and wet periods, can have profound effects on vegetation dynamics, species distribution, and ecosystem resilience.

INNO4CFIs Project and Objectives of this Study

The project "Nature-Based Business Model and Emerging INNOvations to enhance Carbon Farming Initiatives (CFIs) while preserving Biodiversity, Water Security, and Soil Health" (INNO4CFIs) is a European project co-funded by the European Commission under the Interregional Innovation Investments (I3) instrument (Grant Agreement no. 101115156). INNO4CFIs aims to create a Carbon Farm Technology Platform for peer-to-peer carbon credits exchange as an outcome of the model elaborated on the integration of different technologies: Mangrove Technology, Mycelium-based Technology, Carbon Storage Tracker, Satellite-based technologies, UAV-based technologies and Blockchain-based Solution to be validated in four different living hubs (GR, IT, SP, BE) to increase CO2 uptake while promoting crucial environmental co-benefits such as sustainable freshwater production, dry-land and soil restoration and biodiversity promotion.

This paper serves as a comprehensive review, synthesizing findings from various scientific literature papers within the framework of the INNO4CFIs project. Through a systematic examination of existing research, we aim to lighten the current state of knowledge regarding biomass calculation methodologies, and the role of high-resolution remote sensing datasets and AI in Mediterranean ecosystems. Ultimately, this synthesis will contribute to advancing our understanding of climate-friendly solutions and guiding future research endeavors to promote resilience in Mediterranean regions.

Methodology

The methodology employed in this paper follows the systematic review framework delineated by Aromataris (2014), encompassing three primary stages: (1) identification of closely related topics, (2) extraction of pertinent information, and (3) analysis facilitating comprehensive discussion. Figure 1 illustrates the flow of the systematic review flow.

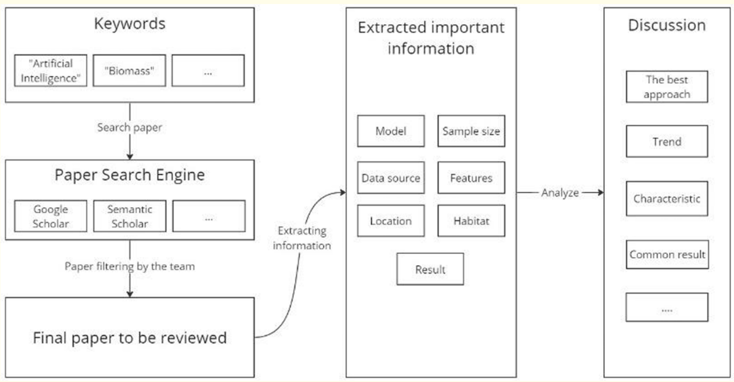

Figure 1: Flow of the systematic review.

This review is dedicated to examining literature related to the utilization of AI in conjunction with high-resolution satellite imagery for AGB within Mediterranean ecosystems. To facilitate the retrieval of relevant literature, specific keywords such as “artificial intelligence”, “machine learning”, “biomass”, “high-resolution imagery”, “agroforestry”, “Europe”, and “Mediterranean” are employed as filters during the literature search process. These keywords are systematically applied across academic databases, including but not limited to Google Scholar, to identify papers that align with the scope of this review.

Subsequently, the extraction of essential information entails the compilation of key data points from the selected papers. Essential information varies depending on the specific focus of the review. In the context of this study, critical information encompasses details regarding the utilized AI or machine learning models, the features or datasets employed for model training, the geographical locations of the research, the habitat, species, or forest types under investigation, and the resultant model outcomes and accuracy metrics. A comprehensive explanation of these extracted data points is provided in Table 1.

After all pertinent data from the gathered papers are collected, we can start the analysis aimed at discerning patterns, evaluating strengths and weaknesses, and identifying optimal approaches for biomass modelling utilizing AI and high-resolution imagery within Mediterranean regions. This analytical endeavor seeks to elucidate the most viable methodologies for the INNO4CFIs project, thereby facilitating informed decisionmaking regarding approach selection.

S. No	Information	Description
1	AI model	AI or ML model used to train and predict biomass. E.g SVM, Random forest.
2	Sample size	How many samples were used to train the model E.g 1000 field samples, 80% for train, 10% for test
3	Data source	Source of data used to train the model such as Landsat, Sentinel-2, SRTM DEM, and Field data.
4	Features	Data derived from data sources that are used
5	Land cover type and species	Characteristics of the forest or species being mapped or modeled on such as Mediterranean arid forest, coniferous forest, and beech tree.
6	Location	Location of the research by region or administrative E.g Ede, Netherlands
7	Result/Accuracy	The accuracy or performance of the model E.g R2=0.8

Table 1: Important Information extracted from each paper analysis.

Body

Reviewed Literature Overview and Locations

After conducting the systematic literature search process, a total of 12 papers were selected and included in this review (see Table 2).

Study	Title	Country
Adar et al. (2022)	Estimation of aboveground biomass production using an unmanned aerial vehicle (UAV) and VENμs satellite imagery in Mediterranean and semiarid rangelands	Israel
Fassnacht et al. (2017)	Estimating stand density, biomass, and tree species from very high resolution stereo-imagery towards an all-in-one sensor for forestry applications?	Germany
Goméz et al. (2012)	Modeling Forest Structural Parameters in the Mediterranean Pines of Central Spain using QuickBird-2 Imagery and Classification and Regression Tree Analysis (CART)	Spain
De Jong et al. (2003)	Above-ground biomass assessment of Mediterranean forests using airborne imaging spectrometry: the DAIS Peyne experiment	France
Kattenborn et al. (2015)	Mapping forest biomass from space Fusion of hyperspectral EO1-hyperion data and Tandem-X and WorldView-2 canopy height models.	Germany
Lourenco et al. (2021)	Estimating tree aboveground biomass using multispectral satellite-based data in Mediterranean agroforestry system using random forest algorithm	Portugal
Maack et al. (2015)	Modeling forest biomass using Very-High-Resolution data Combining Textural, spectral and photogrammetric predictors derived from spaceborne stereo images	Germany
Ploton et al. (2017)	Toward a general tropical forest biomass prediction model from very high resolution optical satellite images	Central Africa
RodriguezLozano et al. (2021)	Non-Destructive Biomass Estimation in Mediterranean Alpha Steppes: Improving Traditional Methods for Measuring Dry and Green Fractions by Combining Proximal Remote Sensing Tools	Spain
Santi et al. (2014)	The potential of multifrequency SAR images for estimating forest biomass in Mediterranean areas. Remote Sensing of Environment	Italy

Santi et al. (2017)	Fine-scale spatial distribution of biomass using satellite images	Italy
Vallet et al. (2023)	High resolution data reveal a surge of biomass loss from temperate and Atlantic pine forests	France

Table 2: List of the 12 selected papers reviewed in this article.

Land Cover Types and Species

The selected list of literature represents a large part of the Mediterranean region. Within the list, there are many papers conducted in southwestern Europe. Regarding the land cover type for which the listed studies aim to estimate AGB, there can be distinguished between four categories; forest, shrublands, (semi) arid rangeland, and agroforestry (see Figure 2). Multiple papers solely rely on satellite-based sensors that focus on estimating AGB in forest areas (Santi, 2017; Goméz, 2012, Kattenborn, 2015; Vallet, 2023) while there are limited papers for other land cover types.

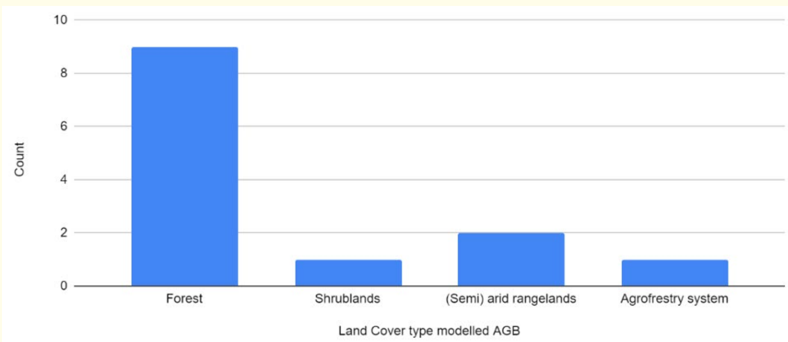

Figure 2: Land Cover type categories in the analyzed research papers.

The complete list contains study areas that in total cover many different species. As mentioned above there are several studies in southwestern Europe. Within this habitat, characterized by relatively low precipitation levels and a temperate climate, study areas predominantly encompass maritime coniferous forests, dryland forests, semi-arid rangelands, and shrublands. Representative species within these categories include Mediterranean Pines, Cypress, Scotch Pine, and Laurel.

For the studies located further north, there are also areas in the context of temperate forests with deciduous and (semi) evergreen tree species included. Species such as Oak, Beech, Hornbeam, and Wild Cherry have been modelled for AGB. Generally, it is observed that most focus in the Mediterranean context goes to evergreen species for AGB modelling applications.

Concerning remote sensing-based AGB modelling for these species, there are several notable characteristics to consider. Relative to the tropical context there is often a lower amount of biomass in these habitats. Also, for evergreen species, there is a lower seasonal fluctuation in chlorophyll content compared to temperate forests. These characteristics hold significant importance in the selection of an appropriate AGB modelling methodology, given the constraints inherent in remote sensing-based approaches. Ploton (2017) summarizes how for two often used data sources for AGB modelling, optical and SAR satellite data, the problem of saturation can occur. Estimated AGB exceeding approximately 150 Mg per hectare presents a challenge for optical sensors, as spaceborne sensors lose sensitivity to variations beyond this threshold. Mermoz et al. (2015) illustrates that the saturation point for L-band SAR data typically occurs around 100 Mg per hectare. This phenomenon indicates that as canopy density increases, L-band SAR data exhibits a negative correlation with biomass, potentially resulting in significant underestimation of biomass levels.

These examples underscore the variability inherent in different contexts of AGB modelling, necessitating diverse methodological approaches. Furthermore, in Mediterranean contexts, the risk of data saturation in selected remote sensing sources must be evaluated for each AGB modelling application.

Data and Features

Numerous studies have harnessed diverse datasets to enhance biomass prediction. Data sources such as near-infrared, renowned for their efficacy in extracting vegetation-related information, have frequently been employed for biomass prediction (Price, 1992). This preference is attributed to their capacity to effectively capture characteristics of the stomata layer in foliage, thereby facilitating the derivation of more refined datasets such as vegetation indices, which exhibit heightened correlation with biomass (Zhu, 2015). Nonetheless, the utility of these indices is constrained by certain limitations; they may only be effective in scenarios characterized by uniform tree density, failing to adequately address complexities inherent in environments featuring diverse tree species and age distributions. In such multifaceted contexts, supplementary variables become requisite for accurate biomass prediction.

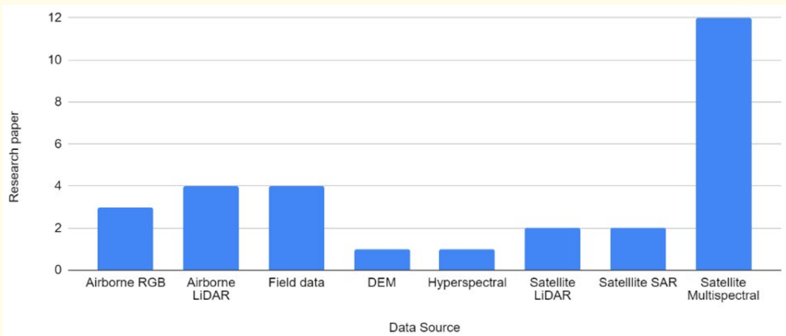

Figure 3: Data Source in the analyzed research papers.

Figure 3 illustrates that multispectral data obtained from satellite platforms remains a prevalent choice. Specifically, high-resolution multispectral imagery from satellites such as WorldView, SPOT, and QuickBird, augmented with near-infrared bands, enables comprehensive extraction of vegetation-related information, and facilitates the derivation of vegetation indices.

Nevertheless, there is a discernible trend towards the utilization of additional data sources, notably Airborne LiDAR, which has garnered increased attention. LiDAR offers distinct advantages by capturing tree height and structure, in contrast to traditional reflectance-based methods focused solely on tree density (Kwak, 2007). Through the generation of a canopy height model derived from LiDAR data, encompassing both DSM and DTM, detailed insights into tree morphology are obtained.

While Airborne LiDAR boasts high accuracy, its widespread adoption is constrained by the associated costs of sensor acquisition and deployment. Additionally, logistical challenges in mounting LiDAR sensors on satellite platforms, attributable to the considerable distance between satellite orbits and ground surfaces, contribute to its elevated expense.

Another noteworthy data source employed in biomass modelling is SAR, which operates as an active remote sensing sensor like LiDAR. SAR technology facilitates the acquisition of detailed information about tree formation and structure through backscatter analysis, thus offering valuable insights for biomass estimation.

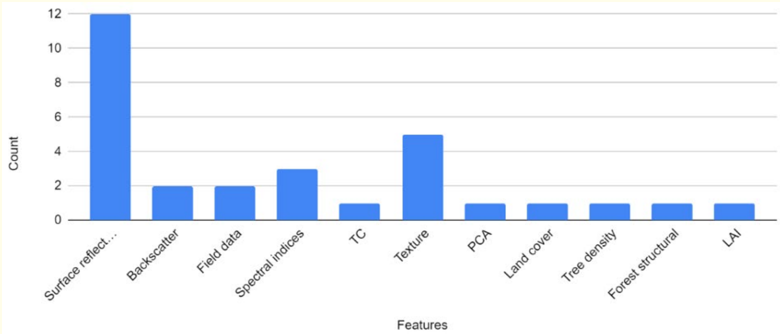

Figure 4: Features extrapolated in the analyzed research papers.

While surface reflectance data and DEM datasets, including DSM and DTM, are integral to biomass modelling, additional derived data from surface reflectance holds utility in certain contexts. Figure 4 illustrates datasets such as tasseled caps (TC), which leverage predefined coefficients to characterize the bareness, greenness, and moisture content of an area, serving as alternatives to spectral indices (Haley, 2006). Principal Component Analysis (PCA) is another pertinent feature extraction technique, facilitating dimensionality reduction by retaining only the most informative data from a dataset, thereby enabling biomass prediction with minimal features (Patel, 2010). Additionally, incorporating land cover data can enhance model accuracy by enabling species-specific modelling, thereby refining predictions. Variables such as density, structure, and Leaf Area Index (LAI), derived from a combination of field measurements, DEM data, and spectral reflectance, can further augment biomass mapping efforts. However, it is imperative to consider the scope of modelling, encompassing factors such as sample size and geographic extent, to ensure the robustness and applicability of the developed models.

Models and Accuracy Assessment

Various modelling techniques are employed in biomass estimation, ranging from simplistic linear regression to intricate artificial neural networks. These models incorporate a diverse array of features and sample sizes, factors which may affect influence beyond the model structure itself. Consequently, generalizing the performance of each model without standardization of parameters may prove suboptimal. Nonetheless, understanding how each model performs in estimating biomass provides important insights into finding the best modeling approach.

Despite the potentially disparate and limited number of models analyzed, discerning overarching trends remains paramount. Aggregating data from various papers, the coefficient of determination (R^2), and root mean square error (RMSE) for each model were plotted, with subsequent calculation of the median values, as depicted in Figure 5. The utilization of median values serves to mitigate the influence of outliers (Zawojewski, 2000).

Linear regression continues to demonstrate noteworthy performance owing to its ability to capture the high correlation between select variables and biomass, a phenomenon well-documented in prior research (Santi, 2014; De Jong, 2003). Specifically, the correlation between normalized difference vegetation index (NDVI) and biomass underscores its efficacy. However, while exhibiting a median R^2 of 0.8, the accuracy of linear regression may be understated due to the limited sample size.

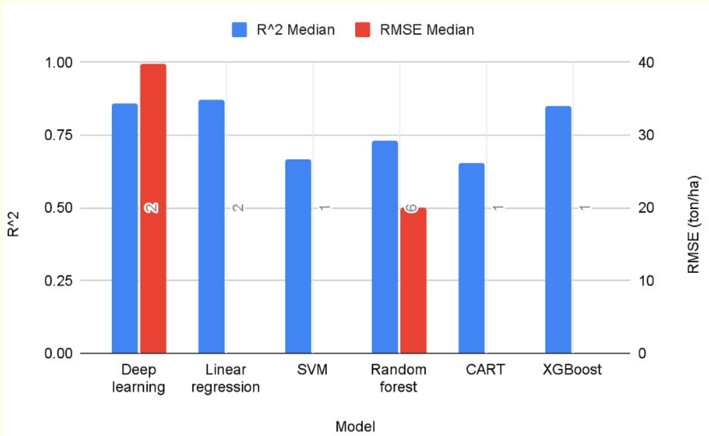

Figure 5: Median R^2 and RMSE of machine learning models on biomass. The number for each model shows the amount of times the selected studies used it.

Random forest emerges as the most frequently employed model within the reviewed literature. Renowned for its adaptability and robustness in remote sensing applications (Belgiu, 2016), this model is extensively employed across various research domains, encompassing both land cover classification and thematic parameter regression. Its adaptability stems from its decision forest architecture, which diverges from conventional methodologies such as support vector machines or regression by employing a multitude of conditional branches based on feature-value thresholds. This approach facilitates binary decisions, enhancing interpretability, although at the expense of increased susceptibility to overfitting.

Random forest regression exhibits a median R^2 of 0.74, a figure comparatively lower than linear regression models. Despite this, an accompanying RMSE of 14 ton/ha underscores its efficacy, particularly in dense forest environments where biomass typically ranges between 200 and 400 ton/ha (Yang, 2020). The RMSE value, when contextualized within this range, signifies a favorable error rate of under 10%, indicative of the model's high accuracy.

Recently, many scientific studies have been using deep learning in various areas of remote sensing. Deep learning involves complex models that mimic human thinking, like artificial neural networks and convolutional neural networks (LeCun, 2015).

Within the examined literature focusing on biomass estimation utilizing high-resolution imagery, instances of deep-learning model utilization were identified. Specifically, Vallet (2023) and Santi (2017) employed artificial neural networks and U-Net architectures, respectively, for this purpose. The objective was to assess the efficacy of deep learning methodologies in biomass estimation relative to conventional approaches. Preliminary findings suggest that deep learning methods may exhibit less performance compared to conventional models. For instance, when contrasted with RF, deep learning models display a notably higher median RMSE of 40 ton/ha compared to 20 ton/ha. Although deep learning models may yield marginally higher R^2 values (0.8 compared to 0.74 for RF), the disparity is not substantial. This observation may be attributed to factors such as limited sample size or discrepancies in feature selection methodologies.

Conclusions

Significance of Data and Features

While numerous features and datasets hold potential for biomass modelling, only select ones prove pivotal. Foundational data such as surface reflectance, while versatile, may not always encompass the information required for robust modelling. Nevertheless, its utilization remains crucial, as it offers nuanced pixel values reflective of diverse environmental characteristics. In scenarios where model complexity precludes the incorporation of numerous features, indices derived from surface reflectance can serve as viable alternatives.

Furthermore, data derived from independent sources such as LiDAR and SAR provide valuable supplementary information beyond that attainable from surface reflectance data alone. These sources offer detailed insights into vegetation height and texture. Particularly, LiDAR data enables the generation of canopy height models, a critical parameter for accurate AGB estimation, given the significant role of height in the calculation.

Optimal Model Accuracy Evaluation

The quality of a model is inherently contingent upon the quality of its input data, thereby emphasizing the paramount importance of features and samples. While this assertion remains valid, it is also imperative to consider the adaptability of the model in question. Among available models, the RF model exhibits remarkable adaptability and possesses the capacity to effectively accommodate multiple features compared to linear models. Additionally, it does not necessitate a larger volume of samples relative to deep learning models. Consequently, the RF model emerges as the most suitable option when utilizing multiple features as predictors.

Optimal Configuration for the INNO4CFIs project

The INNO4CFIs project will leverage high-resolution surface reflectance data obtained from commercial satellites, facilitating the generation of various indices and derived datasets. Additionally, the project aims to incorporate high-resolution DSM and DTM obtained from LiDAR technology. These datasets can be further processed to derive a canopy height model, or SAR data will be considered as supplementary features for biomass prediction. Within the INNO4CFIs project timeline, the launch of the new ESA BIOMASS mission is scheduled for 2024 (ESA website). This P-band radar sensor designed for biomass estimations from space will support future improvements in AGB modelling which can be explored during the project. Given the utilization of multiple features, the RF model emerges as a pragmatic choice due to its capacity to adaptively construct a well-fitted model tailored to the provided samples and features.

Acknowledgments

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