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ORIGINAL RESEARCH ARTICLE

AI-Supported Forecasting of Biomass Availability under Changing Environmental and Resource Conditions

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ABSTRACT

Reliable forecasting of biomass availability is essential for sustainable bioenergy planning, climate mitigation, and efficient resource management. Biomass production is influenced by complex interactions among climate variability, land use, management practices, and socioeconomic drivers, which limits the effectiveness of conventional empirical and process-based models. This study reviews recent advances in artificial intelligence (AI) and machine learning approaches for biomass availability forecasting under dynamic environmental and resource conditions. Emphasis is placed on models that integrate multi-source data, including remote sensing, field observations, climate records, management inputs, and socioeconomic indicators. The reviewed literature shows that AI-based methods capture nonlinear and spatiotemporal relationships more effectively than traditional approaches, resulting in improved prediction accuracy, scalability, and adaptability across regions. Ensemble, hybrid, and probabilistic frameworks further support uncertainty-aware forecasting, which is critical for policy formulation and industrial decision-making. From a sustainability perspective, AI-supported biomass forecasting contributes directly to several United Nations Sustainable Development Goals, particularly SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action). By supporting informed decision-making, resilient biomass supply chains,

and risk-aware planning, AI-based forecasting frameworks provide a practical pathway toward sustainable and climate-resilient bioenergy systems.
Keywords: Artificial Intelligence; Biomass Availability; Machine Learning; Remote Sensing; Supply Chain Optimization

1. Introduction

Biomass, in the form of agricultural residues, forestry remnants and dedicated energy crops, is important for the transition to low carbon and sustainable energy systems. Precise predictions of the amount of available biomass are needed for logistics of feedstock supply, bioenergy planning and supply chain optimization as well as for policy making. Conventional prediction models are commonly based on the empirical, linear, or simple regression and less effective when considered variable climate and resource limitation. Nevertheless, recent developments within artificial intelligence and machine learning promise advanced abilities to capture the complex non-linear relationships that explain biomass production and availability [1]. These sophisticated computational techniques can assimilate a vast array of data such as satellite images, weather conditions, hydraulic properties of soil and genetic information to contribute to an overall understanding of biomass yield determinants [2]. In particular, the AI methodologies such as for example, artificial neural networks (ANNs), and support vector machine (SVMs) have demonstrated to be job capable of predicting biomass properties; performance of conversion processes; biofuel quality attributes, as well as optimization in bioenergy supply chains [3]. Bringing machine learning into the biofuel industry, for example, has a great potential as it can contribute to more efficient and sustainable bioenergy production leading to innovation and a faster implementation of biofuels [1]. Due to the natural variability of biomass feedstocks with seasonal, weather and agricultural conditions, advanced predictive models that can deal with the dynamic environmental factors are required [1]. Such advanced modelling is also essential to refinement of bio resource management, which seeks to establish a stable feedstock supply market for the bioenergy and bio product industry, as well as for environmentally friendly development [4,5]. We aim to provide an overview discussion on the methods and applications of AI in biomass forecasting, focusing specifically on issues when it comes to how such intelligent systems may be able to produce more accurate and adaptive predictions compared with traditional approaches; thus, enabling biomass supply chains to be both more dynamic and resilient [6]. This is even more critical since the world's move towards sustainable energy sources is increasing and it becomes harder to predict global environmental behaviour [1, 7]. The aim of this paper is to investigate a state-of-the-art based review on AI-based biomass prediction techniques including machine learning models, deep learning framework and hybrid approaches.

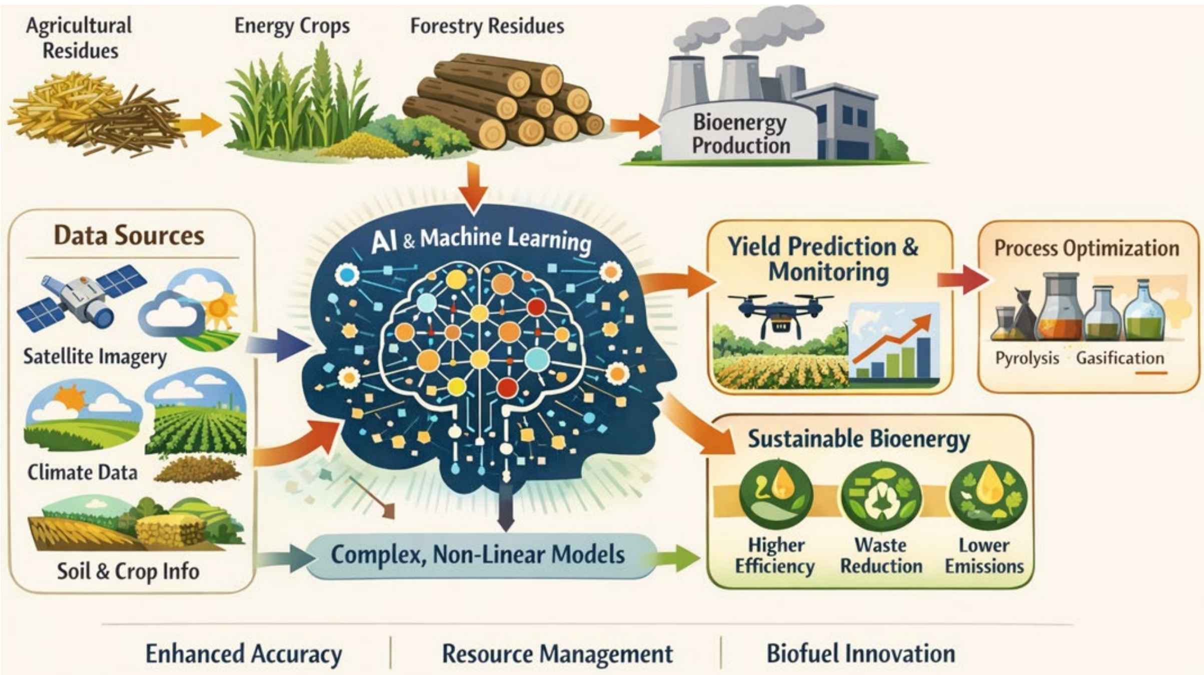

Figure 1. AI-Based Biomass Forecasting Framework for Sustainable Bioenergy Systems

Figure 1 illustrates how diverse biomass resources and multi-source data (satellite, climate, soil) are integrated using AI and machine learning models. These models capture complex non-linear relationships to accurately predict biomass availability and optimize conversion processes. The outcome supports efficient supply chains, higher energy yield, and sustainable low-carbon bioenergy production. AI-aided forecasting relies on computational methods to analyze very large and complex datasets—including weather data, satellite imagery, soil types, crop development and socioeconomic indicators—to make predictions more accurate. In this review, we discuss recent trends in the field of AI-based biomass forecasting under varying environmental conditions. We are concerned with discussing recent works on algorithms for biomass while accounting for inter- and intraspecific differences and processes. These include evaluating how such models consider changes of climate, land use and resource management to ensure that the models can make strong and believable predictions [8]. These advancements are crucial for improving bioenergy systems, eliminating waste and ensuring environmental sustainability with intellectual decision-making and predictive modelling capabilities [9]. In this paper, the recent developments of AI methods for biomass forecasting models are systematically reviewed and a comprehensive investigation is performed to assess the effectiveness of these models, as well as investigate remaining gaps in their performance and generalizability across various global conditions. The use of AI, including machine learning and deep learning, is especially advantageous in the bioenergy industry as it can improve thermochemical conversion processes leading to better overall performance and productivity [10]. This genre of AI-based models can even determine operational conditions for processes such as pyrolysis, gasification and combustion which leads to gain in productivity and efficiency along with lower costs [8]. Furthermore, by improving feedstock selection, process parameters and the prediction of yield (making use of machine learning algorithms), biofuel production can be greatly enhanced in terms of energy output and wastage minimization [8]. Besides, predictive models based on machine learning algorithms could be used to support the selection of biomass feedstock by considering their physicochemical properties and make predictions about the most appropriate treatment pathways [1]. This forward strategy will lead to a better resource utilization and form the base for sustainable bioenergy systems by providing a uniform and high-level feedstock supply. The incorporation of machine learning in this field can enhance feedstock production effectiveness by monitoring aspects such as soil health, weather fluctuations and nutrient content which has the potential to raise yields by 10–20% [11]. This holistic knowledge supports the informed decisions from feedstock growth to final energy production spanning the whole bioenergy supply chain, enabling both cost-effectiveness and environmentally friendly procedures [12]. These more sophisticated machine learning engines also enable the discovery of new catalysts and materials that boost conversion rates and product quality in biomass-to-power processes [8]. Such analytical power can be used to enable a fact-based consideration of the effects of different parameters on biofuel yield and composition, thus offering an advantage for optimal design and operation of bio refineries [13]. Furthermore, AI-guided techniques are significantly involved in bio-oil production optimization and by experimental validations, they have been proven to have high prediction accuracy for yields and energy recovery rates so to make new momentum to energy-rich-utility bio-oil synthesis [14]. In fact, artificial intelligence approaches like ANN (Artificial Neural Network) and SVM have successfully been used to predict bio-oil production yield and quality and have benefited traditional methods usually [14]. Such models also support the optimization of bio refinery processes against challenges, such as varying properties of biomass and its sustainable supply that are paramount to sustainability and cost viability [15]. AI is used for selecting and genetically designing microorganisms and plants, which will in turn improve biofuel production and help to make reliable techno-economic as well as life cycle assessment of biomass-to-biofuel technologies [16]. This development is of special importance to promote faster commercialization of advanced biofuels from non-food sources such as agricultural residues, algae and cellulosic materials, all of which would widen the range of feedstock options and decrease dependence on traditional food crops [1, 17]. Furthermore, AI algorithms are even applied for optimal control of chemical process parameters in waste oils to biodiesel conversion for enhanced yield and quality [18]. In addition, machine learning possesses strong analytical skills to identify the best feedstocks as well as processes variables leading not only to better efficiency but also more sustainability of biofuel production [8]. AI techniques including machine learning and artificial neural networks (ANN) have been applied to optimize process design, evaluate performance and predict key parameters in thermochemical bio-refineries, which would help lower the experimental cost as well as rule out optimal conditions more quickly for such processes as biomass pyrolysis and gasification [15].

Table 1. AI-Based Biomass Forecasting Overview

Biomass Type	Key Data Sources	AI / ML Techniques	Prediction Focus	Applications	Benefits
Agricultural residues	Satellite imagery, climate data, soil properties	ANN, SVM, ML, DL	Biomass availability and yield	Feedstock logistics, biofuel planning	Improved prediction accuracy
Forestry remnants	Weather data, land-use information	ANN, hybrid models	Resource estimation	Supply chain optimization	Reduced uncertainty
Energy crops	Soil, crop growth, genetic data	ML, DL frameworks	Yield forecasting	Bioenergy production	Higher energy output
Mixed biomass	Multi-source datasets	AI-based models	Conversion performance	Process optimization	Cost reduction
Waste biomass	Physicochemical properties	ML algorithms	Biofuel quality	Bio-refinery operations	Waste minimization
Bioenergy systems	Socioeconomic, environmental data	Intelligent AI systems	Supply chain resilience	Policy making and planning	Sustainable development

Table 1 summarizes major biomass types and the data sources used for forecasting their availability. It highlights how AI and machine learning techniques are applied to predict biomass yield, quality, and conversion performance.

The uniqueness of the herein review is its comprehensive and application-value orientation towards AI-mediated biomass prediction. In contrast to previous reviews that are mostly algorithm comparisons, or single data source-based, our review ties artificial intelligence models to multi-source data integration, including remote sensing images and climate variables, field observations and socioeconomic records in a systematic manner. This organized synthesis clarifies how multifarious data environments shape biomass-availability forecasts across spatial and temporal scales.

Moreover, the review draws particular attention to uncertainty-informed and hybrid modelling thus focusing also on the importance of ensemble learning, Bayesian methods, AI–process model coupling in tackling data limitations and environmental variability and realization. Another contribution comes from the attention to operational relevance on that AI-driven forecasting is considered in terms of actual bioenergy supply chain decisions, including feedstock logistics, risk management and planning under varying environmental and resource conditions. By this inter-institutional scheme, the review builds up on previous findings by relating methodological advancements to applied bioenergy system needs.

The Article Selection for this Review was Conducted According to a Systemized and Structured Procedure to Guarantee Relevant, High-Quality Literature with an Academic Standard. Criteria included peer-reviewed journal articles, review papers and authoritative reports (typically published between 2010 and 2025). Any article related to the availability of biomass, estimation/forecasting of yield using artificial intelligence, machine learning and advanced data driven approaches was considered. Emphasis was placed in works that integrated multi-source data (e.g., remote sensing, climate variables, soil information) and management or socioeconomic factors. Studies that did not contain a clear methodology, validation or detail for biomass prediction under varied environmental conditions were excluded. This way we guaranteed a well-compromising exposure between the showcase of methodological contributions and applications and limitations of AI for biomass prediction.

2. Drivers of biomass variability

Biomass availability is governed by a complex interplay of biophysical, management, and socio-economic drivers, each operating across different spatial and temporal scales. Understanding these drivers is essential for developing robust forecasting models capable of capturing real-world variability.

2.1. Climate variability

It is also one of the most crucial elements, determining biomass formation. The temperature variability, the overall amount and distribution of rain, solar radiation and CO_2 concentration in atmosphere directly drive photosynthesis, evapotranspiration and cycles of plant growth. Anthropogenic climate change and extreme events – prolonged droughts, heat waves, untimely rains and floods-lead to high inter-annual variability and uncertainty in biomass yields particularly in rain-fed agriculture and forest systems. These weather-related variations, driven by climate, require advanced prediction models to predict a changing environment and its consequences on biomass quantity and quality [19]. Moreover, the land-use change (agricultural expansion, deforestation and urbanization) directly affects available land for biomass production causing competition and possibly environmental degradation [1, 20]. These human pressures substantially change ecosystem services and biodiversity to the point that it becomes extremely difficult to predict biomass availability in a realistic way and devise sustainable bioenergy directions.

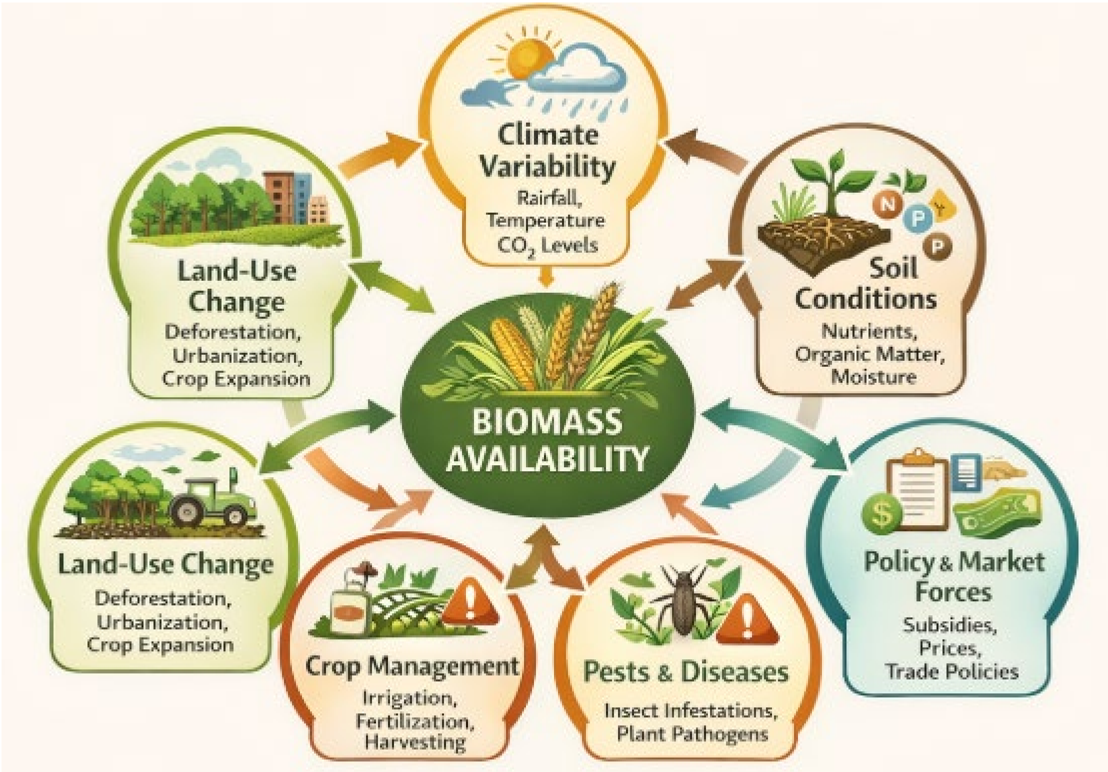

Figure 2. Key Drivers of Biomass Availability and Variability

Figure 2 summarizes the major biophysical, management, and socio-economic drivers controlling biomass availability. Climate variability, soil conditions, land-use change, crop management, pests, and policy forces interact in a non-linear manner to influence biomass yield. Together, these interconnected drivers explain the high spatial and temporal variability observed in biomass resources.

2.2. Soil conditions and fertility gradients

These are important parameters for the estimation of biomass productivity. Root growth and nutrient uptake are all affected by soil texture, organic matter content, available nutrients, water-holding capacity and microbial activity. Spatial variability in soil properties causes a non-uniform distribution of biomass even within the same agroclimatic zone, and long-term degradation of soils by erosion and salinization can markedly decrease the potential for biomass. In addition, the genetics of feedstock, combined with numerous cultivation factors (i.e., irrigation, fertilization and pest control) have a great effect on biomass yield and quality expectations of the degrees-of-freedom associated with genotype × environment × management [21]. The genotype-dependent sensitivity of different feedstocks and cultivars to temperature changes carries even more weight in the variability of biomass yields, where a process-based understanding is required for lowering predictive uncertainties of empirical methods [22]. In addition to these biophysical determinants, socioeconomic and policy mechanisms (e.g., market demand, government subsidies, land tenure and trade policies) also have a clear bearing on the decisions around biomass production as well as the number of feedstocks which are available for conversion into bioenergy [19]. All of these and other reasons make biomass availability prediction extremely complex, particularly when environmental changes interact with human interventions [23].

2.3. Land-use change and deforestation

It modifies the availability of biomass by changing vegetation cover, carrying capacity and ecosystem services. The reduction of biomass reserves in nature by conversion of forests or grasslands to agricultural or urban land (net decrease) contrasts with increased supply due to afforestation, reforestation, and expansion of energy crops (net increase). Such transitions are typically rapid and non-linear, being influenced by economic drivers and population increase which make them difficult to model using standard tools. Therefore, AI-assisted models, especially those that are combined with remote sensing and advanced spatial analytic methods can provide a powerful toolkit to monitor and forecast these intricate land dynamics and their harvestable biomass resource implications [24]. Models of this type are important for estimating the potential total biomass that accounts both for natural variability and human alteration of the landscape [20]. In addition, such models are essential to estimate the dynamic effects of climate change and land use changes on supplying biomass as a fuel for bioenergy crops as globally, there is an expanded demand for bioenergy feedstocks [24,25]. The complexity of the systems interconnected factors that determine the availability of biomass calls for a systemic model and forecasting however considering multiple data streams, feedback loops between environmental, social and economic forces [23].

2.4. Crop management practices

Crop type, planting date, irrigation practice, fertilization rate, stubble management and harvesting intensity are all important factors contributing to better biomass yields. As a result, there are substantial yield variations especially between regions and across seasons which arise from differences in farmer's decision making and input use. While sustainable practices can increase stability of the biomass, poor management can increase susceptibility to climatic stresses. In addition, variability in land use change estimates due to different crop management assumptions and land classifications adds uncertainty to the predictions of biomass availability and environmental implications [21]. The complex nature of these forces requires sophisticated modelling approaches to represent their interactions and forecast future biomass supply under alternative assumptions [26]. This is more complex and has the added challenge of reconciling different management practices across data sets (e.g. application schedule or irrigation regimes) [27]. Spatially explicit, high-resolution data on management practices are largely unavailable, which greatly limits the construction of fine-scale forecasting models [22]. Without incorporating nutrient limitations, that is the explicit application of irrigation and fertilizer into models for example, such yields run the risk of being overstated particularly in circumstances where systems are not necessarily well documented or rationalized [28].

2.5. Pest and disease outbreaks, along with extreme events

This introduces sudden and sometimes unexpected reductions in biomass. Insect pest and plant diseases dooms and invasive may cover large areas in a short time if favorable weather conditions prevail, while cyclones, wind fires frost hail hurts damage at times to massive numbers of plants at one stroke. Such episodic disruptions are hard to model with linear or stationary models. AI-based forecasting models that use real-time observed data and account for non-linear, complex relationships are required to predict and reduce the impacts of these events on biomass supply chains [29]. Such models can integrate multiple data streams, such as satellite data and environmental sensor networks to identify early warning signs of disruptions and predict the spatial and temporal spread of such disturbances to facilitate resilient biomass management approaches [30]. In addition, AI models can enhance risk perceptions by estimating uncertainties associated with biomass predictions which will allow for more informed decisions to be made in view of those environmental volatilities [31]. Of particular importance is that these systems have the potential to merge various data streams — from precision agriculture data to weather predictions — for development of a more nuanced, proactive biomass resource management strategy.

2.6. Policy and market forces affecting cropping decisions

It also adds to variability in biomass. Policies subsidizing crops, bioenergy mandates, land use regulations and water rights affect what gets planted where. Market forces such as high crop prices and demand for bio-based products may change cropping systems and land used indirectly influencing regional biomass supplies. Additionally, the volatile nature of such socio-economic factors — also frequently influenced by geopolitical events and global supply chain disruptions fails to make biomass availability an easily predictable task. Such external drivers, together with the biophysical uncertainties, highlight the importance of sophisticated AI models that can combine information from different data sets and make predictions even in this challenging context. Models, such of those presented here, are paramount for addressing supply chain risks due to the geographical distribution and seasonal variability that characterize the biomass resource availability and frequently tend to undermine economies of scale as well increase the risk of supply shortages [32]. These complications dramatically exemplify the challenge of advanced predictive modelling tools that must account for coupled material, supply chain and carbon economic uncertainties—to-date impediments to many real-world investments in cellulosic bio refineries [19, 33]. This need is further compounded by the requirement of constant volume and quality of biomass, a factor that is paramount for the economic sustainability of bioenergy production at a large scale and often affected by various geographical, climatic and logistic issues [19, 33].

Table 2. Major Drivers of Biomass Availability and Variability

Driver Category	Key Factors	Influence on Biomass	Sources of Variability	Modeling Implications
Climate variability	Temperature, rainfall, solar radiation, CO_2, extreme events	Controls photosynthesis, growth cycles, and yield	Inter-annual fluctuations, droughts, floods, heat waves	Requires non-linear, climate-adaptive models
Soil conditions & fertility	Soil texture, nutrients, organic matter, water retention, microbes	Affects root growth, nutrient uptake, productivity	Spatial heterogeneity, erosion, salinity	Needs spatially explicit and process-based models
Land-use change & deforestation	Agricultural expansion, urbanization, afforestation	Alters vegetation cover and biomass reserves	Rapid, non-linear human-driven transitions	AI and remote sensing-based forecasting
Crop management practices	Crop type, planting date, irrigation, fertilization, harvesting	Determines yield stability and stress resistance	Regional and seasonal management differences	High-resolution management data required
Pests, diseases & extreme events	Insects, pathogens, cyclones, fires, frost	Causes sudden biomass losses	Episodic and unpredictable disturbances	Real-time AI models with early warning
Policy & market forces	Subsidies, mandates, prices, land regulations	Influences cropping decisions and land allocation	Economic and geopolitical volatility	Integrated socio-economic–biophysical models

Table 2 summarizes the major climatic, soil, land-use, management, biological, and socio-economic drivers that influence biomass availability.

It highlights how their non-linear interactions and variability necessitate advanced AI-based models for accurate biomass forecasting. Taken together, these drivers interconnect in a nonlinear, spatially variable and temporally changing manner. Together, these dual effects make statistical forecasting based on simple assumptions impractical. This complexity justifies the use of advanced AI methods capable to fuse information from different sources, to model nonlinear relationships and evolve environmental and socioeconomic conditions for more accurate biomass forecasting.

3. Data sources and integration

Accurate and reliable forecasting of biomass availability relies on the effective use of diverse, multi-scale data sources that capture biophysical processes, management practices, and socio-economic influences. The integration of these heterogeneous datasets is central to AI-supported forecasting frameworks, as it enables models to learn complex spatial–temporal relationships that are not observable from any single data source. **Figure 3** illustrates how remote sensing, field measurements, climate data, and socioeconomic information are integrated within an AI framework. This multi-source data fusion enables accurate, robust, and scalable forecasting of biomass availability across space and time.

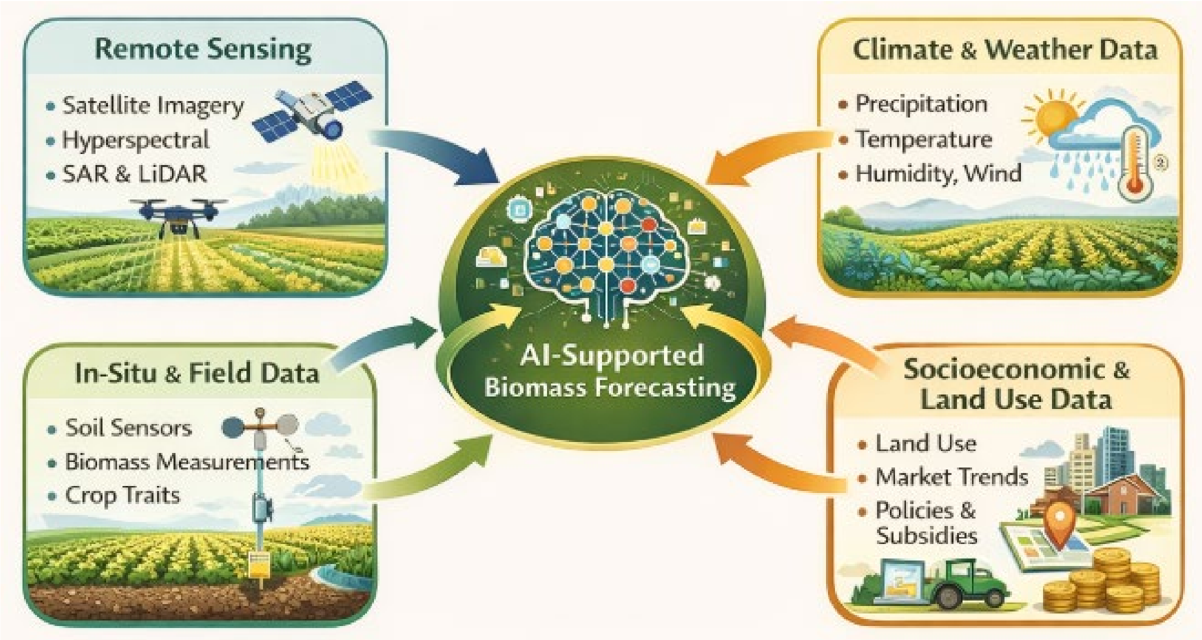

Figure 3. Integrated Data Sources for AI-Based Biomass Forecasting

3.1. Remote sensing

Synoptic remote sensing is the backbone of regional- and global-scale biomass monitoring because of its large spatial extent and high temporal completeness. Multispectral observations from satellite instruments, e.g. Landsat, MODIS, Sentinel and VIIRS, can be generally processed for vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) and Leaf Area Index (LAI). The characteristics of these indices are highly related to plant vigor, canopy architecture and aboveground biomass. Analysis of spectral data over time supports the monitoring of phonological stages, seasonal growth cycles and stress responses due to drought, lack of nutrients or pressure from pests. With the new high-resolution and hyperspectral imagery, finer scale biomass variability across diverse landscapes can now be detected. Additionally, synthetic aperture radar (SAR) and LiDAR provide complementary information on the three-dimensional structure of vegetation, which is critical to enabling more reliable estimation of above-ground biomass compared with optical approaches alone [34]. For example, radar satellites like Sentinel-1, ALOS PALSAR and RADARSAT are valuable data sources for tropical regions defied by near constant cloud cover which imposes optically based observations [31]. Integration of this various remote sensing information with strict calibration processes allows for precise and robust biomass estimates, also in difficult environmental conditions (see [35]). This multi-modal data fusion method, combining different types of remote sensing sensors improves the crop yield and biomass availability estimations [36].

3.2. In-situ and field data

In-situ and field measurements act a critical ground truth for AI models training and validation. Such databases contain direct yield measurements, as well as above- and below-ground biomass data, soil moisture content, soil nutrient concentration values, physiological information on crop traits such as plant height and leaf chlorophyll concentration. Field-scale data collection at high frequency available now through sensor networks and PA technologies, capture the local variability that might be missed by satellites. Finally, management-related information (fertilizer application rates, irrigation depths, crop rotation and residue management) contributes to a better contextualization of model inputs allowing for more accurate or interpretable predictions. Such in situ measurements are paramount to counterbalance the drawbacks of remote sensing data, especially regarding the discrimination among different tree species and for biomass estimation at high dense conditions that may lead to spectral saturation [37,38]. The integration of soil sensing data with aerial or satellite information is technically challenging but it does deliver accurate, local knowledge for the validation and calibration of ground observations, making farm management more supported by these (Figure 5) [39]. Moreover, ground truth is a crucial requirement for training and validating machine learning models, particularly on complex tasks such as species identifications and biomass estimation [39,40]. Such data would be key to optimizing land management strategies and their effect in the long term on biomass productivity and environmental sustainability [39,40]. The incorporation of such rich field data into comprehensive remote sensing surveys, models and fusions workflows can substantially improve the accuracy and robustness of prediction AI models for biomass properties or health across different environments [41,42].

3.3. Climate and weather data

The climate and weather factors are the main components that affect both biomass growth and variability. The precipitation, temperature, solar radiation, humidity and wind speed during 1961–2012 are obtained from historical meteorological observations and reanalysis datasets (CRU-NCEP), whereas future scenarios for these climate parameters are projected by a climate model under different emission pathways. Indicators of extreme weather (like heat stress days, drought indices, frost events and flood occurrences) are especially relevant to the representation of annual yield losses and sudden changes in the amount of vegetal mass. On the hydrologic side, short-term weather forecast (shorter than 7 days) are beneficial to AI-models as they can help predict operational decisions, while long-term climate projection helps in planning strategic biomass. It combines the various meteorological data sets used into a more comprehensive environmental knowledge on the factors affecting biomass stock and distribution, thus improving prediction expertise of AI models related to sustainable resource [43]. In addition, the presence of climate change scenarios enables early strategy for adaptation to minimize the threats posed by changes in biomass production and resources. This integrated consideration of past, present and future climate is essential to building biomass forecasting systems capable of sustaining long-term ecological and economic planning.

3.4. Socioeconomic and land use data

Socioeconomic and land-use data represent the human choice process that influence but do not actually determine biomass availability. Knowledge of market prices for crops, bioenergy demand, policies' incentive to use subsidies and land tenure systems influence the farmers decisions on which type of crop planting area and harvesting intensity. Maps of land use and land cover derived from surveys or satellite classification show us where agricultural practice has expanded, intensified, been abandoned or converted to non-agricultural uses. By taking this into account, AI models can include economic and policy-related processes that classical biophysical models frequently ignore. Such integration offers a potential for greater insight in the relation between humans and environment, space in flux and biomass-production transport, as it allows gaining thus far not reachable insights in all stages of the interacting human-environmental dynamics (and hence indirectly also help to develop more accurate and meaningful forecasting devices) [1]. For example, remote-sensing data and knowledge from historical observations on irrigation managed areas can be combined to estimate an irrigation probability for information of biomass availability under different water resource conditions [44]. This integrated framework also offers invaluable context for forecasting land-use changes by market forces and policy adjustments that are potential wild cards that could radically shift regional biomass supply [45]. In addition, land marginality assessments (lma) that consider soil quality and cost effectiveness for food production can complement prioritization of sustainable biomass to lower potential conflict with food security [46].

3.5. Data integration and fusion

The power of AI-based biomass prediction would be felt in a fusion strategy, which can incorporate RS, ground based measurements, climate data and even socioeconomic information into uniform modelling pipelines. Feature level fusion, spatiotemporal alignment and deep learning-based representation learning techniques have been used to help models mitigate the heterogeneities of scale, resolution and uncertainty present in the datasets. By incorporating information from these complementary data sources simultaneously, AI models can more effectively capture nonlinear interactions, spatial heterogeneity and temporal evolution - resulting in improved and more generic predictions of biomass under varying environmental and resource conditions. This combined modular method can be used to construct more complex models which are able to handle problems such as outlier data, non-linearity, heteroscedasticity and multicollinearity that frequently restrict the applicability of conventional statistical techniques [47]. Such advanced data fusion paradigms (e.g., multi-modal deep learning, and Bayesian hierarchical models) enable AI to synthesize disparate types of biomaterials data, uncovering hidden patterns while bolstering prediction accuracy for highly complex biomass systems. Furthermore, the systematic inclusion of multiple environmental variables associated with local sites as well as socio-economic indicators would greatly improve the robustness and generalization capability of these predictive models [48]. This deep integration is necessary to accommodate the saturation behaviours of vegetation indices at dense canopies (e.g., NDVI) and to incorporate other important indices such as EVI for better biomass estimation [49]. Furthermore, more advanced data fusion approaches may incorporate multiple sources, including radar, lidar, multispectral images and hyperspectral data to compensate the shortcomings of single datasets and improve the general accuracy in simulation [50]. This holistic data integration method, especially with the introduction of deep learning frameworks, enables for re-contextualisation and enhancement of features learnt from point cloud datasets leading to enhanced prediction on individual tree biomass components [50]. The quality of integrated datasets is largely dependent on advanced noise filtering and variation treatment, particularly for spectral and point cloud measurements [51].

Table 3. Data Sources and Integration for AI-Based Biomass Forecasting

Data Source Category	Typical Spatial / Temporal Resolution	Information Captured	Key Strengths	Main Limitations	Role in Biomass Forecasting
Remote sensing data	10–1000 m; daily to monthly	Vegetation indices, canopy cover, structure, phenology	Large-area coverage; repeat observations; scalable	Cloud effects; signal saturation; indirect estimates	Regional and global biomass mapping
In-situ and field data	Plot to farm scale; seasonal to annual	Yield, biomass, soil moisture, crop traits	High accuracy; direct measurements	Limited coverage; costly; sparse records	Model calibration and validation
Climate and weather data	Regional to global; hourly to annual	Temperature, rainfall, radiation, extremes	Captures variability and climate stress	Projection uncertainty; coarse resolution	Yield variability and climate risk analysis
Management data	Field to regional; event-based or seasonal	Irrigation, fertilization, harvesting practices	Links human decisions to yield outcomes	Incomplete and inconsistent availability	Contextual yield interpretation
Socioeconomic and land-use data	Administrative to regional; annual to multi-year	Market prices, policies, land-use change	Represents policy and market influence	Low temporal resolution; reporting delays	Forecasting land allocation shifts
Integrated / fused datasets	Multi-scale; aligned spatial–temporal grids	Coupled biophysical and human drivers	Improved robustness and generalization	Complex processing; high computation	Comprehensive AI-based forecasting

Table 3 summarizes the **key data sources** used in AI-based biomass forecasting, including remote sensing, field measurements, climate, management, and socioeconomic data. It explains how each data type contributes unique information for **model training, validation, and prediction of biomass availability**. Overall, it highlights the importance of **multi-source data integration and fusion** for accurate, robust, and scalable biomass forecasting across space and time.

4. AI and machine learning methods

AI-supported biomass forecasting employs a broad spectrum of machine learning and artificial intelligence techniques, ranging from conventional statistical learning models to advanced deep learning architectures. These methods are designed to capture the nonlinear, high-dimensional, and spatiotemporal relationships that characterize biomass production under varying environmental and management conditions. **Figure 4** presents major AI and machine learning methods—ranging from tree-based models to deep learning and probabilistic approaches—used in biomass prediction. These techniques capture nonlinear, spatial, temporal, and uncertainty-driven patterns to improve the accuracy and robustness of biomass forecasting.

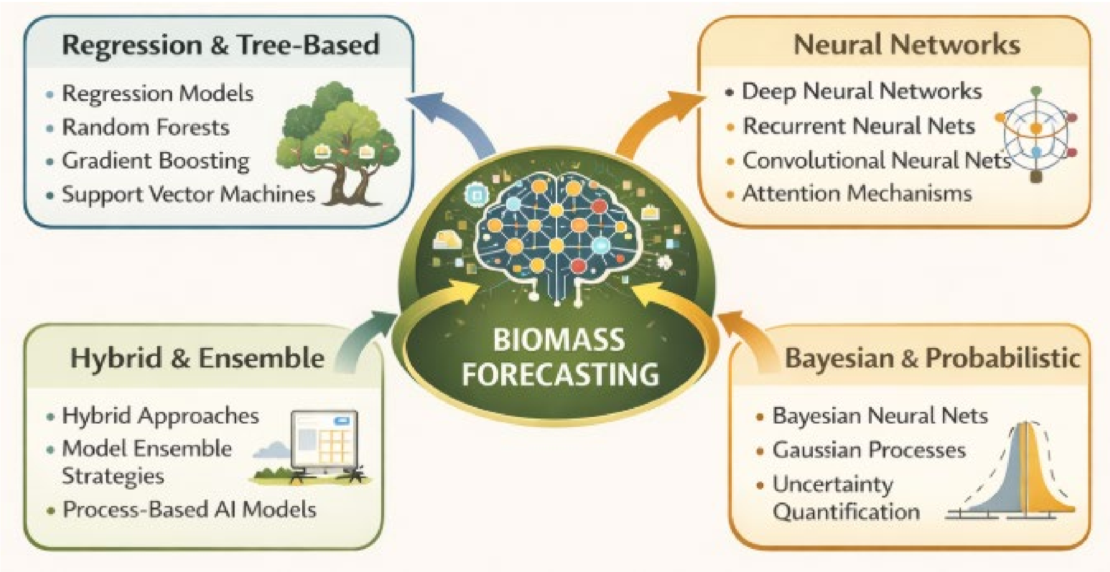

Figure 4. AI and Machine Learning Techniques for Biomass Forecasting

4.1. Regression and tree-based models

Both regressions based and tree-based methods are widely used because they are interpretable, computationally efficient and very effective with heterogeneous data.

Random Forests (RF) have been widely adopted for biomass yield prediction, since that method in known to be resistant against noise, multicollinearity and missing data. By combining predictions of different decision trees, RF models account well for the nonlinear effects of climate variables, soil properties, vegetation indices and management on yield. They also offer variable importance estimates that can be useful to understand dominant drivers of biomass variability. Another ensemble method, Gradient Boosting Machines (GBMs), train a strong predictive model out of an ensemble of weak models, typically decision trees at each iteration and for biomass estimation have performed better than Random Forests through more aggressive reducing prediction error [52]. Support Vector Machines provide a reliable alternative, especially suited to high-dimensional feature spaces and nonlinear relationships via kernel functions, performing well when complex biological interactions exist in biomass predictions. On the other hand, Deep Learning (DL) models such as Deep Neural Networks have captured a lot of attention because of their high prediction performance and ability to handle massive complex datasets containing data at multiple scales by learning abstract patterns through several interconnected processing layers [50].

Ensemble models like GBM (e.g. most used XGBoost, LightGBM) are effective in increasing prediction accuracy by following an iterative learning technique where trees built stepwise correction of errors of the past ones. GBMs are especially good at modelling complex iterations and subtle relationships in very large dataset. They are applicable for measurements at a field and regional scale that can accommodate mixed data types, while quantifying the contribution of features. Their strong predictive power in the estimation of biomass, mainly when accounting for the nonlinear effects of different management practices and environmental conditions, have been also demonstrated by other studies [53–55]. They are also comparatively efficient with large datasets and have a well-documented allowance for outliers and noise which makes them more attractive in remote-sensing plant trait estimation, and yield prediction ([56]).

4.2. Neural networks and deep learning

Deep learning models have attracted increasing attention as the access to data and computational resources increases, due to their strong representation learning capabilities.

Artificial Neural Networks (ANNs) can be implemented to model highly non-linear relationships among several inputs, e.g., spectral indices, meteorological data, soil information and management practices regarding outputs of biomass. Deep neural networks (DNNs) are highly flexible and capable to learn from multi-source datasets, for which traditional models may not be adequate. Recurrent Neural Networks, RNNs, and Convolutional Neural Networks, CNNs expand the usefulness of deep learning networks. Whilst RNNs are particularly adept at analyzing time-series biomass data\cite CNNs can process spatial and spectral optical imagery obtained from remote sensing platforms [2]. Also, attention mechanisms in deep learning architectures can assign dynamic weights on input features so that models may concentrate on the most informative environmental and resource indicators to best predict biomass accurately [37].

RNNs, as well as their sophisticated extensions, such as LSTM networks are particularly appropriate for temporal prediction. They are meant to account for temporal dependence between time steps and allow us to predict future skill of biomass dynamics within growing seasons or years. These models are particularly useful in representing lagged climate influences and accumulation of stress responses. Such as Long Short-Term Memory networks (LSTM), are a powerful tool for pattern recognition over long time periods and capturing nonlinear relationships in crop growth processes, showing advantages over conventional machine learning methods in some scenarios [57].

CNNs can take advantage of spatial structure in data and have been extensively used for high-resolution remote sensing imagery. CNNs learn spatial features, features detectable of canopy structure, texture or heterogeneity (Jahangir and Munoz-Hernandez, 2017), which offers improvements in biomass estimation both at pixel, field and landscape levels. In conjunction with temporal models, CNNs support end learning from spatiotemporal image sequences. Hybrid models have been proposed mixing CNNs with LSTMs, sometimes combined with attention mechanisms to better encompass the spatial hierarchies and temporal dependencies of OMS for better predictive performance regarding crop yield prediction [58–60]. This synergy provides a complete view of complicated agricultural spatiotemporal dataset which benefits the precise and reliable prediction of biomass and yield [61,62].

4.3. Hybrid and ensemble models

Hybrid methods are the combination of two or more different types of models to enhance robustness and generalizability. Introduction of process-based crop or ecosystem models (e.g., APSIM and DSSAT) into AI approach permits to contribute mechanistic principles about plant growth, phenology, resource limitation. AI models can identify residual patterns or parameterize an unknown process, whereas the process-based model offers physical consistency and interpretability. Ensemble strategies such as averaging predictions from a set of models, exercise uncertainties and therefore have great performance under novel or data-limited scenarios. For example, the combination of Convolutional Neural Networks with Long Short-Term Memory networks enable both spatial feature extraction and temporal sequence learning in models which are well adapted to deal with spatiotemporal data such as time series of satellite imagery [41]. This fusion is fundamental for applications, such as next-generation yield prediction and supply-chain control that requires to grasp the spatial patterns, and the way they evolve over time [63]. Hybrid architectures combine the desirable properties of both types, as

CNNs can efficiently model hierarchical structure in visual input, and LSTMs are effective for learning temporal dynamics and dependencies [47,64,65]. For instance, a reciprocal combination of LSTM and CNN model is found to increase the accuracy for the prediction of crop yields based on historical data of weather, soil conditions, land uses in an integrated environment [63].

4.4. Bayesian and probabilistic approaches

Bayesian and probabilistic modelled exist for uncertainty modelling of the biomass forecast. Industry and regional planning are other examples for which there is a need to be able to estimate biomass levels at the highest possible spatial resolution. The probability of low residue availability under unfavorable climatic circumstances is calculated by using Bayesian networks. Probabilistic forecasting is also employed in supply chains to mitigate risks of feedstock shortages and plan storage. Bayesian and probabilistic approaches remedy a key shortcoming of most deterministic AI models: an absence of uncertainty quantification. Bayesian networks model probabilistic relationships between variables and support transparent inference under uncertainty. Gaussian Process Regression (GPR) is a flexible, non-parametric framework that produces predictive distributions as opposed to point estimates. These methods are especially useful for biomass prediction in risk-averse applications (for example, bioenergy planning and climate adaptation strategies), in which constraint bounds of the confidence can be as important as the mean predictions. In addition, hierarchical Bayesian models are well suited for combining different data sources and incorporating spatial and temporal structure between samples, which may lead to more robust estimations of biomass availability under different environmental conditions. These models can incorporate expert knowledge and priors, which can be useful especially if there is little training data or events are rare. Deep learning approaches are now being integrated with probabilistic methods to predict risks and provide forecast uncertainties, particularly important for decision-making under environmental uncertainty [52].

Table 4. Comparative Summary of AI and Machine Learning Models for Biomass Forecasting

Model Category	Representative Techniques	Key Strengths	Main Limitations	Data Requirements	Suitable Application Contexts
Regression-based and Tree-based models	Linear regression, Random Forest, Gradient Boosting, Support Vector Machines	High interpretability; robust to noise; moderate computational cost	Limited spatiotemporal learning; reduced performance for highly nonlinear systems	Low to moderate data volume; tabular climate, soil, and management data	Regional biomass estimation; baseline forecasting; data-limited studies
Deep learning models	ANN, CNN, RNN, LSTM, CNN–LSTM	Strong nonlinear modeling; spatial and temporal feature learning; high accuracy	High computational demand; large data needs; low interpretability	Large, high-resolution multi-source datasets	High-resolution biomass mapping; time-series forecasting
Hybrid models	AI combined with process-based models; CNN–LSTM hybrids	Improved generalization; physical consistency; adaptive to changing conditions	Complex integration; higher calibration effort	Moderate to large datasets plus process-model outputs	Climate-adaptive forecasting; scenario and impact analysis
Probabilistic and Bayesian models	Bayesian networks, Gaussian Process Regression, Bayesian deep learning	Uncertainty quantification; risk-aware predictions	Computationally intensive; requires statistical expertise	Moderate datasets with defined priorities or ensembles	Bioenergy planning; supply chain risk and policy analysis

Table 4 provides a structured comparison of major AI and machine learning approaches used in biomass forecasting by summarizing their strengths, limitations, data requirements, and application scope. It shows that

regression-based models offer interpretability and efficiency, deep learning models achieve high accuracy with large multi-source datasets, and hybrid and probabilistic models improve robustness and uncertainty handling. This comparison helps readers select suitable modeling strategies based on data availability, computational resources, and decision-making needs in bioenergy applications.

5. Applications for biomass forecasting

AI-supported biomass forecasting has found wide-ranging applications across agricultural, forestry, and bioenergy systems. By integrating environmental, management, and socioeconomic data, these models support both strategic planning and operational decision-making along the biomass supply chain. **Figure 5** depicts key application areas of AI in biomass forecasting, including agricultural residues, forest biomass, energy crops, and supply chain optimization. It shows how AI integrates environmental, management, and economic data to support planning and operational decisions.

5.1. Agricultural residues

In farming scenarios, predictive models are now developed using AI for the prediction of availability of crop residues like cereal straw, sugarcane bagasse and rice husk [9]. Those residues are closely correlated with the primary yield of crops and is determined in climate, soil fertility and management operations. Through integration of weather information, remote sensing-based vegetation indices and crop management databases an estimate of residue production from field to region scale can be made with AI models. Such predictions are needed to estimate the potential of bioenergy, to reduce residue burning and to ensure sustainable Manuscript Click here to view linked References residue removal without depleting soil health. The machine learning approaches, especially trained with historical data and real-time correlates, provide a more reliable way to predict the availability of biomass and demand for it (helping facilities in adapting production plans efficiently) [6]and reduce the risk for short-supply or over-production [7]. Improved forecasting can lead to enhanced logistics and warehousing, making the agricultural biomass feedstock supply chain increasingly more stable and cost-effective. In addition, such predictive models may facilitate farm managers to optimize their resources, by identifying the best species mix and height of hedgerow that would reach certain carbon sequestration targets [66-75].

5.2. Forest biomass estimation

In forestry-specific use cases, AI technologies and remote sensing can be used to estimate standing woody biomass. The study harnesses fine-resolution optical imagery, alongside LiDAR and radar measurements to measure forest structure, canopy height and density — with machine learning models then converting these metrics into biomass as well as carbon stock assessments. These projections are essential in carbon accounting, climate mitigation efforts, forest management planning and bioenergy planning (Loehle 2009), especially for altering disturbance regimes such as fires, pests and storms. This makes it possible to estimate forest health and productivity dynamically, so that sustainable harvesting methods and spatial distribution of biomass for bioenergy use can be planned [1]. These AI techniques are also useful in tracking species relocation and the general state of ecosystem, leading to adaptive management plans of forest ecosystems [76-85].

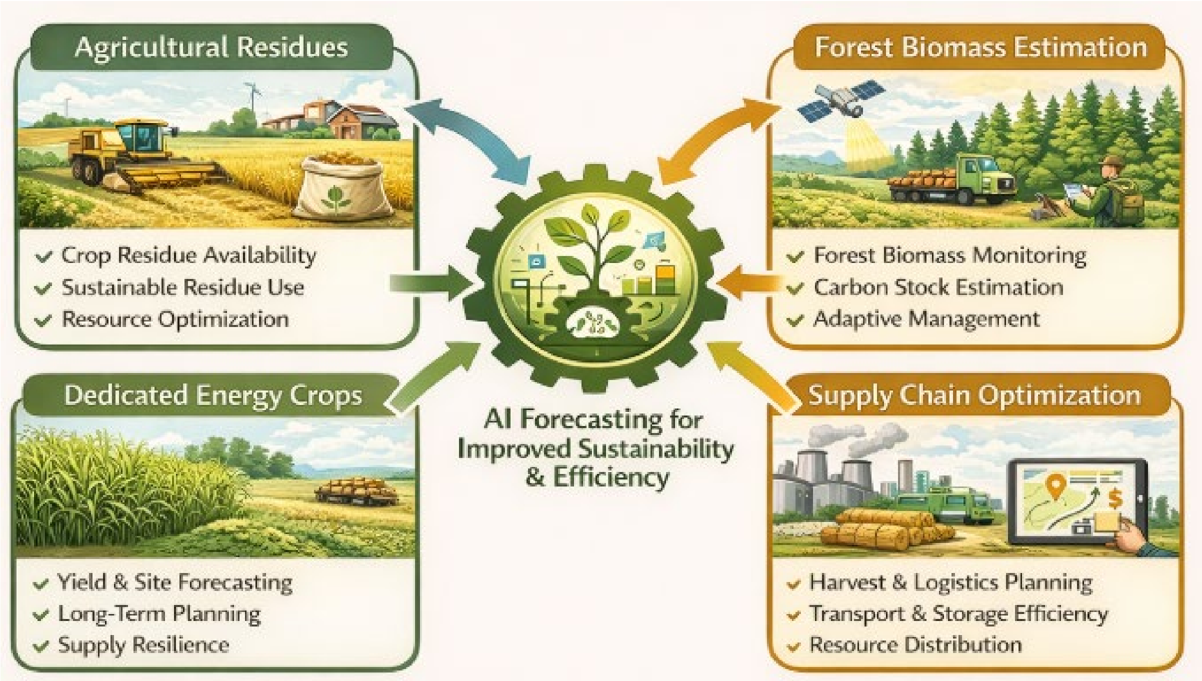

Figure 5. AI-Driven Applications in Biomass Forecasting and Management

5.3. Dedicated energy crops

AI-based forecasting models are a powerful tool for the design of dedicated energy crops, which include Miscanthus, and switchgrass short-rotation coppice species. These models use the combination of soil quality, climate predictions (e.g. rainfall amounts and distribution) and water availability along with potential land-use scenarios to locate sites for planting or conservation areas that can yield power over present day and future conditions. Such considerations provide insight into long-term investment decisions; land commitment plans and strategies to build resilient bioenergy systems with minimal interference in food production. This is especially relevant for the development of sustainable bioenergy supply chains that can be flexible under changing environmental conditions and market requirements [86-90]. There is also the AI-enabled forecasting that helps improve supply chain logistics and storage for better access to suitable feedstock at which bioenergy production facilities can be efficiently located and materials sourced [91].

5.4. Supply chain optimization

In addition to production, AI-based biomass predictions are being increasingly associated with supply chain and logistical models. Estimates of the amount of biomass available guide decisions about when and where to harvest, how much storage capacity is needed at the point(s) of collection or pre-processing, what routes should be used for transportation and how conversion operations (e.g. biogas plants, bio-refineries, biomass power stations) should be scheduled. AI systems that match biomass availability to processing capacity and market demand enhance the supply security, economy, and environmental performance of the entire value chain. This total system integration contributes to a non-stop operation and highly profitable investment for gasification companies, which without any doubt will contribute to the sustainability of renewable energy [92-96]. In addition, predictive analytics can, with the help of machine learning, also optimize resource distribution and reduce the risk for climate change and uncertainty by forecasting yields, pest attacks and market trends [97]. Such high-resolution forecasts enhanced by intelligence can help in making well-timed changes in logistics and storage, necessary for having a good and fast supply chain that is effective regarding cost of biomass feedstock [98].

Overall, these applications demonstrate how AI-supported biomass forecasting bridges the gap between data-driven prediction and practical decision-making, enabling more efficient, sustainable, and climate-resilient biomass utilization.

6. Comparative performance

Comparative evaluations across literature consistently show that **AI-based models outperform traditional statistical and linear regression approaches** in biomass forecasting, particularly under complex and data-rich conditions. The superior performance of AI methods is largely attributed to their ability to learn nonlinear relationships, handle high-dimensional inputs, and integrate diverse data sources.

AI models demonstrate significant gains in forecasting accuracy when **multisource datasets** are incorporated. The joint use of remote sensing products, climate variables, soil properties, management information, and socioeconomic data enables models to capture interacting drivers of biomass variability that are typically oversimplified in conventional regression frameworks. This integration is especially beneficial at regional and landscape scales, where spatial heterogeneity is pronounced. The ability of machine learning to analyze diverse data sources, such as those from remote sensing, significantly improves the precision of above-ground biomass estimations across different forest types [99-102].

Performance improvements are further amplified when **temporal dependencies are explicitly modeled**. Time-aware architectures such as LSTM networks, temporal CNNs, and sequence-based ensemble models effectively capture seasonal dynamics, cumulative climate effects, and lagged responses in biomass growth. In contrast, static regression models often fail to represent these dynamic processes, leading to reduced predictive reliability under variable climatic conditions. Moreover, attention-based deep learning approaches, leveraging data from GEDI LiDAR, Sentinel-1 SAR, ALOS-2 PALSAR-2, and Sentinel-2 multispectral data, have demonstrated superior accuracy in forest aboveground biomass estimation compared to conventional algorithms like Random Forest [103-111]. Specifically, the integration of multi-modal deep learning frameworks, such as Deep Bio Fusion, which utilize LiDAR-derived tree heights, species maps, and high-resolution optical and SAR imagery (X, C, and L bands), further enhances the accuracy of above-ground biomass estimation, moving beyond traditional methods [112-119].

Additionally, **feature selection and model tuning** play a critical role in maximizing AI model performance. Techniques such as recursive feature elimination, regularization, hyperparameter optimization, and attention mechanisms help reduce noise, prevent overfitting, and improve generalization. Well-tuned tree-based and ensemble models often achieve strong performance even with limited training data. Conversely, the integration of multi-sensor data with machine learning techniques has substantially enhanced the accuracy of carbon storage estimations, particularly in complex terrains and diverse species where data noise can be significant [120-128]. These approaches demonstrate a marked improvement over traditional methodologies, which often struggle with the complexity and heterogeneity inherent in large-scale biomass assessment [129-130]. For instance, studies utilizing advanced deep learning algorithms, including CNN-LSTM models with multisource remote sensing data, have achieved higher accuracy ($R^2 = 0.74$, RMSE = 26.43 Mg/ha) compared to traditional methods and even other AI models [131-135].

Despite these advantages, AI model performance is not uniform across applications. Accuracy varies with **data resolution, geographic region, and crop or vegetation type**, reflecting differences in data quality, ecological processes, and management intensity. Models trained in data-rich regions may not readily transfer to data-scarce areas without retraining or domain adaptation. Furthermore, while advanced deep learning algorithms are continuously emerging, their refinement and adaptation for specific remote sensing regression tasks, such as biomass estimation, remain crucial for optimizing their performance [136-137]. This nuanced landscape underscores the ongoing need for rigorous validation and continuous improvement of AI models, particularly through the incorporation of diverse sensor modalities and advanced algorithmic architectures, to ensure their robustness and applicability across varied environmental contexts [138-142].

A persistent challenge remains **model interpretability**, particularly for deep learning approaches with large parameter spaces. While methods such as feature importance analysis, SHAP values, and attention visualization offer partial transparency, fully explaining complex model behavior remains difficult. Balancing predictive accuracy with interpretability is therefore an ongoing research priority, especially for policy-relevant and risk-sensitive biomass forecasting applications.

7. Challenges and limitations

Despite significant advances, AI-supported biomass forecasting faces several challenges and limitations that affect reliability, scalability, and practical adoption. Addressing these issues is essential for translating methodological progress into robust, real-world applications.

7.1. Data quality and gaps

The performance of AI models is highly dependent on data quality. **Incomplete or missing records**, sensor noise, cloud contamination in satellite imagery, and inconsistent land-use or land-cover classification can introduce bias and uncertainty into model predictions. In many regions, especially in developing or data-scarce areas, long-term and high-resolution datasets are unavailable or fragmented. Errors in ground truth measurements and inconsistencies across data sources further degrade model calibration and validation, limiting forecasting accuracy.

7.2. Model generalization

A major limitation of many AI models is **limited transferability**. Models trained on data from specific regions, climates, or crop systems often struggle when applied to different environmental conditions or management regimes. Variations in soil types, climate patterns, crop varieties, and farming practices can lead to performance degradation. Without domain adaptation, transfer learning, or retraining with local data, AI models risk overfitting to site-specific characteristics, reducing their general usefulness.

7.3. Computational costs

Advanced AI models, particularly deep learning architectures operating on **high-resolution spatiotemporal data**, demand substantial computational resources. Training and deploying such models require powerful hardware, large memory capacity, and extended processing times. These requirements can limit accessibility for researchers and practitioners with constrained computational infrastructure and may hinder real-time or operational forecasting applications.

7.4. Uncertainty quantification

Reliable **uncertainty estimation** is critical for risk-informed decision-making in biomass planning, bioenergy investment, and climate adaptation strategies. However, many AI models provide deterministic point estimates without explicit confidence bounds. The lack of robust probabilistic outputs makes it difficult to assess prediction reliability, compare alternative scenarios, or communicate risk to stakeholders. Integrating Bayesian methods, ensemble approaches, and probabilistic deep learning remains an open challenge but is essential for improving trust and usability in AI-based biomass forecasting systems.

8. Conclusion

This study demonstrates that AI-based biomass forecasting offers practical value for both policy makers and industry stakeholders by improving how biomass resources are planned, managed, and utilized under changing environmental and economic conditions. The review confirms that integrating multi-source data with advanced AI models enables more reliable and scalable biomass availability assessments than conventional approaches. First, AI-driven forecasting systems function as effective decision-support tools. By combining remote sensing, climate, management, and socioeconomic data, these models support evidence-based policy design, infrastructure planning, and investment decisions across regional and national bioenergy programs. Second, improved biomass predictions directly strengthen supply chain resilience. Accurate, timely forecasts help industry stakeholders anticipate spatial and temporal variability in feedstock availability, optimize logistics, reduce supply risks, and maintain stable operation of bioenergy facilities under climate and market fluctuations. Third, the inclusion of probabilistic and hybrid AI methods enables uncertainty-aware planning. Explicit representation of prediction uncertainty supports risk-sensitive strategies, allowing policy makers and industry planners to evaluate alternative scenarios and adopt adaptive pathways for long-term sustainable bioenergy systems. Together, these outcomes position AI-supported biomass forecasting as a critical component of sustainable bioenergy planning and climate-resilient resource management.

Author Contributions

Conceptualization and study design were carried out by **Sonali Shrikant Patil** and **Anant Sidhappa Kurhade**, who defined the research scope, objectives, and overall methodological framework. Literature review, data curation, and synthesis of recent advancements in artificial intelligence–based biomass forecasting were performed by **Sonali Shrikant Patil**, **P. Ramani, Snehal Mayur Banarase**, and **Prafulla O. Bagde**. Methodological structuring, interpretation of AI and machine learning models, and preparation of analytical tables and figures were conducted by **Pushparaj Sunil Warke, N. Alangudi Balaji**, and **Muralidhar Ingale**. Writing of the original draft manuscript was completed by **Sonali Shrikant Patil, Snehal Mayur Banarase**, and **Shital Yashwant Waware**. Critical technical review, validation of scientific content, and refinement of discussion and conclusions were undertaken by **Anant Sidhappa Kurhade** and **P. Ramani**. Supervision, project administration, and final approval of the manuscript for publication were provided by **Anant Sidhappa Kurhade** as the corresponding author. All authors reviewed, edited, and approved the final manuscript and agree to be accountable for the integrity and accuracy of the work.

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Conflict of interest

The authors declare no conflict of interest

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