UAV-Based LiDAR, Hyperspectral Imaging, and GIS Integration for Aboveground Biomass Estimation in *Zea mays* L.: A Critical Review and Synthesis

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ABSTRACT
AGB (aboveground biomass) is a popular indicator of maize (*Zea mays* L.) growth status, nutritional sufficiency, and yield potential. Traditional methods for obtaining AGB are time-consuming, difficult, and not well-suited for precision agricultural use. UAV remote sensing has quickly emerged as a promising alternative, resulting in research studies evaluating LiDAR, hyperspectral imaging, and GIS spatial-analysis separately and combined for non-destructive AGB estimations. This review summarizes peer-reviewed studies about combining UAV-mounted LiDAR, hyperspectral sensing, or GIS spatial analysis for AGB measurements. LiDAR canopy height, canopy volume, and point clouds are employed for three-dimensional biomass accumulation data but do not provide information about pigments, water, or nitrogen that can be achieved through hyperspectral data acquisition. GIS methods allow for geostatistics-based interpolation and creating continuous GIS biomass layer. The studies reviewed show that the structural models explain 60-84% of the variance in AGB. The spectral models account for 50-70% of AGB variability. Studies using combination of LiDAR, hyperspectral and GIS data yield increasingly accurate data, with the coefficient of determination of R2>0.85 and lower RMSE than the data obtained using single methods. Machine learning methods such as random forest, support vector regression, and partial least square regression The study shows that the combination of information from various sources enables successful performance of random forest across cropping stages. The article highlights some ongoing issues - high cost of sensors and their payload, effects of canopy saturation in advanced stages of growth, problems with the transfer of models, and processing of complex point-cloud data and hyperspectral data. The article summarizes that, although UAV-GIS integration is a reliable scientific way to monitor biomass, its practical usage for efficient nutrient management, irrigation scheduling, and crop yield forecasting will depend on the advent of standardized data acquisition processes and cross-environment test trials.

Keywords: Precision phenotyping; Multi-sensor data fusion; Canopy structure; Spectral reflectance; Geospatial analytics; Crop monitoring; Site-specific management; Non-destructive biomass assessment

1. Introduction
Compared to others, maize (*Zea mays* L.) is cultivated in a large number of areas and forms the basis of food, feed, and industrial value chains in developed and developing agricultural economies. Aboveground biomass (AGB) is considered the most important physiological attribute in this system since it summarizes the cumulative influence of light interception, uptake of nutrients, water status during the growth period, and is a good predictor of the final grain yield (Wang *et al*., 2017) [1] (Zhu *et al*., 2019) [2]. Traditional methods of AGB estimation depend on destructive plot sampling, oven-drying, and weighing, which is a precise method but not technologically ideal for precision agriculture as it takes a long time and comprises too many operations (Feng *et al*., 2025) [3].
Precision agriculture transforms crop management from a homogeneous issue into one with spatial and temporal variability, thanks to digital crop monitoring technologies (Dlamini *et al*., 2025) [4]. Of these, UAV technology stands out as UAVs seamlessly combine fine-scale resolution available with ground proximity sensors with the wide coverage area offered by aerial platforms, allowing for large quantities of data to be gathered at a scale of centimeters across large fields on one flight (Yue *et al*., 2017) [5]. This ability to gather information has accelerated the adoption of UAVs for remote monitoring applications such as crop phenotyping and precision nutrient, water, and biomass management in the past ten years.
There are two mainstream sensing techniques used in UAV-based research related to aboveground biomass (AGB). First is structural sensing using LiDAR technology which involves generating laser pulses and measuring the time taken for them to return, which is how the three-dimensional point cloud of the crop canopy is constructed. LiDAR-derived models of canopy height (CHMs), canopy volume and point density have been shown to correlate with maize AGB due to their ability to include geometrical aspects related to biomass accumulation. There are some measurements that cannot be carried out using sensors (Wang *et al*., 2017) [1] (Han *et al*., 2019) [6] (Li *et al*., 2015) [8]. The second method employed is hyperspectral imaging, which permits the recording of the reflectance in many different spectral bands, ranging from several dozens to hundreds, collecting

data from the visible light, red edge, and near infrared regions. Hyperspectral vegetative indices as well as different spectral characteristics are very responsive to chlorophyll level, water resources and the nitrogen content in the atmosphere thus providing physiological data together with the LiDAR structural information (Wang *et al*., 2017) [1] (Guo *et al*., 2023) [15].

Technology of Geographic Information Systems (GIS) has a possibility of implementing the spatial analysis so as to make the connection between point and plot estimates of biomass to be turned into field surfaces. Such techniques as geostatistical interpolation methods (ordinary kriging and inverse distance weighting (IDW)) are quite popular in the context of modeling the spatial structure of cropping and soil parameters (Heuvelink and Webster, 2001) [20] (Grego *et al*., 2014) [21].

The research works on the use of LiDAR, hyperspectral, and GIS technologies for maize AGB estimation have increased significantly. The individual resulting applications of LiDAR or hyperspectral techniques were effective, yet not quite precise due to the limitations specific to each technologies: LiDAR lacks necessary physiological information while hyperspectral technology has limitations related to heavy canopy biomass. In the process of developing predictive models, data fusion has become highly popular and produced very promising results (Wang *et al*., 2017) [1] (Zhu *et al*., 2019) [2] (Zhang *et al*., 2021) [13].

However, there are still important points missing from the analysis. Specifically, many scientists focus on the data from one location and/or a single season of analysis. Besides, very few scientists combine GIS technology with AGB measurements using the other two technologies mentioned (LiDAR and hyperspectral).

This review bridges that gap by synthesizing peer-reviewed findings regarding the use of UAV-based LiDAR, hyperspectral imaging, and GIS for estimating the above-ground biomass of maize. The paper has been organized around four objectives: (i) summarize the structural and spectral sensing principles of each method, (ii) compare accuracy of models based on individual sensors with those constructed with integrated methods, (iii) consider GIS methods suitable for biomass mapping and management zone identification, and (iv) highlight methodological gaps and future research areas in UAV-GIS biomass monitoring of maize production systems.

2. UAV Platforms and Multi-Sensor Data Acquisition

Rotary-wing multirotor UAVs are the dominant platform in maize AGB research, favored over fixed-wing systems for their vertical take-off capability, hovering stability, and suitability for carrying multiple simultaneous payloads, including LiDAR, hyperspectral, RGB, and thermal sensors (Yue *et al*., 2017) [5] (Feng *et al*., 2021) [12]. Flight planning in the reviewed literature typically balances spatial resolution against coverage: lower flight altitudes and slower airspeeds increase point-cloud density and spectral signal-to-noise ratio but reduce area covered per flight, a trade-off that becomes particularly consequential for larger commercial fields (Bendig *et al*., 2015) [9] (Yuan *et al*., 2018) [10].

Accurate georeferencing is a prerequisite for meaningful data fusion across sensor types and flight dates. Real-Time Kinematic (RTK) or Post-Processed Kinematic (PPK) GPS positioning, typically achieving centimeter-level horizontal accuracy, is now standard practice in high-accuracy UAV phenotyping studies, replacing earlier reliance on ground control points alone (Jimenez-Berni *et al*., 2018) [11] (Feng *et al*., 2021) [12]. This precision is essential because LiDAR point clouds, hyperspectral image cubes, and RGB orthomosaics must be co-registered to a common spatial reference before structural and spectral features can be jointly modeled.

Sensor payload characteristics reported across the literature vary considerably by manufacturer and study design, but several general patterns are consistent. Survey-grade UAV LiDAR systems typically operate in the near-infrared region (around 903–1550 nm), acquire point densities ranging from tens to several hundred points per square meter depending on flight altitude and speed, and provide vertical accuracy on the order of a few centimeters (Li *et al*., 2015) [8] (Yuan *et al*., 2018) [10]. UAV hyperspectral pushbroom and snapshot sensors typically span the 400–1000 nm range (with some systems extending into the shortwave infrared), offering spectral resolutions of a few nanometers across dozens to hundreds of bands, which enables the calculation of both broadband and narrowband vegetation indices (Wang *et al*., 2017) [1] (Guo *et al*., 2023) [15]. Representative configurations synthesized from the reviewed studies are summarized in Table 1.

Table 1: Representative UAV Platform and Multi-Sensor Configurations Reported in Maize Phenotyping Literature

Component	Typical Reported Specification	Representative Sources
UAV platform type	Rotary-wing multirotor (quad/hexacopter); RTK-enabled navigation	[5, 10, 12]
LiDAR sensor	Near-infrared operating wavelength (~903–1550 nm); point density from tens to several hundred pts/m² depending on altitude	[8, 10, 14]
Hyperspectral sensor	Spectral range ~400–1000 nm; spectral resolution of a few nm; pushbroom or snapshot acquisition	[1, 15]
RGB camera	Consumer or survey-grade optical sensor for orthomosaic and structure-from-motion products	[5, 19]
Positioning system	RTK/PPK GPS, centimeter-level horizontal accuracy	[11, 12]
Typical flight altitude	20–60 m above ground level, varying with sensor resolution needs	[9, 10]

3. LiDAR-Based Structural Assessment of Maize Canopies

LiDAR-derived structural metrics form the geometric backbone of UAV-based biomass estimation. The most fundamental derived product is the canopy height model (CHM), computed as the difference between a digital surface model (DSM), representing the top of the canopy, and a digital terrain model (DTM), representing bare ground elevation (Li *et al*., 2015) [8] (Yuan *et al*., 2018) [10]. Plant height extracted from CHMs shows strong, consistent correlation with maize AGB across the reviewed studies, reflecting the close physiological coupling between vertical growth and dry matter accumulation during vegetative development (Wang *et al*., 2017) [1] (Han *et al*., 2019) [6].

Beyond simple height, canopy volume, computed by integrating the CHM surface across the ground area of interest, and point-cloud density metrics, which characterize canopy porosity, leaf layering, and structural complexity, have been shown to add explanatory power beyond height alone, particularly at later growth stages when height growth plateaus but stem and leaf biomass continue to accumulate (Han *et al*., 2019) [6] (Zhu *et al*.,

2019) [14]. Wang *et al*. [1] reported that among individual LiDAR-derived metrics, the coefficient of variation of normalized point-cloud height (H_CV) outperformed mean height alone in predicting maize biomass, underscoring the informational value of canopy structural heterogeneity rather than central-tendency height statistics in isolation.

A well-documented limitation of LiDAR-only structural models is their reduced sensitivity to physiological status: two canopies of identical height and volume can differ substantially in chlorophyll content, nitrogen status, or water stress, none of which LiDAR alone can resolve (Wang *et al*., 2017) [1] (Zhang *et al*., 2021) [13]. This limitation motivates the pairing of LiDAR with spectral sensing modalities, discussed in the following section. Reported associations between commonly extracted LiDAR structural parameters and maize AGB are summarized in Table 2.

Table 2: LiDAR-Derived Structural Parameters and Reported Associations with Maize Aboveground Biomass

Structural Parameter	Derivation	Reported Relationship with AGB
Canopy height model (CHM)	DSM minus DTM elevation difference	Strong positive correlation, particularly during vegetative growth stages [1, 6, 8]
Canopy volume	Integration of CHM surface over ground area	Adds explanatory power beyond height, especially post-height-plateau [6, 14]
Point-cloud density / height CV	Statistical distribution of normalized point heights	Outperformed mean height alone in several studies (H_CV metric) [1]
Leaf area estimation (LiDAR-derived)	Point-cloud return intensity and canopy gap fraction	Moderate correlation; sensitive to canopy occlusion at high density [6, 8]
Structural indices (composite)	Combinations of height, volume, and density metrics	Improve robustness relative to single structural metrics [8, 14]

4. Hyperspectral Imaging for Biophysical and Biochemical Assessment

Hyperspectral imaging captures the fine-grained spectral response of the maize canopy across contiguous narrow bands, enabling the calculation of vegetation indices (VIs) that are sensitive to chlorophyll content, canopy water status, and structural chlorophyll-independent features such as leaf area (Guo *et al*., 2023) [15]. Broadband indices such as the Normalized Difference Vegetation Index (NDVI) remain widely reported due to their simplicity and long observational history, but narrowband red-edge indices, including the Normalized Difference Red Edge index (NDRE) and Modified Chlorophyll Absorption Ratio Index (MCARI), consistently show stronger correlation with maize biomass and nitrogen status in the reviewed literature, particularly under moderate-to-high canopy density where broadband indices begin to saturate (Wang *et al*., 2017) [1] (Guo *et al*., 2023) [15] (Duan *et al*., 2017) [25].

Spectral index saturation is among the most consistently reported limitations of hyperspectral-only AGB models. As canopy leaf area index increases beyond a threshold typically reached around mid-vegetative growth stages, reflectance in the near-infrared and red-edge regions plateaus, causing VI-based models to underestimate biomass at later growth stages even though structural growth continues (Wang *et al*., 2017) [1] (Han *et al*., 2019) [6]. This saturation effect is a primary driver behind the reported accuracy advantage of LiDAR-hyperspectral fusion over either modality used independently, since canopy height and volume continue to differentiate biomass classes after spectral indices have saturated.

Spectral preprocessing steps commonly reported in the literature include atmospheric and illumination correction, radiometric calibration using reference panels, band selection or dimensionality reduction (for example, via successive projection algorithms or competitive adaptive reweighted sampling), and first- or fractional-order spectral derivative transformation to enhance subtle absorption features associated with chlorophyll and water content (Guo *et al*., 2023) [15]. A summary of vegetation indices frequently applied in maize biomass and chlorophyll assessment is provided in Table 3.

Table 3: Vegetation Indices Commonly Applied in UAV Hyperspectral Assessment of Maize Biomass and Chlorophyll Status

Index	Spectral Basis	Primary Application
NDVI (Normalized Difference Vegetation Index)	Red / near-infrared reflectance contrast [24]	General canopy vigor; prone to saturation at high LAI [1,6]
NDRE (Normalized Difference Red Edge)	Red-edge / near-infrared reflectance	Reduced saturation; sensitive to chlorophyll/nitrogen status [1, 15]
SAVI (Soil-Adjusted Vegetation Index)	Red / near-infrared with soil-brightness correction factor	Improves performance at low canopy cover / early growth [15]
MCARI (Modified Chlorophyll Absorption Ratio Index)	Green, red, and red-edge reflectance	Chlorophyll concentration estimation [15, 25]
PRI (Photochemical Reflectance Index)	Narrowband reflectance near 531 and 570 nm	Photosynthetic light-use efficiency and stress detection [15]
Red-edge modified simple ratio	Red-edge / near-infrared band ratio	Reported as most strongly correlated single VI with maize biomass in Wang *et al*. [1]

5. GIS-Based Spatial Analysis and Site-Specific Management

While LiDAR and hyperspectral sensors generate dense per-pixel or per-point observations, GIS provides the spatial analytical framework needed to convert these observations into continuous, interpretable biomass surfaces and to translate biomass variability into actionable management units. Geostatistical interpolation techniques, most commonly ordinary kriging and inverse distance weighting, are used to model spatial autocorrelation in biomass, soil, and vegetation index data, allowing prediction at unsampled locations while quantifying the associated spatial uncertainty (Heuvelink and Webster, 2001) [20] (Grego *et al*., 2014) [21] (de Souza *et al*., 2016) [22].

Kriging-based approaches have a theoretical advantage over deterministic interpolators such as IDW because they explicitly model the spatial dependence structure through a variogram, but reported empirical comparisons show that interpolator choice can meaningfully affect the resulting biomass or vegetation index surface, and that the appropriate method depends on sampling density, spatial variability structure, and the specific variable being interpolated (de Souza *et al*., 2016) [22]. Comparative geostatistical studies emphasize that no single interpolation method is universally optimal, reinforcing the recommendation that interpolator selection be validated against held-out field data for each application context (Grego *et al*., 2014) [21] (de Souza *et al*., 2016) [22].

Once continuous biomass or vegetation index surfaces are generated, GIS-based classification and clustering techniques, frequently combined with principal component analysis to reduce covariate dimensionality, are used to delineate site-specific management zones (SSMZs), which group spatially contiguous areas of the field with statistically similar biomass, soil, or spectral characteristics (Heuvelink and Webster, 2001) [20]. These zones form the operational basis for variable-rate fertilizer and irrigation prescriptions, allowing management inputs to be allocated according to demonstrated spatial variability rather than applied uniformly across the field. A synthesis of GIS-based spatial interpolation and management-zone delineation approaches reported in the literature is presented in Table 4.

Table 4: GIS-Based Spatial Interpolation and Management-Zone Delineation Approaches Reported in the Precision Agriculture Literature

Method	Type	Reported Application
Ordinary kriging	Geostatistical (variogram-based)	Spatial prediction of biomass, soil, and vegetation index surfaces [20,21]
Inverse distance weighting (IDW)	Deterministic	Widely used baseline interpolator; comparative accuracy is site- and variable-dependent [22]
Space-time geostatistics	Geostatistical (spatiotemporal)	Multi-date NDVI/biomass surface interpolation across growing season
Principal component analysis (PCA)-based zoning	Multivariate classification	Dimensionality reduction prior to management-zone clustering [20]
Unsupervised clustering (e.g., fuzzy c-means, k-means)	Classification	Delineation of site-specific management zones (SSMZs) for variable-rate application [20]

6. Data Fusion and Machine Learning for Integrated Biomass Prediction

The consistent finding across the reviewed literature is that combining structural (LiDAR), spectral (hyperspectral), and, where available, spatial covariates through machine learning regression substantially improves AGB prediction accuracy relative to any single data source (Wang *et al*., 2017) [1] (Zhu *et al*., 2019) [2] (Feng *et al*., 2025) [3] (Zhang *et al*., 2021) [13] (Zhu *et al*., 2019) [14]. Random forest regression is the most frequently applied algorithm in this domain, valued for its robustness to multicollinearity among correlated spectral and structural features, its built-in variable importance ranking, and its comparatively strong performance without extensive hyperparameter tuning (Wang *et al*., 2017) [1] (Feng *et al*., 2025) [3] (Breiman, 2001) [23]. Support vector regression and partial least squares regression are also widely reported, particularly in earlier studies and in cases with a comparatively small number of training samples, while more recent work has begun to explore gradient boosting methods (including XGBoost) and neural network architectures for multimodal fusion tasks (Feng *et al*., 2025) [3] (Maimaitijiang *et al*., 2020) [7].

The specific mechanism of improvement differs by fusion pathway. LiDAR-hyperspectral fusion primarily addresses the spectral saturation problem described above, since structural metrics remain informative after vegetation indices plateau (Wang *et al*., 2017) [1] (Han *et al*., 2019) [6]. Fusion incorporating GIS-derived spatial covariates, such as slope, terrain position, and interpolated soil attributes, addresses a different limitation: purely canopy-based sensing cannot account for spatial drivers of biomass variability that originate below the canopy, such as topography-driven water redistribution or spatially variable soil fertility (Feng *et al*., 2025) [3]. Feng *et al*. [3] reported that incorporating structural covariates derived from LiDAR-based slope alongside vegetation indices and plant density improved random forest AGB estimation accuracy relative to vegetation-index-only models, with validated R^2 values reaching approximately 0.90–0.93 at key vegetative and reproductive growth stages, though model robustness declined in more environmentally heterogeneous validation regions, underscoring the transferability challenge discussed further below.

Growth-stage dependence is a recurring theme in the fusion literature. Structural features tend to dominate variable-importance rankings during early-to-mid vegetative growth stages when height differences are most discriminative, while spectral and texture-based features become comparatively more informative during reproductive stages when height growth has plateaued but canopy density and physiological status continue to vary (Feng *et al*., 2025) [3] (Zhang *et al*., 2021) [13]. This pattern has led several studies to recommend stage-specific feature weighting or stacked ensemble modeling rather than a single static feature set applied uniformly across the growing season.

Reported comparative performance of machine learning algorithms and fusion strategies for UAV-based maize AGB estimation is summarized in Table 5, and a broader cross-study comparison spanning maize and related row crops is provided in Table 6. Figure 3 synthesizes the general accuracy pattern observed across the reviewed literature: single-sensor models (hyperspectral-only or LiDAR-only) typically explain 50–84% of AGB variance, GIS-assisted models incorporating spatial covariates occupy an intermediate range, and integrated LiDAR-hyperspectral-GIS models consistently achieve the highest reported accuracy, with several studies documenting R^2 values above 0.85 and correspondingly reduced RMSE relative to single-sensor baselines (Wang *et al*., 2017) [1] (Zhu *et al*., 2019) [2] (Feng *et al*., 2025) [3] (Han *et al*., 2019) [6].

Table 5: Reported Machine Learning Model Performance for UAV-Based Maize Aboveground Biomass Estimation Across Selected Studies

Study	Data Source(s)	Best Model	Reported R^2	Reported RMSE
Wang *et al.* [1]	Hyperspectral VIs + LiDAR structural metrics (fused)	Partial least squares regression	0.883	321.1 g/m²
Wang *et al.* [1]	LiDAR structural metrics only	Partial least squares regression	0.835	374.7 g/m²
Zhu *et al.* [2]	LiDAR + multispectral (stem-leaf separated)	Regression fusion model	Improved by ~0.13–0.30 over single-source models	Reduced by 22.9–54.9 g/m²
Feng *et al.* [3]	Vegetation indices + plant structure + LiDAR-derived slope	Random forest	0.90–0.93 (stage-dependent)	84–1327 kg/ha (stage-dependent)
Han *et al.* [6]	Multi-source UAV RGB/multispectral features	Machine learning ensemble	Reported as competitive with LiDAR-fused approaches	Not directly comparable across studies

Table 6: Comparative Summary of International Studies Integrating UAV LiDAR, Hyperspectral, and/or GIS/ML Approaches for Row-Crop Biomass Estimation

Crop	Sensing Technologies	Key Finding	Source
Maize	Hyperspectral + LiDAR	Fusion improved R^2 from 0.835 (LiDAR-only) to 0.883	Wang *et al.* [1]
Maize	LiDAR + multispectral, stem-leaf separated	Separated biomass components improved fused-model accuracy	Zhu *et al.* [2]
Maize	Multispectral + digital imagery + LiDAR slope	Structural covariates improved random forest AGB accuracy to $R^2 \approx 0.90–0.93$	Feng *et al.* [3]
Wheat	UAV RGB/multispectral + crop height	Height metrics combined with VIs improved biomass monitoring over VI-only models	Bendig *et al.* [9]
Wheat	Terrestrial and UAV LiDAR	LiDAR height estimation outperformed ultrasonic sensing accuracy	Yuan *et al.* [10]
Soybean	UAV multimodal deep learning fusion	Multimodal fusion improved yield/biomass-related prediction over single-sensor models	Maimaitijiang *et al.* [7]

7. Conceptual and Comparative Illustrations

Figure 1 presents the conceptual workflow synthesizing UAV mission planning, LiDAR and hyperspectral acquisition, GIS-based spatial analysis, and machine learning-assisted biomass prediction, as described across the reviewed literature. Figure 2 provides a schematic illustration of simultaneous UAV-based LiDAR and hyperspectral data acquisition over a maize canopy with RTK-referenced ground positioning. Figure 3 synthesizes the general comparative accuracy pattern reported across single-sensor and fused modeling approaches in the reviewed studies.

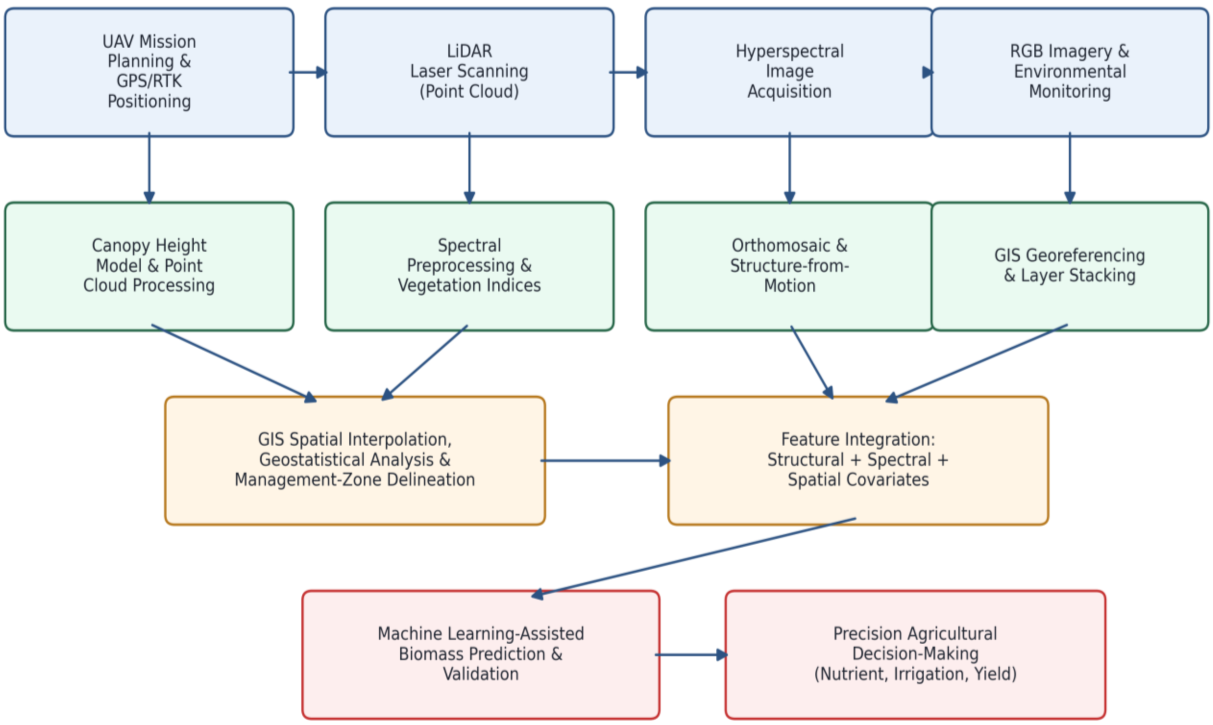

Fig 1: Conceptual workflow integrating UAV mission planning, LiDAR scanning, hyperspectral acquisition, GIS spatial analysis, and machine learning-assisted biomass prediction, synthesized from the reviewed literature.

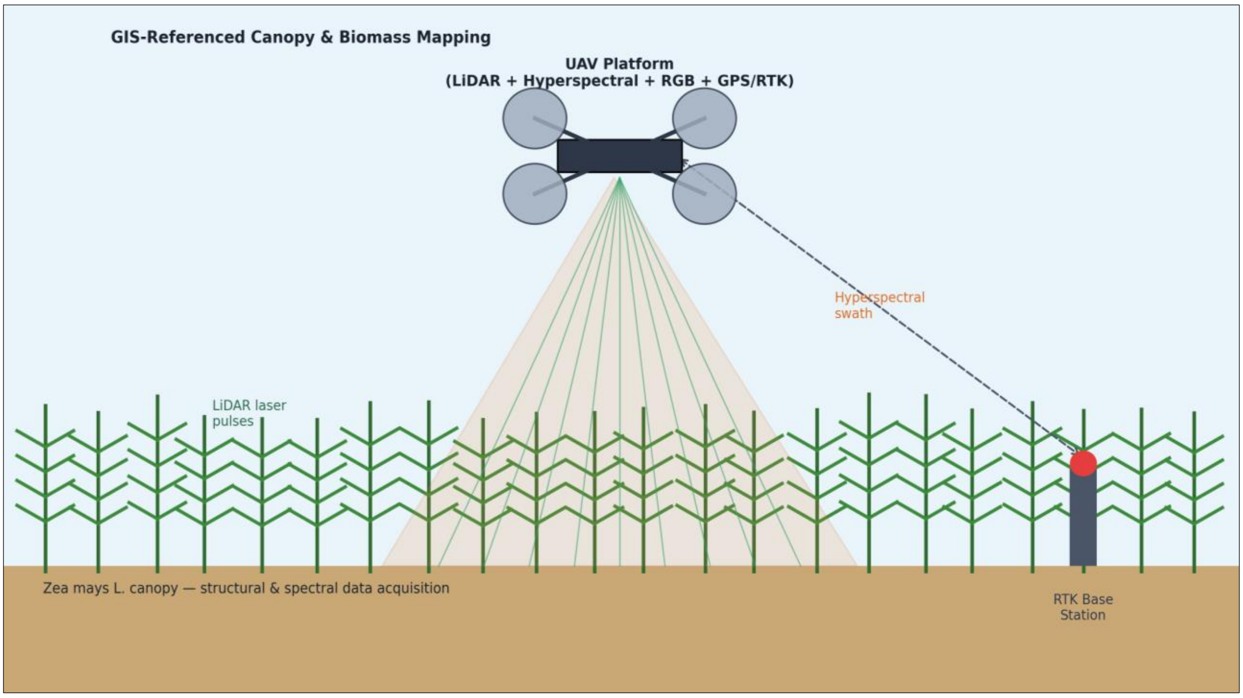

Fig 2: Schematic of simultaneous UAV-based LiDAR and hyperspectral data acquisition over a *Zea mays* L. canopy with RTK-referenced ground positioning.

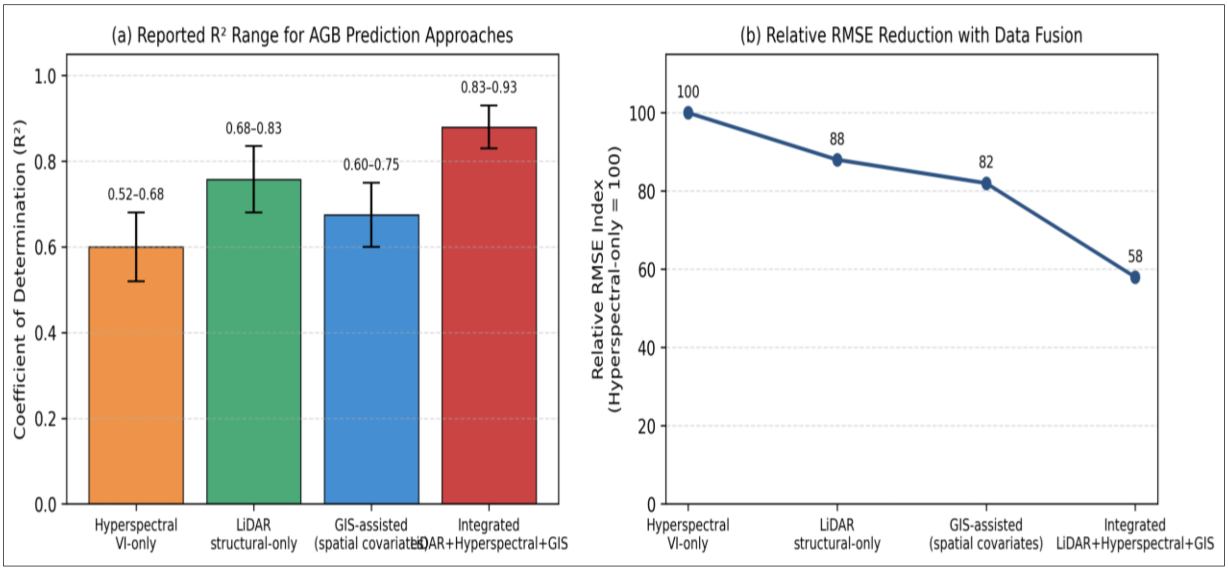

Fig 3: Literature-synthesized comparative accuracy (R^2 range and relative RMSE index) of hyperspectral-only, LiDAR-only, GIS-assisted, and integrated modeling approaches for maize aboveground biomass estimation, drawn from the studies summarized in Table 5 and Table 6.

8. Discussion

The reviewed literature converges on a clear and mechanistically coherent conclusion: UAV-based LiDAR and hyperspectral sensing capture complementary rather than redundant information about maize canopy status, and their fusion, particularly when embedded within a GIS-based spatial analytical framework, produces more accurate and more spatially actionable AGB estimates than any single sensing modality (Wang *et al*., 2017) [1] (Feng *et al*., 2025) [3] (Han *et al*., 2019) [6] (Zhang *et al*., 2021) [13] (Zhu *et al*., 2019) [14]. This finding is consistent with the broader precision agriculture literature on multi-sensor data fusion for other row crops, including wheat, soybean, and sorghum, where analogous structural-spectral fusion strategies have produced comparable accuracy gains (Maimaitijiang *et al*., 2020) [7] (Devia *et al*., 2019) [16] (Roth and Streit, 2018) [17] (Näsi *et al*., 2018) [18], suggesting that the underlying principle, combining geometric and physiological sensing dimensions, generalizes reasonably well across cereal and legume crop systems.

At the same time, several practical and methodological challenges temper the translation of these research findings into routine operational use. First, survey-grade LiDAR and hyperspectral payloads remain substantially more expensive than RGB or standard multispectral sensors, and the combined weight of dual or triple sensor payloads can constrain flight endurance and increase the number of flights required to cover larger commercial fields (Yue *et al*., 2017) [5] (Feng *et al*., 2021) [12]. Second, canopy saturation effects in hyperspectral indices and occlusion effects in dense, later-stage LiDAR point clouds both introduce systematic, growth-stage-dependent bias that single validation snapshots may not fully reveal, reinforcing the value of multi-temporal validation across the full growing season (Wang *et al*., 2017) [1] (Han *et al*., 2019) [6].

Third, model transferability across sites, seasons, and genotypes remains incompletely resolved. Several studies report meaningfully reduced accuracy when models trained in one environment are applied to spatially or environmentally distinct validation sites, a pattern attributed to genotype-by-environment interactions affecting canopy architecture and spectral response (Feng *et al*., 2025) [3] (Maimaitijiang *et al*., 2020) [7]. This limitation suggests that widely generalizable, transferable AGB models may require substantially larger and more environmentally diverse training datasets than are represented in most individual published studies, an argument that supports continued investment in multi-site, multi-season, and multi-genotype UAV data collection initiatives.

Fourth, the computational burden of processing dense LiDAR point clouds and high-dimensional hyperspectral cubes is non-trivial, and reporting of processing time, storage requirements, and software dependencies remains inconsistent across the reviewed studies, complicating direct cost-benefit comparisons between sensing strategies for prospective adopters (Feng *et al*., 2021) [12]. Relatedly, the GIS-based spatial interpolation literature demonstrates that interpolator choice materially affects resulting biomass surfaces, yet interpolation method selection is often reported without accompanying sensitivity analysis, an area where methodological standardization would improve cross-study comparability (Grego *et al*., 2014) [21] (de Souza *et al*., 2016) [22].

Future research priorities emerging from this synthesis include: standardized multi-site, multi-season field trials explicitly designed to test cross-environment model transferability; more consistent reporting of computational and operational cost alongside predictive accuracy; deeper exploration of growth-stage-adaptive or stacked ensemble modeling strategies that explicitly weight structural versus spectral features by phenological stage; and closer integration of GIS-based spatial uncertainty quantification into biomass mapping workflows, so that management-zone delineation reflects not only predicted biomass but also the confidence associated with that prediction. Continued cost reduction in miniaturized LiDAR and hyperspectral sensors is also likely to be a key enabling factor for broader adoption beyond well-resourced research settings.

9. Conclusion

This article provides a review of peer-reviewed literature relating to the application of UAV-based LiDAR, hyperspectral imaging and GIS-based spatial analysis for estimating aboveground biomass in maize crops. This literature review shows that metrics derived from LiDAR provide structural information while those derived from hyperspectral imaging provide spectral and physiological information. Their merging in the majority of cases with the help of machine learning methods including random forest and support vector regression allows for better prediction of AGB than that using any of the aforementioned techniques on their own. GIS-based geostatistical interpolation makes it possible to turn point and field level predictions into continuous biomass maps and consequently create zones for site specific management of nutrient and irrigation use.

Some of the areas of research that need to be pursued by researchers are identified above. This would lead to increased usage of research knowledge that has already been proven over a long period of time. The current focus of this research can be useful for agricultural specialists. According to the results of research, the development of UAV-GIS technology is a positive sign. It’s also important that policymakers understand what needs to be done in order for UAV technology to be successfully implemented in agricultural work.

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