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RESEARCH ARTICLE

Machine Learning Approaches for Biomass Resource Mapping and Sustainable Energy Planning

Smita Desai[1,9], Sushama Shirke[2], Vishvas V. Kalunge[3], Sireesha Koneru[4], Gaurav Raju Khobragade[5], Vidhi Rajendra Kadam[6], Shyamsing Thakur[7], Govindarajan Murali[4], Anant Sidhappa Kurhade[8,9*]

[1] *Department of Electronics and Telecommunication, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune – 411018, Maharashtra, India.*

[2] *Department of Computer Engineering, Army Institute of Technology, Dighi Hills, Pune – 411015, Maharashtra, India.*

[3] *Department of Computer Engineering, Dhole Patil College of Engineering, Wagholi, Pune – 412207, Maharashtra, India.*

[4] *Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation, Greenfields, Vaddeswaram, Guntur – 522502, Andhra Pradesh, India.*

[5] *Department of Mathematics, Ramdeobaba University, Ramdeo Tekdi, Katol Road, Nagpur – 440013, Maharashtra, India*

[6] *Department of Computer Engineering, Bharati Vidyapeeth College of Engineering, Navi Mumbai – 400614, Maharashtra, India.*

[7] *Department of Mechanical Engineering, D. Y. Patil College of Engineering, Akurdi, Pune – 411044, Maharashtra, India, Affiliated to Savitribai Phule Pune University Maharashtra, India.*

[8] *Department of Mechanical Engineering, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune – 411044 411018, Maharashtra, India.*

[9] *Dnyaan Prasad Global University (DPGU), School of Technology and Research – Dr. D. Y. Patil Unitech Society, Sant Tukaram Nagar, Pimpri, Pune – 411018, Maharashtra, India*

***Corresponding author:** Anant Sidhappa Kurhade; a.kurhade@gmail.com

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ABSTRACT

Biomass resource mappings are essential tasks for sustainable energy planning, since it offers information on the potential supply, geographical availability of resources, plant sitting, transportation opportunities and roadmap towards long term renewable energy concepts that have policy relevance. Its relevance is increasing as countries are embracing low carbon economy's roadmaps which demand for reliable spatial quantitative estimations of forest and waste residues–based biomass potentials. Despite the significant headway, there are still some loopholes in applying remote sensing and machine learning techniques. These limitations comprise scarcity of good quality field data for model calibration, poor integration of socio–economic drivers and difficulties in representing fine–scale spatial variability that hinder accurate estimate of yields at different spatial levels. This paper surveys recent machine learning methods for AGB estimation, discusses their methodological limitations, and proposes future research avenues toward scalable and robust forest biomass mapping. A combination of satellite observations, GIS–based layers and ground inventory data sets are included in the analysis as well as a variety of regression, tree based, kernel based, neural network, deep learning and hybrid modelling approaches over various land coverage areas. According to the previous works, evidence is gathered from the surveyed studies that ensemble and deep learning approaches can enhance prediction performance on multi–source data; GIS–machine learning integration contributes to better site selection and logistics analysis. The results also demonstrate the potential for a combined framework that exploits transfer learning approaches and digital twin methodologies to reduce prediction uncertainty, especially in low–data areas. Such information could help support rational decision–making activities for policymakers, planners and industry actors that consider the role of bioenergy in national energy security, climate change mitigation strategies, resource sustainability and long–term renewable energy planning.

Keywords: Biomass resource; GIS–based layers; renewable energy planning, Sustainable Energy Planning

1. Introduction

Together with the increasing of world energy demands and the necessity of reducing carbon emissions, biomass has recently constructed a resurgence as a clean and locally available energy resource. Accurate mapping of biomass availability is a prerequisite for supply chain planning, energy potential estimation, as well as infrastructure construction in renewable energy systems. It can provide very fast inspection over vast swathes of territory that cannot be efficiently covered by labor–intensive field surveys. Machine learning has proven to have a high potential to handle vast datasets, model nonlinear associations and obtain better accuracy spatial predictions. In this article, we review machine learning approaches that have been employed in biomass resource mapping and assess how they can be applied to sustainable energy planning.

By 2050, it is estimated that biomass will be providing almost 50% of the energy used in developing economies, dominated by agro–residues, forest resources and wood industry waste [1]. Correct determination of this potential is necessary for energy utilization management and could be achieved by reliable analytical tools [2]. Biomass resource assessment is increasingly using machine learning models, because they can be applied to analyze complex environmental variables and predict supply chain behavior [3]. These approaches can help identify appropriate land–use types in biomass production and provide the quota of bioenergy that reason policy making [4]. Model building is still a challenge since the biomass yield is influenced by several interacting factors that make it difficult to assess performance and generate general conclusions [5]. It illustrates the requirement for learning frameworks that can characterize nonlinear relationships between NFIs from heterogeneous data sets in different climatic and geographical regions [2].

Integrated information from various sources like satellite imagery, LiDAR, and forest inventory data is used in 'comprehensive estimation' of biomass [6]. Sophisticated techniques, including deep learning and ensemble models, are successful in integrating these inputs into coherent, high resolution biomass maps used to underpin an energy strategy [7] [9] [10]. Such methods can model complex spatial and temporal patterns not directly modellable using traditional statistical techniques, resulting in better estimates of parameters and improved predictions [4,8]. Algorithms, like Random Forest, Support Vector Machines and Gradient Boosting are found to perform well in capturing nonlinear dependencies of geospatial data [8]. There have been various ensembled methods, often achieving better performance than traditional regression models in the face of data complexity [9], from inputs like Enhanced Vegetation Index.

Machine learning is also used beyond estimation, with other critical areas of biomass supply chain management such as transport and conversion processes being modelled [4,10]. Application to optimize biofuel pre–treatment OLUP has potential application for improved energy return and waste minimization along the entire pre–treatment pathway [4]. The combination of advanced analytics and multi–source data allows for detailed information about biomass availability to make informed decision planning towards sustainable energy transitions [11]. Recent machine learning techniques for biomass resource mapping are comprehensively reviewed in this paper, most of these concepts focuses on comparing and analyzing their performance, scalability and application across geospatial datasets. It also discusses the challenges and future research directions to enhance the accuracy and practical application in managing biomass resources [12].

New research has demonstrated a sharp rise in the application of machine learning for forest biomass estimation, especially based on remotely sensed data [13]. Supervised learning techniques use image–based values to learn links between environmental factors and biomass over more spatially related performances [7]. Methods like Support Vector Machines, Artificial Neural Networks and Random Forest are commonly used since they can easily work with high dimensional geospatial dataset [8]. Methods based on a decision–tree like construction, such as Random Forest and Gradient Boosting, are strong in situations where nonlinear effects prevail [14,15]. It has been indicated in some studies [16] that Random Forest models based on combined satellite and field measurements provide high prediction accuracy. Integrating LiDAR, radar, and optical data enhances the characterization of vegetation structure and condition, which in turn increases confidence in biomass estimates across a wide range of forest types and environments [7].

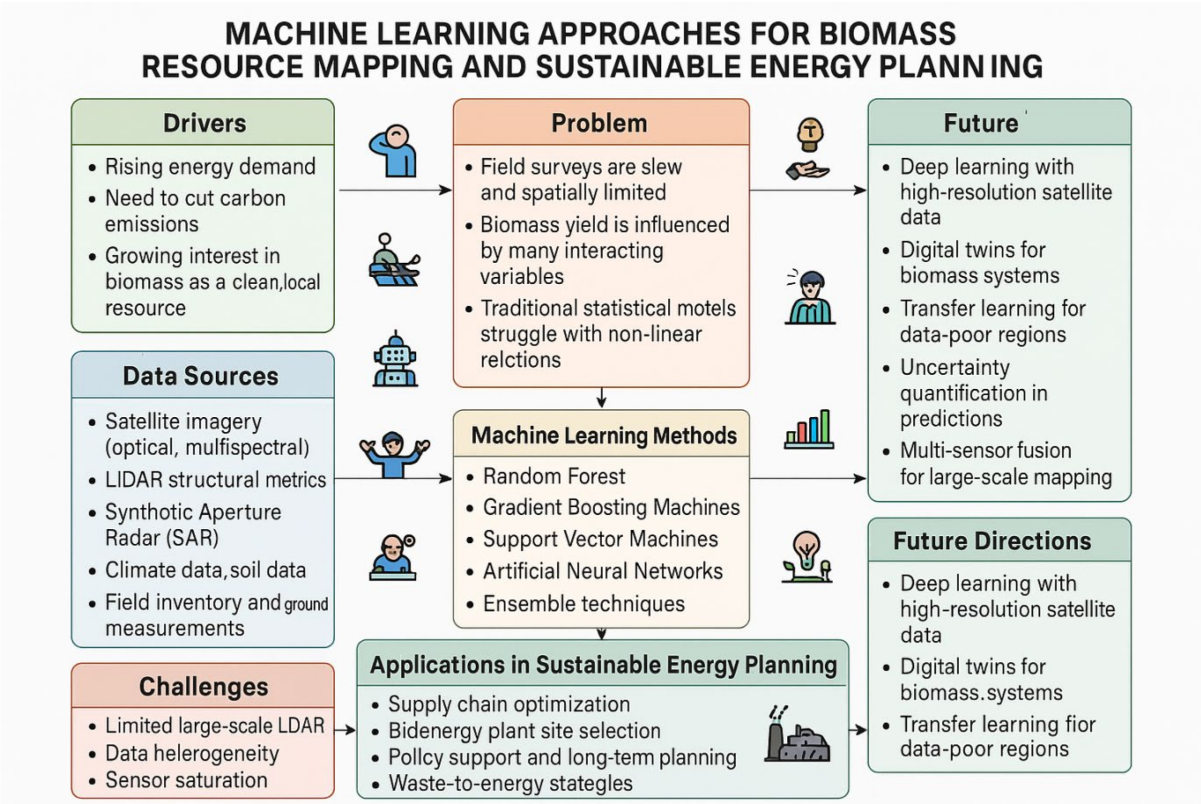

Figure 1. Machine Learning Framework for Biomass Resource Mapping and Sustainable Energy Planning

The overall research framework is illustrated in **Figure 1**, including the operation of machine learning for processing multi–source environmental data and spatial analysis to produce biomass maps. The figure highlights the logic path from data gathering to decision–support outputs and underlines again the use of ML as a unified approach for biomass estimation and sustainable energy strategies.

Their inherent capability to account for nonlinear effects between dependent and independent variables render such models highly suitable to the nature of remote sensing data, where linear relationships with AG biomass are typically poor [7]. Apparently, such models are successful in fusing LiDAR–metric with multispectral and radar backscatter data sets resulting in a decrease of the bias especially for high biomass regions [8]. At early stages of biomass estimations, the availability of data generally constrained to simple regression models and technical limitations limited analysis with fuzzy algorithms. With the rapid development of high–performance computing and high–resolution remote sensing data availability, advanced machine learning methodologies have been widely used for biomass mapping [17].

This has led to the rise in popularity of ensemble learning algorithms such as Random Forest and Gradient Boosting Machines that are capable of capturing complex, non–linear associations in remotely sensed response variables [18–19]. These methods generally accommodate spatial heterogeneity in forest AGB more flexibly and hence perform better than traditional parametric techniques [20]. They are also compatible with the fusion of multi–source remote sensing data (e.g., optical imagery, SAR) which overcomes single–sensor limitations (e.g., signal saturation in dense forests) [21]. It is generally reported that fusion of optical and SAR observables will increase prediction accuracy compared to either source individually [7].

LiDAR data deliver precise three–dimensional structural information, which is positively related with aboveground biomass; however, their wide application is limited by the high cost of acquisition, computing requirements and narrow spatial coverage [22]. Those restrictions emphasize on the necessity to combine LiDAR–based features with optical and SAR optical features, as well as climate variable using proper machine learning paradigm for scalability [8]. Such integrative complementarity of information contributes to a more comprehensive description of the forest structure and biomass, and thus to better performing models [23]. Airborne LiDAR and optical–SAR data fusion is shown to provide improved accuracy of volume estimation compared to that using the above datasets individually [24].

When combined with advanced learning algorithms, multi–sensor integration attenuates sensor–specific limitations like optical saturation in high biomass areas and geometric distortions or speckle noise in SAR imagery. Optical Images are useful with spectral bands and vegetation indices related to canopy density and chlorophyll content, but they are affected by the effects of cloud cover and saturation [24]. Spaceborne LiDAR measures directly vertical vegetation structure, but its irregular spatial sampling implies interpolation that can result in the definition of uncertainties in heterogeneous forests [26]. SAR systems are all–weather, penetrate canopy of vegetation and provide independent structural information, albeit with similar geometrical distortions and noise as those found in NDT for surface waves [13].

The **table 1** summarizes the main ideas presented in the introduction by organizing them into seven thematic elements. It outlines how biomass mapping, machine learning methods, data sources, and existing challenges connect to sustainable energy planning. It offers a concise structure that reflects how each component contributes to the broader context of biomass resource assessment.

Table 1. Structured Overview of Key Themes in the Introduction to Machine Learning–Based Biomass Resource Mapping

Theme / Section	Core Idea	Key Points	ML Techniques / Data Sources Mentioned	Challenges Highlighted	Relevance to Biomass Mapping & Energy Planning
Context & Importance	Rising energy demand and need for low–carbon solutions	Biomass as a clean, local renewable resource; need for reliable mapping and forecasting	–	Traditional surveys are slow and limited	Establishes the need for advanced analytical tools for planning
Biomass Potential & Need for Accurate Estimation	Biomass may supply over 50% of energy needs in developing countries by 2050	Depends on agricultural, forestry and wood wastes; accurate quantification is essential	–	Complex interactions in biomass yield variables	Accurate estimation guides sustainable energy decisions
Role of Machine Learning	ML improves precision in	Captures nonlinear patterns; supports	General ML algorithms	Difficulty in modeling	Demonstrates ML's value for high–resolution mapping

Theme / Section	Core Idea	Key Points	ML Techniques / Data Sources Mentioned	Challenges Highlighted	Relevance to Biomass Mapping & Energy Planning
	biomass assessment	land use planning and forecasting		multivariate interactions	
Data Integration for Biomass Estimation	Need to combine diverse data sources	Satellite imagery, LiDAR, field inventory data	Deep learning, ensemble models	Heterogeneous datasets across regions	Enables comprehensive spatial predictions for planning
Advances in ML Models	Modern ML models outperform traditional methods	RF, SVM, GBM, ANN; superior handling of non–linearity	RF, GBM, ANN, SVM	Data saturation, local minima	Enhances prediction accuracy using geospatial features
Remote Sensing & Multi–Sensor Fusion	Integration of optical, SAR, and LiDAR improves accuracy	SAR penetrates canopy; optical gives vegetation indices; LiDAR provides structure	RF, ensemble methods	Optical saturation; SAR geometric distortions; LiDAR high cost	Multi–sensor fusion yields robust large–scale biomass maps
Evolution & Motivation for the Review	Shift from basic regression to advanced ML with powerful computing	Adoption of ensemble models; high–resolution datasets	RF, GBM, deep learning	Scalability, computational demand	Frames the need to evaluate ML advancements and future research routes

Table 1. (*Continued*)

Many existing studies have used machine learning for estimating biomass, however they are fragmented in terms of their data sources, the area they cover and specific models. Most of the literature applies narrow scopes, such as only considering forest biomass or single remote sensing sensors and isolated machine learning methods, without a general comparison of how different ML approaches perform for heterogeneous landscapes and multi–sources of data. There is also a gap in synthesis which bridges methodological choice – for example data fusion approach, model choice and validation practice – to implication for sustainable energy planning and policy decisions. This review fills this gap offering a comprehensive overview on machine learning methods which have been applied to the mapping of biomass resources, outlining their pros and cons and suitability for large scale decision–oriented applications. Given the burgeoning size of high–resolution satellite data, progress on ensemble and deep learning algorithms, as well as heightened policy attention to bioenergy in low–carbon transitions, there is an urgent requirement for an up–to–date synthesis that can inform both research and planning.

2. Biomass resource mapping: Need and Scope

Biomass resource mapping is the process of estimating and recording a biomass resource, primarily agricultural residues, forest–based derivable or organic waste streams such as municipal solid waste. It is also the foundation for sustainable planning of bioenergy systems, as it integrates resource availability with technical, economic and environmental considerations. An informative resource map enables us to focus on areas with credible and adequate biomass potential and facilitates regional–, national– and community–level planning. This communication not only quantifies the biomass, but also architectural details such as type, quality, access, important factors for optimal implementation of supply chain logistics and conversion technologies. In addition, detailed mapping pinpoints regions with untapped sustainable biomass resources and thus opportunities for new bioenergy enterprises and regional development [27]. Reliable assessment of biomass is also important for studies on carbon sequestration potential and use in programs related to climate change which rely on data from carbon accounting, monitoring and verification [28].

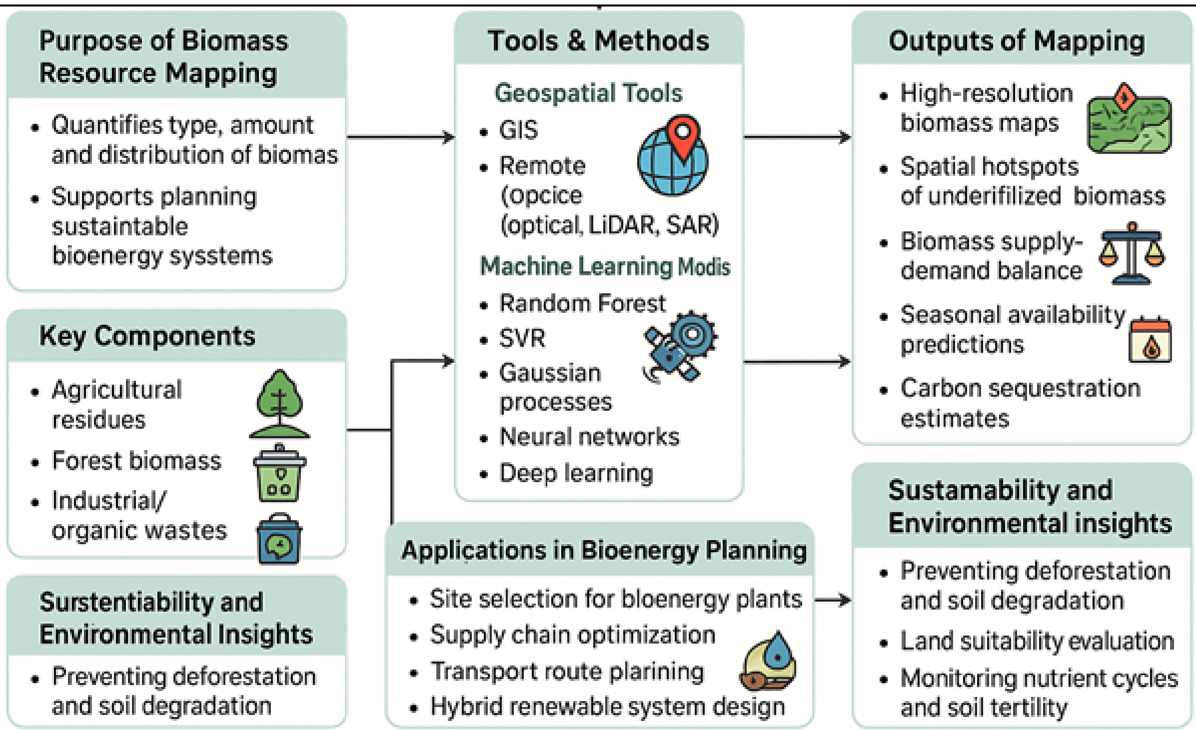

Figure 2. Biomass Resource Mapping: Need and Scope

Figure 2 illustrates the integration of biomass availability, spatial distribution and temporal variability into planning targets such as logistics, site selection and sustainability assessment in a graphic representation of the range of areas where resource mapping can make an important contribution. This figure confirms the argument by illustrating how mapping results can be translated into useful planning information.

Biomass resource (map) facilitates the environmental impact studies related to biomass use, a requirement to ensure that sustainability standards are done according to the level of deforestation and land degradation. Utilization of modern machine learning approaches, e.g., deep learning techniques and artificial neural networks for highly accurate and reliable biomass mapping has been suggested [29]. When trained on high–resolution satellite images and state–of–arts remote sensing data, these models provide detailed and transient maps of the biomass at a given spatial location in time assisting optimal resource allocation for efficient energy–planning [7, 29]. These tools represent a solid foundation for evidence–based decisions concerning construction of bioenergy infrastructure, policy making and strategic localisation of the biomass conversion installations, such as site locating, logistics identicalation or environmental impact assessment [30].

An exact spatial mapping is important to secure the residual biomass supply, because it also estimates what amount of biomass can be used for energy– or heat–generation [31]. Providing a spatial structure is also important to locate potential sites for bioenergy plants by showing areas where residues and waste streams aggregate. It also in support as to the matching of biomass provision to energy demand in long–term viability studies. Transportation and logistics are planned based on these data, as collection costs and storage feasibility is associated with the distance to be hauled, nature of road network and terrain characteristics. Biomass supply is also influenced, in addition to the seasonal fluctuation, by cropping periods and climatic variations. It is also possible to use biomass along with other renewable sources when mapping the resources for hybrid energy systems, where a reliable supply description is needed.

As biomass resources are commonly geographically dispersed, the routing becomes more efficient and transportation costs are lowered which had eventually benefited economic viability of a bioenergy project [32]. Accurate estimation of agricultural residues requires a geospatial analysis based on soil properties, water availability and land–use restrictions [30]. The integration of GIS (geographical information system) and remote sensing technology supports decisions on biomass estimation, land evaluation as well as transport network analysis [12,33]. These GIS–based tools are fundamental in estimating biomass availability of the forest, choosing suitable plant sites and sustainably managing them through nutrient recycling and soil conservation [32, 34–35]. Information on spatial locations is valuable for easing transport bottlenecks and the informed planning of biomass utilization [36,37]. GIS tools also facilitate determining transportation costs and optimising plant locations and supply lines which is necessary because logistics can represent 15–20% or more of the total cost of producing electricity [32,38,39]. Nmapproaches integrating spatial, infrastructure and environmental data will enhance strategic planning for bioenergy supply chains (while considering geotechnical variables such as soil characteristics [34] that impact the suitability of sites and temporal variability in feedstock types which influence overall cost).

Recent studies reveal rising trend in application of machine learning for biomass resource mapping. These procedures consider the nonlinear interrelations between climate, soil, land use, terrain and EO variables. Machine learning models including Random Forest, support vector regression, Gaussian process and neural networks significantly improve prediction accuracy with the potential for high–resolution spatial mapping. This trend can be attributed to the increasing interest in data–driven methods to inform sustainable bioenergy planning and decision–making.

3. Data sources for biomass mapping

Modern biomass resource assessment draws on multiple data streams to capture spatial, temporal, and environmental variability. These datasets provide the foundation for generating accurate maps and for training machine learning models that predict biomass availability at different geographic scales. The reliability of a biomass map depends on how well these data sources represent real conditions across agricultural lands, forests, and urban regions.

3.1. Satellite imagery

Satellite data is an integral part of biomass mapping due to covering substantial areas and also having a consistent temporal coverage. Land surface indices are frequently derived from products of platforms such as Landsat, MODIS, and Sentinel. Indexes such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Leaf Area Index (LAI) and canopy height are indirect measures of plant growth, greenness & biomass density. These indices assist in estimating the potentials of crop residues, forest biomasses and vegetation seasonal dynamics. Innovations in remote sensing technologies such as Light Detection and Ranging, specifically the estimation of tree height [41–42], and Synthetic Aperture Radar imaging 6 enable vegetation three–dimensional structure analysis and biomass assessment in areas where dense foliage or cloud cover may limit measurements with optical sensors. Furthermore, cloud–based computation such as Google Earth Engine has great potential for processing and analyzing large collectives of satellite data to estimate aboveground biomass, particularly in studies with broad spatial extents or time–series analysis [7]. High, medium and low–resolution spatial combined with the satellite data have developed an end–to–end retrieval for biomass through spectral reflectance and vegetation indices based on machine learning techniques [7]. Although field measurements are reliable, remote sensing–based techniques have gained wide–ranging attention for AGB estimation since such methods can be applied to large areas and fed with useful Eco physiological information [43].

3.2. GIS–based spatial data

Spatial modeling is facilitated by Geographic Information System (GIS) datasets that provide detailed layers of topography, soil type, rainfall, temperature and land use. These factors affect the productivity of crops, distribution of vegetation and generation of residue. You can build a closer to reality biomass availability estimation with GIS layers integration thanks mainly to spatial interpolation and machine learning methods. This will enable identification of the best places for bioenergy infrastructure and sustainable biomass harvesting practices [8]. For example, GIS enables establishing reliable radiometric connections between satellite imagery and field inventory data, which could facilitate the generation of strong regression models to estimate above ground biomass [43]. Furthermore, GIS data can be used to map the land suitable for energy crops by incorporating ecological (soil pH, soil nutrient content and water holding capacity) and economic or logistical factors [29]. This GIS–based multi–criteria evaluation can be used to conduct and apply comprehensive assessments of potential biomass feedstock zones, while taking into account both the biophysical viability and the socio–economic suitability. Moreover, these tools could use fine spatial datasets to simulate the consequences of land management strategies and climate scenarios on biomass yield, which are essential for adaptive management actions [22] [7]. The combination of GIS and remote sensing data, in particular the remotely sensed information from optical sensors, enables the derivation of biomass functions with predictive variables like spectral reflectance or crown properties to estimate biomass [29]. These geospatial tools also allow the integration of heterogeneous datasets (e.g., forest inventory data) with a view to having more reliable and more accurate biomass estimates, as well as supporting sustainable energy planning [29].

Figure 3. Integrated Data Streams for Comprehensive Biomass Resource Assessment

The framework in which satellite imagery, GIS layers, ground inventories as well as socio–economic variables are integrated into a unified modeling platform is depicted schematically in **Figure 3**. The result further breeds the conclusion that biomass estimation must be based on the fusion of multi–source datasets instead of being established on one dataset.

3.3. Agricultural and forest databases

Ground–based observations are crucial in validating and calibrating remote sensing products. Field biomass measurement, crop yield report from agriculture department and Forest inventory data were reference points for model training. These data increase the reliability of predictions and generate final biomass estimates that are consistent with observed values in a simple manner for whole regions of various vegetation types. These reference field measurements are crucial for the generation of reliable allometric equations (formulas that establish relationships between easily measurable tree or crop dimensions and total biomass) and when validating estimates produced with advanced machine learning techniques applied on remote sensing data [7]. In addition, these databases offer important historical perspective that can be used to examine biomass dynamics over time and support future projection under a range of land–use and climate change scenarios. Moreover, by inputting the baseline data, detailed analysis of soil suitability for particular energy crops such as slope, aspect and land use are provided to determine suitable areas for cultivation [44]. This is very important for creating full information required to analysis bioenergy potentials at regional and national level [45]. This integration is further facilitated by WebGIS systems that enable for automated and holistic sustainability assessment by bringing together static and spatialized dataset (administrative, demographic, agroecological factors) [46]. Such databases frequently integrate ground surveying and the manual interpretation of aerial images to collect spatially extensive data on the supply of biomass resources that is critical for modeling feedstock allocations [36]. These types of datasets are critical to the development of spatially explicit methods that include location–specific factors that impact on the availability of biomass and result in a richer knowledge than is possible with purely statistical approaches [45]. A long–term and globally standardized on–site biomass reference measurement system based on high–quality ground data is crucial for validating airborne products and deriving consistent estimates of forest biomass [47].

3.4. Socio–economic and waste data

Urban and industrial areas have substantial biomass potential in MSW, food waste, as well as industrial by–product. Information obtained from waste management authorities and reports of the industry support the estimation of potential supplies for biodegradable waste streams. These datasets are crucial for urban and town level biomass mapping, where the resource distribution is different from that in agricultural or forested landscapes. Precise socio–economic information, such as population density, income status and waste generation factors are vital to the evaluation of the feasibility of bioenergy ventures in urban areas [48]. Additionally, socioeconomic elements like dominant land use, current agricultural practices and population density are essential to frame the sustainability and feasibility of biomass energy projects as they also determine supply chains and potential demand [46]. For instance, by characterizing socioeconomic data could help classify biomass potential based on theoretical, potential and exploitable biomass" categorization which is vital for integrated planning [49]. This elaboration in turn provides guidance for prioritizing resource investments and devising policies for maximizing biomass use on the basis of regional demand and limitations [50]. Socio–economic factors like population density, landholding size, mechanization level, income and use of residue play a vital role in availability of biomass. When incorporated in remote sensing and GIS as spatial covariates in machine–learning models, these variables enable to separate theory embedded biomass potential from realizable biomass by considering human, economic and policy limitations. The **table 2** summarizes the major data sources used for biomass mapping and highlights their roles, features, and limitations. It offers a concise view of how different datasets support accurate biomass estimation across varied landscapes.

Table 2. Key Data Sources Utilized for Biomass Resource Mapping

Data Source Category	Purpose / Role in Biomass Mapping	Key Features / Indicators	Strengths and Limitations
Satellite Imagery	Provides large–area, repeatable observations for estimating vegetation health, density, and structural attributes	NDVI, EVI, LAI, canopy height; Landsat, MODIS, Sentinel; LiDAR and SAR; Google Earth Engine	Strengths: Wide coverage, spectral richness. Limitations: Optical saturation, cloud issues.
GIS–Based Spatial Data	Supports spatial modeling by linking environmental, climatic, and land–use variables	Soil type, rainfall, temperature, elevation, land use, ecological suitability	Strengths: Enables multi–criteria assessments. Limitations: Dependent on dataset resolution.
Agricultural and Forest Databases	Provides ground–truth measurements for model calibration and validation	Field biomass data, crop yield records, forest inventories, allometric equations	Strengths: Accurate validation. Limitations: Labor–intensive, limited coverage.
Socio–economic and Waste Data	Supports biomass estimation in urban and industrial regions	Municipal waste records, food waste data, by–products, demographic indicators	Strengths: Captures urban biomass. Limitations: Variability and inconsistent reporting.
Integrated Multi–Source Datasets	Combines multiple data types for comprehensive biomass assessment	Fusion of optical, SAR, LiDAR, inventory, land–use, WebGIS	Strengths: High accuracy. Limitations: Requires complex preprocessing.

As outlined in the previous section, due to heterogeneous and complex networks of interactions, its integration with production data requires that analysis methods can accommodate nonlinear relationships, high–dimensional backgrounds and spatial dependence. This opportunity is offered by machine learning methods that associate multi–sourced geospatial, environmental and socio–economic data with biomass estimation problems. We then proceed to review the primary machine learning methods employed in transforming these data inputs into accurate and scalable biomass predictions.

4. Machine learning techniques for biomass estimation

Machine learning is extensively used in biomass estimation, as it considers spatial heterogeneity, nonlinear effects and seasonal dynamics not fully addressed by traditional methods; using inputs of various kinds (satellite indices, climate factors, soil properties and field measured values), it provides accurate and high–resolution maps. The preference of using a model would vary based on the size and complexity of the data and based on the nature prediction task.

4.1. Regression–based models

Baseline biomass estimation is carried out through the application of regression models, such as linear, polynomial or regularized (e.g., Lasso and Ridge) regression. They are most effective in cases where the relationship between predictors and unknown biomass values are relatively consistent and linear. Their performance is affected by datasets that present strong variability due to climate change, heterogeneous landscapes or mixed crop patterns. On the other hand, advanced regression models (e.g., support vector regression, k–nearest neighbors' regression, decision tree regression and random forest) as well as their variations for instance CatBoost and neural network can effectively cope with the complexities of these relationships since they are able to model complex non–linear relationship in biomass datasets [5]. These more complex regression models have proven to perform well on the prediction of biomass potential, as these incorporate a variety of variables like climatic data and agricultural land characteristics [2]. For example, Random Forest algorithm and k–Nearest Neighbors have shown high performance in prediction of agricultural biomass using environmental and climatic inputs to reduce convincing theoretical computations [2]. These approaches enable spatial prediction of vegetation attributes under its own uncertainty with probabilistic models needed to provide predictions in locations without observations [43]. Although deterministic models could be less suitable when there is not enough information on spatial property variability, the probabilistic model provides predictions at unobserved locations and an estimate of underlying uncertainty [43]. Among these, non–parametric models such as Random Forest, Support Vector Machine and Gradient Boosted Decision Trees have attracted attention for ABM prediction in order to capture complex non–linear relationships and interactions among predictors [51]. These non–parametric models are quite efficient in capturing forest aboveground biomass heterogeneity, even in comparison with parametric models [7].

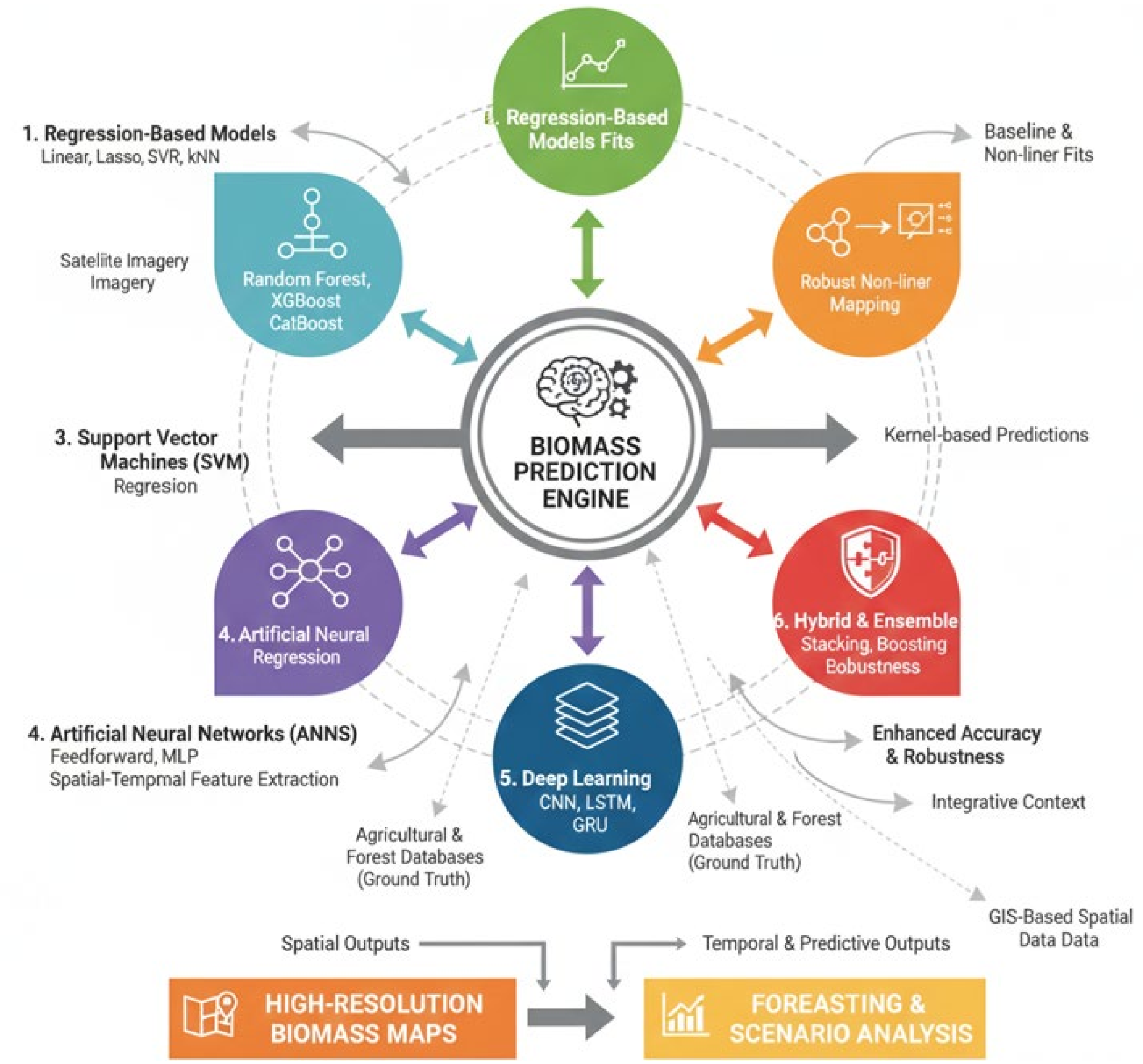

Figure 4. Machine Learning Techniques for Biomass Estimation

Figure 4 summarizes in a structured manner a variety of ML methods used to estimate biomass, including regression–based and tree–based models, deep learning as well as hybrid methods. The latter visual complement to the comparison of algorithms allows us to observe how increasingly complex and adapted they are to high–dimensional, non–linear biomass data.

4.2. Tree–based models

Tree–based methods are common in biomass modelling as they are capable of addressing the nonlinear, large–scale and noisy information. Models such as Random Forest (RF), Gradient Boosting Machines (GBM) and XGBoost are applied most often. These approaches can serve various applications such as prediction of agricultural residues yields, estimation of forest aboveground biomass and definition of promising bioenergy zones. Their internal importance features can also help understanding the dominant environmental drivers on biomass. For example, because Random Forest Regressor is an ensemble model it have the possibility of aggregating predictions from trees with different "optimums," so that a problem as non–continuous response variable (biomass) can have converged to their optima. Its effectiveness to handle multicollinearity along with complex nonlinear relationships, has made it a popular method for biomass prediction which often outperforms other algorithms including KNN and Gradient Boosting in accuracy [18] [2]. The Random Forest approach is also more tolerant to random noise in the training set sample, which makes it capable of achieving better estimation accuracy than classical statistical regression and other machine learning methods [52]. This approach creates many uncorrelated decision trees through building such trees from bootstrapped random samples of the data set considered, thereby together increasing predictive stability and decreasing overfitting [7] [53]. But one of the well recognized limitations of Random Forest is being ignoring spatial auto–correlation in data when modeling feature distribution which may have effect on the precision of spatial predictions [54].

4.3. Support vector machines (SVM)

Support Vector Machines work well on small to moderately large sized datasets, and provides stable predictions using kernel–based transformations. They were used on crop biomass estimation, vegetation classification, and land–cover mapping where crisp decision boundaries tend to improve model performance. SVMs are suitable for processing non–linear relationships and outliers with high adaptability, however still have a relatively poor generalization capability compared to other methods , especially in complex data patterns [55] [56]. maximum entropy method (ME): a general–purpose machine learning technique for inferring target probability distribution from incomplete information, which is especially useful when there are not much available data [57]. Besides, Support Vector Machines have been widely used for biomass estimation in the context of remote sensing by successfully classifying land cover and inferring biomass across ecosystems with different characteristics, frequently achieving similar or better prediction accuracy compared to other machine learning methods 7. 4 Discussion For the expert users, SVM has been recognized as the better choice in biomass estimation with accuracy more than other methods [58]. The performance of SVMs as compared to other machine learning algorithms for biomass estimation, however, may be considerably different depending on the specific dataset and biophysical variable being estimated [58]. For the SVM performance, it is important to choose a suitable candidate of kernel function and regularization term so as not to suffer from overfitting problem, particularly in implicit feature mappings into higher–dimensional space for nonlinear classification [59].

4.4. Artificial neural networks (ANNs)

Artificial Neural Networks, by learning weights to propagate information through layers of interconnected nodes, learn complex non–linear relationships. They can be applied to forest biomass modeling, predict the generation of municipal or industrial waste, and forecast crop yield under various climate conditions. It can provide a flexible approach, for example, as based on satellite indicators combined with climate variables and ground monitoring data. In particular, Artificial Neural Networks are extremely good at dealing with varied input and can therefore be employed in tasks such as image segmentation to separate forested and non–forested areas and detect early indicators of degradation [60]. They also excel in modeling human brain as an associative memory (it creates probabilistic associations between any of its inputs and known outputs on the basis of an iterative learning principle) [20] [61]. This is possible because ANNs can generalize from previous examples, after processing enough data and storing associations in their net data structure [7]. The flexibility of Artificial Neural Networks to detect complex non–linear associations between input and output data, makes them suitable for biomass estimation when standard statistical methodologies are not enough, because represent a simplification of complex interactions [61]. However, with small sample size and complex data samples, ANNs can be overfitting; thus, models such as Random Forest may have better robustness and generalization ability [62]. Notwithstanding, approaches such as "save best" and early stopping may reduce overfit on ANNs to make more stable predictions [63]. ANNs, which have an architecture consisting of many hidden layers and at least one non–identity activation function, are capable of approximating any continuous functions and are therefore excellent tools for complex biomass modeling 64.

4.5. Deep learning models

Deep learning methodologies further enhance the potential of traditional ANNs by learning spatial and temporal features directly from raw data. CNNs are used to process satellite–based imagery for detailed spatial estimates of vegetation biomass, and RNN (e.g., LSTM/GRU) equipped to predict availability across the seasons or years. These models work well when long–term tracking or pixel–wise prediction are the concern. It provides for a more complete characterization of biomass dynamics, in particular when multi–sensor data is considered that include Synthetic Aperture Radar and optical imagery [64] [65]. Deep learning models, predominantly Deep Neural Networks, are able to discover abstract features from input data by multiple inter–connected layers, which have gained much attention due to their predictive performance and the potential to exploit large–scale datasets [67]. The ability to extract hierarchical features in non–linear fashion allows them to model complex relationships contained in biomass data more effectively than classical machine learning algorithms, and consequently has been successful for improved performance in a number of remote sensing applications [68]. However, it is important to consider that not all deep learning approaches lead to better accuracy, calling for careful tuning of network architectures, parameter settings and validation over different environmental scenarios [66]. For example, although some deep– learning models such as UNet might demonstrate greater bias in mapping AGC than Random Forest, some like Convolutional Neural Networks have also demonstrated potential for predicting biomass in crops (e.g. wheat and barley) [66] [62]. Moreover, deep learning models may have interpretation problem and high computational complexity when data set is not large enough [69]. Although deep learning and hybrid modeling have shown promising performance in terms of biomass mapping, the predictive accuracy depends upon the availability and quality of training data as well as validation strategy. Most of the deep learning complaint systems are learned with large and well–distributed training data so as to avoid the instable learning process and spatial bias, which makes them less effective for data–sparse area. Their high computational burden and poor interpretability also limit their operational application in the framework of routine planning. Hybrid and ensemble approaches address some of these issues, through combining complementary strengths of several models or incorporating biophysical understanding. These methods enhance the robustness and generalization across various landscape types at the expense of complex models and high implementation effort. To guarantee feasibility in large–scale biomass surveys, sound validation with independent spatial datasets and uncertainty–conscious assessment are indispensable steps for these advanced models.

4.6. Hybrid and ensemble models

Hybrid methods hybridize machine learning with physical model, GIS layers or empirical relations to better precision. Examples include blending Random Forest with GIS–based suitability mapping and coupling ANN models with crop growth simulations to increase predictive reliability. For uncertainty reduction in large–

scale biomass maps and improved generalization over regions, ensemble models integrating the output from multiple algorithms are also applied. These advanced models, e.g. stacked convolutional, gated–recurrent– and transformer encoders on fused Sentinel–1/2 sequences have shown good performance for pixel–wise classification and yield prediction [70]. The robustness of ensemble machine learning techniques for combining multiple sensor measurements and model simulations is an important point [8]. Ensemble methods such as (bagging, boosting and stacking) has been proved to be highly useful for enhancing the prediction accuracy for biomass estimation, especially in combination with multimodal convolutional fusion from different satellite and environmental data [71] [72]. This is evidenced in additional studies where hybrid models are developed and they perform better than the individual machine learning algorithms (e.g., CatBoostr, LightGBM, Random Forest and XGBoost) to predict biomass [68]. In particular, hybrid approaches combine the biophysical basis of process–based models with the pattern recognition of DL to improve predictive accuracy and expand applicability in more difficult modeling environments [69]. Such hybrid approaches frequently exploit mechanism components like soil moisture dynamics or crop growth processes to guide the learning process of deep learning models, so that they can focus on complex high–dimensional patterns [69]. This inclusion leads to more robust predictions, particularly given noisy or small datasets, because hybrid models have been found to generalize better across new locations and conditions than simple approaches do [73].

Table 3 summarizes the major machine learning approaches used for biomass estimation, highlighting their characteristics, strengths, and limitations.

Table 3. Machine Learning Techniques for Biomass Estimation

Technique / Model Type	Key Characteristics	Applications	Strengths	Limitations
Regression–Based Models	Capture linear to complex nonlinear patterns; performance depends on data variability and model choice	Baseline biomass prediction; integration of climate, soil, and satellite indices	Interpretable (linear); advanced models capture nonlinear interactions	Linear models struggle with variability; advanced models need larger data; spatial uncertainty remains
Tree–Based Models (RF, GBM, XGBoost)	Ensemble decision trees; handle noisy, nonlinear, high–dimensional data	Forest AGB estimation, crop residue prediction, bioenergy zone identification	High accuracy; manages multicollinearity; robust to noise	Less sensitive to spatial autocorrelation; possible overfitting; lower interpretability
Support Vector Machines	Kernel–based; suited for small–medium datasets; supports nonlinear boundaries	Crop biomass prediction, vegetation classification, land–cover mapping	Effective for nonlinear patterns; stable with limited samples	Kernel choice sensitive; variable performance; computationally heavy
Artificial Neural Networks	Multilayer networks; learn nonlinear functions by weight adjustment	Forest biomass modeling, waste prediction, climate–driven yield estimation	Handle diverse inputs; strong for image segmentation and pattern extraction	Overfitting risk; high training time; sensitive to architecture
Deep Learning Models (CNN, RNN, LSTM, GRU, UNet)	Learn spatial and temporal features from raw data; hierarchical feature extraction	Satellite–based AGB mapping, seasonal biomass forecasting, SAR–optical data fusion	Capture deep patterns; high accuracy with big data; pixel–level prediction	Need large datasets; computationally heavy; interpretability challenges
Hybrid and Ensemble Models	Combine ML with physical models, GIS layers, or multiple algorithms	Large–scale biomass mapping, uncertainty quantification, sensor fusion	Higher accuracy; strong generalization; integrate biophysical knowledge	Complex design; high computational cost; harder to interpret

The performance of ML algorithms is spatial heterogeneity, volume of data, and type sensor dependent We also have performed comparisons across different types of ML approaches . Ensemble methods based on trees (e.g. RF and GB) always deliver good results in mixed land–use areas and few training samples thanks to their resistance against noise and multicollinearity. SVM tend to obtain good accuracy on small–medium sized datasets, however it is very much dependent on the kernel and tuning of its parameters which means it may not be easily scalable.

For pixel–based biomass mapping, dense multi–temporal and high–resolution data allow deep learning models to perform better than the traditional methods. Their performance degrades in regions with limited ground truth data or non–coherent temporal information. In practice, challenges such as extensive data prepossessing overheads, computational costs, lack of standard validation protocols and model's transferability across regions are still prevalent. Overcoming these limitations is essential to translate methodological innovations into functional biomass mapping and energy planning systems.

Table 4. Relationship between Remote–Sensing Sensors, Machine–Learning Models, and Biomass Estimation Performance

Sensor Type	Common ML Models Applied	Observed Performance Trend	Key Reason for Performance	Typical Application Context
LiDAR	Random Forest, Gradient Boosting, ANN, CNN	Highest and most stable accuracy	Direct capture of canopy height and vertical structure strongly correlated with AGB	Forest AGB benchmarking, regional high–accuracy studies
Optical (Sentinel–2, Landsat)	Random Forest, SVM, GBM, ANN	Moderate to high accuracy in low–medium biomass	Spectral indices capture vegetation vigor but saturate at high biomass	Croplands, grasslands, seasonal monitoring
SAR (Sentinel–1, ALOS PALSAR)	Random Forest, SVR, GBM	Moderate and variable accuracy	Backscatter sensitive to structure and moisture but affected by noise	Cloud–prone regions, dense canopies
Optical + SAR fusion	Random Forest, XGBoost, ANN	Higher accuracy than single–sensor models	Complementary spectral and structural information	Large–scale mapping without LiDAR
LiDAR + Optical/SAR fusion	Random Forest, CNN, hybrid ensembles	Consistently highest accuracy across studies	Combines detailed structure with spatial continuity	Operational biomass mapping, policy–scale assessments
Multi–temporal optical/SAR	LSTM, GRU, CNN–RNN hybrids	Improved temporal consistency	Captures seasonal and interannual dynamics	Forecasting and trend analysis

Table 4 shows the influence of the synergistic selection of remote–sensing sensor and machine–learning model on biomass estimation accuracy. It is a well–established fact that LiDAR–based inputs, especially when combined with optical or SAR data, result in the most accurate biomass estimates due to incorporation of vegetation structure. Optical and SAR sensors also have only fair accuracy, and are particularly useful in low–to–moderate biomass or cloud–impacted areas. In summary, the table illustrates that multi–sensor fusion in combination with suitable ML models results in most robust and scalable solutions for biomass mapping.

5. Applications in sustainable energy planning

Machine learning reinforces sustainable energy planning as it increases the accuracy and reliability of analysis of biomass. They assist planners in developing cost–effective supply chains, making decisions on where to site plants, and integrating biomass resources into wider renewable energy–bioenergy policies. Finally, database–supported methods help secure continuous surveillance of a service ability for both short– and long–term monitoring to maintain the biomass use on an environmentally and economically guaranteed level. **Figure 5** illustrates how predictive biomass models produced using machine learning culminate in actionable objectives including supply chain optimization, site selection, forecasting, and grid integration. The figure enhances the storytelling by linking methodological improvements to real world energy planning practice.

5.1. Biomass supply chain optimization

A precise prediction of the biomass's availability is core in order to design a lean supply chain. ML models predict feedstock amount and quality, seasonal variation to enable better planning of transport routes, storage requirements and cost constituents. These understandings can reduce the cost of collections and uncertainties in feedstock delivery. These advances in the field enable market and policy approaches to capture value of these advantages, and form a cost–effective biomass energy industry [4]. On a process level, machine learning can help optimize the entire biofuel supply chain from feedstock procurement to distribution by analyzing massive volumes of agricultural data about weather patterns, soil quality and crop health [4]. This analytical function will ensure that harvesting schedules and logistics can be dynamically optimized to maximize efficiency and reduce waste, supporting the ability of industry to access a reliable and consistent biomass supply. Furthermore, by studying market trends, oil prices and policy impacts machine learning algorithms can construct their predictions about biofuel demand, pricing, competitiveness which helps the producers and investors in making smart decisions. Such prediction is important to tackle complexities associated with biomass supply chain management starting from cultivation and harvesting to conversion and distribution [10].

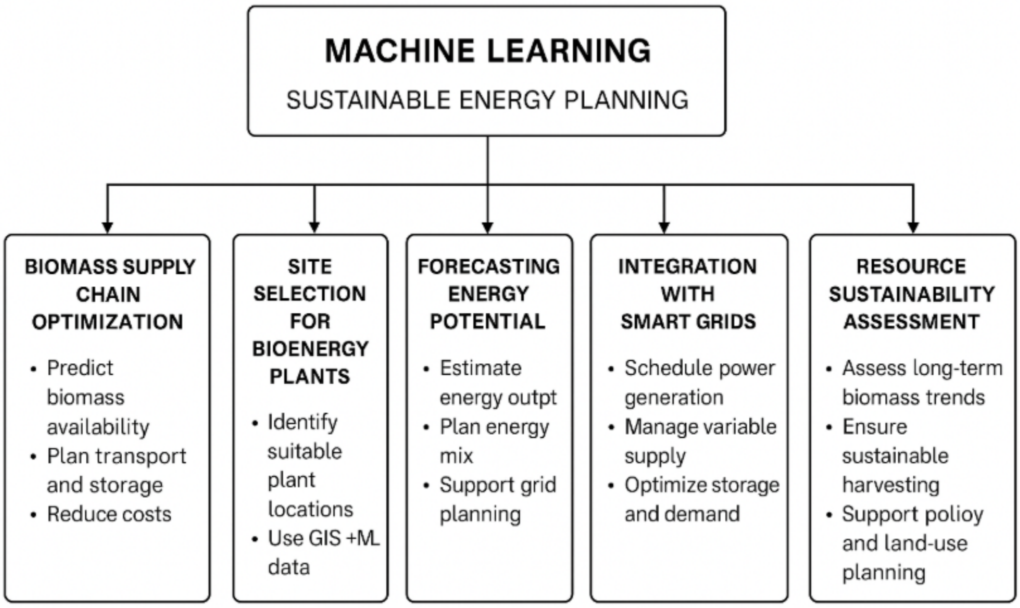

Figure 5. Applications of Machine Learning in Sustainable Energy Planning

5.2. Site selection for bioenergy plants

GIS–ML systems integrate spatial data and the predictive model to map areas that have a high concentration of biomass density and suitable land. They also assess accessibility, the presence of a road network, environmental constraints and other land uses vying for the territory in question. This integrated model can help determine the optimal bioenergy plant location in terms of stable feedstock supply and lower logistics cost. On the other hand artificial intelligence helps to mitigate inefficiencies of the biomass supply chain by predicting demand, optimizing transportation routes and scheduling operations in order to minimize cost figure [4] [10]. This is critically important for biofuel production distributed from the point of production to end users, so that it can be efficiently transported into high-demand markets at a reduced cost and with fewer emissions [4]. Application of machine leaning even broader, range from location–based similarity analysis to identify best possible locations for storage depots depending on the moisture content and ash, closeness to power plants [74]. Machine learning, particularly reinforcement learning, has the ability to manage dynamically complex supply chain systems such as biomass supply chains by doing better than classical mathematical programming approaches in addressing many constraints and real–time large problems [10]. In addition to site selection and supply chain optimization, machine learning also supports market analysis and policy making by analyzing evolving market trends and estimating policy impacts [4]. This ability will lead to an informed decision–making process of economic feasibility and regulatory support for the bioenergy projects, helping sustainable development [75]. Artificial intelligence comes into stage by forecasting properties of biomass, the performance of conversion processes, characteristics of biofuels as well as optimization of a supply chain to address measurement issues and improve classical models for bioenergy systems [75–83].

5.3. Forecasting energy potential

Machine–learning–based forecasting tools predict seasonal and yearly biomass energy yields. These prognostics assist in designing energy mix scenarios, and evaluating plant load factors to make investment plans. They further provide a basis for grid planning by discerning when biomass availability is high and low. In addition, machine learning models have the potential to include different environmental, economic and social parameters in predictions that can help refine these [84] so we can better understand the potential of including biomass for energy. This level of advanced forecasting is crucial to help enable robust energy systems to adjust to differing resource availabilities and demands, and thus enhance the overall stability and sustainability of the energy supply [85–90]. They are also capable of establishing the optimal feedstock mixes for co–firing purposes wherein energy output is maximized and emissions, as well as operations costs are minimized [4]. This capacity of predicting and optimizing the different dimensions of bioenergy systems (resource assessment to energy conversion and supply chain management) provide evidence of enabling nature of machine learning in sustainable energy innovations [91–94]. The integral development can contribute to fulfilling a sustainable bioeconomy due to strong improvement of GHG reduction and mitigation of global warming [3]. Furthermore, they provide insight into the intricate biochemistry of pathways underlying biofuel production to streamline procedures and conditions for energy saving and waste minimizing [95–97]. This predictive expertise also encompasses the specific determination of optimal operating conditions for biomass conversion technologies (Pyrolysis, Gasification, and Combustion) in order to increase efficiency and yield while minimizing operational costs [1].

5.4. Integration with smart grids

In the case of biomass in integrated renewable systems, predictive models help to manage power generation on a real time basis. ML–enabled scheduling, using biomass predictions together with solar or wind readings, to enhance grid stability and manage transition supply. This combines for dispatch optimization and energy system decentralization planning. Furthermore, state–of–the–art machine learning algorithms are able to optimize in real time the energy storage and demand side management schemes of these smart grids, leading to improved reliability and economic efficiency [98–105]. ML is also used in LCA and TEA to offer a comprehensive view of both environmental and economic impacts related to bioenergy systems [77]. This ensures a holistic assessment of biomass potential, from resource mapping to conversion and end–use applications, ultimately for an sustainable integration into the overall energy system [106–110]. In particular, machine learning has proven useful in the optimization of feedstock selection, process parameters and predicting yield in the biofuel sector, which results in enhanced efficiency/confidence towards sustainability at large scale [1]. This function comprises the selection and deployment of microorganisms and plants that are genetically optimized to increase biofuel production yields as well as accurate prediction for techno–economic analyses and life cycle assessments of biomass–to–biofuels technologies [111–112]. Also, ML models have played a crucial role in biorefineries where they become efficient tools for increasing process efficiency, energy production, resource utilization and finally overall system performance [113–124]. For example, such ML methods can be used to monitor and control key parameters during fermentation, which result in improved yields, better conversion rates and more efficient operation of the bioreactor [1]. Moreover, it is possible to predict bio–oil yield, nitrogen content and energy recovery rate with high accuracy based on machine learning algorithms [125–130], which can provide new approaches for improving quality of engineering bio–oil production.

5.5. Resource sustainability assessment

Machine Learning models evaluate long–term trends of productivity in biomass by considering climatic variability, changes in land use, and indicators related to soil health. These assessments inform sustainability harvesting practices to prevent land depletion and weakened resilience. Those findings are relevant for policy making and the sustainable management of bioresources in the long run. Furthermore, they can recognize regions where the scarcity of biomass might occur or have occurred to avoid drastic interventions, develop regenerative practices and ensure that ecosystem integrity and continuity of resources are preserved. Additionally, machine learning aids carbon accounting and reduction policy formulation by precisely estimating biomass growth to store carbon in distinct land–use management structures for building balanced climate change mitigation strategies [131–133]. This ability to add and remove constraints enables more informed land–use planning decision making processes, supporting compatibility of bioenergy development with ecological conservation and sustainable management. Additionally, ML models contribute to predictions of biomass availability and quality, which are important for the optimization of biofuels production processes and a stable supply of feedstocks [134–138]. Such tools are necessary to facilitate research and development teams in the optimization of bioprocess technology by informing about input parameters affecting sustainability score values [139]. This ML integration with bioprocess optimization guarantees economic and environmental viability of bioenergy initiatives as it is aligned with the principals of circular economy [140].

Key applications of machine learning in sustainable energy planning are illustrated in the **table 5**. Five main application areas are defined, together with fundamental elements, data sets required, benefits and other findings.

Table 5. Applications of Machine Learning in Sustainable Energy Planning

ML Role	Key Data Used	Outputs Generated	Practical Benefits	Examples	Contribution to Sustainability
Predicts feedstock availability, quality, and seasonal trends	Weather data, soil parameters, crop health, market trends	Availability forecasts, route plans, cost estimates	Reduces transport cost, minimizes delays, improves supply reliability	ML–based logistics planning, demand forecasting	Supports efficient biofuel production and reduces wastage
Integrates GIS with ML for spatial suitability mapping	Biomass density, land use, terrain, road networks, environmental limits	Optimal plant locations, depot siting, storage plans	Cuts logistics cost, ensures steady supply, supports regional planning	Reinforcement learning for route and depot optimization	Enhances land–use planning and reduces emissions
Predicts seasonal and annual biomass energy output	Climate data, productivity trends, economic factors	Output forecasts, feedstock blend suggestions, plant load estimates	Guides investment, improves grid planning, supports risk reduction	ML for process optimization, pyrolysis/gasification prediction	Helps maintain energy stability and reduces greenhouse gases
Schedules biomass power generation in hybrid systems	Biomass forecasts, solar/wind data, demand patterns	Real–time dispatch schedules, energy storage plans	Improves grid stability, reduces curtailment, supports decentralization	ML in techno–economic analysis, LCA, biorefinery control	Enables flexible, cleaner, and reliable grid operations

Evaluates long–term biomass trends and land suitability	Climate change indicators, land–use maps, soil health, ecological data	Sustainability scores, carbon estimates, risk maps	Supports policy, prevents overharvesting, ensures ecological balance	ML for carbon accounting and land management	Strengthens climate action and circular economy goals

6. Challenges and research gaps

There remain several limitations to the robustness and scalability of carbon density estimation using machine learning for biomass. A major bottleneck is the lack of high quality ground truth. Unevenness of field measurements, lack of crop residue record and forest inventories at regional scale hampers the robust calibration and validation varnishing up the finalized model, small number of ground data limit testing under various landscapes. It is challenging to measure fine–grained biomass variation, especially in diverse agro–climatic conditions. Local variability in crops, soil, irrigation and micro–climate is frequently at a finer scale than can be measured by satellite or coarse grid data which may cause over– or underestimation of biomass. Prediction is also hindered through variability from season and climate. Biomass creation is influenced by precipitation, temperature and extreme events therefore predictive modelling is problematic where reliable long–term climate records or forecasts are scarce. There is also relatively low incorporation of social–economic and environmental aspects, such as market demand, waste disposal, land– use decisions or soil degradation despite the impact on biomass supply. This literature also does not have standardized protocols to map large extent of biomass. Discrepancies in data collection, pre–processing technique and model settings makes it difficult to compare and the generalizability across regions is limited. Tackling these challenges will need better data availability, greater inclusion of climate and socio–economic drivers, and commonalities for routine monitoring efforts at different levels.

7. Future directions

The further concern for researches in the fields of biomass mapping and machine learning is the necessity to develop methods that improve accuracy, scalability, as well as real–time decision support. A promising avenue is the application of high–resolution satellite data and deep learning models. These methods are able to detect fine spatial patterns in the canopy growth, forest structure and waste generation respectively, a feature that may explain why the biomass inventory is more accurate at different landscape levels.

An additional critical area is the integration of logistics planning and energy system design to biomass prediction in unified framework. Linking prediction models to transport routing, storage planning and energy supply calculations will enable end–to–end decision–support systems for bioenergy projects. Transfer learning also has promising prospects, particularly in areas with few ground truth data. When models are already trained in country A, they can ‘easily’ be used/tuned for another area.

The combination of these methods with machine learning and digital twin platforms is becoming available for real–time track cropping biomass availability supply chain volatility and process constraints. These systems are currently providing the capability for dynamic feedstock flow simulation and quick adaptation to different climate or market scenarios. Inclusion of uncertainty quantification methods in the prediction models will also enhance policy decisions by reporting the level at which model was confident and lower/upper bounds along with risks.

8. Conclusion

Machine learning has revolutionized how biomass feedstock potential is estimated, mapped and integrated in sustainable energy planning. The approaches we have considered in this work illustrate that data-driven models can represent the spatially heterogeneous, nonlinear and time-variable effects much more effectively than traditional methods. The combination of satellite images, GIS overlays, field inventories and socio–economic information can provide a completer and more realistic picture of availability to biomass at different landscapes. Tree–based models, deep learning architectures and their monolithic mixtures deliver high predictive performances for such multi–sourced datasets with significant enhancements in terms of accuracy, scalability and robustness. The review underlines that these breakthroughs are not limited to estimation, they have impact also on choosing site, planning of the supply chain routing and energy forecast as well as long–term sustainability assessment. Machine learning models assist planners in selecting optimal sites for plants, forecasting seasonal variability in the flow of feedstocks entering a plant, assessing resource risks, and designing more resilient energy systems. Nonetheless, long–standing gaps in the data remain – especially sparse top–quality ground measurements, non–uniform standards of records and some matters regarding the modelling of fine–scale spatial processes. These constraints highlight the importance of richer databases, harmonized processing chains and greater use of climate and socio–economic information. Onward achievements should be concentrating on the utilization of high–resolution remote sensing, transfer learning, uncertainty quantification and digital twin platforms for enhanced real–time decision support. ML–predictions can be combined with logistic optimizations and energy system–level modelling to effectively set up end–to–end frameworks connecting resource assessment straight to planning and operation. Collectively, these advances indicate that in order biomass mapping is not only advancing due to machine learning and is taking a central role towards reliable, cost–efficient and environmentally compatible bioenergy strategies. The possible future machine learning applications to biomass mapping encompasses movement away from static estimates towards real–time management based on near–real time satellite data, UAVs, IOT sensors and smart monitoring systems. On the other hand, adaptive ML models and digital twin (DT) architectures can in turn sustain dynamic planning, uncertainty–aware decision–making as well as more realistic use of biomass data for sustainable energy systems.

List of Abbreviations

AGB – Aboveground Biomass

AGC – Aboveground Carbon

AI – Artificial Intelligence

ANN – Artificial Neural Network

BRC – Biomass Resource Characterization

CNN – Convolutional Neural Network

DL – Deep Learning

EVI – Enhanced Vegetation Index

GBM – Gradient Boosting Machine

GEDI – Global Ecosystem Dynamics Investigation

GIS – Geographic Information System

GEE – Google Earth Engine

GRU – Gated Recurrent Unit

IoT – Internet of Things

KNN – k–Nearest Neighbors

LAI – Leaf Area Index

LiDAR – Light Detection and Ranging

LSTM – Long Short–Term Memory

ML – Machine Learning

MODIS – Moderate Resolution Imaging Spectroradiometer

MSW – Municipal Solid Waste

NDVI – Normalized Difference Vegetation Index

OLS – Ordinary Least Squares

PCA – Principal Component Analysis

RF – Random Forest

RNN – Recurrent Neural Network

SAR – Synthetic Aperture Radar

SVM – Support Vector Machine

SVR – Support Vector Regression

TEA – Techno–Economic Analysis

UAS – Unmanned Aerial System

UNet – U–shaped Convolutional Neural Network

WebGIS – Web–based Geographic Information System

XGBoost – Extreme Gradient Boosting

Author Contributions

Smita Desai and **Sushama Shirke** contributed to the conceptualization of the review framework and identification of key research themes. **Vishvas V. Kalunge** and **Sireesha Koneru** were responsible for the systematic literature survey, data collection, and classification of machine learning approaches. **Gaurav Raju Khobragade, Vidhi Rajendra Kadam** and **Shyamsing Thakur** contributed to the analysis of data sources, remote sensing techniques, and GIS integration aspects. **Govindrajan Murali** supported the methodological structuring, preparation of tables and figures, and critical comparison of models. **Anant Sidhappa Kurhade** led the overall supervision of the study, refined the technical content related to biomass mapping and sustainable energy planning, and coordinated manuscript development. All authors contributed to writing the original draft, reviewing and editing the manuscript, and approved the final version for submission.

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Conflict of interest

The authors declare no conflict of interest

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