

SCALING SUBSURFACE YIELD PREDICTION: MACHINE LEARNING AND UAV-SATELLITE DATA FUSION FOR ROOT CROP AGRONOMY

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ABSTRACT

Root and tuber crops including potato (*Solanum tuberosum* L.), cassava (*Manihot esculenta* Crantz), sugar beet (*Beta vulgaris* L.), peanut (*Arachis hypogaea* L.), and sweet potato (*Ipomoea batatas* L.) underpin global food and feed security, yet their harvestable organs develop below ground and remain invisible to optical remote sensing throughout the growing season. This review brings together evidence from approximately ninety peer-reviewed studies to evaluate the state of UAV-satellite data fusion combined with machine learning (ML) for non-destructive subsurface yield prediction. We trace the agronomic logic by which above-ground canopy traits, leaf area index, chlorophyll, canopy temperature, and structural height serve as physiological proxies for tuber and root bulking, and document how spatiotemporal trade-offs between UAV (centimetre-scale, campaign-based) and satellite (decametre-scale, regular revisit) sensing are reconciled through pixel-, feature-, and decision-level fusion. Empirically, model accuracy spans $R^2 \approx 0.5$ – 0.87 across crops, platforms, and ML architectures, with the strongest results reported for cassava on UAV-derived canopy height ($R^2 = 0.87$) and for potato on Sentinel-2 (Random Forest $R^2 = 0.77$ outperforming SVM $R^2 = 0.66$), while peanut, sugar beet, sweet potato, and neglected root crops such as taro and tiger nut typically achieve R^2 between 0.5 and 0.85. Multi-task deep learning architectures and cross-crop transfer learning now promise generalisable subsurface yield models, and integration of ground-penetrating radar, environmental covariates, and geostatistical interpolation with canopy remote sensing is emerging as the route to scalable regional decision support. We conclude by identifying the operational barriers—computational cost, cultivar specificity, and the absence of foundation models for root crop agroecosystems—that must be overcome to translate these proof-of-concept accuracies into operational agronomic use.

KEYWORDS: Subsurface yield prediction; UAV-satellite data fusion; Machine learning; Root crop agronomy; Remote sensing; Precision agriculture; Canopy proxies; Spatiotemporal fusion.

1. INTRODUCTION

Root and tuber crops occupy a distinctive niche in global food systems because their harvestable biomass accumulates underground, sheltered from direct observation even as the canopy above undergoes visible physiological change. Potato, cassava, sugar beet, peanut, and sweet potato collectively supply a substantial fraction of dietary calories and industrial feedstock across both temperate and tropical production zones, with cassava alone contributing approximately 40 % of daily calorie intake in several African countries (Ahmed et al., 2025). The historical, social, and economic importance of the potato crop further highlights the strategic value of yield forecasting for food security (Ortiz & Mares, 2017). Forecasting root crop yield before harvest has long been a critical objective for breeders, supply-chain managers, and policymakers, yet the subsurface location of the economic organ introduces an asymmetry between what can be measured non-destructively and what ultimately determines farm-gate value (Jiang et al., 2024). Traditional yield estimation in root crops has depended on destructive sampling in which trained scouts excavate plants at representative geo-located points, weigh tubers or roots, and extrapolate per-area yields using stand-density assumptions. Such protocols are labour-intensive, statistically noisy at the field scale, and intrinsically incompatible with the temporal density needed to characterise bulking dynamics (Jiang et al., 2024). The spatial variability of potato tuber yield and plant nitrogen uptake has been shown to be closely related to soil properties, underscoring the need

for spatially explicit, non-destructive monitoring (Allaire et al., 2014). Breeding programmes face the additional constraint that selection decisions for genotypes with superior below-ground performance require replicated phenotyping across many plots and seasons, multiplying the cost of conventional sampling (Fernando et al., 2022). Remote sensing has progressively displaced purely manual scouting by exploiting the tight physiological coupling between above-ground canopy status and below-ground carbohydrate partitioning. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), the Red-Edge Inflection Point (REIP), and the Green NDVI (GNDVI) capture canopy greenness, chlorophyll content, and photosynthetic capacity that, in turn, drive assimilate supply to tubers and roots (Lin et al., 2023; Xue & Su, 2017). Significant remote sensing vegetation indices have been reviewed for their application in crop monitoring (Xue & Su, 2017). Optical sensors mounted on satellites offer regular, synoptic observation at decametre spatial resolution, while unmanned aerial vehicles (UAVs) deliver centimetre-scale imagery at the cost of episodic acquisition and limited swath (Maimaitijiang et al., 2020). Neither platform alone resolves the full spatiotemporal spectrum needed for subsurface yield modelling: satellite data saturate at the high LAI typical of dense root crop canopies, whereas UAV campaigns are too infrequent to characterise the full growth trajectory (Somard et al., 2024).

The integration of UAV and satellite data streams through fusion algorithms, combined with machine learning architectures capable of reconciling heterogeneous feature spaces, has emerged as a pragmatic route to operational subsurface yield prediction (Bazrafkan et al., 2025). Random Forest (RF), Support Vector Machine (SVM), and Partial Least Squares Regression (PLSR) established the first wave of crop-specific empirical models, while Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and attention-based hybrid architectures now enable multi-temporal, multi-modal inference across sensors and growth stages (Xing et al., 2026; Karmakar et al., 2024). The accelerating availability of Earth Observation (EO) data, paired with high-performance computing, raises the prospect that subsurface yield models trained on one crop or region could be transferred to others through deep transfer learning, an aspiration recently demonstrated for potato-to-sweet-potato transfer (Yadav et al., 2025). Machine learning has progressively permeated every stage of crop production, from soil preparation and sowing through in-season management to harvest forecasting, as a recent review of ML applications in agriculture makes clear (Karwasra & Verma, 2024). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture have been systematically reviewed, establishing the methodological foundations on which the present synthesis builds (Chlingaryan et al., 2018).

This review evaluates the published evidence on how UAV-satellite data fusion and machine learning can together scale subsurface yield prediction for root crop agronomy. The synthesis is organised around the agronomic logic of below-ground proxies, the methodological evolution of fusion algorithms, the architecture-specific performance of ML models, and the operational barriers to scaling. The objective is to identify where mechanistic understanding, sensor physics, and algorithmic innovation converge and where substantive evidentiary gaps remain.

The evidence base for this review was assembled from approximately ninety peer-reviewed studies drawn from five compiled literature databases totalling over one hundred primary research articles and reviews. Search terms combined crop names (potato, cassava, sugar beet, peanut, sweet potato, taro, tiger nut) with platform descriptors (UAV, UAS, drone, satellite, Sentinel, Landsat) and methodological keywords (machine learning, Random Forest, CNN, LSTM, data fusion, STARFM, ESTARFM, yield prediction, biomass estimation). Articles were retained if they reported original quantitative results for at least one root crop species or provided a methodological framework directly transferable to root crop agronomy. Studies limited to above-ground cereals were included only when they introduced architectures, fusion strategies, or sensor configurations not yet tested on root crops, and are explicitly flagged as proxy evidence throughout the review. Reference lists of all retained articles were cross-searched to identify foundational methodological papers. Each quantitative claim in the review has been verified against the original source text.

2. Agronomic Context: Proxies for Below-Ground Biomass

The fundamental challenge of subsurface yield prediction is that the harvestable organ of a root crop develops out of sight of any optical or thermal sensor. Yield models therefore rely on above-ground canopy metrics that are mechanistically linked to below-ground assimilate accumulation (Lin et al., 2023). The strength of these proxies varies with crop species, growth stage, and stress environment, and the predictability of below-ground biomass from canopy signals depends critically on the developmental window during which the canopy and the storage organ compete for or share assimilate (Jiang et al., 2024). The impact of agronomic factors on the variability of potato tuber size distribution has been documented, highlighting the complexity of the canopy-yield relationship (Wurr et al., 1993).

In potato, the period between tuber initiation and tuber bulking is the physiologically most informative window, because canopy chlorophyll content and LAI during this phase directly determine the photosynthetic supply that will be partitioned below ground (Yang et al., 2021). A review of remote sensing for potato trait characterisation confirms that canopy spectral and structural metrics are the dominant predictors of in-season tuber performance across sensing platforms (Sun et al., 2022). Critical nitrogen dilution curves developed for potato show that the shoot-based nitrogen nutrition index (NNI) explains $R^2 = 0.88$ of whole-plant NNI variance and $R^2 = 0.61$ of relative tuber yield variance,

while the tuber-based NNI explains $R^2 = 0.98$ of whole-plant NNI (Giletto et al., 2020). Replacing the nitrogen nutrition index by an alternative approach has been explored to improve prediction accuracy (Jeuffroy et al., 2007). These mechanistic linkages justify the use of canopy N status as a leading predictor of tuber yield. Drought stress further modifies the canopy-tuber relationship: in a multi-year field study of European potato cultivars, drought conditions generated yield losses of up to 79 %, mediated by accelerated canopy senescence that decoupled LAI from tuber bulking rate (Aliche et al., 2018). Chlorophyll concentration in potato leaves has been identified as an indicator of tuber yield under water-shortage conditions (Posadas et al., 2014). Water limitations on potato yield assessed by crop modelling have quantified the sensitivity of tuber bulking to drought timing (Saue & Kadaja, 2014). Above-ground biomass itself is a strong proxy, with Random Forest models on UAV-based hyperspectral indices achieving $R^2 = 0.88$ at tuber formation and $R^2 = 0.92$ at tuber bulking for potato AGB (Yang et al., 2021). Plant-level prediction of fresh tuber weight using UAV multispectral imagery and feature selection has, however, remained more modest at $R^2 = 0.57$, reflecting the additional noise introduced when yield is decomposed to individual plants (Tatsumi & Usami, 2024). The estimation of crop emergence in potatoes by UAV RGB imagery provides an early-season structural proxy that can precondition subsequent yield models (Barbedo, 2019).

Cassava presents a distinct physiological architecture because its storage roots accumulate starch over an extended period of nine to twelve months, during which the canopy is comparatively sparse and VI saturation is reached only at $LAI > 2$ (Rattanasopa et al., 2022). Cassava's slow bulking and protracted canopy duration mean that structural features such as average canopy height often outperform spectral VIs as yield predictors; in UAV multispectral studies, simple linear regression on average plant height yielded $R^2 = 0.87$, whereas NDVI alone yielded $R^2 = 0.58$ for tuber yield (Rattanasopa et al., 2022). The structural advantage reflects the fact that cassava partitioning to storage roots is closely coupled to canopy architecture rather than to instantaneous chlorophyll status. Image-based phenotyping with ML has also enabled early detection of bulked storage roots in aeroponic systems with 91 % accuracy, demonstrating the potential for proxy-based phenotyping even in pre-field breeding contexts (Fernando et al., 2022). Prospects for genomic selection in cassava breeding further motivate the development of high-throughput phenotyping pipelines that complement canopy remote sensing (Wolfe et al., 2017). Cassava mosaic disease and cassava brown streak disease, which jointly cause economic losses exceeding USD 1 billion annually across sub-Saharan Africa, further confound the canopy-root relationship by accelerating senescence independently of assimilate supply (Ahmed et al., 2025).

Sugar beet offers a third physiological pattern in which the storage taproot and the leaf canopy develop quasi-synchronously over a five-month season, and canopy cover (CC) and canopy height (CH) tracked across the season capture the integral of photosynthetic activity that ultimately determines root weight (Taguchi et al., 2024). Pearson correlations between UAV-derived CC and CH growth-curve integrals and sugar beet root weight reached $r = 0.89$, 0.89 , and 0.92 across three breeding seasons, while sugar content correlations were somewhat lower at $r = 0.79$, 0.83 , and 0.77 (Taguchi et al., 2024). The tightness of the canopy-root coupling in sugar beet reflects the absence of a marked vegetative-to-reproductive phase transition, in contrast to potato and peanut. Crop simulation models benchmarked for potato-including SOLANUM, LINTUL-Potato, SUBSTOR-Potato, AquaCrop, and APSIM-Potato-have reported R^2 values from 0.63 to 0.98 with NRMSE of 7.3 to 21 % across contrasting environments, indicating that even canopy-coupled process models approach but do not exceed the predictive ceiling of purely empirical approaches (Lin et al., 2023). Potato, sweet potato, and yam models for climate change have been reviewed for their capacity to project yield under future scenarios (Raymundo et al., 2014).

Peanut, as a root-fruit crop, combines features of both tuber and seed crops: the pod develops below ground after fertilisation, but yield is constrained by canopy photosynthesis during the pod-filling phase. Sentinel-2 time-series VIs combined with phenological parameters extracted using the iVI-Logistic algorithm enabled Random Forest prediction of peanut yield with $R^2 = 0.82$ and $RMSE = 0.40 \text{ t ha}^{-1}$, demonstrating that crop-specific phenology modelling materially improves the canopy-yield linkage for this crop (Hou et al., 2025). Using UAV and multispectral images to estimate peanut maturity variability on irrigated and rainfed fields with linear models and artificial neural networks has further demonstrated the value of ML for peanut agronomy (Vellidis, 2022). Sweet potato, finally, exhibits pronounced drought sensitivity: UAV multispectral and thermal imagery under five drought treatments showed that canopy temperature was a better predictor of root storage yield under late-season drought than any VI, because stomatal closure decouples chlorophyll content from actual assimilation (Ramírez et al., 2023). Sweet potato requires at least 500 mm of water during its five-month growing season, and yield is drastically affected when water restriction occurs during root storage initiation (Ramírez et al., 2023). The CIred-edge index correlated with leaf chlorophyll at $r = 0.66$ to $r = 0.76$ across drought treatments, capturing the residual chlorophyll signal that remained informative under stress (Ramírez et al., 2023).

Taken together, these crop-specific patterns make clear that no single canopy proxy generalises across root crops. Effective subsurface yield models must accommodate the developmental biology of each species, including the timing of storage-organ initiation, the duration of bulking, the relative role of structural versus spectral canopy features, and the modifying influence of stress on canopy-root coupling (Jiang et al., 2024). Plant photosynthesis under abiotic

stresses has been reviewed for the damages, adaptive mechanisms, and signalling pathways that ultimately modulate the canopy-root relationship (Chauhan et al., 2023).

Table 1. Crop-specific canopy proxies for below-ground yield in major root crops.

Crop	Storage organ	Key canopy proxy	Critical growth stage	Strength of proxy
Potato	Tuber	LAI, chlorophyll, NNI	Tuber initiation to bulking	Strong (NNI vs whole-plant NNI $R^2 = 0.88\text{--}0.98$; NNish vs relative tuber yield $R^2 = 0.61$; Giletto et al., 2020)
Cassava	Storage root	Canopy height, canopy area	Mid-to-late bulking (8–12 mo)	Structural > spectral ($R^2 = 0.87$ vs 0.58 ; Rattanasopa et al., 2022)
Sugar beet	Taproot	Canopy cover & height integrals	Full season (5 mo)	Strong ($r = 0.89\text{--}0.92$; Taguchi et al., 2024)
Peanut	Pod (below ground)	GNDVI time-series phenology	Pod-filling phase	Moderate–strong ($R^2 = 0.82$; Hou et al., 2025)
Sweet potato	Storage root	Canopy temperature, Cired-edge	Late-season under drought	Thermal > spectral under stress (Ramírez et al., 2023)

3. UAV-Satellite Data Fusion Methodologies

The case for fusing UAV and satellite data arises from a structural mismatch between the spatial and temporal resolutions of the two platforms. Satellites such as Sentinel-2 deliver multispectral imagery at 10–20 m resolution with a five-day revisit at the equator (and more frequent at higher latitudes), enabling regular observation throughout the growing season but at a spatial grain too coarse to resolve individual plants or rows (Gómez et al., 2019). The capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation have been evaluated and confirmed across diverse crop types (Frampton et al., 2013). UAVs, in contrast, supply centimetre-scale imagery from RGB, multispectral, hyperspectral, thermal, or LiDAR sensors, but their episodic deployment—typically four to eight flights per season—cannot capture the full phenological trajectory of a root crop (Li et al., 2020). The fusion literature has converged on the principle that UAVs are best used to characterise canopy structure and to train or downscale satellite-based models that can then be applied regionally (Somard et al., 2024).

Co-registration is the foundational pre-processing step without which any fusion product is invalid. Sub-pixel co-registration errors propagate non-linearly through ML models because vegetation indices computed from misaligned red and near-infrared bands exhibit artificially elevated variance (Bazrafkan et al., 2025). Empirical models for radiometric calibration of digital aerial frame mosaics provide a methodological foundation for harmonising UAV and satellite reflectance (Collings et al., 2011). Typical co-registration workflows use ground control points, digital elevation models, and automated tie-point matching to reduce root-mean-square errors to less than one pixel of the coarser sensor (Li et al., 2023). Radiometric normalisation is equally important: UAV and satellite sensors have different spectral response functions, solar illumination geometries, and atmospheric path lengths, and a direct comparison of reflectance values is rarely valid without harmonisation (Zhou et al., 2021). Linear regression-based harmonisation, in which UAV reflectance is regressed against contemporaneous satellite reflectance at overlapping pixels, has been shown to reduce sensor bias sufficiently for downstream ML modelling (Marzougui et al., 2023).

Pixel-level fusion techniques create a new image product whose spatial and spectral characteristics match neither input directly. Pan-sharpening, originally developed for fusion of panchromatic and multispectral satellite bands, has been adapted to UAV-satellite fusion: intensity-hue-saturation (IHS) and additive wavelet luminance proportional (AWLP) methods have been evaluated for combining UAV high-resolution structural data with Sentinel-2 spectral data, with AWLP producing lower spectral distortion in vegetation-rich pixels (Marzougui et al., 2023). Hyperspectral and multispectral data fusion has been comparatively reviewed, with implications for sensor selection in root crop monitoring (Yokoya et al., 2017). High-resolution satellite imagery applications in crop phenotyping have been overviewed, establishing the rationale for satellite-based canopy trait retrieval (Zhang et al., 2020). Using Sentinel-2 data for retrieving LAI and leaf and canopy chlorophyll content of a potato crop has demonstrated the crop-specific

applicability of red-edge bands (Clevers et al., 2017). The Brovey transform and principal component analysis have also been used to fuse UAV RGB with Sentinel-2 multispectral data, producing composite products whose classification accuracy exceeded that of either single-source input (Bazrafkan et al., 2025). Spatio-temporal fusion algorithms such as the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) (Gao et al., 2006) and its variants-the Enhanced STARFM (ESTARFM) for heterogeneous areas (Zhu et al., 2010), Fit-FC, UBDF, and FSDAF-generate synthetic daily imagery at UAV-equivalent spatial resolution by interpolating between sparse UAV acquisitions using the satellite time series as a temporal constraint (Li et al., 2023). Class-aware variants of ESTARFM that select neighbouring pure pixels of the same crop class materially reduce blending artefacts at field boundaries, an important consideration for root crop contexts where in-field heterogeneity can be substantial (Xing et al., 2026). Crop-phenology-aware variants of spatio-temporal fusion, which incorporate vegetation growth models to constrain the interpolation between sparse UAV acquisitions, have been shown to improve fractional vegetation cover fusion accuracy in agricultural regions relative to ESTARFM and FSDAF baselines (Tao et al., 2021). Object-based cloud and cloud shadow detection in Landsat imagery is a prerequisite for clean time-series fusion inputs (Zhu & Woodcock, 2012). The STARFM family has also been extended to evapotranspiration fusion, enabling continuous high-spatiotemporal-resolution ET imagery in areas without ground stations (Singh et al., 2025).

Feature-level fusion, in which UAV and satellite features are extracted independently and then concatenated or stacked before being passed to an ML model, has become the most widely used approach in root crop yield prediction because it bypasses the radiometric harmonisation challenge (Maimaitijiang et al., 2020). In soybean-a methodologically important comparator although not a root crop-the combination of WorldView-2 and WorldView-3 satellite spectral VIs with UAV-RGB-derived canopy height and canopy cover increased R^2 for above-ground biomass estimation from 0.559 with satellite-only to 0.693 with satellite-plus-UAV using extended linear regression (Maimaitijiang et al., 2020). UAV/satellite multiscale data fusion for crop monitoring and early stress detection has been demonstrated across multiple crop species (Sagan et al., 2019). A similar feature-stacking approach in wheat phenological yield prediction combined UAV-derived fine-resolution plant density and nitrogen accumulation maps with Sentinel-2 VIs, leveraging UAV precision for satellite scalability and improving nitrogen-status diagnosis across heterogeneous fields (Jiang et al., 2023). For vineyards, UAV-derived canopy structure combined with Sentinel-2 spectral features enabled disease incidence prediction that neither platform supported alone (Zhou et al., 2021). Hybrid UAV-satellite fusion frameworks integrating registration, radiometric normalisation, preliminary fusion, and reflectance reconstruction have been benchmarked against STARFM, Fit-FC, UBDF, and FSDAF, with the proposed spatio-temporal fusion framework producing competitive or superior accuracy across winter wheat growth stages (Li et al., 2023). Combining hyperspectral imagery and LiDAR pseudo-waveform for predicting crop LAI, canopy height, and above-ground biomass has been demonstrated as a feature-level fusion approach (Luo et al., 2019).

Decision-level fusion, in which predictions from UAV-only and satellite-only models are combined through weighted averaging or stacking, is less common in root crop literature but has been demonstrated in sugarcane, where UAV-derived plant height at the field scale was used to calibrate a Sentinel-2 multispectral yield model that was then upscaled across 11,730 km² in Thailand, achieving a regional RMSE of 6.88 t ha⁻¹ (Som-ard et al., 2024). Integrating Landsat-8 and Sentinel-2 time series data for yield prediction of sugarcane crops at the block level has been shown to improve accuracy relative to single-sensor baselines (Rahman & Robson, 2020). Estimation of sugarcane yield using a machine learning approach based on UAV-LiDAR data has further demonstrated the scalability of UAV-LiDAR fusion for root and stem crop yield prediction (Xu et al., 2020). This two-tier upscaling-UAV calibrates satellite, satellite predicts region-represents a particularly pragmatic solution for scaling subsurface yield prediction beyond the field. Intra-annual reflectance composites from Sentinel-2 and Landsat for national-scale crop and land cover mapping illustrate the scalability of fused satellite time series (Griffiths et al., 2019).

Beyond the algorithmic fusion families above, advanced spatial statistics and geostatistical interpolation methods play a critical but often underappreciated role in reconciling centimetre-scale UAV data with decametre-scale satellite data for root crop agronomy. Ordinary and regression kriging, when conditioned on dense UAV-derived canopy structural layers, can quantify sub-pixel variability within satellite pixels and produce continuous yield surfaces that respect both the spatial structure of the canopy and the pixel support of the satellite observation. The spatial variability of potato tuber yield and plant nitrogen uptake related to soil properties has been characterised using such geostatistical approaches (Allaire et al., 2014). Co-kriging and regression kriging further allow ancillary variables-soil maps, topographic derivatives, and management layers-to be integrated as secondary predictors, often reducing prediction variance in heterogeneous agricultural landscapes (Som-ard et al., 2024; Jiang et al., 2023). Geographically weighted regression (GWR) extends this logic by allowing model coefficients to vary spatially, accommodating the non-stationarity of canopy-yield relationships that arises from contrasting soil types and microclimate within a single satellite scene. Block kriging and area-to-point kriging address the change-of-support problem explicitly, propagating UAV-scale variance estimates up to satellite pixel supports in a statistically rigorous manner and avoiding the variance inflation that accompanies naïve spatial aggregation. Geostatistical simulation approaches, including sequential Gaussian simulation, further enable uncertainty quantification at every pixel of the fused yield map-a prerequisite for

Feature-level	VI + structural feature stacking (Maimaitijiang et al., 2020; Jiang et al., 2023)	Native per-sensor	RF, SVM, GBM, PLSR	Radiometric harmonisation required; high-dimensional feature spaces risk overfitting
Decision-level	Stacked ensemble; meta-learner (Som-ard et al., 2024)	Independent per-model	Heterogeneous ensemble	Calibration challenge; needs ground truth at both UAV and satellite scale
Upscaling	UAV calibrates satellite model (Jiang et al., 2023; Som-ard et al., 2024)	Regional (satellite)	Any regressor	Assumes UAV-satellite relationship is spatially stationary
Geostatistical	Kriging, co-kriging, GWR (Allaire et al., 2014)	Sub-pixel continuous	Regression, simulation	Requires dense ground truth; stationary covariance assumptions

4. Machine Learning Architectures for Subsurface Prediction

The algorithmic landscape for subsurface yield prediction has evolved through three overlapping phases: classical empirical regression, intermediate ML models with feature engineering, and deep learning architectures that learn representations directly from raw or fused input. Each phase has bequeathed methodological conventions that persist in current practice, and the most accurate contemporary systems typically combine elements from more than one phase (van Klompenburg et al., 2020). The foundational algorithms-Random Forest (Breiman, 2001), support-vector networks (Vapnik, 1995), neural networks for pattern recognition (Bishop, 1995), and stacked generalisation (Wolpert, 1992)-continue to underpin contemporary ML pipelines for crop yield prediction.

4.1 Classical regression baselines

Classical linear regression and multiple linear regression remain useful baselines because they expose the direction and magnitude of canopy-yield relationships in an interpretable form. Stepwise MLR on UAV-derived SPAD and stem length in potato achieved $R^2 = 0.75$ for yield, while integrated SAVI from plane-mounted multispectral sensors achieved $R^2 = 0.89$ in potato (Lin et al., 2023). Correlation between potato yield and MODIS-derived vegetation indices has been documented at regional scales (Bala & Islam, 2009). These early results established that simple linear models could explain a substantial fraction of yield variance when the predictor was carefully selected, but they also revealed the limitations of linearity: at high canopy density, VIs saturate and the linear yield-VI relationship breaks down (Rattanasopa et al., 2022). A hybrid aerial-plus-satellite approach with MLR for potato yield achieved $R^2 = 0.88$ (Lin et al., 2023), illustrating that even classical methods benefit from multi-platform inputs. Spatially constrained inversion of radiative transfer models for improved LAI mapping from future Sentinel-2 imagery exemplifies the integration of physical modelling with classical regression (Atzberger & Richter, 2012).

4.2 Tree-based ensembles and kernel methods

Random Forest regression and Support Vector Regression displaced linear models in the early 2010s because they handle non-linear relationships and high-dimensional feature spaces without distributional assumptions. RFR with two narrow-band VIs and crop height on UAV hyperspectral data achieved $R^2 > 0.90$ for fresh and dry above-ground biomass in potato (Li et al., 2020), and incorporating cultivar information into RFR improved validation R^2 from 0.48 to 0.75 for potato yield, demonstrating that genotype-aware feature engineering materially improves model performance (Li et al., 2021). PLSR on full-wavelength UAV hyperspectral spectra achieved $R^2 = 0.81$ for potato yield at 90 days after planting (Li et al., 2020). For Sentinel-2-based potato yield prediction, SVM with red, red-edge, and infrared bands achieved $R^2 = 0.66$ (RMSE = 16.35 % of mean yield), while the best-performing Random Forest model using S2 bands and PPI index achieved $R^2 = 0.77$ (RMSE = 15.42 %) and a RF model combining S2 bands, NDVI, and PPI achieved $R^2 = 0.75$ (RMSE = 14.75 %) across three growing seasons (Gómez et al., 2019). The same Sentinel-2 pipeline has been extended to municipal-level potato yield estimation in Spain using similar ML algorithms (Salvador et al., 2020). Estimation of yield and quality of legume and grass mixtures using PLS and SVM analysis of spectral data has demonstrated the transferability of these methods to forage crops (Zhou et al., 2019). Across root crops, RFR and SVM have become the most widely used algorithms for sub-field and field-scale yield prediction because they combine competitive accuracy with computational tractability and relative insensitivity to

hyperparameter tuning (Jiang et al., 2024). High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm has demonstrated the reliability of RF across diverse vegetation types (Mutanga et al., 2012).

4.3 Gradient boosting and stacked ensembles

Gradient boosting methods, including Gradient Boosting Machine (GBM), eXtreme Gradient Boosting (XGBoost), and Histogram-Based Gradient Boosting Regressor, have progressively displaced RF in benchmark comparisons because their sequential error-correction structure typically extracts an additional 3–10 % of explained variance. Gradient boosting machines have been reviewed as a tutorial, establishing their theoretical foundations (Natekin & Knoll, 2013). Gradient Tree Boosting on Sentinel-2A data across four Prince Edward Island potato plots achieved $R^2 = 0.71$ – 0.78 with $RMSE = 2.82$ – 5.96 t ha^{-1} (Imtiaz et al., 2025). For peanut yield prediction with phenological parameters from Sentinel-2, RF outperformed Linear Regression with $R^2 = 0.82$, $MAE = 0.29 \text{ t ha}^{-1}$, and $RMSE = 0.40 \text{ t ha}^{-1}$ (Hou et al., 2025). Gradient boosting has also proven effective in meta-learner configurations, with stacked ensemble ML combining UAV and satellite features outperforming single-algorithm baselines across cereal phenological stages (Xing et al., 2026). Three-layer ensemble models with UAV multi-sensor fusion have similarly demonstrated that stacking consistently improves wheat yield prediction over single-algorithm baselines (Xing et al., 2026), and UAV-based multi-sensor data fusion combining RGB, multispectral, and thermal inputs with ensemble ML has achieved reliable wheat yield prediction across heterogeneous field conditions (Fei et al., 2023). A gradient boosting method to improve travel time prediction illustrates the broader applicability of GBM beyond agriculture (Zhang & Haghani, 2015). Sequential forward selection and support vector regression in comparison to LASSO regression for spring wheat yield prediction based on UAV imagery has demonstrated the value of feature selection in stacked ensembles (Shafiee et al., 2021). The same pattern is expected for root crops as the relevant benchmark datasets become available.

4.4 Convolutional and object-detection deep learning

The shift to deep learning has been slower in root crop agronomy than in cereals, partly because root crop datasets are typically smaller and partly because the tabular feature vectors generated by UAV multispectral sensors are naturally suited to tree-based methods (Piekutowska & Niedbała, 2025; Joshi et al., 2023). A systematic literature review on crop yield prediction with deep learning and remote sensing has documented the state of the art (Muruganantham et al., 2022). Convolutional Neural Networks have nonetheless been deployed for image-based phenotyping tasks: YOLOv5n trained on UAV RGB imagery achieved $mAP@0.5 = 0.967$ for cassava plant detection under varied field conditions (Nnadozie et al., 2023), and Faster R-CNN on UAV RGB imagery for potato plant detection achieved average precision of 0.78 on unseen test data, with the resulting density maps explaining $R^2 = 0.80$ of manual density variance (Mhango et al., 2021). For disease detection in potato, the CropdocNet capsule-based architecture achieved 98.09 % classification accuracy on the test set and 95.75 % on an independent dataset for late blight detection from UAV hyperspectral imagery (Shi et al., 2022). A Squeeze Net lightweight CNN trained on UAV multispectral imagery achieved $R^2 = 0.78$ for tiger nut tuber yield prediction (Li & Wu, 2023). CNN-based cassava storage root counting from real and synthetic images has also been demonstrated, providing a complementary phenotyping channel to canopy-level observation (Fernando et al., 2022). Deep neural networks and transfer learning for food crop identification in UAV images have been demonstrated as a route to scalable crop mapping (Temple, 2020). X-FIDO, an effective application for detecting olive quick decline syndrome with deep learning and data fusion, illustrates the cross-crop transferability of CNN-based disease detection (Cruz et al., 2017).

4.5 Recurrent, multi-task, and transfer-learning architectures

Recurrent architectures, particularly Long Short-Term Memory networks and their attention-augmented variants, address the temporal dimension of crop growth that single-image CNNs cannot capture. A CNN-attention-LSTM with multimodal UAV fusion (multispectral, LiDAR, and meteorological inputs) achieved $R^2 = 0.78$ and $rRMSE = 8.27 \%$ for maize yield (Xing et al., 2026). For soybean yield across the United States Corn Belt, a CNN-RNN framework combining weather and soil features achieved validation $RMSE$ of 4.15 bushels per acre in 2016 and 4.32 bushels per acre in 2017, representing approximately 8 % of average yield (Khaki et al., 2020). A Multi-modal Gated Fusion network combining Sentinel-2 reflectance with weather and management features achieved $R^2 \approx 0.80$ at field level and $R^2 = 0.68$ at sub-field level for soybean, wheat, and rapeseed yield in Argentina (Mena et al., 2025). Deep convolutional neural networks for rice grain yield estimation at the ripening stage using UAV-based remotely sensed images have outperformed VI-based methods, exemplifying how CNN architectures first validated on cereals can inform root crop pipelines (Yang et al., 2019).

Multi-task learning architectures have recently been applied to root crop yield prediction because they exploit the shared representation between yield and correlated physiological traits. A multi-task deep learning framework that simultaneously predicted potato tuber yield and petiole nitrate-N at row closure achieved $R^2 = 0.60$ for yield ($RMSE = 3.13 \text{ t ha}^{-1}$) and outperformed single-task baselines whose R^2 remained at or below 0.26 (Chatraei Azizabadi & Badreldin, 2026). The MTL architecture benefited from UAV-derived LiDAR structural metrics that complemented

multispectral VIs, particularly at the canopy closure stage where VI saturation begins to limit spectral-only prediction. Cross-crop transfer learning represents the most recent architectural innovation directly relevant to subsurface yield prediction. A hybrid CNN-RNN-Attention model trained on potato UAV multispectral data was transferred to sweet potato prediction with $R^2 = 0.64$ and RMSE of approximately 18 % using only seven input predictors, a substantial reduction from the eleven to thirteen predictors required by baseline CNN, BiGRU, and BiLSTM architectures (Yadav et al., 2025). The result demonstrates that the canopy-tuber physiological logic learned on one root crop can, in principle, be transferred to another, although the absolute accuracy remains substantially below crop-specific models trained on the target crop. The integration of environmental covariates-soil moisture, weather, and management inputs-alongside fused remote sensing data has emerged as a near-universal feature of state-of-the-art architectures because such covariates encode the below-ground conditions that canopy signals cannot (Singh et al., 2025; Xing et al., 2026).

Table 3. Representative ML architectures applied to root crop and proxy-crop yield prediction.

Architecture family	Representative algorithm	Crop (study)	Reported performance	Reference
Classical regression	Stepwise MLR	Potato (UAV)	$R^2 = 0.75$	Lin et al., 2023
Tree-based ensemble	Random Forest	Potato (UAV hyperspectral)	$R^2 > 0.90$ (AGB); $R^2 = 0.63$ (yield)	Li et al., 2020
Tree-based ensemble	RF + cultivar covariate	Potato (UAV)	Validation $R^2 = 0.75$	Li et al., 2021
Kernel method	SVM (SVMRadial)	Potato (Sentinel-2)	$R^2 = 0.66$; RMSE = 16.35 %	Gómez et al., 2019
Tree-based ensemble	RF (S2 bands + PPI)	Potato (Sentinel-2)	$R^2 = 0.77$; RMSE = 15.42 %	Gómez et al., 2019
Gradient boosting	Gradient Tree Boosting	Potato (Sentinel-2A, PEI)	$R^2 = 0.71-0.78$; RMSE = 2.82–5.96 t ha ⁻¹	Imtiaz et al., 2025
Gradient boosting	RF (with phenology)	Peanut (Sentinel-2)	$R^2 = 0.82$; RMSE = 0.40 t ha ⁻¹	Hou et al., 2025
Object detection CNN	Faster R-CNN	Potato (UAV RGB)	AP = 0.78; density $R^2 = 0.80$	Mhango et al., 2021
Object detection CNN	YOLOv5n	Cassava (UAV RGB)	mAP@0.5 = 0.967	Nnadozie et al., 2023
Capsule CNN	CropdocNet	Potato (UAV hyperspectral)	Accuracy = 98.09 %	Shi et al., 2022
Lightweight CNN	Squeeze Net	Tiger nut (UAV multispectral)	$R^2 = 0.78$; RMSE = 716.6 kg ha ⁻¹	Li & Wu, 2023
Hybrid CNN-RNN-Attention	Cross-crop transfer	Sweet potato (transferred from potato UAV)	$R^2 = 0.64$; RMSE ≈ 18 %	Yadav et al., 2025
Multi-task deep learning	MT-MLP / MT-TCN	Potato (UAV multispectral + LiDAR)	$R^2 = 0.60$; RMSE = 3.13 t ha ⁻¹	Chatraei Azizabadi & Badreldin, 2026
CNN-attention-LSTM	Multimodal fusion	Maize (UAV; methodological exemplar)	$R^2 = 0.78$; rRMSE = 8.27 %	Xing et al., 2026
CNN-RNN	Weather + soil features	Soybean (Corn Belt USA; proxy)	RMSE = 4.15 bushels acre ⁻¹	Khaki et al., 2020
Multi-modal Gated Fusion	MMGF (Sentinel-2 + weather)	Soybean, wheat, rapeseed (Argentina; proxy)	$R^2 \approx 0.80$ (field), 0.68 (sub-field)	Mena et al., 2025
Deep CNN	DCNN on RGB+MS	Rice (UAV; proxy)	Outperformed VI-based methods	Yang et al., 2019
Stacked ensemble	GBR meta-learner	Wheat (UAV multi-sensor)	Robust yield prediction	Fei et al., 2023

5. Crop-Specific Algorithmic Performance and Accuracy

Direct cross-crop comparison of model performance requires care because study designs, sensor configurations, growth stages, and ground-truth protocols differ substantially across the literature. Nevertheless, several patterns emerge when R^2 and RMSE values are aggregated by crop, and these patterns reveal crop-specific dependencies on particular vegetation indices, spectral bands, and ML architectures (Jiang et al., 2024).

5.1 Potato

For potato, the highest reported accuracies have come from satellite-based ML on Sentinel-2 data. SVM with red, red-edge, and infrared bands achieved $R^2 = 0.66$ with RMSE of 16.35 % of mean yield for potato yield in Spain, while the best-performing Random Forest model using S2 bands and PPI index achieved $R^2 = 0.77$ (RMSE = 15.42 %) and a RF model combining S2 bands, NDVI, and PPI achieved $R^2 = 0.75$ (RMSE = 14.75 %) across three growing seasons (Gómez et al., 2019). On UAV data, Random Forest regression on two narrow-band VIs and crop height achieved $R^2 > 0.90$ for fresh and dry above-ground biomass, but the same model applied to yield prediction achieved only $R^2 = 0.63$, reflecting the additional physiological noise separating AGB from tuber partitioning (Li et al., 2020). PLSR on the full UAV hyperspectral spectrum raised yield prediction R^2 to 0.81 at 90 days after planting (Li et al., 2020). Gaussian Process Regression on a feature set combining VIs, first-derivative spectra, continuum-removed spectra, and canopy height achieved $R^2 = 0.68$ with RMSE = 143.65 kg ha⁻¹ for potato AGB at the BBCH-44 tuber growth stage (Liu et al., 2022). Multi-feature fusion using RF on VIs, texture, canopy cover, and growing degree days achieved $R^2 = 0.79$ with rRMSE = 0.24 t ha⁻¹ for potato AGB across the whole growth period (Xian et al., 2024). In-season UAV-based hyperspectral imagery with ML has also been used to predict end-of-season tuber yield and tuber set (Jiang et al., 2024). At field scale on commercial Prince Edward Island farms, Gradient Tree Boosting on Sentinel-2A achieved $R^2 = 0.71$ –0.78 with RMSE = 2.82–5.96 t ha⁻¹ for potato yield (Imtiaz et al., 2025), while Bagged Tree models on UAV imagery achieved relative RMSE of 12.7 % for in-season petiole nitrate concentration and relative RMSE of 13.8–20.5 % for pre-harvest tuber yield (Javed et al., 2025). While active optical sensing was initially perfected for cereal systems-Crop Circle canopy sensors for rice nitrogen status (Cao et al., 2013, 2016)-the ML-enabled N diagnosis pipeline is directly transferable to preconditioning potato yield models. Similarly, UAV-based rice nitrogen nutrition index prediction with machine learning (Zha et al., 2020) demonstrates a methodological template that root crop researchers have begun to adapt. For potato, red-edge and shortwave-infrared Sentinel-2 bands, and narrow-band hyperspectral indices combining red-edge with near-infrared wavelengths, consistently emerge as the most important predictors across studies (Yang et al., 2021; Jiang et al., 2024). Hyperspectral remote sensing of vegetation provides the spectral foundation for these indices (Thenkabail & Lyon, 2016). Remote estimation of crop and grass chlorophyll and nitrogen content using red-edge bands on Sentinel-2 and -3 has been demonstrated across crop types (Clevers & Gitelson, 2013).

5.2 Cassava

For cassava, the picture is markedly different because cassava's storage roots develop over an extended period under a comparatively sparse canopy, and structural features often outperform spectral VIs. Simple linear regression on UAV-derived average canopy height achieved $R^2 = 0.87$ (RMSE = 3.51 t ha⁻¹), whereas canopy area achieved $R^2 = 0.65$ and NDVI achieved only $R^2 = 0.58$ for cassava tuber yield (Rattanasopa et al., 2022). Among ML algorithms applied to UAV multispectral imagery for cassava root yield, k-Nearest Neighbours achieved $R^2 = 0.67$, Random Forest achieved $R^2 = 0.66$, and SVM achieved $R^2 = 0.64$ (Selvaraj et al., 2024). Notably, UAV-derived canopy height in cassava correlated with ground truth at $r = 0.92$, indicating that structural features are the strongest single predictor class for this crop (Selvaraj et al., 2024). Non-optical proxies also matter for cassava: ground-penetrating radar combined with Bayesian Ridge Regression achieved $r = 0.64$ and $R^2 = 0.41$ for cassava root biomass, a relatively modest performance but one achieved entirely without canopy observation (Agbona et al., 2021). GPR has separately been used to estimate cassava root bulking rate in field conditions (Agbona et al., 2021), and a low-cost aeroponic phenotyping system has enabled cassava storage root development studies that complement UAV observation (Fernando et al., 2022). Cassava disease pressure-cassava mosaic disease and cassava brown streak disease jointly causing annual losses exceeding USD 1 billion across sub-Saharan Africa-further constrains the canopy-root proxy and argues for disease-aware yield models (Ahmed et al., 2025). Beyond yield prediction per se, UAV-based unsupervised classification of cassava fields using K-means clustering with spectral trend analysis has achieved kappa = 0.96 for cassava, weed, and soil discrimination, providing a precondition for plot-level yield modelling in smallholder systems where field boundaries are ambiguous (Boonrang et al., 2024).

5.3 Sugar beet

For sugar beet, the most accurate results have come from UAV-RGB time-series approaches that track canopy cover and canopy height as growth curves. Pearson correlations between UAV-derived CC and CH growth-curve integrals and root weight reached $r = 0.89$, 0.89, and 0.92 across three breeding seasons, while correlations with sugar content were somewhat lower at $r = 0.79$, 0.83, and 0.77 (Taguchi et al., 2024). On UAV multispectral imagery, second-order polynomial regression on GNDVI vegetation pixels has been reported for sugar beet cultivar discrimination, although the published accuracy for direct yield estimation from a single VI remains modest (Drimzakas-Papadopoulos et al.,

2024). Across seven ML models trained on spectral VIs for sugar beet under different irrigation treatments, k-Nearest Neighbours achieved training $R^2 = 0.99$ but testing $R^2 = 0.64$, exposing substantial overfitting risk in high-dimensional VI feature spaces (İrik et al., 2024). For sugar beet, GNDVI and OSAVI consistently rank among the most important VIs, and the structural information encoded in canopy cover and height appears to compensate for the spectral saturation that affects NDVI in dense canopies. Process-based crop models including AquaCrop and DSSAT-SUBSTOR-Potato have been benchmarked for potato (Lin et al., 2023), but the analogous comparison for sugar beet remains less developed.

5.4 Peanut, sweet potato, and neglected root crops

For peanut, the most accurate published model combines Sentinel-2 time-series VIs with phenological parameters extracted using the iVI-Logistic algorithm. Random Forest achieved $R^2 = 0.82$ with $MAE = 0.29 \text{ t ha}^{-1}$ and $RMSE = 0.40 \text{ t ha}^{-1}$ for summer peanut yield (Hou et al., 2025). The phenological parameters-derived from GNDVI time series-encoded the timing of vegetative and reproductive transitions that control pod filling, and their inclusion outperformed models using VIs alone. Integrating satellite and UAV data to predict peanut maturity with normalised difference vegetation index has been demonstrated as a complementary approach (Silva, 2022). For sweet potato, UAV multispectral and thermal imagery under drought conditions identified canopy temperature as the best predictor of root storage yield under late-season drought, with CRed-edge correlating with leaf chlorophyll at $r = 0.66\text{--}0.76$ across drought treatments (Ramírez et al., 2023). Hybrid PROSAIL radiative transfer modelling combined with active learning and Kernel Ridge Regression has also been applied to LAI retrieval over twenty sweet potato varieties, achieving $R^2 = 0.52$ with $RMSE = 0.88 \text{ m}^2 \text{ m}^{-2}$ and providing a canopy structural input that can be combined with yield models (Tsele et al., 2025). For tiger nut (*Cyperus esculentus* L.), a non-traditional but increasingly studied root crop, Squeeze Net lightweight CNN on UAV multispectral imagery achieved $R^2 = 0.78$ with $RMSE = 716.6 \text{ kg ha}^{-1}$ for tuber yield (Li & Wu, 2023), demonstrating that deep learning can match or exceed Stepwise Multiple Linear Regression ($R^2 = 0.775$, $RMSE = 688.4 \text{ kg ha}^{-1}$) on the same input data while offering greater potential for transfer learning. Taro (*Colocasia esculenta* L.) and sweet potato have also been mapped using UAV multispectral and thermal imagery with Gradient Tree Boost classifiers, achieving overall accuracy of 0.95 and kappa of 0.9419 with object-based image analysis (Abrahams et al., 2026), and UAV multispectral-thermal data with deep neural networks has achieved $R^2 = 0.92$ for canopy equivalent water thickness prediction in taro, demonstrating the value of thermal bands and index-based soil-background segmentation for root crop water status monitoring (Ndlovu et al., 2024). Together these studies demonstrate that UAV-ML can support crop identification and water-status monitoring as preconditions for crop-specific yield modelling in smallholder cropping systems where mixed stands are common. A systematic review of UAV applications for mapping neglected and underutilised crop species' spatial distribution and health has documented 171 relevant studies, confirming the breadth of this emerging field (Abrahams et al., 2023).

5.5 Cross-crop synthesis

Cross-crop synthesis reveals three consistent patterns. First, structural features (canopy height, canopy cover, plant density) consistently improve yield prediction across all root crops, and their inclusion often exceeds the marginal benefit of additional spectral bands (Yu et al., 2023; Selvaraj et al., 2024). Estimating vertically growing crop above-ground biomass based on UAV remote sensing confirms the dominant role of structural features (Yue et al., 2023). Second, red-edge and shortwave-infrared spectral regions are disproportionately important across root crops because they capture chlorophyll and water content dynamics that standard indices like NDVI fail to resolve due to premature saturation (Gómez et al., 2019; Yang et al., 2021). Retrieval of crop biophysical parameters from Sentinel-2 remote sensing imagery has been demonstrated across multiple crops (Xie et al., 2019). Vegetation indices combining the red and red-edge spectral information for LAI retrieval have been developed specifically to address NDVI saturation (Xie et al., 2018). Third, the absolute accuracy gap between best-performing models ($R^2 \approx 0.87$ for cassava on UAV-derived canopy height) and typical models ($R^2 \approx 0.5\text{--}0.7$ for sugar beet on UAV) is largely explained by the maturity of the satellite-based pipeline for potato, the structural sparsity of cassava canopies, and the comparatively limited ML literature on sugar beet and peanut (Jiang et al., 2024).

Table 4. Crop-specific quantitative performance summary for UAV-satellite-ML subsurface yield prediction.

Crop	Best algorithm	Sensor/platform	Best R^2 / correlation	RMSE / MAE	Reference
Potato	SVM (SVMRadial)	Sentinel-2 (red, red-edge, NIR)	$R^2 = 0.66$	RMSE = 16.35 % of mean yield	Gómez et al., 2019
Potato	RF (S2 bands + PPI index)	Sentinel-2	$R^2 = 0.77$	RMSE = 15.42 %	Gómez et al., 2019
Potato	RF (S2 bands + NDVI + PPI)	Sentinel-2	$R^2 = 0.75$	RMSE = 14.75 %	Gómez et al., 2019

Potato	Random Forest	UAV hyperspectral + crop height	$R^2 > 0.90$ (AGB); $R^2 = 0.63$ (yield)	-	Li et al., 2020
Potato	PLSR (full spectrum)	UAV hyperspectral	$R^2 = 0.81$ (yield at 90 DAP)	-	Li et al., 2020
Potato	RF + cultivar covariate	UAV multispectral	Validation $R^2 = 0.75$ (from 0.48)	-	Li et al., 2021
Potato	Gradient Tree Boosting	Sentinel-2A (PEI, Canada)	$R^2 = 0.71\text{--}0.78$	RMSE = 2.82–5.96 t ha ⁻¹	Imtiaz et al., 2025
Potato	Bagged Trees (petiole NO ₃)	UAV multispectral	RRMSE = 12.7 %	RMAE = 9.6 %	Javed et al., 2025
Potato	Multi-task MLP (yield)	UAV multispectral + LiDAR	$R^2 = 0.60$ (test)	RMSE = 3.13 t ha ⁻¹	Chatraei Azizabadi & Badreldin, 2026
Cassava	Simple Linear Regression (avg height)	UAV multispectral	$R^2 = 0.87$	RMSE = 3.51 t ha ⁻¹ ; $r = 0.95$	Rattanasopa et al., 2022
Cassava	k-Nearest Neighbours	UAV multispectral	$R^2 = 0.67$	-	Selvaraj et al., 2024
Cassava	Bayesian Ridge Regression	Ground-penetrating radar	$R^2 = 0.41$	$r = 0.64$	Agbona et al., 2021
Cassava	K-means + spectral trend	UAV RGB	$\kappa = 0.96$	-	Boonrang et al., 2024
Sugar beet	Multiple regression (CC, CH integrals)	UAV RGB time-series	$r = 0.89\text{--}0.92$ (RW)	$r = 0.77\text{--}0.83$ (sugar content)	Taguchi et al., 2024
Sugar beet	Polynomial regression (GNDVI)	UAV multispectral	$R^2 = 0.34$	MAPE = 17.62 %	Drimzakas-Papadopoulos et al., 2024
Sugar beet	k-Nearest Neighbours (testing)	Proximal sensing VIs	$R^2 = 0.64$	Training $R^2 = 0.99$ (overfitting)	İrik et al., 2024
Peanut	Random Forest + phenology	Sentinel-2 time-series	$R^2 = 0.82$	MAE = 0.29 t ha ⁻¹ ; RMSE = 0.40 t ha ⁻¹	Hou et al., 2025
Sweet potato	UAV multispectral + thermal (drought)	UAV multispectral + thermal	$r = 0.66\text{--}0.76$ (CIred-edge vs Chl)	Canopy temperature best for yield under drought	Ramírez et al., 2023
Sweet potato	PROSAIL + AL + KRR (LAI)	UAV multispectral	$R^2 = 0.52$ (LAI)	RMSE = 0.88 m ² m ⁻²	Tsele et al., 2025
Tiger nut	Squeeze Net CNN	UAV multispectral	$R^2 = 0.78$	RMSE = 716.6 kg ha ⁻¹	Li & Wu, 2023
Taro	DNN (EWT) with ExGR segmentation	UAV multispectral + thermal	$R^2 = 0.92$ (EWT)	RMSE = 8.04 g m ⁻²	Ndlovu et al., 2024
Taro / Sweet potato	OBIA-GTB classifier	UAV multispectral (MicaSense Altum)	Overall accuracy = 0.95	$\kappa = 0.9419$	Abrahams et al., 2026

6. Current Challenges, Scalability, and Future Directions

Operationalising UAV-satellite-ML yield prediction for root crops at regional scale faces four interlocking challenges: computational cost, model transferability, environmental covariate integration, and the absence of foundation models tailored to root crop agroecosystems. Each challenge has begun to be addressed in the recent literature, but substantive evidentiary gaps remain that collectively define the research agenda for the next phase of the field.

Computational cost rises steeply with the fusion strategy. Pixel-level fusion of UAV and satellite imagery generates synthetic products whose volume can exceed that of either input stream by an order of magnitude, and the training of CNN or LSTM architectures on such products can require GPU resources that are inaccessible to many agronomic research groups (Xing et al., 2026). A systematic review of 162 UAS-satellite fusion studies in precision agriculture documented that the majority of published workflows remain at proof-of-concept scale, with regional deployment limited by both computational cost and by the difficulty of maintaining co-registration quality across heterogeneous landscapes (Bazrafkan et al., 2025). Feature-level fusion, in which UAV and satellite features are extracted independently and then concatenated, is computationally lighter and is the dominant approach in current root crop literature (Jiang et al., 2024). Decision-level fusion, in which independent model predictions are combined through ensembling, offers an intermediate computational profile and is particularly well suited to scaling because the satellite-only component can be applied across large regions while the UAV-only component is reserved for calibration (Somard et al., 2024). A review of precision agriculture and machine learning of machine learning and AI vision has documented the computational trade-offs across ML families (Padhiary et al., 2024).

Model transferability across regions, cultivars, and crop species remains the most consequential limitation. A model trained on one potato cultivar in one growing region cannot be directly applied to another cultivar or region without substantial accuracy loss, because cultivar-specific canopy architectures, planting densities, and stress responses modify the canopy-yield relationship (Li et al., 2021). The inclusion of cultivar information as a categorical covariate in RFR for potato yield improved validation R^2 from 0.48 to 0.75, demonstrating that even simple genotype-aware feature engineering can recover substantial accuracy (Li et al., 2021). Cross-crop transfer learning, in which a model trained on one root crop is fine-tuned on another, has been demonstrated for potato-to-sweet-potato transfer with $R^2 = 0.64$, but the absolute accuracy of the transferred model remains well below that of crop-specific models (Yadav et al., 2025). Random Forest models trained on Irish potato and maize in Rwanda achieved $R^2 = 0.875$ for potato yield, illustrating that transferability across agro-ecologies within the same crop species is feasible but not yet systematically benchmarked (Jiang et al., 2024). Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning has demonstrated the scalability of satellite-based DL pipelines (Sagan et al., 2021). To our knowledge, no study has directly examined cross-region transfer of UAV-satellite fusion models for cassava or sugar beet, and this remains an untested assumption in the literature. Direct evidence on the performance degradation of satellite-ML yield models when applied across contrasting soil types within a single crop species is also currently limited, and the available cross-soil comparisons focus on above-ground rather than below-ground biomass.

Environmental covariate integration is widely recognised as necessary but unevenly implemented. Soil moisture, weather, and management inputs encode the below-ground conditions that canopy signals cannot capture, and their inclusion in ML feature spaces typically improves yield prediction accuracy (Singh et al., 2025). Multi-task learning architectures that share representations between yield and correlated physiological traits-petiole nitrate, canopy temperature, leaf water content-offer a more principled route to covariate integration than simple feature concatenation, and have been demonstrated for potato at the row-closure stage (Chatraei Azizabadi & Badreldin, 2026). The systematic review of remote sensing for potato irrigation management documented $R^2 > 0.81$ –0.90 for canopy transpiration and leaf water content models that fuse UAV thermal imagery with proximal soil moisture sensors, illustrating the value of paired ground-canopy observation (Singh et al., 2025). Irrigation management in potato production has been reviewed for its sustainability implications (Djaman et al., 2021). Hybrid models that fuse weather data, soil properties, and management features alongside remote sensing inputs have consistently outperformed single-source architectures for cereal crops (Xing et al., 2026), and the same pattern is expected for root crops as the relevant benchmark datasets become available. Maize canopy temperature extracted from UAV thermal and RGB imagery and its application in water stress monitoring exemplifies the integration of thermal covariates (Zhang et al., 2019). Estimation of soil moisture content under high maize canopy coverage from UAV multimodal data and machine learning demonstrates the value of proximal-soil covariates (Cheng et al., 2022).

Earth Observation Foundation Models, pre-trained on massive multi-sensor satellite archives and adaptable to downstream tasks with limited labelled data, represent the most promising route to scalable subsurface yield prediction (Xing et al., 2026). To our knowledge, no published study has directly evaluated an EO Foundation Model for root crop yield prediction, and this represents a substantive evidentiary gap. The closest available evidence comes from transfer learning experiments in cereal crops, where pre-trained CNN features have been fine-tuned for wheat and maize yield with competitive accuracy, but the transfer of EO Foundation Model features to root crop yield prediction-where the canopy-target relationship is structurally different from cereals-has not been systematically tested. A systematic review of deep learning for crop yield prediction noted that vegetation indices remain the most used feature class in current DL workflows, and that the integration of foundation-model-derived embeddings with crop-specific canopy proxies is an open research question (Muruganantham et al., 2022). The potential of EO Foundation Models to replace bespoke architectures is considerable, because they would reduce the per-crop, per-region labelling burden that currently constrains the field, but their applicability to the subsurface yield prediction problem requires empirical

validation. Remote-sensing data and deep-learning techniques in crop mapping and yield prediction have been systematically reviewed for their DL architecture implications (Joshi et al., 2023).

Several additional substantive evidentiary gaps define the research agenda for the next phase of the field. First, no published study has directly evaluated an EO Foundation Model for root crop yield prediction; the closest available evidence concerns cereal crops and was treated as a proxy throughout this review. Second, cross-region transfer of UAV-satellite fusion models for cassava and sugar beet remains untested in the literature reviewed here; cross-crop transfer has been demonstrated only for the potato-to-sweet-potato case (Yadav et al., 2025). Third, performance degradation of satellite-ML yield models across contrasting soil types within a single root crop species is not systematically reported in the available literature, with the cross-soil comparisons that do exist focusing on above-ground rather than below-ground biomass. Fourth, the integration of ground-penetrating radar with UAV-satellite fusion for cassava root biomass has been explored only for radar alone (Agbona et al., 2021), and the three-way fusion of GPR, UAV, and satellite data for subsurface yield prediction appears to be untested. Fifth, standardised benchmark datasets spanning multiple cultivars, seasons, and stress conditions for each root crop species are not currently available, and their absence is a structural impediment to cross-study comparison and to the training of transferable models.

Methodological transparency and reproducibility remain uneven across the literature. The MAPE threshold for acceptable yield prediction is conventionally set at less than 15 %, with advanced algorithms targeting less than 10 % (Piekutowska & Niedbała, 2025), but the heterogeneity of ground-truth protocols, train-test splits, and cross-validation schemes makes direct cross-study comparison hazardous. Standardised benchmark datasets-covering multiple cultivars, seasons, and stress conditions for each root crop species-would substantially accelerate progress, and their absence is a structural impediment to the field (Jiang et al., 2024). The convergence of mechanistic agronomy, multi-scale remote sensing, and representation learning is now sufficient to make subsurface yield prediction for root crops a tractable problem; the remaining barriers are operational rather than conceptual, and their resolution will determine whether the proof-of-concept accuracies documented in this review translate into regional decision support.

Table 5. Operational challenges and future research directions for scaling subsurface yield prediction.

Challenge	Current state	Evidentiary gap	Future direction
Computational cost	Feature-level fusion dominant; CNN/LSTM pipelines GPU-bound (Bazrafkan et al., 2025)	Public benchmarks of fusion-pipeline compute cost vs accuracy not available	Lightweight CNNs (e.g., Squeeze Net; Li & Wu, 2023); cloud-native fusion pipelines
Model transferability	Cultivar covariate improves potato RFR from 0.48 to 0.75 (Li et al., 2021); cross-crop transfer to sweet potato $R^2 = 0.64$ (Yadav et al., 2025)	Cross-region transfer for cassava, sugar beet, peanut untested	Domain-adversarial training; standardised multi-region benchmarks
Environmental covariate integration	Multi-task learning for potato ($R^2 = 0.60$; Chatraei Azizabadi & Badreldin, 2026); hybrid weather+RS in cereals	Quantitative marginal-accuracy gain of covariate integration in root crops not benchmarked	Multi-task architectures with shared representations; paired ground-canopy sensor networks
Foundation models	Pre-trained CNN features in cereals only; no root-crop evaluation	EO Foundation Models for root crop yield prediction not tested	Adapt Prithvi / SatMAE / Clay to potato, cassava, sugar beet; benchmark vs bespoke models
Three-way GPR + UAV + satellite fusion	GPR alone for cassava root biomass ($R^2 = 0.41$; Agbona et al., 2021)	Three-way fusion of GPR, UAV, satellite for subsurface yield prediction untested	Multi-sensor calibration frameworks integrating GPR depth profiles with canopy RS
Reproducibility	MAPE < 15 % accepted; < 10 % advanced (Piekutowska & Niedbała, 2025)	Heterogeneous train/test splits; no shared benchmark datasets	Open benchmark datasets spanning cultivars, seasons, stress conditions; standardised reporting

7. CONCLUSION

The synthesis of evidence from approximately ninety peer-reviewed studies establishes that UAV-satellite data fusion combined with machine learning has reached a level of maturity at which subsurface yield prediction for root crops is

operationally feasible at the field scale, with crop-specific best accuracies reaching $R^2 = 0.77$ for potato on Sentinel-2 RF (Gómez et al., 2019), $R^2 = 0.87$ for cassava on UAV-derived canopy height (Rattanasopa et al., 2022), $r = 0.89$ – 0.92 for sugar beet on UAV-derived growth-curve integrals (Taguchi et al., 2024), and $R^2 = 0.82$ for peanut on Sentinel-2 phenological features (Hou et al., 2025). The mechanistic logic connecting above-ground canopy traits to below-ground storage organ biomass is now well characterised for each of the major root crops, and the spatiotemporal trade-offs between UAV and satellite sensing are routinely reconciled through pixel-, feature-, or decision-level fusion depending on the prediction problem (Bazrafkan et al., 2025). Random Forest, Support Vector Machine, and gradient boosting methods dominate current yield prediction pipelines because they combine competitive accuracy with computational tractability, while CNN, LSTM, and multi-task architectures increasingly enable multi-temporal and multi-modal inference that captures the dynamic nature of canopy-root coupling across the growing season (Piekutowska & Niedbała, 2025).

Definitive next steps to operationalise these models for real-world agronomic use fall into four categories. First, the community must develop standardised benchmark datasets for each root crop species, spanning multiple cultivars, soil types, and stress conditions, to enable rigorous cross-study comparison and to support the training of transferable models. Second, cross-region and cross-crop transfer learning must be systematically evaluated, with explicit reporting of accuracy degradation relative to in-region and in-crop baselines. Third, Earth Observation Foundation Models must be adapted and benchmarked for root crop yield prediction, because they offer the most credible route to reducing the per-crop, per-region labelling burden that currently constrains the field. Fourth, environmental covariate integration must move beyond feature concatenation toward principled multi-task architectures that share representations between yield and correlated physiological traits. The convergence of mechanistic agronomy, multi-scale remote sensing, and representation learning is now sufficient to make subsurface yield prediction for root crops a tractable problem; the remaining barriers are operational rather than conceptual, and their resolution will determine whether the proof-of-concept accuracies documented in this review translate into regional decision support.

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