



## Review article

## A comprehensive analysis of the use of modelling and remote sensing techniques for monitoring and managing rangelands

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## ABSTRACT

Sustainable rangeland management supports livestock production, food security, and key ecological services such as carbon sequestration and water regulation. However, rangelands face increasing pressure from climate change, land degradation, and agricultural expansion, requiring effective management strategies. This review follows the PRISMA guidelines and systematically examines 102 peer-reviewed publications selected from 511 initially identified studies across multiple databases, including Scopus, Google Scholar, ScienceDirect, AJOL and Web of Science. This review explores the latest tools enabling accurate monitoring and prediction of rangeland dynamics. The results show that key technologies include machine learning algorithms, unmanned aerial vehicles (UAVs), and multispectral sensors, all of which have revolutionized biomass estimation. Satellite remote sensing, particularly Sentinel-2 and Landsat 8/9, represents a transformative advancement by delivering consistent, scalable, and repeatable observations from regional to global scales. Methods such as Deep Neural Networks (DNN), Random Forest (RF), and Object-Based Image Analysis (OBIA) have outperformed conventional algorithms, achieving performance metrics such as  $R^2 > 0.85$ . Generalized Linear Models (GLM) have also been widely applied, particularly for environmental impact assessment. The development of multispectral sensors, especially bands such as NIR and red-edge, has improved vegetation index calculations, while LiDAR technology has enhanced biomass prediction by incorporating terrain structure and canopy height data. Despite these advances, challenges remain, including issues related to data quality, sensor integration, and harmonizing datasets for predictive modelling. This review highlights both the strengths and limitations of current approaches and emphasizes the need for further integration of advanced technologies such as hyperspectral sensors.

## 1. Introduction

Sustainable rangeland management is essential not only for maintaining livestock production but also for safeguarding key ecosystem services, including water-cycle regulation, carbon sequestration, and nutrient cycling (Podvebradská et al., 2019). These landscapes also contribute to food security by providing a primary source of forage for livestock, supporting rural economies and global food systems (DiMaggio et al., 2020). However, rising challenges from agricultural expansion, climate variability, and land degradation threaten the long-term viability of rangeland ecosystems (Worku et al., 2023). To address this situation, resilient rangeland management strategies that enhance the

productivity and the ecological integrity of the systems under growing environmental stressors are needed (Podvebradská et al., 2019). Traditionally, rangeland management has relied on manual field surveys and visual inspections, which, although valuable, are limited by time, labour, and subjectivity. Recent advances in modelling and remote-sensing technologies offer more precise and objective tools for monitoring environmental change and forecasting future trends, thereby strengthening decision-making in land management.

Advanced modelling techniques such as Generalized Linear Models (GLM), Deep Neural Networks (DNN), Random Forest (RF), and Support Vector Machines (SVM) have proven effective for analysing

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ecosystem dynamics, predicting biomass productivity, and optimizing resource management under varying environmental conditions (Vawda et al., 2024; Liu et al., 2023). These models support the optimal use of essential resources such as water and soil nutrients thereby helping to maintain rangeland productivity.

Furthermore, advances in remote-sensing technologies have revolutionized pasture monitoring by providing cutting-edge tools for assessing vegetation health and landscape dynamics. Satellite-based multispectral and hyperspectral sensors capture data across multiple spectral bands (visible, near-infrared, red-edge), enabling precise estimation of vegetation indices such as the Normalized Difference Vegetation Index (NDVI) (Soto et al., 2024). Unmanned aerial vehicles (UAVs) offer real-time, high-resolution imagery of vegetation cover and biomass at fine spatial scales, while LiDAR technology enhances terrain mapping and canopy-height assessment (Hütt et al., 2024). These tools greatly enhance the quantification of vegetation cover, biomass estimation, and plant-health monitoring, all of which are essential for developing predictive models and supporting data-driven land-management decisions (Wang et al., 2019; John et al., 2023).

Various modelling methods have been used to describe pasture ecosystems, presenting each specific advantages and limitations. Basic linear regression models are simple to use and provide fast estimations but often cannot perceive the complex, nonlinear links between environmental variables. On the other hand, advanced machine learning algorithms, such as deep neural networks (DNN) and random forests (RF), are better in handling large, high-dimensional datasets and showing intricate patterns. As for Object-Based Image Analysis (OBIA), it is often associated with RF classifiers and is extremely effective in areas with low spectral contrast, thus offering a powerful tool for vegetation mapping and pasture condition assessment (Shoshany and Karnibad, 2015; Silver et al., 2019). These advanced methods have an important impact on large-scale vegetation monitoring, including the detection and control of invasive species, which are essential for ecosystem stability (Wu et al., 2022).

Despite significant advances, several challenges continue to limit the effective use of mathematical and statistical models in rangeland management. One major constraint is the quality and availability of data especially in remote or resource-limited areas which reduces both model accuracy and applicability. Moreover, the inherent complexity of rangeland ecosystems, characterized by heterogeneous vegetation, dynamic interactions, and high spatial variability, introduces additional uncertainty into modelling efforts (Snow et al., 2014). In response to these challenges, there is growing interest in developing simplified yet robust models that rely on easily accessible inputs, such as daily weather data.

Such models have potential to improve monitoring efforts and extend their application to a wide range of ecological and socio-economic contexts. This systematic review offers a comprehensive synthesis of modelling and remote sensing approaches for pasture management. It addresses central questions for the evolution of the field such as: How can remote sensing technologies be leveraged to optimize pasture monitoring? Which machine learning techniques are most effective in estimating grassland biomass? How can the integration of mathematical modelling and remote sensing improve ecosystem management? What are the main challenges related to data quality in pasture modelling? By critically evaluating the strengths and limitations of existing approaches, this review proposes evidence-based strategies for advancing pasture management. Ultimately, it aims to support the sustainable management of agricultural systems and the long-term conservation of natural resources at a global scale.

## 2. Conceptual framework: Mathematical and statistical modelling and remote sensing techniques

### 2.1. Mathematical and statistical modelling techniques

Mathematical and statistical models are essential for predicting pasture productivity, optimizing resource use, and understanding the

dynamic interactions between environmental variables and ecosystem functions. Linear regression is commonly used to examine the relationship between environmental factors (rainfall, temperature, soil properties) and pasture biomass. It quantifies the linear relationship between biomass (dependent variable) and environmental predictors. The general form of the linear regression equation is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \epsilon, \quad (1)$$

where  $Y$  represents the predicted biomass,  $X_1, X_2, \dots, X_n$  are the environmental predictors, and  $\beta_0, \beta_1, \beta_2, \dots, \beta_n$  are the coefficients evaluating the relationship between each predictor and the dependent variable. This technique is best suited for simple linear relationships, as shown by Podvebradská et al. (2019), who modelled pasture productivity using climatic data.

For more complex and non-linear relationships, machine learning algorithms like Random Forest (RF) are often preferred. RF creates multiple decision trees during the training process and averages their outputs to make predictions. This reduces overfitting and enables the model to capture complex non-linear patterns that traditional approaches may fail to detect. Feng et al. (2020) applied RF to predict alfalfa yield using UAV-based hyperspectral imagery. In their study, RF achieved higher predictive accuracy than linear regression models, highlighting its ability to handle non-linear interactions between hyperspectral reflectance values and biomass. The model's performance was evaluated using Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}, \quad (2)$$

where  $y_i$  represents the observed biomass values, and  $\hat{y}_i$  represents the predicted values.

Beyond random forests, advanced techniques like Deep Neural Networks (DNNs) and Support Vector Machines (SVMs) are increasingly used in pasture modelling, especially for handling high-dimensional datasets derived from remote sensing imagery. These machine-learning models are highly effective at capturing complex, non-linear interactions and have consistently outperformed traditional regression approaches in numerous studies. For instance, Vawda et al. (2024) employed a Convolutional Neural Network (CNN) to predict grass biomass using Sentinel-2 satellite imagery.

Process-based models represent another major class of modelling approaches in pasture management. Unlike empirical models, process-based models simulate the biological processes governing plant growth, nutrient cycling, and carbon sequestration. One of the most popular is the CENTURY model, which simulates carbon and nitrogen dynamics in grassland ecosystems. The change in carbon over time in this model is represented by the following equation:

$$\frac{dC}{dt} = P - R - L, \quad (3)$$

where  $P$  represents photosynthesis (carbon uptake),  $R$  represents respiration (carbon release), and  $L$  represents carbon losses due to harvest or herbivory. Process-based models like CENTURY are particularly valuable for identifying long-term ecosystem responses to environmental variability (Snow et al., 2014).

### 2.2. Remote sensing techniques

Remote sensing has reshaped rangeland ecosystem monitoring by providing high-resolution data on vegetation cover, biomass, and plant health. These technologies rely on sensors that can detect electromagnetic radiation reflected from the Earth's surface, spanning wavelengths from visible to infrared light. When combined with statistical and machine learning methods, these data enable accurate vegetation classification and biomass estimation.

Multispectral imaging, which collects data in discrete spectral bands (e.g., visible and near-infrared), is frequently used for general vegetation analysis. In contrast, hyperspectral imaging captures data in

hundreds of contiguous spectral bands, offering better spectral resolution to detect subtle changes in vegetation health and early signs of stress. For example, Feng et al. (2020) showed that hyperspectral imagery significantly outperformed multispectral data in accurately predicting alfalfa yield.

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used indices for assessing vegetation health and greenness. Its formula is:

$$NDVI = \frac{NIR - RED}{NIR + RED}, \quad (4)$$

where NIR and RED represent near-infrared and red reflectance, respectively. NDVI values range from  $-1$  to  $+1$ , with higher values indicating healthier vegetation. As shown in the study by DiMaggio et al. (2020), NDVI has been extensively applied for biomass estimation.

Enhanced Vegetation Index (EVI) improves upon NDVI by correcting for soil background and atmospheric effects, making it particularly effective in densely vegetated areas where NDVI tends to saturate. The formula for EVI is:

$$EVI = 2.5 \times \frac{NIR - RED}{NIR + 6 \times RED - 7.5 \times BLUE + 1}, \quad (5)$$

where BLUE represents reflectance in the blue band. Studies, including those by Feng et al. (2020), highlight EVI's enhanced performance and accuracy in biomass estimation.

LiDAR (Light Detection and Ranging) is another powerful remote sensing tool that captures terrain structure and canopy height by emitting laser pulses and measuring their return time. The distance to the target is calculated as follows:

$$d = \frac{c \times t}{2}, \quad (6)$$

where  $c$  is the speed of light and  $t$  is the time taken for the laser pulse to return. When combined with vegetation indices like NDVI, LiDAR data significantly enhances the accuracy of biomass predictions, as shown by Podvebradská et al. (2019).

Integrating remote sensing data with machine learning algorithms (e.g., RF, DNN) has been widely explored to develop scalable, accurate predictive models of pasture productivity. For instance, Chen et al. (2021) used Sentinel-2 imagery and machine learning techniques to forecast pasture biomass, demonstrating the prospects of such approaches in advancing sustainable pasture management solutions.

Likewise, Vahidi et al. (2023) combined Sentinel satellite imagery and machine learning algorithms to predict bale grazing and sacrificed pasture biomass, leading to more precise determination of pasture status. Besides, Vawda et al. (2024) compared Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) on Sentinel-2 MSI data to estimate the dry season aboveground grass biomass, highlighting the utility of deep learning models in pasture productivity estimation.

These studies highlight the central role of integrating remote sensing data with advanced machine learning techniques to develop precise, scalable pasture productivity models.

Satellite multispectral time series (Sentinel-2/Landsat) underpin rangeland monitoring by jointly offering broad coverage and high revisit frequency. Red-edge and NIR bands improve sensitivity to canopy biochemistry and structure, while SAR complements optical signals under cloud cover. A satellite-first pipeline is recommended for regional biomass mapping, with UAV data used for local calibration, validation, and structural cues.

### 3. Methods

#### 3.1. Search and selection of papers

This systematic review critically examines the application of mathematical and statistical modelling techniques in pasture management.

The study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a transparent and rigorous process for identifying, selecting, and including relevant studies (Page et al., 2021). A comprehensive literature search was conducted across major scientific databases including Scopus, Google Scholar, Science Direct, AJOL, and Web of Science to ensure broad coverage of peer-reviewed research on pasture ecosystem modelling, biomass estimation, and sustainable management practices.

For more accurate results, Boolean operators were combined with the following key terms: (“natural pastures” OR “pastures” OR “grasslands”) AND (“West Africa” OR “Africa”) AND (“spatiotemporal modelling” OR “mathematical modelling” OR “statistical modelling” OR “process models” OR “plant growth models” OR “simulation models”) AND (“ecosystem models” OR “remote sensing methods” OR “vegetation indices”) AND (“modelling” OR “numerical simulation” OR “data analysis” OR “predictive analysis”) AND (“pasture productivity” OR “forage yield” OR “forage productivity” OR “woody forage productivity”) AND (“climate change” OR “sedentarization”).

The search was limited to articles published between January 2014 and July 2024 to ensure that the review captures recent advancements in remote sensing and modelling applied to pasture ecosystems. This interval was set to capture the rapid growth of research in this area. The initial search yielded 511 papers, which were then imported into Zotero for reference management. After the removal of 16 duplicate entries, 495 papers remained for screening.

The selection process was conducted in multiple stages. First, a title and abstract review was performed, leading to the withdrawal of 381 papers that were outside the scope of the study. These papers primarily addressed animal behaviour, socio-economic impacts, genetic studies, or other topics unrelated to pasture modelling. Following this, 114 papers proceeded to the full-text review phase, during which an additional 12 papers were excluded for lacking a quantitative modelling component applicable to pasture ecosystems. Thus, 102 papers were included in this systematic review (see Fig. 1).

#### 3.2. Inclusion and exclusion criteria

The inclusion and exclusion criteria applied during the study selection process are detailed below. These criteria ensured that only studies with a strong methodological foundation in mathematical or statistical modelling were considered.

The inclusion and exclusion criteria applied during the study selection process were as follows:

- **Language:** Only studies written in English were included; non-English papers were excluded.
- **Publication period:** Studies published between 2014 and 2024 were included; studies published before 2014 were excluded.
- **Study focus:** Only peer-reviewed journal articles and, where applicable, peer-reviewed conference papers published between 2014 and 2024 on pasture modelling and ecosystem analysis were included; preprints and studies primarily addressing socio-economic or genetic topics were excluded.
- **Methodology:** Studies that employed mathematical, statistical, or remote sensing models were included; non-quantitative approaches were excluded.
- **Full-text availability:** Only papers with full-text access were included; inaccessible papers were excluded.

#### 3.3. Synthesis and literature analysis

The 102 selected studies were systematically analysed to identify key research trends, methodological advancements, and thematic contributions to pasture ecosystem modelling. A temporal analysis was conducted to examine publication frequency between 2014 and

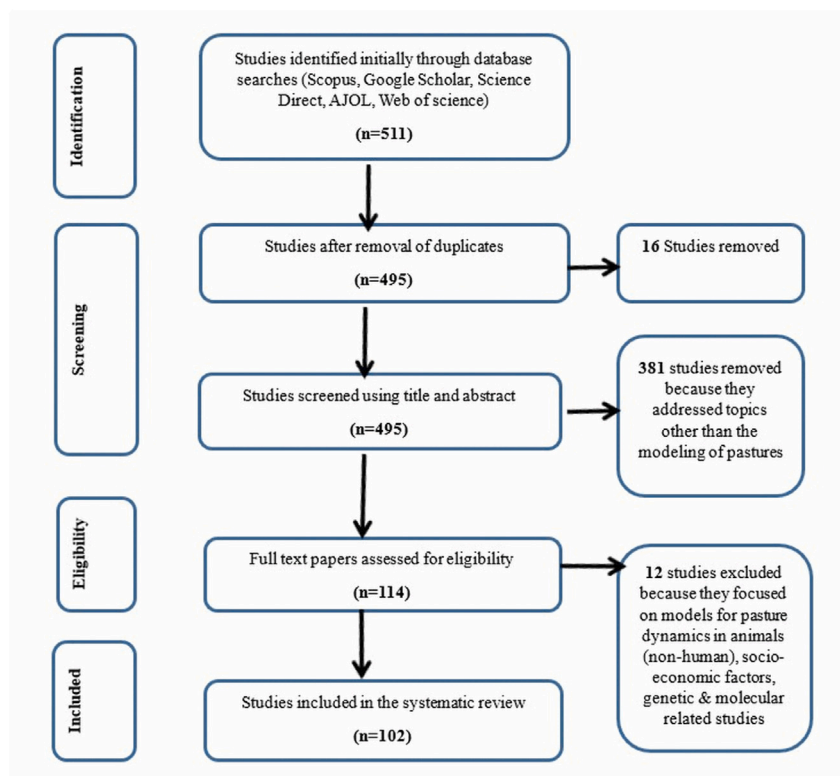


Fig. 1. PRISMA flow diagram of the study selection process.

2024, highlighting shifts in research focus and the growing adoption of advanced modelling techniques.

To structure the analysis, studies were classified into three main thematic areas:

- **Biomass estimation** – Research on pasture productivity, forage yield modelling, and biomass assessment.
- **Vegetation dynamics** – Studies examining land cover changes, pasture degradation, and vegetation monitoring through remote sensing techniques.
- **Environmental factors** – Investigations into the effects of climate change, soil characteristics, and grazing patterns on pasture growth.

Beyond thematic classification, modelling methodologies were evaluated. The models were grouped based on two primary factors:

- **Model type** – Distinguishing between static and dynamic models, where static models offer snapshots of pasture conditions, while dynamic models incorporate time-dependent variables.
- **Scale of analysis** – Categorizing studies based on whether they applied population-level or individual-level modelling approaches.

Additionally, the review examined pasture management interventions such as grazing strategies, fertilization, irrigation, and rotational grazing practices to determine their integration into predictive modelling frameworks. Understanding these management strategies in relation to modelling approaches provides insights into their practical implications for sustainable pasture management.

To enhance the quantitative assessment, a two-phase data analysis was conducted. The first phase involved the use of descriptive statistics to characterize publication trends, geographical distribution, and thematic focus. The second phase focused on the relative prevalence of different modelling techniques, identifying which methods are most frequently used, where innovations are occurring, and how these approaches have been applied across various ecological settings.

## 4. Results and discussion

### 4.1. Spatiotemporal coverage and study distribution

The temporal distribution of the selected studies revealed two major peaks in research activity. The first notable increase occurred in 2014, marking an early adoption of mathematical and statistical modelling techniques for pasture management. During this period, research efforts primarily focused on integrating process-based and empirical modelling approaches to enhance pasture productivity and sustainability.

A second, more substantial peak was observed in 2022, accounting for over 22% of the total reviewed publications (Fig. 2). This surge in research corresponds to rapid advancements in remote sensing technologies, machine learning algorithms, and large-scale environmental monitoring techniques, emphasizing the growing reliance on data-driven methods for pasture ecosystem assessment.

The sustained research output in 2021 and 2023 reflects the continued interest in refining pasture ecosystem modelling, understanding grazing dynamics, and developing climate-resilient management strategies.

Geographically, the reviewed studies mainly originated from Asia (32.93%) and North America (14.93%), underscoring the strong research interest in pasture management across these regions. European countries also contributed significantly, with Italy (7.32%), Germany (2.44%), and Portugal (2.44%) producing relevant studies.

In Africa, the representation was relatively modest. South Africa accounted for 7.32% of the reviewed research, while Sub-Saharan Africa contributed 2.44%, indicating limited yet growing attention to pasture modelling across the continent. Australia, with its vast grassland and savanna ecosystems, contributed 6.1% of the total research output.

Other regions with smaller contributions included Canada (3.66%), Spain (2.44%), the Hindu Kush Himalayan region (2.44%), and India (2.44%) (Fig. 3).

Thematic analysis of research topics within pasture modelling revealed that 43% of the studies focused on remote sensing techniques,

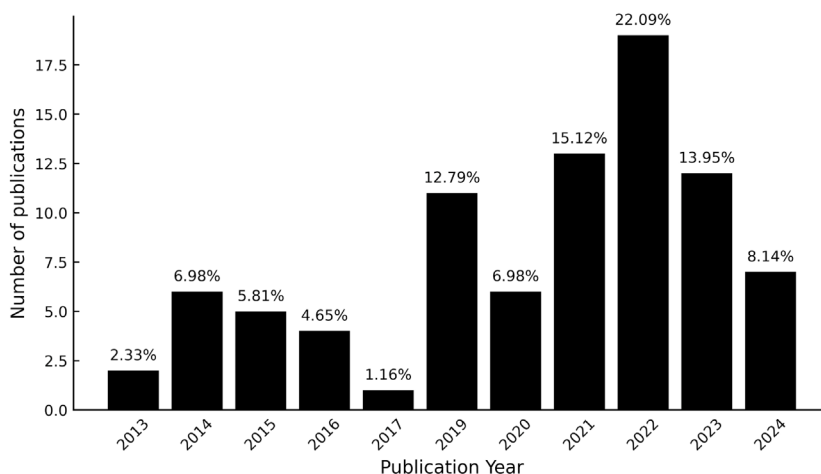


Fig. 2. Temporal distribution of reviewed studies.

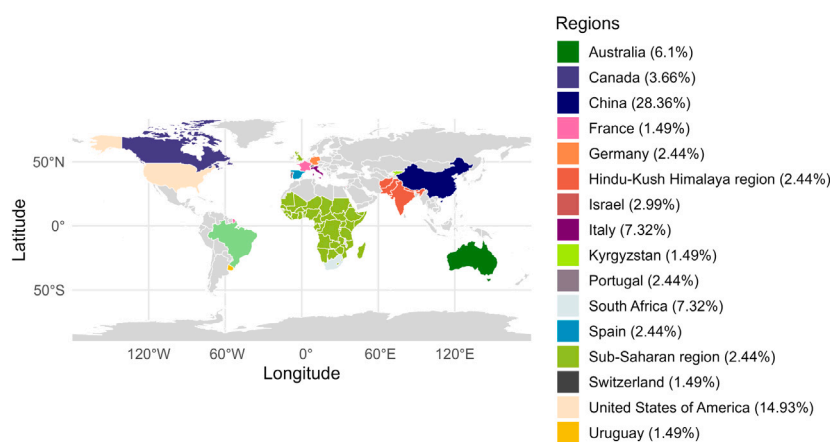


Fig. 3. Spatial distribution of reviewed studies.

particularly for biomass and vegetation monitoring. This indicates the growing integration of satellite and UAV-based technologies in large-scale environmental assessments. Between 2014 and 2024, research on remote sensing demonstrated consistent growth, with notable acceleration in the past five years. Emerging technologies, such as UAVs and aerial imaging, accounted for 10% of the studies, reflecting their increasing presence in pasture research. Studies addressing pasture management and grazing made up 28% of the reviewed literature, often incorporating computational models to optimize land-use strategies. Meanwhile, 19% of the studies addressed carbon stock assessments and climate change impacts, highlighting the role of pasture ecosystems in conservation policy and sustainable resource management. .

#### 4.2. Overview of key methodological approaches

The reviewed studies employed a range of methodologies, which were categorized into four main research objectives: biomass estimation, environmental typology, trend detection, and spatiotemporal modelling. A significant proportion of the studies (74.27%) employed mathematical and statistical models, underlining their crucial role in predicting pasture productivity, ecosystem dynamics, and sustainable land-use planning. Among these, 30% of the studies focused on biomass estimation, while 5.96% utilized regression techniques, incorporating key environmental variables such as rainfall, temperature, and soil properties to model pasture growth. Additionally, 5.69% employed spectral indices like NDVI, demonstrating their effectiveness in assessing vegetation health and biomass availability.

In environmental classification studies, 20% of the reviewed papers addressed pasture typology and classification, with 5.13% employing forest-based models, recognized for their high accuracy in land cover classification tasks. Clustering techniques, though less represented (0.55%), were used to categorize environmental variables, facilitating the identification of management-relevant typologies.

The growing integration of machine learning into pasture modelling is reflected in 15% of the reviewed studies, where methods such as Neural Networks, Deep Neural Networks (DNNs), and Convolutional Neural Networks (CNNs) were applied. Among these, 2.77% applied DNNs and CNNs, leveraging large-scale datasets from remote sensing platforms and UAVs. Spatial and temporal data analyses were comparatively underrepresented, with 0.28% and 0.14% of studies employing these approaches, respectively, though they remain crucial for trend detection and spatial modelling of pasture dynamics (see Fig. 4).

A cluster analysis further highlights the relationships between research objectives and modelling techniques, revealing an integration of traditional ecological methods, such as regression modelling and remote sensing, with computational approaches like neural networks (Fig. 5). This growing convergence underscores the interdisciplinary nature of modern pasture ecosystem modelling and the increasing reliance on advanced computational techniques for improving predictive accuracy in environmental assessments.

#### 4.3. Modelling techniques in pasture management and biomass estimation

Machine learning models play a significant role in biomass estimation and pasture ecosystem assessment, with Artificial Neural Networks

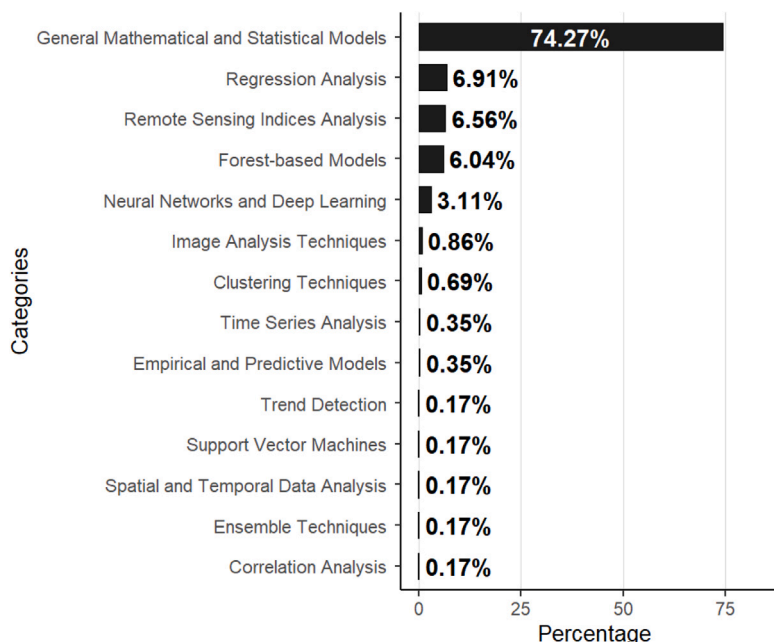


Fig. 4. Key methodological approaches in pasture management and environmental impact studies.

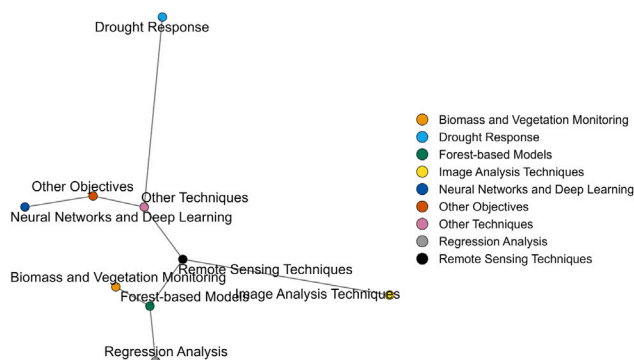


Fig. 5. Cluster map of research objectives and associated modelling techniques.

(ANNs) demonstrating strong predictive performance. For instance, ANNs trained with Sentinel-2 multispectral data achieved  $R^2 = 0.83$  and RMSE of  $6.68 \text{ kg}/100 \text{ m}^2$ , underscoring their capability to model complex non-linear relationships in pasture ecosystems (Vahidi et al., 2023). At the same time, differences reported between CNN- and ANN-based approaches often reflect the sensor and its spatial resolution rather than the architecture alone: on UAV imagery (centimetre-scale GSD, rich texture), CNNs have shown higher predictive accuracy than ANNs (e.g.,  $R^2 = 0.943$  vs  $0.885$ ) (Dong et al., 2020), whereas with Sentinel-2 (10–20 m) the textural advantage diminishes and performance typically converges across algorithms (Vawda et al., 2024; Campos-Taberner et al., 2020). In like-for-like Sentinel-2 settings, CNNs commonly perform on par with strong tabular/image baselines, and clear CNN gains reappear primarily when very-high-resolution inputs are available. Consequently, claims of CNN superiority should be interpreted in light of input resolution, sensor modality, and feature engineering; comparative evaluations ought to control for these factors.

Beyond these architectures, other procedures such as multi-granular spectral segmentation (MGSS) and  $k$ -Nearest Neighbours (KNN) have been employed to refine biomass estimation by improving spectral data selection and classification accuracy. The integration of remote sensing techniques with advanced modelling approaches has further

enhanced biomass estimation: traditional linear and non-linear regressions remain fundamental tools for aboveground biomass assessment, notably in Senegal where exponential and power models achieved  $R^2 > 0.80$  (Diouf et al., 2016). Hybrid formulations that combine ANNs with analytical datasets have also been developed to predict net primary production (ANPP) in grasslands and have outperformed conventional models (Paruelo et al., 2024).

Advancements in Random Forests (RFs), Support Vector Machines (SVMs), and Deep Neural Networks (DNNs) contribute to more accurate plant species classification and biomass estimation. RFs have shown robust predictive capabilities in biomass classification tasks, while SVMs are effective for high-dimensional data common in hyperspectral analyses. CNNs remain valuable for image-based biomass estimation from remote sensing, with studies reporting  $R^2$  up to 0.94 for general vegetation monitoring and about 0.83 in rangeland biomass applications (Campos-Taberner et al., 2020; Vawda et al., 2024). Overall, the diversity of modelling approaches illustrates a balance between established statistical methods and modern learning frameworks; remaining challenges concern computational requirements, data availability, and cross-site generalization. Priority should be given to sensor-/resolution-controlled comparisons, multi-sensor fusion, and hybrid designs that couple learning algorithms with process-based ecology to improve predictive accuracy and decision support for sustainable pasture management.

#### 4.4. Strengths and weaknesses of modelling approaches

Sentinel-2 satellites make it possible to monitor vegetation over large areas at relatively low cost, but their use is often hampered by cloud cover. This is why radar data (SAR), which can operate in all weather conditions, are increasingly used to complement optical sensors. In the same way, the tendency of NDVI to saturate in areas with dense biomass has encouraged researchers to turn to red-edge indices or other vegetation metrics that remain more reliable under such conditions. UAVs, for their part, provide very detailed local information that is extremely useful for calibration and validation, even though their limited coverage and operational constraints make them less suitable for large-scale mapping. Taken together, these examples show how the strengths and weaknesses listed in Table 1 have shaped

**Table 1**  
Strengths and weaknesses of techniques used in remote sensing and biomass estimation.

Category	Technique	Strengths	Weaknesses	Example refs
Data acquisition (Remote sensing)	Satellite (Sentinel-2/Landsat, optical)	Scalable coverage; dense time series; consistent radiometry; supports regional mapping	Cloud contamination; coarser GSD vs. UAV; need for atmospheric correction	Chen et al. (2021), Soto et al. (2024), Chen et al. (2024)
	Satellite (SAR)	All-weather imaging; structure/roughness sensitivity; complements optical	Speckle noise; feature engineering required; interpretation complexity	Chen et al. (2024), Belenguer-Plomer et al. (2021)
	UAV/Aerial	Very-high-resolution detail; flexible tasking; fine-scale calibration/validation	Limited spatial extent; weather/logistics constraints; operational cost	DiMaggio et al. (2020), Hütt et al. (2024), Feng et al. (2020)
Pre-processing/Indices	NDVI/red-edge metrics	Simple, well-validated; sensitive to canopy chemistry/structure (red-edge)	NDVI saturation at high biomass; sensor harmonization needed	DiMaggio et al. (2020), Soto et al. (2024), Yue et al. (2018)
Regression models	Linear/Non-linear; GLM	Interpretable, fast; baseline for AGB assessment	Limited for complex non-linearities; site-specific fits	Diouf et al. (2016), Wang et al. (2019)
Machine learning	RF/SVM/KNN	Strong tabular baselines; robust to mixed predictors	Tuning and feature design; interpretability can be limited	Liu et al. (2023), Nakayama (2022), Chen et al. (2024)
Deep learning	ANN/CNN	Powerful representation learning; leverages image texture and context	Data-hungry; compute-intensive; benefits depend on input resolution	Vawda et al. (2024), Dong et al. (2020), Kattenborn et al. (2020)
Hybrid/Ensemble	Model fusion (e.g., DL + process-based)	Improved robustness and accuracy; complementary strengths	Pipeline complexity; validation and generalization challenges	Paruelo et al. (2024), Shahhosseini et al. (2021)

*Abbreviations:* NDVI = Normalized Difference Vegetation Index; SAR = Synthetic Aperture Radar; UAV = Unmanned Aerial Vehicle; GLM = Generalized Linear Model; AGB = Above-Ground Biomass; RF = Random Forest; SVM = Support Vector Machine; KNN = k-Nearest Neighbours; ANN = Artificial Neural Network; CNN = Convolutional Neural Network; DL = Deep Learning.

methodological choices and explain many of the trends observed in the studies reviewed.

The strengths and weaknesses of different modelling techniques are summarized below:

#### 4.5. Technological advances and future prospects

The incorporation of advanced machine learning approaches, particularly deep neural networks (DNNs), represents a significant advancement in pasture ecosystem modelling, showcasing the increasing role of artificial intelligence in environmental sciences. These models have demonstrated remarkable proficiency in handling large, complex datasets, excelling in species discrimination, nonlinear decision-making, and the identification of ecological patterns. In pasture management, DNNs have proven particularly effective in enhancing decision-making processes by delivering precise and scalable solutions for monitoring vegetation dynamics and predicting biomass yields. For instance, Jin et al. (2020) reported that a DNN-based model achieved an  $R^2$  of 0.83 and RMSE of 1.96 t/ha in estimating maize biomass, demonstrating the model's capacity to capture intricate environmental interactions. Similarly, Maimaitijiang et al. (2020) applied a DNN framework to soybean grain yield prediction, where multimodal data fusion resulted in an  $R^2$  of 0.720 and an RMSE of 15.9%, highlighting the importance of integrating diverse data sources for improved predictive performance. This aligns with the findings of Liu et al. (2023), who demonstrated that RF and CNN models are also highly effective for biomass estimation under variable ecological conditions.

Despite these advancements, significant gaps remain in the application of other machine learning techniques in pasture management. Clustering algorithms, which are highly effective for analysing large, heterogeneous datasets, have not yet been widely explored in this domain. These techniques have the potential to detect hidden patterns within complex ecological datasets, which is essential for developing more adaptive and targeted pasture management strategies. Additionally, ensemble learning methods, which enhance prediction accuracy by combining multiple models, present a promising but underutilized approach. These methods have been successfully applied in crop yield prediction studies, where they improved model robustness and reduced

bias (Shahhosseini et al., 2021). Their application in grassland management could significantly enhance the reliability of pasture ecosystem models, ensuring more accurate assessments of biomass dynamics and environmental sustainability (Wang et al., 2019) also emphasize the potential of ensemble and hybrid methods in capturing the spatial temporal dynamics of rangeland transformations.

Looking ahead, validating these models under diverse ecological conditions should be a research priority. Although machine learning-based models have demonstrated high potential, their applicability is often dependent on specific environmental conditions. Validation across varied geographic and climatic regions is necessary to ensure that these models can be effectively implemented in different ecosystems. Studies such as Bocchiola et al. (2017) highlight the importance of ecological context in determining model effectiveness. Expanding such validation efforts would enhance model credibility and practical applicability in grassland ecosystem monitoring and management. This concern is echoed in Xu et al. (2022), who showed that soil characteristics significantly impact species diversity prediction using UAV spectroscopy in alpine pastures.

The next phase of development in pasture modelling should focus on the integration of machine learning techniques with emerging technologies such as IoT-based monitoring systems and drone-based remote sensing. Real-time data collection from sensor networks and high-resolution aerial imagery would allow for more adaptive, data-driven decision-making in grazing ecosystem management. By incorporating continuous environmental data streams into predictive models, land managers could improve the responsiveness of pasture monitoring systems, enabling more proactive and sustainable management interventions.

While significant technological progress has been made, further advancements are required in the application of clustering and ensemble learning techniques, as well as in the validation of these models under varied ecological conditions. The future of machine learning in pasture management will depend on continued interdisciplinary collaboration, the integration of advanced AI-driven techniques, and the development of hybrid modelling approaches that combine deep learning architectures with process-based ecological models. Ensuring the sustainability of grassland ecosystems will require ongoing

research investments, cross-sector innovation, and the refinement of predictive modelling techniques for enhanced accuracy and practical implementation worldwide.

## 5. Conclusion

Remote sensing, combined with advanced modelling techniques, is profoundly changing the way rangelands are monitored and managed. Mid-resolution satellite programs such as Sentinel-2 now provide regular and affordable observations over large areas, and when combined with statistical and machine-learning models, including random forests and neural networks, they have achieved high predictive accuracies for biomass estimation (often  $R^2 \approx 0.8\text{--}0.85$ ). These results confirm the potential of satellite data as a cornerstone for large-scale rangeland monitoring.

Nevertheless, most of these performances are obtained under specific local or regional conditions, and their generalization across different ecological zones remains a major challenge. The main limitations come from uneven data representativeness, variable label quality, differences in sensor characteristics, and the lack of observations in under-studied regions such as sub-Saharan Africa. In practice, strong local performance does not guarantee reliable results when models are applied outside their original domain.

To overcome these barriers, a satellite-first, multi-sensor strategy appears essential. The complementarity between optical and radar data (e.g., combining red-edge or NIR bands with SAR) can ensure more continuous and weather-independent monitoring, while UAVs, especially UAV-LiDAR, remain valuable for calibration and fine-scale validation. Such an approach requires consistent preprocessing across sensors and more rigorous evaluation frameworks, including cross-regional validation and standardized benchmarks, to guarantee reproducibility and comparability of results.

Finally, future progress will depend not only on technical innovation but also on strengthening data infrastructures and capacities, particularly in regions with limited resources. Integrating statistical and process-based models with predictive methods can also improve both interpretability and transferability. By combining multi-sensor data, robust validation, and investment in training and infrastructure, current advances can be translated into reliable and operational tools that support sustainable and equitable rangeland management worldwide.

## CRedit authorship contribution statement

**Renaud Kévin Houinato:** Writing – original draft, Investigation, Conceptualization. **Rodrigue Idohou:** Writing – review & editing, Data curation. **Romain Lucas Glèlè Kakaï:** Writing – review & editing, Validation, Supervision. **Yves Brostaux:** Writing – review & editing, Methodology.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data availability

Data will be made available on request.

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