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TOPICAL REVIEW

Optimal machine learning algorithms and UAV multispectral imagery for crop phenotypic trait estimation: a comprehensive review and meta-analysis

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Abstract

The rapid development of unmanned aerial vehicles (UAVs) and imaging technologies has opened new research avenues for precision agriculture, particularly in the context of plant phenotyping where their utilization has been intensive over the last decade. This review focuses on the interplay of machine learning, UAV-based multispectral imagery and plant phenotyping. We systematically reviewed the current literature to catalog and assess the variety of machine learning methodologies applied to multispectral UAV data for the prediction of key phenotypic traits such as biomass, yield and nitrogen. In this study, we conducted a comprehensive meta-analysis to analyze the relationship between the machine learning model performance and variables such crop type, the type of aerial phenotyping platform, the phenological stage, etc A trait-based comparison of the efficiency and popularity of machine learning algorithms was conducted. Our findings showed that the multiple linear regression is the most effective model in predicting biomass while artificial neural networks showed up as the top performing algorithm in determining nitrogen content. Random forest was identified as the most popular algorithm in estimating those key phenotypic traits. The best combinations of UAV and sensors that significantly enhance model performance for predicting critical agronomic traits were thoroughly examined. Results highlighted, for instance, that pairing the DJI 2 UAV with Micasense sensor led to better machine learning performance in predicting biomass while Parrot Sequoia was identified as the most efficient multispectral sensor to phenotype leaf nitrogen content. Ultimately, the challenges and future research prospects of UAV-based predictions related to the phenotype data variability, the choice of UAV platform, the model complexity and interpretability are discussed. Since previous studies described the broad applications of UAVs and sensors in agriculture, this review aimed to provide a targeted, systematic and quantitative analysis of optimal use of machine learning algorithms and UAV-based multispectral imagery for plant phenotyping.

1. Introduction

Agriculture is at the center of societal challenges of the 21st century driven by climate change, population growth, economic pressures and resource scarcity (Bernhardt *et al* 2021). The increasing food demand emphasized with the depletion of resources such water or arable lands (Prăvălie *et al* 2021) poses serious issues to meet food security by 2050 when world population is expected to reach 10 billion according to the 2015 revised median estimates of the United Nations (Lee 2011). Precision agriculture arises a paradigm shift to overcome those constraints as it offers a way to increase food production's resilience sustainability, and efficiency, enabling the world to meet its nutritional needs while protecting resources for coming generations (Lindblom *et al* 2017).

Precision agriculture leverages the power of advanced analytics and multiple data sources to increase crop yields efficiently by optimizing crop farming practices including irrigation management, fertilizer inputs and application of pesticides (Friedl 2018). Collecting data through phenotyping (referred to the process of measuring and analyzing observable traits of plants) is a key step to gain information on plant health, stress and fertilizer responses, water status and yield potential (Chawade *et al* 2019).

Utilizing unmanned aerial vehicles (UAVs) with various sensors is now a crucial method for efficient and non-invasive field crops phenotyping. This innovative approach allows for quick and detailed aerial imaging, enhancing the speed and flexibility of high throughput data collection. The development and deployment of new reliable sensors and high-performance computing have fostered and eased the progress in the development of field-based high throughput and high-resolution phenotyping tools over the last 10 years (Shakoor *et al* 2017). These advances have resulted in the genesis of many automated aerial sensing phenotyping platforms capable of rapidly collecting spatial and temporal data with improved resolution. Consequently, the automated image acquisition procedures developed in these platforms allow a significant increase in the throughput of plant phenotypic measurements, considered as a limiting factor in the functional analysis of specific genotypes or in the evaluation of genotypic performance in breeding programs (Furbank and Tester 2011). One of the main advantages of UAV imaging is the possibility to non-invasively analyze a wide range of plant structural and physiological traits related to plant performance (Dhondt *et al* 2013) under different environmental stress conditions, including nutrient deficiency (Costa *et al* 2022a), water stress (Gago *et al* 2015, Dong *et al* 2024), and crop disease (Blasch *et al* 2023) at different phenological stages with an impressive speed, precision, and accuracy. The development of increasingly high-performance sensors for imaging plants ranging from Light Detection and Ranging (Omasa *et al* 2007), visible to far-infrared (Wahabzada *et al* 2015), multispectral (Potgieter *et al* 2017), hyperspectral (Bauriegel *et al* 2011), thermal (Gómez-Candón *et al* 2014), fluorescence (Calderón *et al* 2013) to trichromatic (RGB) (Bargoti and Underwood 2016, Sa *et al* 2016a) imaging systems has led to the production of colossal amounts and diversity of data that required to be efficiently stored and rapidly processed for analysis.

For all the autonomous field-based UAVs platforms that can carry multiple sensors, huge numbers of images are taken in near real time to cover experimental field plot and monitor plant growth and development dynamics throughout its life cycle, i.e. from germination to maturity resulting in huge gigabytes of data (Singh *et al* 2016, RAFI *et al* 2024). Those remotely captured images and data with different spectral, temporal, spatial, and radiometric resolutions depending on the sensors used. They must be archived, retrieved, pre-processed, analyzed, and interpreted in an iterative and holistic way. Such a process facilitates to extract the key information on plant key traits and variables of the breeding lines in order to support various types of decision analysis for sustainable agricultural development. For that purpose, machine learning (ML) seems to be the most advanced set of techniques to efficiently convert images into actionable information and knowledge by automatically pre-processing imagery and extracting the most relevant plant features of interest, particularly in plant phenotyping where many applications have been developed (Ubbens and Stavness 2017, Singh *et al* 2016, 2018, Mochida *et al* 2019, Yu *et al* 2019). The ML-based feature extraction allows drastic dimensionality reduction that leads to better human interpretations, especially for hyperspectral data, which can have more than several hundreds to one thousand total bands (Aasen *et al* 2015, Gonzalez-Dugo *et al* 2015). Due to significant advantages in reducing size and dimensionality of the raw data (Khalid *et al* 2014), ML enables agronomists and breeders to automatically recognize interesting patterns and simultaneously analyze extracted features.

Unlike the previous reviews (Xie and Yang 2020, Feng *et al* 2021, Zualkernan *et al* 2023) that go for a more comprehensive perspective on the application of UAVs in agriculture, our study focuses on the specific use of case of crop phenotyping using UAV multispectral imagery. The main motivation why we exclusively focus on multispectral imagery are: (1) there is no in-depth work to our knowledge regarding the use of machine learning methods on UAV multispectral image data in the context of crop phenotypic trait estimation, (2) the relevance of multispectral imagery on plant phenotyping and the balance between the quality of the data and complexity of processing it offers. This work provides a comprehensive analysis of nuances associated in optimizing UAV multispectral imagery and machine learning techniques for this specific application. Moreover, the novelty of our review lies in its dual approach: a systematic review that catalogs and assesses the existing knowledge on machine learning used along with UAV multispectral imagery for plant phenotyping, followed by a meta-analysis that quantitatively evaluates the factors that most explain trait-specific model performance. This combination offers a more exhaustive and data-driven approach outlook than the narrative approaches utilized in other reviews. The annex A summarizes how our review fills the gaps of the previous works and provides additional value.

Our objectives are to:

- Provide a comprehensive analysis of current state of knowledge on the ML algorithms used for phenotypic trait estimation using UAV multispectral imagery

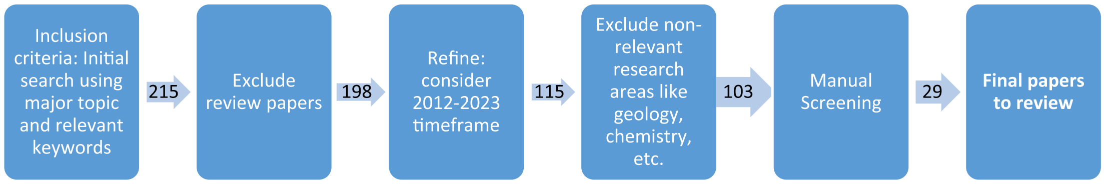

Figure 1. Step-by-step process of paper selection for the systematic review.

- Conduct a meta-analysis to determine the best combinations of UAV and sensors that optimize ML models' performance
- Identify the top performing ML methods for predicting critical agronomic traits
- Identify the major trait-based drivers that drive model performance to inform better model selection and application in UAV multispectral imagery-based crop phenotyping

2. Methodology

2.1. Bibliometric analysis

We queried the Web of Science (WOS) database as our primary source of data with UAV multispectral imagery as the theme. Crop phenotyping using aerial multispectral imagery is mostly devoted to yield estimation, postharvest quality, plant morphology, physiology, disease detection, nitrogen status, etc (Yu *et al* 2016a, Pádua *et al* 2022, Ganeva *et al* 2022, Shao *et al* 2022a, Costa *et al* 2022b). We customized and extended the research query used by Zang *et al* (2022) on their bibliometric analysis on agricultural multispectral research. Annex B shows the refined search query that was used to retrieve the relevant literature. The timeframe covered by the literature search was from January 2012 to December 2023. Figure 1 explains the different steps to narrow down the initial number of papers from 215 to 103 papers. From 103 papers, we reviewed 28 papers as follows: yield (13), biomass (7), and nitrogen content (8).

2.2. Meta-analysis

2.2.1. Data compilation

We collected a range of variable data listed from the different 28 papers. We focused mainly on biomass, nitrogen and yield because their importance in plant phenotyping and due to the number of data points we for those traits. The data included details about crop, the phenological stage, the type of UAV, the sensor, the spectral bands, the flight height, the phenotypic trait of interest, the ML algorithm used, the standard deviation of the measured response, the R2 and the root mean square error (RMSE). Additionally, we calculated the ratio of performance (RPD) (equation (1)) to evaluate the ML model performance across studies and investigate the key factors that drive predictive capabilities of models. The accuracy of model prediction can be categorized into three classes: excellent (RPD > 2.0), reliable ($1.40 \leqslant$ RPD $\leqslant 2.00$) and unreliable (RPD < 1.4) (Chang *et al* 2001). A good and reliable model typically achieves high R2 and RPD, as well as low RMSE values. We used the RPD as a comparability indicator over R2 because it's a dimensionless and standardized measure that facilitates direct comparison across different datasets and models, even if the scales and variances of datasets differ. Secondly, RPD is more intuitive in the context of data variability and is less sensitive to data distribution, providing a consistent measure across various distributions while R2 expresses the proportion of variance explained by the model, so less intuitive, particularly when comparing models across diverse datasets.

$$RPD = \frac{\sigma_y}{RMSE} \tag{1}$$

Where:

- σ_y is the standard deviation of the observed values.
- RMSE is the Root Mean Square Error of the model defined by:

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

- y_i is the observed value for the *i-th* observation.
- $\hat{y}_i$ is the predicted value for the *i-th* observation.
- n is the number of observations.

2.2.2. Analysis of the review data

We conducted all analyses using R version 4.2.3 and RStudio (R Core Team 2023; RStudio Team 2023). We performed a thorough exploratory data analysis using tidyverse (Wickham *et al* 2019) and ggplot2 (Villanueva and Chen 2019) packages to visualize the distribution of RPD values per ML across the type of UAV, the sensor and the trait, helping us indicating the best aerial phenotyping platform that optimize ML predictive capabilities by trait. Additionally, we also investigated the top performing ML algorithms in predicting traits of interest utilizing the forest plots from the meta package (Schwarzer 2007).

To further understand the key determinants of ML model performance (RPD), we employed an Elastic Net regression model that leverages the strengths of LASSO and ridge regression to handle challenges posed by multicollinearity and overfitting, particularly when dealing with limited sample sizes. The Elastic Net's mathematical formulation is an extension of the ordinary least squares (OLS) regression, in which a term of penalty is incorporated into the loss function to restrict or shrink the model coefficients.

The optimization problem that Elastic Net solves is:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}}\left(\frac{1}{2n}\sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2 + \lambda\left(\alpha\sum_{j=1}^{p}|\beta_j| + \frac{1-\alpha}{2}\sum_{j=1}^{p}\beta_j^2\right)\right) \tag{3}$$

Where:

- y_i is the response variable for the i-th observation
- x_{ij} is the j-th predictor for the i-th observation
- β_i is the response variable for the i-th observation
- n is the number of observations
- p is the number of predictors
- λ is the regularization parameter that that handle how strong is the penalty
- α is the mixing parameter that defines the balance between Ridge ($\alpha = 0$) and LASSO regression ($\alpha = 1$)

The initial term of the loss function represents the standard least squares error, while the second term signifies the penalty. The L1 penalty ($\alpha\sum_{j=1}^{p}|\beta_j|$) fosters sparsity by constraining some coefficients to become exactly zero, efficiently conducting feature selection. The L2 penalty $\frac{1-\alpha}{2}\sum_{j=1}^{p}\beta_j^2$ mitigates multicollinearity by shrinking the correlated predictors towards each other.

We tested potential interactions between predictors utilizing the *stats* package in R. Consequently, we investigated how the impact of one predictor on RPD would change based on the values of other predictors. This method improves the explanatory capacity of the model and reveals complex relationships between the variables influencing RPD. Then we used the *glmnet* package to implement the Elastic Net regression. We tuned the regularization parameter λ via cross-validation, ensuring model performance.

3. Results

3.1. Geographical distribution of the papers

A total of 16 countries are involved at the intersection of artificial intelligence, UAV multispectral imagery research and crop phenotyping (figure 2). The analysis of research countries reveals that China (28%), United States (26%), Brazil (17%), Japan (5%) and Australia (2%) are top five countries with highest number of publications. We noticed that the global distribution of scientific production is quite skewed toward those countries. Such an uneven global distribution could reflect disparities due many factors including institutional priorities, funding or regulations (Nakamura and Kajikawa 2018). In fact, research on UAV-based crop phenotyping with AI concentrated in the top-tier mentioned countries because of huge investments in agricultural R&D, sophisticated UAV supply chains, and favorable regulatory environments for drone operations, which facilitate the swift collection and processing of high-quality datasets by well-funded teams (Bongomin *et al* 2022, Felipetto *et al* 2023). Furthermore, top-leading universities and national research labs in these countries develop high-level expertise and proficiency in remote sensing and AI, which promotes extensive networks of collaboration and boost publication outcomes (Osco *et al* 2021).

In contrast, numerous low-income countries, located mainly in the global South, confronting pressing agricultural issues are deficient in both continuous funding and computational resources, alongside ambiguous UAV regulations, hindering the generation of extensive labeled datasets and the large-scale training of deep

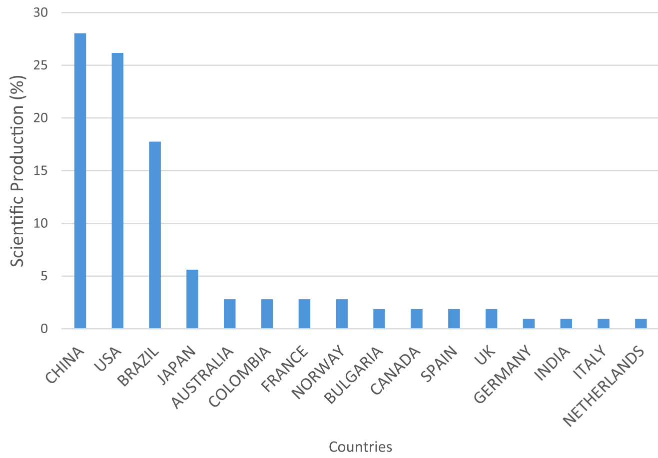

Figure 2. Global distribution of scientific production per country at the crossroads of machine learning, multispectral UAV imagery and crop phenotyping.

learning models (Bongomin *et al* 2022, Felipetto *et al* 2023). As a result, despite high demand, the limited adoption of UAV-AI phenotyping in these locations is constrained by small-scale farming systems and dispersed research infrastructures, thereby diminishing their representation in the literature (Mafuratidze *et al* 2024).

3.2. Distribution of ML algorithms in UAV multispectral imagery-based crop phenotyping

Figure 3 is a tree map plot showing the diversity of ML models identified from the meta data extracted across the reviewed research papers. Each rectangle in the plot represents the proportion with which the model was utilized in the reviewed studies.

Random forest arises as the most frequently used model (13%), highlighting its popularity to handle highly dimensional phenotypic data, followed by Support Vector Machines (SVM) and Multiple Linear Regression (MLR) with a prevalence of 11% each, showcasing its utilization in regression tasks with complex limited datasets. Artificial Neural Network (ANN) each represents 9% of the models. Models such eXtreme Gradient Boosting (XGBoost), Backpropagation network (BP) and Partial Least Squares (PLS) are each employed in 3% of the studies, highlighting their specific uses in predictive modeling. The Cubist algorithm is utilized in only 2% of the research papers, considering a combination of decision trees with linear regression to achieve accurate predictions. Additional techniques, such as Deep Neural Networks (DNN), Gaussian Processes (GP), K-Nearest Neighbors (KNN), Multivariate Adaptive Regression Splines (MARS), and others, each have a 1% contribution, indicating their specific and specialized uses. The findings illustrate the wide range of machine learning techniques utilized in crop phenotyping research, with RF, SVM, and taking the lead. These techniques offer useful insights for choosing suitable algorithms depending on unique forecasting requirements.

3.3. ML-based processing of multispectral UAV imagery for plant phenotyping

We identified and prioritized biomass, nitrogen content and yield as major critical plant traits in this study because (1) 90% of the papers were focused on them due to their measurability using UAVs, (2) of their prominent contributions to food security, crop management, and agronomic decision-making. Yield is the most critical parameter for decision-makers, as it is a definitive measure of economic viability and crop success. Nevertheless, because yield is an end-of-season trait, early-stage estimations are based on biomass and nitrogen content, which offer critical insights on crop growth and nutrient status. Biomass serves as a proxy of productivity and plant vigor but is limited without additional physiological information. Nitrogen content is crucial for streamlining fertilization and enhance resource-use efficiency but necessitates biomass data to contextualize its influence on the performance of crops. Integrating those three traits significantly improves the accuracy of decision-making, as each of them gives complementary information essential to optimize productivity outcomes.

3.3.1. Crop biomass

Biomass is a crop parameter well-known to evaluate crop growth and health status, and crucial for prediction of crop yield. Traditional methods to directly measure biomass are destructive, expensive and time-consuming. From various remote sensing data sources, several methodologies including involving empirical statistical analysis and ML have been deployed to estimate crop biomass (Ali *et al* 2015). Those methodologies mainly utilized four approaches—the analysis of 3D structure crop parameters (i.e. height), regression based on spectral

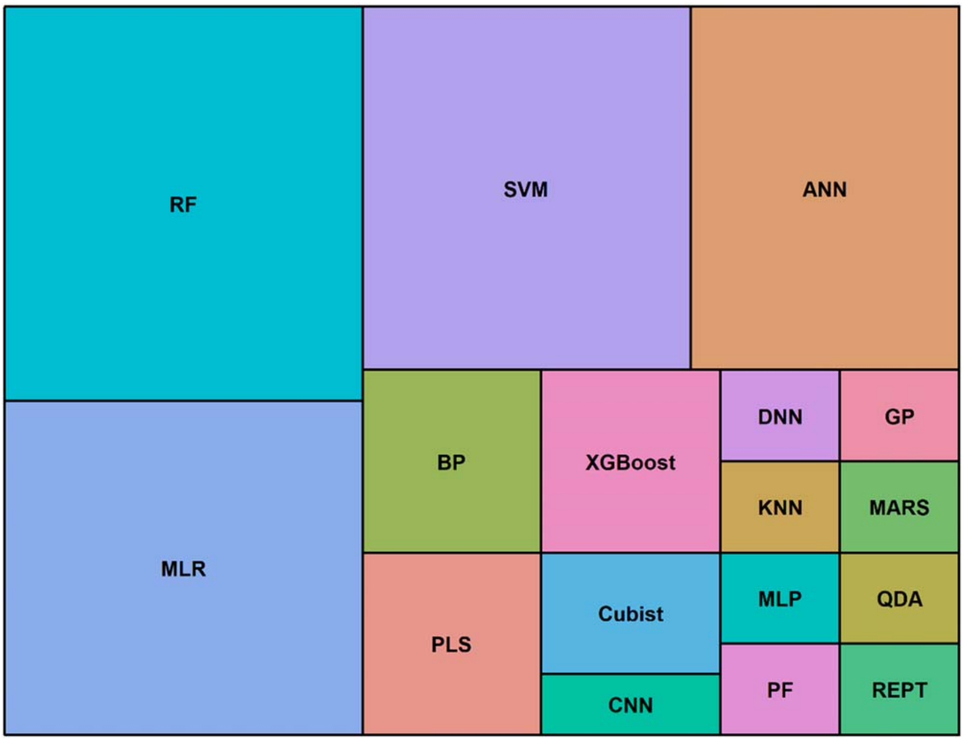

Figure 3. Distribution of ML algorithms in UAV multispectral imagery-powered phenotypic trait prediction Studies.

indices only, hybrid structural-spectral models, and time-series transpiration-derived techniques (Kolanuvada and Ilango 2021, Tatsumi *et al* 2021, Alckmin *et al* 2022, Shao *et al* 2022b)—each harnessing the types of data and machine learning algorithms to rationalize the applicability and the accuracy depending on the studied crops (table 1).

Many research studies leverage metrics of 3D structure-mostly crop height or volume of crown-from UAV-derived point clouds to estimate crop biomass. Zhu *et al* 2019 use UAV-based 3D information derived from point clouds of multispectral structure from motion (SfM) cameras and LiDAR to evaluate above-ground biomass of maize using classical multivariate linear regression model (MLM) and ML algorithms (random forest, back-propagation neural network and SVM). They found crop height (CH) is a prominent, RF and SVM slightly outperformed better. Similarly, Kolanuvada and Ilango (2021) used crown area-based approach to appraise biomass from UAV imagery and neural networks. They employed a Tensorflow-CNN object detection model on 4-band multispectral dataset to delineate and segment tree crowns achieving an overall accuracy of 96.1%, and applied allometric equations to calculate net per-crown bionass.

Other studies used vegetation indices from multispectral data to determine biomass. For instance, Sharma *et al* 2022 examine the potential of PLS, SVM, ANN and RF and UAV multispectral vegetation indices in estimating the oat biomass in three different fields located at Volga, South Shore, and Beresford, South Dakota, USA. Findings indicate that in Beresford, SVM, PLS and RF could broadly explain 70% of data variation while in Volga and South Shore we observed R2 ranging from 0.15 to 0.25. Alckmin *et al* 2022 proposed to use a mix of multispectral UAV camera and handheld spectrometer to develop an observational system based on ML to estimate perennial ryegrass biomass. They found that post-calibrated UAV vegetation indices matched spectrometer data and the Cubist regression-tree based model outperformed RF, bagged trees, and BRT in interpretability, accuracy, and deployment speed. These spectral-only approaches provide fast, non-invasive and cost-effective monitoring; however, may suffer sensor or spatial variability.

Combining structural metrics and spectral indices often improve accuracy. Zheng *et al* (2022a) fed photogrammetric DSM-derived geometric parameters and with multispectral vegetation indices in 6 contrasted supervised regression models (MLR, RF, SVR, Multivariate adaptive regression splines (MARS), XGBoost and ANNs), finding ANNs best predictive model (R^2: 0.89–0.93 and RMSE: 7.16–8.98 g) and red-edge-derived vegetation indexes as the most influential variables in predicting biomass. Tatsumi *et al* (2021) retrieved first-order statistics and textural features from VIs and plant height (750 variables), followed by feature selection (RFE, GA, Boruta, DALEX) before RF, ridge regression, and SVR, resulting in a rRMSE of 8.8%. These hybrid approaches show that structural and spectral synergies, together with dimensionality reduction, produce accurate biomass forecasts.

Table 1. Comparative summary of machine learning approaches for crop biomass estimation.

Study (Year)	Crop	Sensor/data	Features	ML models	Key performance	Main insight/limitation
Zhu *et al* (2019)	Maize	UAV SfM, LiDAR	Crop height	MLM, RF, BPNN, SVM	$R^2 \approx 0.8–0.9$	Height dominates; RF/SVM best
Kolanuvada & Ilango (2021)	Trees	4-band multispectral + DSM	Crown area, height	CNN + allometry	96.1% crown det.; biomass computed	Automated crown → allometric biomass
Sharma *et al* (2022)	Oat	UAV multispectral	Vegetation indices	PLS, SVM, ANN, RF	R^2 up to 0.70	Good in one site; poor transferability
Alckmin *et al* (2022)	Ryegrass	UAV multispectral; handheld spectrometer	Reflectance	Cubist, RF, BRT, Bagged Trees	Comparable to spectrometer	Cubist best: interpretable & fast
Zheng *et al* (2022a)	Strawberry	Photogrammetric DSM + multispectral	Height + VIs	MLR, RF, SVR, MARS, XGBoost, ANN	$R^2 = 0.89–0.93$; RMSE≈8 g	ANN top; red-edge VIs critical
Tatsumi *et al* (2021)	Tomato	UAV multispectral	750 VI stats & texture + height	RF, Ridge, SVR (after feature sel.)	rRMSE = 8.8%	First-order VI stats & height most important
Shao *et al* (2022b)	Maize	Time-series UAV multispectral	Time-series VIs → CTc	ABR, MLR, RF, SVR; exponential model	$R^2 = 0.76$	CTc-based exponential model works well across irrigation regimes

Trajectories of time-series vegetation and calculated transpiration coefficients (CTc) provide dynamic information about biomass accumulation. Shao *et al* (2022b) used ABR, MLR, RF, and SVR to calculate CTc from temporal multispectral VIs under varying irrigation. RF provided the best CTc estimates ($R^2 = 0.91$; rRMSE = 9.07%). They then fit exponential, linear, logistic, and sigmoid models to determine the AGB, with the exponential form achieving a R^2 of 0.76 (rRMSE = 39.2%). This time-series CTc system has the potential to integrate phenotypic monitoring and irrigation control at the field size.

3.3.2. Yield estimation

UAV multispectral imagery coupled with artificial intelligence emerged the last years as a novel technology to automate yield estimate at plant and field scale under different conditions (Yu *et al* 2016b). Approaches utilized to phenotype yield have been clustered in 4 methodological categories including, phenology-guided spectral regression methods, deep learning image-based algorithms, feature selection with traditional ML, and hybrid and ensemble multi-source models. Table 2 summarize key crops, sensors, models, and performance metrics employed for yield estimation and underscores the main benefits and limitations of each strategy.

Studies utilizing phenology-guided techniques first identify the optimal growth phase for the UAV flight, and then model yield using vegetation indices. Eugenio *et al* (2020) demonstrated that monitoring at soybean V6 stage maximizes the correlation between grain yield and predictors and trained a MLP algorithm to predict yield with a R of 0.92 (RPD>2). Ganeva *et al* (2022) determined the grain-filling period as most suitable for prediction, employing both parametric and non-parametric vegetation index models to achieve a R2 of 0.49 (rRMSE = 6.1%). Yu *et al* (2016c) used extracted geometric features and a RF model to predict yield from soybean plots at plant maturing, resulting in Spearman's R coefficient of 0.80. They highlighted the importance of timing and feature selection in breeding trials.

Other several works rather rely on end-to-end convolutional networks with the capability to learn spatial and temporal patterns directly from UAV images to estimate yield. Bellis *et al* (2022) compared 3D-CNNs (spatio-temporal) to 2D-CNNs (single-date) on rice, finding rRMSE = 8.8% for 3D. and 7.4%–8.2% for 2D from booting onward. Sa *et al* (2016b) improved Faster R-CNN with RGB+NIR fusion to recognize sweet peppers and rock melons, reaching $F_1 = 0.838$ and robust transferability across seven types of fruit, demonstrating deep learning's potential for object-based yield assessment.

The feature-selection methods improve the performance of classic regression models and optimize inputs by pre-ranking or selecting the most relevant features or vegetation indices. Ramos *et al* (2020) ranked 33 UAV-derived indices using RF-based merit, then fused the top 3 features (NDVI, GNDVI, and NDRE) in the RF to predict maize yield (R = 0.70; MAE = 853 kg ha^{-1}).

The hybrid + ensemble frameworks used data using (geometric metrics, multispectral, LiDAR, etc) and ensemble learners to take advantage of complementary data. Ballesteros *et al* (2020) integrated vegetation indices with canopy-fraction cover into an ANN to estimate vineyard yield (RMSE = 0.5 kg $vine^{-1}$; RE = 12.1%), underscoring the segmentation of canopy as an important preprocessing step to maximize accuracy. Chen *et al* (2022) collected spectral and morphological qualities from multispectral imaging and LiDAR, then utilized a KNN+SVR ensemble—highlighting three essential features (crown area, volume, RVI)—to achieve $R^2 = 0.813$ (validation) and $R^2 = 0.758$ (test) for apple yield mapping.

3.3.3. Nitrogen

The estimation of crop nitrogen status through UAV-based multispectral imagery has been driven by 4 methodological themes- phenology-guided regression, feature-selection based models, data fusion from multiple sources, and classification-to regression workflows. Table 3 provides a summary of key crops, sensors, models, and performance metrics utilized for predicting nitrogen.

As like for biomass, the phenology-guided approach pinpointed the ideal growth phase that maximizes the relationship between vegetation indices and nitrogen, then apply traditional regressors. Colorado *et al* (2020a) demonstrated that when imaging at specific times (vegetative and reproductive stages), high accuracies (R2 of 0.98 and 0.94 respectively) for rice leaf nitrogen estimation using MLR, SVM, and NN. Likewise, Jiang *et al* (2022) also identified the jointing/booting stages as ideal for predicting nitrogen in wheat using random forest ($R^2 = 0.83$–0.84; RMSE = 13–17.5 kg ha^{-1}), emphasizing that the timing of flights can enhance model efficacy.

For feature selection-driven methodologies, extensive preprocessing of vegetation indices is performed prior to modeling, enhancing both parsimony and predictive accuracy. Luo *et al* (2022a) extracted 28 spectral indices and used the top five from a correlation-based ranking and test different ML models (PLS, SVM, and NNs) to estimate tea nitrogen status, finding SVM as the best model (R2 = 0.75). Barzin *et al* (2021) assessed 8 ML algorithms on maize using raw bands and 26 vegetation indices, showing gradient boosting and RF best (R2 = 0.8) and finding that the combination of red-edges indices maximizes the leaf nitrogen estimation.

The data fusion methodologies combine spectral, textural or topological variables to gain supplementary nitrogen indicators. Zheng *et al* (2020) integrated spectral and texture parameters from multispectral UAV

Table 2. Comparative summary of machine learning approaches for crop yield estimation.

Study (Year)	Crop	Sensor/data	Methodology	Models	Key metrics	Main insight/limitation
Eugenio *et al* (2020)	Soybean	UAV multispectral (phenology-timed)	V6-stage selection + spectral regression	MLP	R = 0.92 RPD>2	Phenology timing crucial
Ganeva *et al* (2022)	Wheat	Four-band multispectral	Parametric/nonparametric VI models	Linear & nonparametric regression	$R^2 = 0.49$; rRMSE = 6.1%	Grain fill phase optimal
Yu *et al* (2016c)	Soybean lines	UAV multispectral (geom. features)	Geometric-feature RF	RF	R = 0.80	High-throughput breeding potential
Bellis *et al* (2022)	Rice	Time-series UAV multispectral	3D-CNN versus 2D-CNN	3D/2D convolutional networks	rRMSE = 7.4%–8.8%	Temporal depth boosts accuracy
Sa *et al* (2016b)	Pepper/Melon	RGB + NIR multispectral	Faster R-CNN with fusion	Faster R-CNN (VGG16 backbone)	$F_1 = 0.838$	End-to-end detection for yield & harvest automation
Ramos *et al* (2020)	Maize	UAV multispectral (VIs)	VI ranking + RF	RF	R = 0.70; MAE = 853 kg/ha	Feature pruning improves RF efficiency
Shafiee *et al* (2021)	Spring wheat	UAV multispectral	SVR+SFS versus LASSO	SVR, LASSO	(not specified)	Comparison of selection strategies
Ballesteros *et al* (2020)	Vineyard	UAV multispectral (VIs + canopy fraction)	VI + fraction fusion	ANN	RMSE = 0.5 kg vine^{-1}; RE = 12.1%	Canopy segmentation key in viticulture
Chen *et al* (2022)	Apple orchard	Multispectral + LiDAR	Spectral & morphological ensemble	KNN + SVR ensemble	$R^2 = 0.813/0.758$	Multi-source fusion with minimal feature set

Table 3. Comparative summary of machine learning approaches for crop nitrogen estimation.

Study (year)	Crop	Sensor/data	Methodology	Models	Key metrics	Main insight/limitation
Colorado *et al* (2020a)	Rice	UAV multispectral; VIs at vegetative & reproductive phases	Phenology-guided spectral regression	MLR, SVM, NN	$R^2 = 0.98$ (veg.); $R^2 = 0.94$ (rep.)	Flight timing is critical; introduced wind-disturbance mitigation
Jiang *et al* (2022)	Wheat	Fixed-wing UAV multispectral	Phenology-guided spectral regression	RF	$R^2 = 0.83$–0.84; RMSE = 13–17.5 kg ha^{-1}	Jointing/booting stages optimal for in-season assessment
Luo *et al* (2022a)	Tea	UAV multispectral; 28 raw spectral parameters	Feature-selection–driven regression	PLS, SVM, BPNN	SVM: $R^2 = 0.758$; RMSEP = 0.4086	Correlation-based ranking reduces feature set size
Barzin *et al* (2021)	Maize	UAV multispectral; 26 VIs + raw spectral bands	Feature-selection–driven regression	Elastic Net, Lasso, Ridge, GB, RF, SVM, MLP	GB & RF: $R^2 \approx 0.80$	Combining VIs with raw bands boosts %N estimation
Moghimi *et al* (2020a)	Grapevine	High-res UAV multispectral	Classification-to-regression pipeline	QDA, SVM, XGBoost, RF, DNN	SVM $F_1 = 82.24\%$; XGBoost: $R^2 = 0.50$; RMSE = 0.23%	SVM excels in classifying N status; XGBoost best for regression
Osco *et al* (2020)	Maize	UAV multispectral; NDVI, NDRE, GNDVI, SAVI	Classification-to-regression pipeline	9 supervised models (RF best)	$r = 0.91$; RMSE = 1.9 g kg^{-1}	Random forest consistently outperforms alternatives
Yu *et al* (2021)	Corn	UAV multispectral; VIs, crop height, topo, soil	Multi-source data fusion	RF, SVR	RF: $R^2 = 0.73$; RMSE = 2.21 g m^{-2}	Crop height is the top predictor; multi-domain features add value

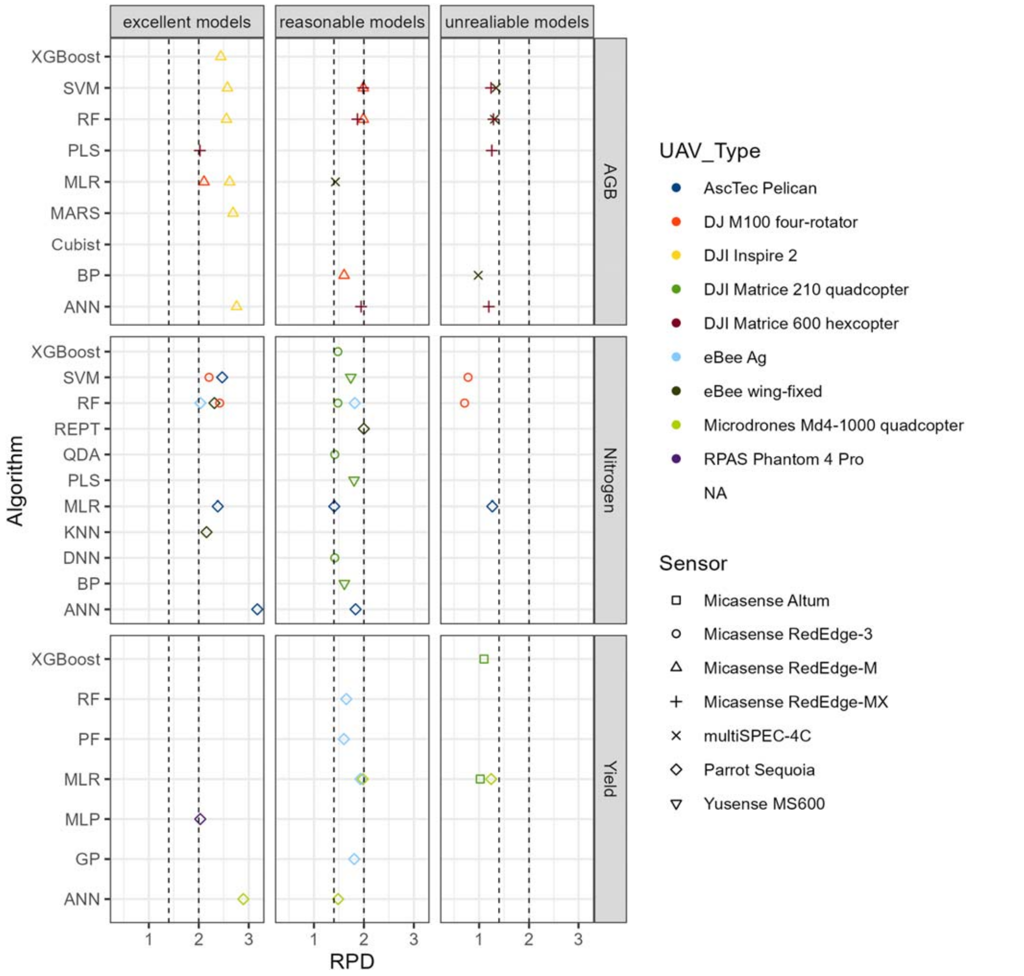

Figure 4. Comparative Analysis of RPD Values for Predicting AGB, Nitrogen, and Yield Using Different ML Algorithms, UAV Types, and Sensors. Each symbol represents a specific sensor, while the colors show different UAV types used in the studies. Dashed lines represent the thresholds of the RPD for model accuracy classification as defined in the methodology part.

imagery to refine the quantification of nitrogen. Another 2021 research study by J. Yu *et al* combined plant height, vegetation indices, topographic curvature and soil properties and employed RF and SVM for corn canopy nitrogen, with RF topping at a R2 of 0.73, demonstrating the value of multi-domain predictors.

Classification-to-regression pipelines evaluated classifiers prior to fine-tuning regression for N estimation. Moghimi *et al* (2020a) categorized grapevine nitrogen at bloom as high/low classification task, utilizing SVM with a F1 score of 82.2%. They subsequently reformulated it as a regression problem, where XGBoost attained a R2 of 0.5 and a RMSE of 0.23%. Osco, Marcato, *et al* (2020) evaluated 9 models, with RF showing superior performance, highlighting the reliability of RF in spectral-based nitrogen determination.

3.4. Insights from meta-analysis

3.4.1. What UAV and sensor characteristics maximize ML performance?

For biomass, ML models such as XGBoost, SVM, RF, MLR, MARS and ANN exhibit excellent prediction performance with RPD values above 2. Similarly, sensors from Micasense (RedEdge-M and -MX) combined with UAVs like DJI Inspire 2 and DJI Matrice 100 are commonly associated with these high-performing algorithms (figure 4).

Reasonable biomass prediction performances are also achieved by BP, MLR, SVM and RF methods, specifically when using Micansense RedEgdge M derived sensors mounted on DJI Matrice 600 or DJ Matrice 100 UAVs (figure 4).Biomass unreliable predictive models with RPD values less than 1.4 are mainly associated with eBee wing-fixed UAV and multiSPEC-4C camera (figure 4).

The ML algorithms involving SVM, RF, KNN and ANN are the top-performing models when fed mainly with Parrot Sequoia multispectral data acquired from AscTec Pelican vehicle to determine nitrogen content.

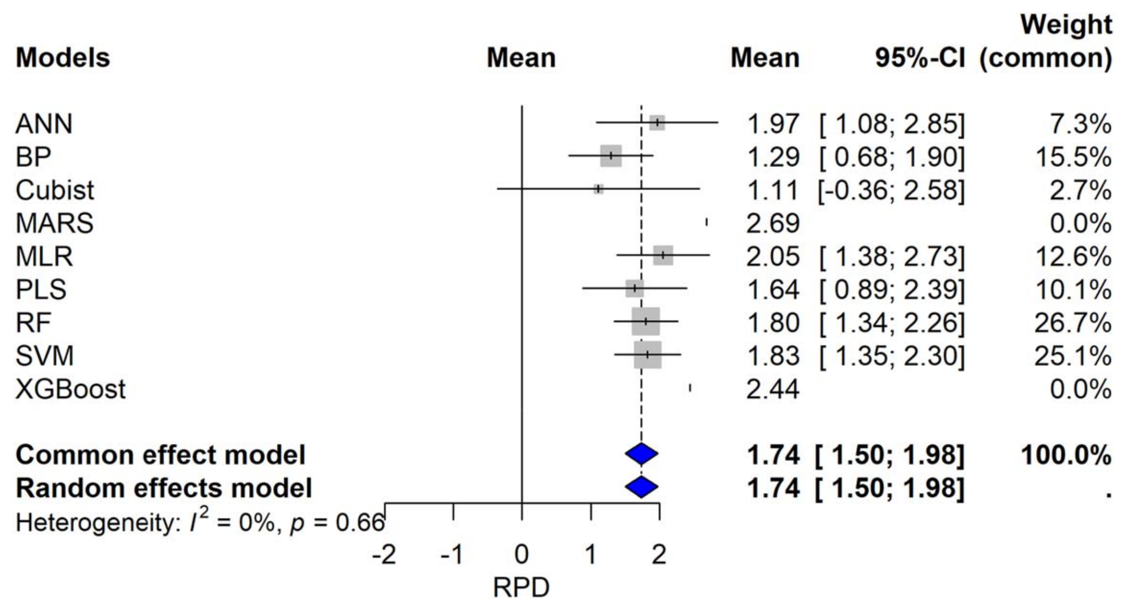

Figure 5. Forest Plot of RPD Values for Various ML Models Used in Biomass Prediction Across Multiple Studies. The forest plot presents the **mean RPD values** and their **95% confidence intervals (CI)** for the different machine learning models. Each model's mean RPD is shown as a square, with the size representing the weight assigned in the meta-analysis (right column). The horizontal lines indicate the 95% confidence intervals (CI) for each model's mean RPD, providing insight into the variability of model performance. The diamond at the bottom represents the pooled effect size (RPD) from both common and random effects models, summarizing the overall effectiveness of these models in biomass prediction.

All models except KNN perform reasonably well in determining nitrogen content when commonly associated UAVs like DJI Matrice 210 and Micasense RedEge-3 and Yusense MS600 multispectral sensors (figure 4).

MLP and ANN are among the models that exhibit exceptional performance in the prediction of yield. Effective aerial phenotyping platforms combining UAVs such as RPAS Phantom 4 or Microdrones Md4-100 and Parrot Sequoia multispectral are prominently used in these scenarios (figure 4).

Reasonable performance in determining yield can also be also obtained with RF, PF, MLR, GP and ANN with Parrot Sequoi multispectral sensor and UAVs like eBee Ag or Microdrones Md4-100 contributing to the performance (figure 4).

Yield prediction by some models like XGBoost or MLR, using sensor data from Micasense Altum and Parrot Sequoi and collected from DJI Matrice 210 and Microdrones Md4-100 UAVs, fall into unreliable predictive performance category (figure 4).

The figure 4 showed that sometimes same ML methods fed with same sensor data acquired from same UAVs types might lead in different results (e.g. MLR model used to predict nitrogen based on Parrot Sequoi sensor data and eBee UAV) due probably to the data quality and preprocessing techniques used across studies, the environmental conditions during data collection or soil and crop types, the experimental design, the model architecture (parameters and hyperparameters), and algorithm implementations using various software packages and libraries that might lead in important variations in model performance.

3.4.2. Which models are the best performers?

We explored forest plots commonly used in meta-analysis to summarize and visualize results of multiple research papers, enabling an easy comparison of effect sizes and a general evaluation of the research outputs. Here, the forest plots present the mean and the corresponding 95% confidence intervals for the RPD values of the various ML identified across studies and their performance in predicting biomass, nitrogen and yield.

Figure 5 shows that the best performing model in estimating biomass is MLR with a RPD mean of 2.05 and the narrowest confidence interval that doesn't cross zero, indicating a robust and reliable predictive power for biomass.

RF has the highest weight (26.7%) among the ML methods, suggesting that it's the most popular model in the studies for biomass prediction followed by SVM (25.1%).

The statistics (I2 and p-value) support that there is no heterogeneity in the RPD value range across different studies, meaning that the variability of RPD values in low, suggesting highly consistent model performance across datasets and conditions.

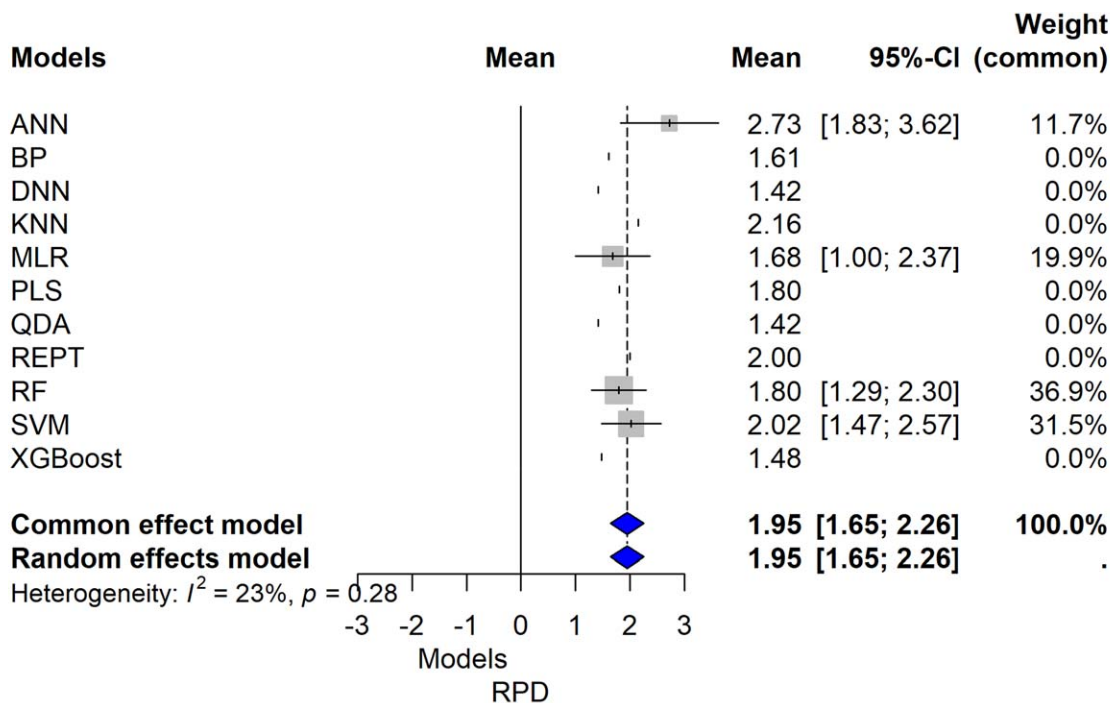

Figure 6. Forest Plot of RPD Values for Various ML Models Used in Nitrogen Prediction Across Multiple Studies. The forest plot presents the **mean RPD values** and their **95% confidence intervals** (**CI**) for the different machine learning models. Each model's mean RPD is shown as a square, with the size representing the weight assigned in the meta-analysis (right column). The horizontal lines indicate the 95% confidence intervals (CI) for each model's mean RPD, providing insight into the variability of model performance. The diamond at the bottom represents the pooled effect size (RPD) from both common and random effects models, summarizing the overall effectiveness of these models in biomass prediction.

Figure 6 reports that ANN, KNN and SVM are the top performing models in predicting nitrogen content with mean RPD values >2, indicating excellent and strong performance.

The most frequently used algorithm for nitrogen prediction is RF with a significant weight of 36.9%, followed by SVM (31.5%) and MLR (19.9%).

Results showed moderate heterogeneity (I2 = 23%) indicates that the variability in RPD values among studies is not significant, suggesting that model performance is relatively consistent across the diverse studies.

Figure 7 presents the ANN as the top performing model in appraising yield with a mean RPD of 2.42, suggesting excellent and reliable performance.

MLR model is the most commonly used algorithm for yield with prediction with a huge weight of 90.1% (common effect) and 68.6% (random effect).

Results highlight a substantial higher variability (I2 = 54%) compared to biomass and nitrogen, indicating that there is a significant variability in RPD data through the studies. This suggests that certain models exhibit consistent performance, while others may show varying degrees of efficacy based on study-specific factors.

3.4.3. What are the top performing UAV-sensor-model combinations?

Table 4 summarizes key insights from figure 4 and forest plots (figures 5–7) and outlines the best combinations of algorithms, sensors and UAV platforms for different key traits (biomass, nitrogen and yield).

When estimating biomass, the association of MLR model and Micasense RedEdge-M sensor on DJI 2 UAV platform demonstrated excellent use of high-resolution multispectral imagery for accurate biomass assessment. For nitrogen estimation, the ANN model combined with the Parrot Sequoia sensor on the AscTec Pelican UAV excels effectively. Lastly, the same ANN paired with the Parrot Sequoia sensor, but on a different UAV platform, the Microdrones Md4-100, showcased versatility across various UAV systems while maintaining high predictive accuracy of yield determination. The diversity in performing setups indicates the prominent importance of matching the right sensor and ML model to the right UAV platform to optimize remote sensing-based phenotyping outcomes.

3.4.4. What are the key drivers of model performance?

We conducted a regression analysis using Elastic Net model to examine the primary factors that influence the performance of ML algorithms in predicting biomass, yield, and nitrogen (as measured by the RPD).We considered the crop, the type of UAV, the multispectral sensor, the spectral bands and the flight height/altitude

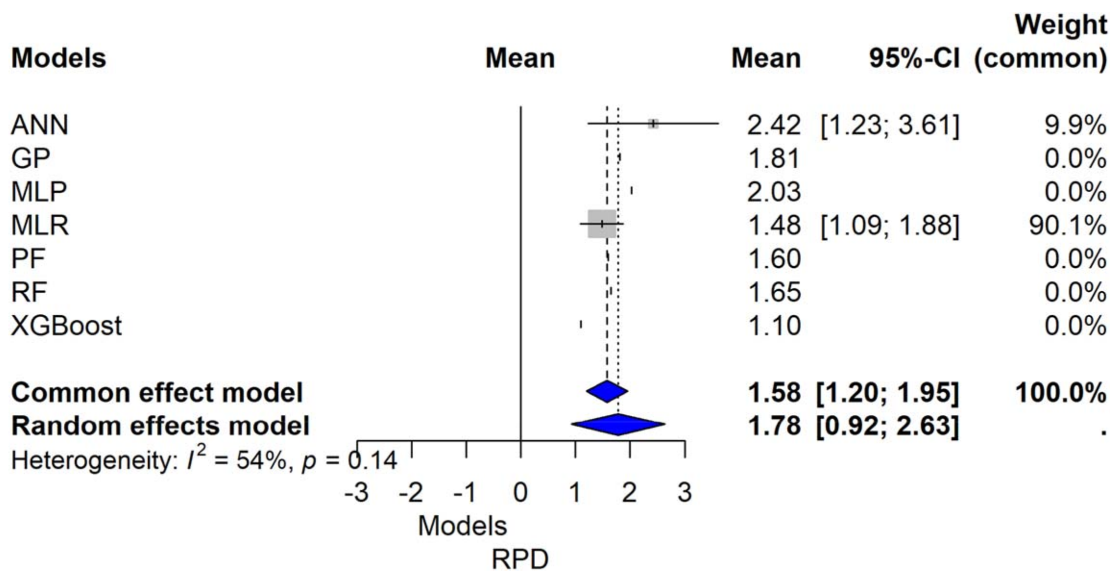

Figure 7. Forest Plot of RPD Values for Various ML Models Used in Yield Prediction Across Multiple Studies. The forest plot presents the **mean RPD values** and their **95% confidence intervals (CI)** for the different machine learning models. Each model's mean RPD is shown as a square, with the size representing the weight assigned in the meta-analysis (right column). The horizontal lines indicate the 95% confidence intervals (CI) for each model's mean RPD, providing insight into the variability of model performance. The diamond at the bottom represents the pooled effect size (RPD) from both common and random effects models, summarizing the overall effectiveness of these models in biomass prediction.

Table 4. Top performing UAV-sensor-ML model across phenotypic traits.

Trait	Algorithm	Sensor	UAV Platform	Performance
Biomass (AGB)	MLR	Micasense RedEdge-M	DJI Inspire 2	Excellent
Nitrogen	ANN	Parrot Sequoia	AscTec Pelican	Excellent
Yield	ANN	Parrot Sequoia	Microdrones Md4-100	Excellent

and the ML algorithm as the main factors in the analysis as described in the methodology. The objective is to understand how these factors can explain the variability of RPD values among the various studies.

3.4.4.1. Biomass

The analysis of the Elastic Net model for biomass estimation reveals various main and interactions effects that influence the RPD. The intercept of the model corresponds to the reference levels is at 1.6 which represents the expected RPD for biomass when the cereal is used as a crop, AscTec Pelican as a UAV, MicaSense RedEdge as sensor with blue, green, red and near-infrared bands, and MLR as an algorithm. It constitutes the baseline against which other factor levels are being compared.

Results showed that biomass predictive models are more accurate when dealing with strawberry crops compared to cereals, as evidenced by positive coefficient for strawberries (table 5). DJI Inspire 2 UAV significantly increases the RPD compared the reference eBee wing-fixed UAV. In another hand, when combined with other baseline variables, the Micasense RedEdge is notably effective, improving the RPD compared to other sensors in similar conditions. However, RPD decreases when sensors other than Micasense RedEdge are employed (table 5). Likewise, excluding the blue band from the baseline band combination results in a drop in RPD.

The examination of interactions effects in the Elastic Model relative to the baseline setup highlighted that when strawberries are investigated with DJI Inspire 2 UAV, the positive deviation from the baseline is observed. This indicates that the model accuracy in predicting biomass is substantially better than when cereals are studied using eBee wing-fixed UAVs (table 5, figure 8). Similarly, the Micasense RedEdge sensor utilized on strawberry crops led to a significant increase in RDP. This implies that the sensor is more efficient when used on strawberries, outperforming its utilization on cereals (table 5, figure 8). The interaction of DJI M100 four-rotator with baseline and Micasense RedEdge sensor and bands slightly improved the RPD compared to the based combination with eBee wing-fixed (table 5 and figure 8). When diagnosed with sensors other than Micasense RedEdge and baseline band combination excluding blue, cereal crops showed a decline in RPD (figure 8).

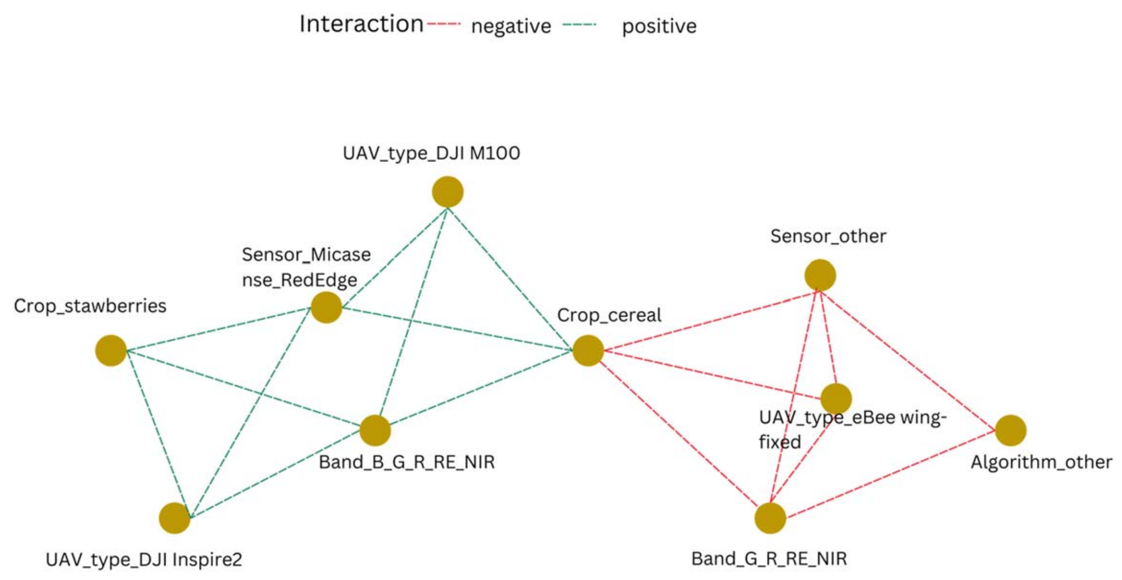

Figure 8. Interaction network of key factors influencing RPD in Biomass estimation using elastic net modelling.

Table 5. RPD elastic net model coefficients for biomass estimation: main effects and interactions.

Var1	Var2	Coef_estimates
(Intercept)		1.649289859
Crop_strawberry		0.106646326
'UAV_Type_eBee wing-fixed'		−0.024523562
'UAV_Type_DJ M100 four-rotator'		0.003517774
'UAV_Type_DJI Inspire 2'		0.107037929
'Sensor_Micasense RedEdge'		0.02427495
Sensor_Other		−0.023128764
Band_B_G_R_RE_NIR		0.021126885
Band_G_R_RE_NIR		−0.018805155
Crop_cereal	'UAV_Type_eBee wing-fixed'	−0.016751948
Crop_cereal	'UAV_Type_DJ M100 four-rotator'	0.002432787
Crop_cereal	'Sensor_Micasense RedEdge'	0.002445542
Crop_cereal	Sensor_Other	−0.015512055
Crop_cereal	Band_B_G_R_RE_NIR	0.002408289
Crop_cereal	Band_G_R_RE_NIR	−0.015260447
Crop_strawberry	'UAV_Type_DJI Inspire 2'	0.104263773
Crop_strawberry	'Sensor_Micasense RedEdge'	0.103901373
Crop_strawberry	Band_B_G_R_RE_NIR	0.103773956
'UAV_Type_eBee wing-fixed'	Sensor_Other	−0.016554829
'UAV_Type_eBee wing-fixed'	Band_G_R_RE_NIR	−0.018499208
'UAV_Type_eBee wing-fixed'	Algorithm_Other	−0.027837592
'UAV_Type_DJ M100 four-rotator'	'Sensor_Micasense RedEdge'	0.003566913
'UAV_Type_DJ M100 four-rotator'	Band_B_G_R_RE_NIR	0.003862932
'UAV_Type_DJI Inspire 2'	'Sensor_Micasense RedEdge'	0.104128619
'UAV_Type_DJI Inspire 2'	Band_B_G_R_RE_NIR	0.104394089
'Sensor_Micasense RedEdge'	Band_B_G_R_RE_NIR	0.020730122
Sensor_Other	Band_G_R_RE_NIR	−0.022969318
Sensor_Other	Algorithm_Other	−0.029478321
Band_G_R_RE_NIR	Algorithm_Other	−0.028845291

3.4.4.2. Nitrogen

The results of RDP Elastic model for nitrogen prediction showed how different variables and their interactions contribute to the RPD. The baseline RDP is 1.8 when variables are their reference levels (crop = cereal, UAV type = eBee wing-fixed, Sensor = Micasense RedEdge, band = (B, G, R, Re, NIR), and algorithm = MLR).

Results of main effects showed that using Parrot Sequoia sensor and a combitation of green, red, rededge and near-infrared bands slightly increase the RPD in nitrogen estimation compared to the use of the baseline

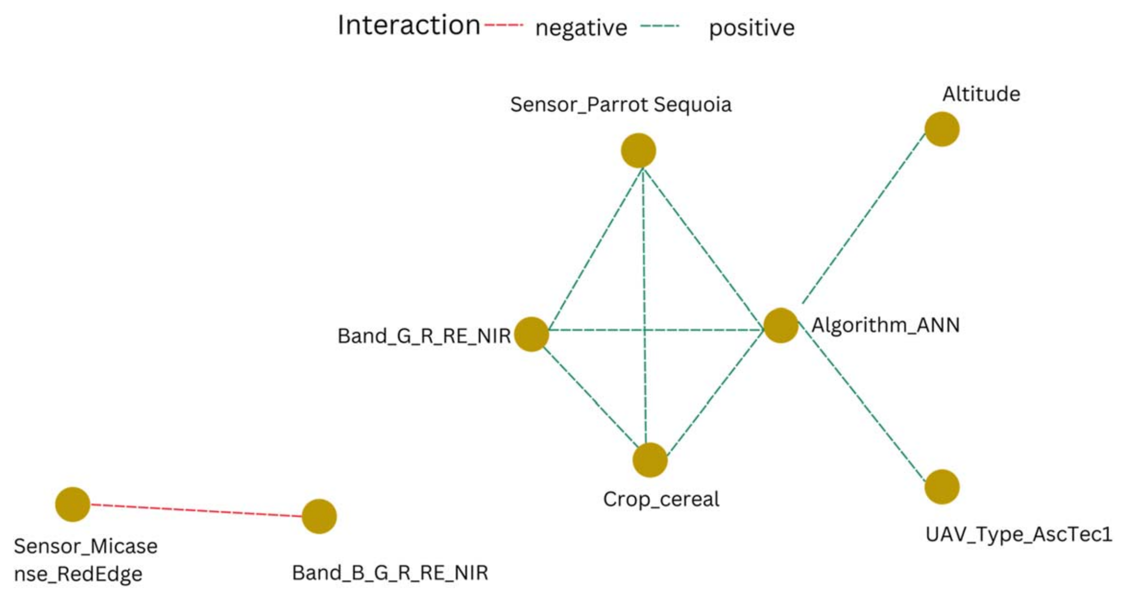

Figure 9. Interaction network of key factors influencing RPD in nitrogen estimation using elastic net modelling.

Table 6. RPD elastic net model coefficients for nitrogen estimation: main effects and interactions.

Var1	Var2	Coef_estimates
(Intercept)		1.82321
'Sensor_Micasense RedEdge'		−0.00129
'Sensor_Parrot Sequoia'		0.03396
Band_B_G_R_RE_NIR		−0.03349
Band_G_R_RE_NIR		0.032514
Algorithm_ANN		0.029094
Altitude_m	Algorithm_ANN	0.001444
Crop_cereal	'Sensor_Parrot Sequoia'	0.031835
Crop_cereal	Band_G_R_RE_NIR	0.032068
Crop_cereal	Algorithm_ANN	0.02866
'UAV_Type_AscTec Pelican'	Algorithm_ANN	0.028689
'Sensor_Micasense RedEdge'	Band_B_G_R_RE_NIR	−3.50E-05
'Sensor_Parrot Sequoia'	Band_G_R_RE_NIR	0.032875
'Sensor_Parrot Sequoia'	Algorithm_ANN	0.028911
Band_G_R_RE_NIR	Algorithm_ANN	0.028951

Micasense RedEdge and band combination (table 6). Similarly, the utilization of ANN algorithm over the MLR led to a rise in RPD, suggesting their efficiency in nitrogen estimation (table 6). The interaction of altitude with ANN algorithm slightly improved the RPD, suggesting ANNs could handle the the flight height-related variability effectively (table 6 and figure 9).

The interactions of cereal crops with Parrot Sequoia sensor or green, red, rededge, nir band combination or ANN ML algorithm resulted in increase in RPD compared to the use of reference Micasense sensor, band combination and MLR model (table 6 and figure 9). Pairing AsTec Pelican UAV with ANN algorithm showed a positive contribution to RDP, enhancing model performance in nitrogen prediction. Combining red, redge and nir band combination with Parrot Sequoia sensor and ANN algorithm yield to a small increase in RPD (table 6 and figure 9).

3.4.4.3. Yield

The analysis of RPD Elastic Net model didn't statistically explain the variance of RPD data and revealed that none of the examined factors, such as crop type or ML algorithms have a significant impact on the Ratio of Performance to Deviation (RPD) for yield prediction. However, the RPD in when predicting yield using defined baseline levels is 1.75.

4. Discussions

The integration of UAV and sensor platforms and machine learning algorithms greatly improves the prediction and the accuracy of biomass, yield and nitrogen estimations in plant phenotyping. The RPD Elastic Net model results emphasize the complex interactions between different variables such UAV platform, sensor choice, crop type, spectral bands and algorithm selection to drive to the model performance in predicting these phenotypic traits.

4.1. Biomass prediction

The results from the meta-analysis indicate that the MLR emerged as the most effective algorithm for predicting biomass from UAV image data, while random forest was identified as the most common algorithm for estimating biomass (figure 5). This finding is consistent with previous research that has underscored the efficacy of ML methodologies in crop phenotyping, particularly in the determination of biomass. For example, (Gano *et al* 2021) demonstrated the efficiency of MLR to estimate biomass and LAI from multispectral UAV for West African sorghum under different water conditions and (Moeckel *et al* 2018) showed that ML approaches such as RF can manage collinearity between variables more efficiently than traditional regression models, thus improving the prediction accuracy for phenotypic traits.

The RPD Elastic Net model for biomass prediction demonstrates that specific combinations of UAVs, sensors, and bands considerably increase model performance. For instance, the DJI Inspire 2 UAV paired with the Micasense RedEdge sensor frequently contributed positively to RPD, particularly in strawberries. The high-resolution multispectral imaging capabilities of MicaSense sensors and the reliability and stability of DJI drones are likely to improve data quality as a result of this combination. Previous studies reported the importance of the sensor quality and the performance of the UAV platform in enhancing the accuracy of biomass estimation (Tsouros *et al* 2019).. In another hand, negative interactions, such as those between the eBee wing-fixed UAV and alternative sensors, demonstrate that not all configurations are equally effective, emphasizing the importance of careful selection based on specific crop and climatic conditions.

4.2. Nitrogen prediction

Our findings from the analysis revealed that the efficiency of ANN, KNN and SVM in estimating nitrogen content from UAV multispectral imagery. These algorithms were identified to be the top performing ones in terms of prediction accuracy, a finding aligned with prior studies that highlight the robustness of ML models in leaf nitrogen phenotyping (Lee *et al* 2020, Colorado *et al* 2020b). Indeed, a recent study (Luo *et al* 2022b) found that SVM outperformed other ML models in predicting tea nitrogen status. Similarly, (Moghimi *et al* 2020b) developed a segmentation model to define high- and low-N concentration pixel for grapevine and SVM emerged as best model outperforming RF, QDA, XGBoost and DNN. Similarly, results from Osco *et al* demonstrated that algorithms like ANN, SVM, and RF performed well in predicting plant nutritional status using UAV imagery (Osco *et al* 2019)

The interactions identified from the RDP elastic model highlight the combination of the Parrot Sequoia sensor with the green, red, red edge, and near-infrared bands, yielded improved predictions for leaf nitrogen content. This finding is consistent with the work of Yang *et al* who underscored the significance of particular spectral bands in improving the accuracy of nitrogen estimation through UAV-based multispectral phenotyping (Yang *et al* 2020). The red edge and near-infrared bands are especially efficient and critical for evaluating the health and nutrient status of plants, as they are sensitive to chlorophyll content and can discriminate between healthy and stressed vegetation (Yang *et al* 2020). That result corroborates the work of Lu *et al* (2019) who showed that the red edge and NIR bands are highly informative for nitrogen prediction.

4.3. Yield prediction

The findings for yield estimation suggest that any of factors including crop type, UAV platform, sensor choice, spectral bands and algorithms do not contribute to the variability in RPD for yield in the scope of study. We may need more data points from more papers to enlarge the RPD database of yield predictive models.

5. Current challenges

Although the results are insightful, there are still many challenges to overcome in the optimization of multispectral UAV-based estimations for biomass, yield and nitrogen.

5.1. Data variability and generalization

One of the major challenges to UAV-based prediction models for the phenotypic traits is the data variability resulting from diverse environmental conditions, growth phases and crop types (Zheng *et al* 2022b). This variability can limit the generalizability of models, causing them to perform well in one context but badly in another one. The negative combinations observed in certain combinations of UAV and sensor indicate that not all configurations and protocols can be used universally. This means that models need to be customized to suit specific conditions. Recent deep learning developments have produced robust fruit-counting models that perform very well across a large diversity of datasets (Nagpal *et al* 2023). Nevertheless, the generalization of these models to predict more complex phenotypic traits such as nitrogen response or biomass remains a great challenge due to environmental heterogeneity and high data variability (Ding *et al* 2023, Singh *et al* 2023).

5.2. Sensor-specific sensitivity

While sensors like Parrot Sequoia showed good performance in nitrogen estimation, others like Micasense RedEge are more relevant in predicting biomass. This suggests that various sensors capture various aspects of the crops, indicating that there is a challenge in selecting the right sensor for specific phenotypic traits. Consequently, researchers might need to use a lot of sensors to get a full picture, which can be costly and hard to set up. Besides, integrating multiple sensors in a single aerial platform can pose many computational and practical challenges.

First, collecting data from multiple sensors necessitates significant on-board storage. Limited computational capacity of UAVs may be a limiting factor in managing simultaneous multi-sensor data collection, requiring high-performance embedded processors (Fei *et al* 2022, Qazi *et al* 2022). Such configurations, however, increase energy consumption, which might affect the endurance of the UAV flight.

Second, the integration of sensors adds a layer of complexity in synchronizing, and calibrating. Different resolutions, wavelengths and exposure periods characterize sensors; hence, exact alignment and co-registration are necessary to guarantee correct comparison analysis (Shahi *et al* 2023, Dolatabadian *et al* 2024).

Third, major challenges still include the cost and the logistical difficulties of successfully implementing multi-sensor UAV systems. Along with the necessary onboard computer units, high-end sensors greatly raise the total cost of UAV-based monitoring systems (Marques *et al* 2023), which makes them less available for smaller farms or research facilities with limited budgets. Furthermore, arranging multi-sensor systems necessitates knowledge in UAV payload balancing, software integration and power management, which could restrict the adoption among non-specialist end users.

5.3. Data fusion: addressing data gaps

Data fusion is the process of merging data from different sources, such as multispectral, thermal and hyperspectral. The complexity and the variability of data sources are the major challenges. There are difficulties in aligning and syncing this data for effective integration since different sensors gather data at different spectral ranges and resolutions. For example, whereas multispectral sensors such as the Parrot Sequoia have been effective in nitrogen estimate, sensors such as the Micasense RedEdge showed lower performing results in biomass prediction, combining various data streams can be challenging because of their unique properties and characteristics (Yue 2024).

Data fusion techniques such as machine learning-driven sensor harmonization or deep-learning-based feature extraction can improve usability but require supplemental computational resources over the post-processing. Cloud-based platforms could fix partially these issues but necessitate stable data transmission channels and higher computational power. Overcoming those challenges would enable to get the most value of various data sources to improve the precision and the reliability of nitrogen and biomass predictive models as highlighted by previous studies (Reddersen *et al* 2014, Elarab *et al* 2015, Tilly *et al* 2015).

6. Future research perspectives

6.1. Hybrid models

There is a need for an evolution of traditional ML and deep learning techniques to more sophisticated approaches to deal with the increasing complexity and dimensionality of phenotypic data but also to improve prediction accuracy as average model performance for nitrogen and biomass remain 1.8 (RPD). One possible solution we could imagine is to associate machine learning techniques with genetic algorithms (GAs) which represent a game-changing and highly innovative approach to advance data analytics for better crop phenotyping and beyond. Such a combination can harness the strengths of both methodologies, offering outstanding advantages for UAV multispectral imagery-based plant phenotyping.

GAs can be utilized to optimize the architecture of convolutional neural networks by finding the best parameters including the number of layers, the number of neurons per layers or the edges between the neurons. There are few successful stories in the literature that could inspired and guided the application of GA and ML on aerial multispectral image data to tremendously enhance crop trait estimation. For instance, Bi and Hu (2021) employed a genetic algorithm-powered deep learning method for crop yield estimation. They used a two-step approach to screen the best initial weight using the GA, then introduced random perturbation to prevent vanishing gradient and local optimum issues. The outcomes demonstrate that the proposed method is more accurate and converges faster than gradient-based methods.

A new approach of hybridizing and ensembling machine models was developed by (Hammouch *et al* 2024) to estimate nitrogen content from UAV-captured RGB of sorghum crops. Authors demonstrated that a methodology combining Multi-Layer Perceptron (MLP) with CNN-VGG16 (i.e., associating features from the CNN with predictive capacity of an MLP) achieved higher performance (with an R2 of 0.733 and MAE of 0.264 N%) on an independent test data from the following season. This suggested that hybrid and ensembled AI systems are more robust to concept drift and individual models. Such hybridized AI strategies and could be extended to multispectral image that integrate additional spectral bands to significantly improve the robustness and the accuracy of the prediction of crop traits such nutrient content, under field conditions.

Over the last years, the integration of geostatistics and machine learning appeared as a promising approach in precision agriculture (Roupsard *et al* 2020, Rodrigues *et al* 2021). (Soares Cardoso *et al* 2024) successfully applied ordinary kriging and machine learning on UAV-derived GNDVI to map and evaluate areas of higher vegetation in sugarcane plantations, that are prone to the infestation M. pruriens, an invasive weed species. Subsequently, their approach enables to delineate management zones that allowed farmers to apply targeted treatments, optimizing herbicide costs and reducing environmental impacts. Utilizing geostatistical and AI systems could help streamline and enhance the precision of phenotypic trait estimation models when applied to UAV multispectral imagery of crops.

6.2. Explainable AI (XAI)

Despite the impressive success of ML and deep learning in many engineering fields including UAV remote sensing (Pan *et al* 2021, Bellis *et al* 2022, Li *et al* 2022), black-box AI models with strong and clear explainability, transparency and interpretability remain hurdles.

Explainable artificial intelligence (XAI)- the set of techniques and methods that make the predictions and decisions of machine learning models understandable and interpretable to human beings- is an emerging field that is tasked with making ML models more interpretable and transparent. This is especially important in the context of UAV imagery-driven plant phenotyping where the interpretation and the communication of the results is essential for the breeders to link phenotypic traits to genetic markers through genome-wide association studies (GWAS). Successful use of XAI techniques on multispectral satellite imagery has been demonstrated recently in understanding crop yield variability (Wolanin *et al* 2020) and multi-label classification (Kakogeorgiou and Karantzalos 2021).

Methods like Regression activation maps used by Wolanin *et al* (2020) could also be applied to UAV multispectral image data to develop more efficient, transparent, and interpretable crop trait deep-learning models. A very recent study from (Nayak *et al* 2024) explore the power of SHapley Additive exPlanation (SHAP)-based approach to determine the relative contribution of management practices and environmental factors to rice yield predictions in India. SHAP is a promising post-hoc technique to interpret machine learning models and identify heterogeneous effects of predictors on response prediction. Using SHAP-backed machine learning model interpretation techniques on UAV-based plant phenotyping could critically enhance the interpretability of complex UAV image-based models. By providing a quantitative estimate of each input feature—such as sensor-specific variable, spectral bands or vegetation indices- to the model prediction, SHAP helps reveals which spectral and physiological variables are most prominent in predicting key phenotypic traits. This promotes more transparent decision-making but helps researchers determine meaningful patterns and remove redundant variables, thereby enhancing model robustness and generalizability.

6.3. Generalizability and scalability of models

Advancement of precision agriculture depends critically on the generalization and scalability of prediction models for calculating biomass and nitrogen content from UAV multispectral data. Even though current models like RF, ANN, KNN and SVM showed great predictive capacity, their generalizability across crop varieties, growth phases and environmental conditions remains a challenge (Teshome *et al* 2023). Transposing these models to vast, varied agricultural environments depends on their scalability being improved. For example, the incorporation of multi-source data fusion and domain adaptation techniques could enhance the adaptability of models to a variety of conditions and broaden their applicability beyond localized datasets (Brugler *et al* 2024).

Moreover, hybrid modeling techniques combining machine learning with process-based models have shown promise in improving scalability and lowering overfitting, so enabling models to keep predictive accuracy over a range of environmental conditions (Attia *et al* 2022).

6.4. Model validation and reproducibility

Despite the advancements on the effective use ML models in the context of plant phenotyping, wide adoption of those models, inconsistencies in data pre-processing, lack of standardized ML pipelines, and the utilization of proprietary datasets still remain major challenges to model reproducibility and validation (Sharma *et al* 2021). Future research endeavors must address these issues to improve reproducibility and validation of ML models.

The adoption of standardized protocols for data collection, pre-processing and model assessment is one the most urgent recommendations. Researchers need more efforts and commitment in documenting all steps in detail ranging from sensor calibration and data augmentation to feature engineering and model development. Developing open benchmarks and publicly available, annotated datasets based on FAIR principles (findable, accessible, interoperable and reproducible) helps cross-study comparisons and allows researchers to reproduce experiments more readily (Tamayo-Vera *et al* 2024). By utilizing version-controlled repositories (e.g., GitHub) and containerization tools (Docker, Singularity) for sharing open-source code, the community can create reproducible workflows that encapsulate the entire computational environment.

The use of advanced model validation techniques, such as nested k-fold cross validation and the utilization of external independent data, are crucial to evaluate the generalizability of the ML models. Comprehensive performance metrics including significant tests, confidence intervals, and standardized error measures should be reported in future studies to evaluate model uncertainty. This not only enhances the credibility of the predictive performance but also offers clear understanding of strengths and weaknesses of the models (Condran *et al* 2022). Furthermore, automated machine learning (AutoML) models can be used to significantly streamline hyperparameters and model topologies, hence lowering the subjectivity in model selection.

7. Conclusions

The potential of utilizing ML to analyze UAV multispectral data for the estimation of critical phenotypic traits, including biomass, yield, nitrogen, has shown substantial growth over the last decades. Through this systematic review, we have investigated a plethora of ML techniques for these objectives ranging from classical regression methods to sophisticated convolutional neural networks, elucidating their limitations and strengths. We also conducted a comprehensive meta-analysis to empirically identify (1) the most used ML models in nitrogen, biomass and yield estimation powered by UAV multispectral imagery, (2) the optimal combination of aerial platforms (UAVs and sensors) that maximize model performance, and (3) uncover trait-based key drivers of model performance. The Parrot Sequoia sensor proved to be quite efficient for nitrogen estimation, while the DJI Inspire 2 UAV and the Micasense RedEdge sensor stood out as notable positive contributors for biomass estimation, especially for crops like strawberries. The models also highlighted the complexity and variability present in these systems by showing how some combinations, like using the eBee wing-fixed UAV with different sensors, might have a negative effect on predictive performance.

The results' discussions highlighted the complex interactions between the different variables, demonstrating that the efficiency of UAV-based models highly depend on the context/trait. We also raised the data variability, sensor constraints and ML model complexity as persisting challenges to be addressed to enhance the generalizability and the reliability of trait predictive models. Additionally, we also point out that data fusion is an issue to overcome with its own challenges associated with the synchronization, the alignment and the computational demands that impact overall model performance.

Looking forward, several research avenues have been identified to address the challenges. Future investigations should explore the development of crop-specific models, the integration of multi-source and time-series data. Moreover, harnessing hybrid models that combine machine learning with genetic algorithms and leveraging the power of explainable AI would help balancing the trade-offs between model performance and explainability. Ultimately, ensuring the accessibility, the scalability of technologies and their alignment with the regulatory frameworks would be critical for their widespread adoption in plant phenotyping and precision agriculture.

Author contributions

All authors significantly contributed to the preparation of the manuscript.

Adama Ndour: Conceptualization, Methodology, Data collection, Analysis and Interpretation of the data, Writing the original draft. **Tesfaye Sida**: Conceptualization, Methodology, Analysis and Interpretation of data, Revision of the manuscript, and Supervision. **Gerald Blasch**: Conceptualization, Methodology, Analysis and Interpretation of data, Revision of the manuscript. **João Valente**: Conceptualization, Methodology, Analysis and Interpretation of data, Revision of the manuscript. **Bisrat Haile Gebrekidan**: Conceptualization, Methodology, Analysis and Interpretation of data, Revision of the manuscript.

All authors reviewed and approved the final manuscript for submission.

Declaration of interest

The authors declare that there are no conflicts of interest or competing financial interests related to the content of this review paper.

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Data availability statement

The data that support the findings of this study will be openly available following an embargo at the following URL/DOI: https://github.com/adamavip/uav_ml_review_paper. Data will be available from 22 February 2025.

Annex A. Comparison with previous reviews and novel contributions of this study in machine learning for UAV-based plant phenotyping

Aspect	Previous review 1 (Xie and Yang 2020)	Previous review 2 (Feng et al 2021)	Previous review 3 (Zualkernan et al 2023)	Our review
Primary Focus	Broad applications of machine learning in agriculture	UAVs and sensors for general agricultural applications	Technological advancements in UAVs for precision agriculture	Optimal combination of UAV and machine learning algorithms for plant phenotyping
Analysis of Machine Learning Methods	General discussion, no systematic comparison	Limited analysis of machine learning algorithms	General overview, lacks in-depth analysis	Systematic review of machine learning methods specifically for multisepctal UAV imagery-based plant phenotyping
Examination of UAV characteristics on the efficiency of the crop phenotyping	Discussed broadly, no focus on specific UAV configurations	Discussed but not in-depth for phenotyping	Emphasis on UAV technology, but not optimized for phenotyping	Detailed analysis of how UAV type and characteristics impact model performance
Focus on Multispectral Imagery	Mentioned, not the primary focus	Discussed but not systematically analyzed	Covered, but not with a focus on machine learning models	In-depth analysis of multispectral imagery in conjunction with machine learning for phenotyping
Systematic Review Approach	Narrative approach	Narrative approach	Technological overview	Systematic review summarizing knowledge on ML methods for different key phenotypic traits
Meta-Analysis of Performance Metrics	Not included	Not included	Not included	Conducts a meta-analysis to extract and analysed the relationship between RPD and variables such as crop type, UAV type, and other variables
Practical Recommendations	General recommendations for agriculture	General recommendations for UAVs	Focus on technological adoption	Provides specific recommendations based on quantitative analysis on existing literature data for optimizing UAV-machine learning configurations for optimal phenotyping
Novelty	Broad insights into ML in agriculture	Overview of UAV and sensor potential	Technological potential of UAVs	Detailed insights into the best-performing configurations of UAVs, sensors, and ML algorithms for plant phenotyping

Annex B. Search query used in Web of Science to retrieve relevant review papers, with TS representing the topic sentence. The asterisk (*) represents any group of words with the indicated phrase, including none. Quotation marks are used for exact matching.

Web of Science Query
TS = ('*UAV multispectral imagery*') AND TS=('phenotyping' OR 'crop' OR 'corn' OR maize' OR 'tomato' OR 'wheat' OR 'rice' OR 'citrus' OR 'cotton' OR 'soybean' OR 'yield' OR 'potato' OR 'precision agriculture' OR 'Sugar cane' OR 'Nitrogen' OR 'tea' OR 'biomass' OR 'vegetables' OR 'Agricultural Remote Sensing' OR 'Chlorophyll' OR 'sorghum' OR 'millet' OR 'peanut' OR 'cereal') AND TS = ('*machine learning*' OR '*convolutional neural network*' OR '*deep learning*' OR '*transfer learning*' OR 'artificial intelligence*' OR '*data analytics*' OR '*big data*').

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