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SYSTEMATIC REVIEW

Remote monitoring of soil physicochemical properties via UAV in precision agriculture: Systematic review and comparative analysis

[version 1; peer review: awaiting peer review]

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Abstract

The monitoring of soil physicochemical properties represents a fundamental requirement for precision agriculture, enabling site-specific resource management and the optimization of crop productivity. This systematic review analyses 21 scientific studies published between 2020 and 2025 on the application of UAV (Unmanned Aerial Vehicle) technologies for the remote monitoring of soil properties in agricultural contexts. The articles were selected through the PRISMA protocol from international scientific databases, focusing on applications related to soil moisture, fertility and nitrogen content, salinization, and organic matter. The comparative analysis highlights the clear predominance of indirect approaches based on vegetative response, with differentiated indices for each target parameter: NDRE proves superior to NDVI for leaf nitrogen, while the thermal indices TDDI and TVDI reach R^2=0.966 for water content. Random Forest and ensemble methods demonstrate systematic superiority over SVM and linear models, with accuracy gains ranging from 3% to 15%. UAV-Satellite integration produces gains in R^2 of up to 0.384, combining the high spatial resolution of UAV with regional satellite coverage. Spectral mixing issues in row crops require specific unmixing or threshold optimization techniques, while acquisition timing proves critical for maximising correlations with agronomic parameters. Accuracy varies with soil depth, being optimal for surface layers (0–10 cm). Future directions include the development of sensors with greater penetration depth, integration with emerging technologies (such as LiDAR and hyperspectral sensing) and deep learning techniques, as well as the standardisation of multi-temporal protocols for the quantitative assessment of management practices

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over the long term.

Plain Language summary
Knowing what is happening beneath our feet is essential for modern farming. Healthy soil means better crops, less waste, and fewer chemicals. But measuring soil properties across large fields has traditionally been slow, expensive, and labour-intensive. This review analysed 21 scientific studies published between 2020 and 2025 to understand how agricultural drones — small, unmanned aircraft equipped with sensors and cameras — can help monitor key soil properties such as moisture, nitrogen, salinity, and organic matter, without touching the ground. The main finding is that drones do not usually "see" the soil directly. Instead, they read the health signals of the plants growing above it. A stressed or nutrient-deficient crop reflects light differently, and drone sensors can detect those differences with great precision. Specialised vegetation indices — essentially mathematical combinations of different light wavelengths — allow scientists to estimate what is happening in the soil from above. When drone data is combined with satellite imagery, accuracy improves even further, offering both fine detail at field level and broader regional coverage. Among the analytical methods tested, machine learning algorithms — particularly Random Forest — consistently outperformed traditional statistical models, improving prediction accuracy by up to 15%. One important limitation is depth: drone-based remote sensing works best for the topmost 10 cm of soil. Deeper layers remain harder to assess remotely. Looking ahead, researchers point to hyperspectral sensors, LiDAR, and artificial intelligence as the next frontier — tools that could make routine, large-scale soil monitoring faster, cheaper, and more accessible for farmers everywhere.

Keywords
Unmanned Aerial Vehicles, precision agriculture, soil monitoring, machine learning, remote sensing, vegetation indices



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1. Introduction

1.1 Precision agriculture and soil monitoring

The sustainable management of agricultural soils represents one of the main challenges for modern agriculture, which is called upon to meet growing global food demand (FAO et al., 2024) while minimising its environmental impact. The physicochemical properties of the soil, such as moisture content, nutrient availability, salinity, and organic matter content, directly determine crop productivity and the quality of agricultural produce. However, these properties are characterised by high spatial and temporal intra-field variability, requiring differentiated management approaches to optimise resource use.

Traditional soil monitoring methods rely on point sampling followed by laboratory analyses (Zhang et al., 2025; Avioz et al., 2024). However, these approaches present significant limitations: they are time- and cost-intensive, require specialised labour, and are inherently destructive. Moreover, the point-based nature of the measurements does not adequately capture the spatial variability of soil parameters at the level of individual plots, making the implementation of site-specific management strategies difficult. These limitations make it necessary to develop alternative methodologies that allow for rapid, non-destructive, and spatially exhaustive monitoring of soil conditions.

1.2 UAV-based remote sensing: Opportunities and advantages

Remote sensing has revolutionised agricultural monitoring over recent decades. Traditionally, satellite platforms have provided regional-scale data, enabling the monitoring of large agricultural areas. However, satellite systems present limitations related to spatial resolution (generally in the order of metres or tens of metres), temporal resolution constrained by revisit times, and dependence on atmospheric conditions that can compromise acquisition quality.

In recent years, remotely piloted aircraft (*UAV, Unmanned Aerial Vehicles*) have opened new perspectives in agricultural remote sensing. These systems offer significant advantages over satellite platforms and traditional aircraft: they allow for the acquisition of images at very high spatial resolution (down to a few centimetres), guarantee operational flexibility with the possibility of planning acquisitions synchronised with specific phenological stages, and present contained operational costs for farm-scale monitoring.

UAVs can be equipped with various types of sensors. Multispectral sensors, featuring discrete bands in the visible and near-infrared regions, allow the calculation of vegetation indices widely used for estimating crop parameters and, indirectly, soil properties. Hyperspectral sensors acquire hundreds of contiguous spectral bands, enabling detailed analyses of the absorption and reflectance characteristics associated with specific soil and vegetation components. Thermal infrared sensors detect surface temperature, providing information on the water status of crops and soil. The integration of these different sensor types has given rise to multi-sensor approaches that have significantly improved estimation accuracy (Zhu et al., 2024; Khose and Mailapalli, 2024; Avioz et al., 2024).

1.3 Knowledge gap and objectives

Despite growing interest in the use of UAVs in precision agriculture, the majority of published studies focus on the monitoring of vegetation characteristics, such as biomass, chlorophyll content, leaf area index, and crop nutritional status. Comparatively less attention has been devoted to the direct monitoring of soil properties, and a systematic synthesis of the most effective methodologies for this specific purpose is lacking. This imbalance is likely due to the traditional approach that has always considered the plant as the exclusive focus of agronomic practices. The supply of nutrients in the form of mineral fertilisers has been regarded as the most effective method for meeting crop requirements, treating nitrogen, phosphorus, and potassium as “medical therapies” to be administered to a sick organism. However, growing scientific evidence demonstrates the need for a paradigm shift in order to reverse the trend, documented over recent decades, of a slow but steady decline in organic matter in agricultural soils (Wiesmeier et al., 2016; Lal, 2020). Instead of exclusively monitoring and feeding “the patient”, i.e., the plant, attention should shift to nourishing the soil itself, so that the conditions for healthy crop growth are guaranteed a priori. A soil in good health inherently produces healthy plants, and in the long term this approach represents the winning strategy for improving the soil's capacity to retain and supply nutrients, reducing losses through volatilisation and leaching, and increasing organic matter content, while minimising the need for external inputs. In this context, it becomes essential to distinguish between direct approaches, based on spectral analysis of bare soil, and indirect approaches, which estimate soil parameters through the spectral response of vegetation used as a biological indicator. Both strategies focus on the soil; however, each presents advantages and limitations that require in-depth comparative evaluation. The present work aims to fill this knowledge gap through a systematic review of recent scientific literature focused on the use of UAV systems for the monitoring of soil physicochemical properties in precision agriculture contexts. The main objective is to provide an integrated overview of the methodologies developed, comparing the performance of different methodological approaches, sensors, spectral indices, and data processing algorithms.

The research questions guiding this review are:

1. What are the most effective methodologies for estimating soil moisture, nutrient content and availability, and salinity through UAV remote sensing?

2. How do direct and indirect approaches perform in estimating soil parameters?

3. Which sensors, spectral indices, and machine learning algorithms provide the most accurate results for each parameter considered?

4. What are the advantages of integrating UAV data with other sources of information (satellite, proximal sensors, field sampling)?

5. What are the current limitations and future prospects for the operational implementation of these technologies for soil monitoring?

2. Materials and methods

2.1 Systematic review methodology

This systematic review was conducted following the PRISMA (*Preferred Reporting Items for Systematic Reviews and Meta-Analyses*) guidelines. The PRISMA protocol provides a structured approach in four main phases: identification, screening, eligibility assessment, and inclusion of studies, transparently documenting the selection criteria and the reasons for exclusion at each stage of the process. The risk of bias was minimised by having two reviewers work independently. Any disagreements were resolved through discussion with a third reviewer.

The selection process followed three progressive filtering phases, described below.

Initial filter. The first search phase was based on the use of specific keywords related to the subject of study. The Boolean search terms used were: “Dron” OR “UAV” (to identify studies based on unmanned aerial platforms), “Monitor” OR “assess” (to focus attention on monitoring and assessment), “Soil” (to restrict studies to soil properties), and “Health” OR “quality” OR “index” (to include parameters related to soil health and quality). This search strategy produced a total of 161 potentially relevant articles.

First selection. The second phase applied more stringent inclusion/exclusion criteria. Only articles addressing the specific subject of interest were selected, published in English to ensure accessibility and comparability of results, available in open access mode to allow full access to the content, and published from 2018 onwards to ensure the temporal relevance of the methodologies and technologies described. This screening phase reduced the corpus to 69 articles.

Second selection. The final phase involved an in-depth evaluation of the studies through reading the abstracts and analysing the correlation between the analysis methodology employed and the use of drones/UAVs for soil monitoring. Only studies presenting a clear integration between UAV remote sensing and soil property analysis were included in the final review, excluding research focused exclusively on vegetation or other aspects not directly relevant. At the end of this process, 21 articles were selected for in-depth analysis and inclusion in this review; to facilitate reading, they are referred to as reported in Table 1.

The literature search was conducted on Google Scholar, with the last search performed on 31 October 2025. The abbreviations used in the text are listed in Table 0, in the attachments section.

3. Results and discussion

3.1 Agricultural productions and topics addressed

The studies included in the review cover a wide range of cropping systems, reflecting the versatility of UAV technologies in soil monitoring across different agronomic contexts. With regard to agricultural productions, three articles focus on vineyards, three on maize, three on citrus orchards, two on wheat, two on agroforestry systems, two on cotton, two on horticultural crops, and two on other crops. Individual studies are dedicated to kiwifruit and to the restoration of former quarry sites, demonstrating the applicability of these technologies in non-strictly agricultural contexts as well. The breakdown of articles by type of land use is reported in Table 2.

Table 0. **List of abbreviations.**

Acronym	Full Name
Vegetation Indices	
NDVI	Normalized Difference Vegetation Index
NDRE	Normalized Difference Red Edge
EVI	Enhanced Vegetation Index
EVI2	Two-Band Enhanced Vegetation Index
GNDVI	Green Normalized Difference Vegetation Index
SAVI	Soil Adjusted Vegetation Index
MSAVI	Modified Soil Adjusted Vegetation Index
OSAVI	Optimized Soil Adjusted Vegetation Index
RDVI	Renormalized Difference Vegetation Index
RVI	Ratio Vegetation Index
WDRVI	Wide Dynamic Range Vegetation Index
RESAVI	Red Edge Soil Adjusted Vegetation Index
RERVI	Red Edge Ratio Vegetation Index
REDVI	Red Edge Difference Vegetation Index
RERDVI	Red Edge Renormalized Different Vegetation Index
TVI	Triangular Vegetation Index
DVI	Difference Vegetation Index
ARVI	Atmospherically Resistant Vegetation Index
VARI	Visible Atmospherically Resistant Index
NDREg	Normalized Difference Red-Edge Green
MCARI	Modified Chlorophyll Absorption in Reflectance Index
TCARI	Transformed Chlorophyll Absorption in Reflectance Index
GI	Green Index
NDGI	Normalized Difference Greenness Index
NDSI	Normalized Difference Spectral Index
CRSI	Canopy Response Salinity Index
CI-g	Chlorophyll Index Green
MSR	Modified Simple Ratio
GRVI	Green Ratio Vegetation Index
RECI	Red-Edge Chlorophyll Index
GCI	Green Chlorophyll Index
SCCCI	Simplified Canopy Chlorophyll Content Index
PSRI	Plant Senescence Reflectance Index
NPCI	Normalized Pigment Chlorophyll Index
SRPI	Simple Ratio Pigment Index
Thermal and Drought Indices	
CWSI	Crop Water Stress Index
TDDI	Three-Dimensional Drought Index
TVDI	Temperature Vegetation Drought Index
Nitrogen and Biomass Parameters	
CNC	Canopy Nitrogen Content
LNC	Leaf Nitrogen Content

Table 0. *Continued*

Acronym	Full Name
ABG	Aboveground Biomass
LAI	Leaf Area Index
PFPN	Partial Factor Productivity of Nitrogen
NUE	Nitrogen Use Efficiency
Nmin	Mineral Nitrogen Available in Soil
Soil Parameters	
SMC	Soil Moisture Content
SOC	Soil Organic Carbon
TN	Total Nitrogen
SOM	Soil Organic Matter
SNN	Soil Nitrate Nitrogen
SAL	Total Soil Salinity
EC	Electrical Conductivity
Machine Learning Algorithms	
RF	Random Forest
GA-RF	Genetic Algorithm-Random Forest
SVM	Support Vector Machine
ANN	Artificial Neural Network
PLSR	Partial Least Squares Regression
CatBoost	Categorical Boosting
Texture Features	
GLCM	Gray Level Co-occurrence Matrix
Other Parameters	
PS	Planting Structure
SL	Slope
UAV	Unmanned Aerial Vehicle

From a thematic standpoint, the analysis of the articles reveals a distribution of content across several key issues in soil management. Eight articles address the monitoring of soil moisture and water stress, representing the most studied thematic area, followed by six articles on fertility and nutrient management. Two articles focus on soil compaction, two on contamination, two on spatial heterogeneity of the soil, two on erosion, and two on salinization. Individual studies address topics such as spectral background noise and soil organic matter. The breakdown of articles by topic is reported in Table 3.

This distribution highlights how UAV remote sensing has been applied predominantly to the monitoring of dynamic parameters such as moisture and nutritional status, while more stable soil properties have received comparatively less attention in recent literature.

3.2 Analysis algorithms

The processing of data acquired via UAV has relied predominantly on machine learning algorithms, with particular emphasis on ensemble methods. *Random Forest* (RF) emerges as the most frequently used algorithm, followed by *Support Vector Machine* (SVM), artificial neural networks (ANN), and *CatBoost.* Some studies have adopted hybrid approaches combining UAV data with satellite imagery (mainly from Sentinel-2) and field measurements, exploiting synergies across different spatio-temporal scales. Model validation was conducted through *cross-validation* techniques and comparison with reference measurements obtained from field sampling and laboratory analyses.

Table 1. Classification of articles.

ID	Titolo
N2	Drone multispectral imaging captures the effects of soil mineral nitrogen on canopy structure and nitrogen use efficiency in wheat.
N5	Optimization of multi-dimensional indices for kiwifruit orchard soil moisture content estimation using UAV and ground multi-sensors.
N8	Assessment of vineyard vigour and yield spatio-temporal variability based on UAV high resolution multispectral images.
N10	Assessing mixed-pixels effects in vineyard mapping from Satellite: A proposal for an operational solution.
N14	Soil moisture content estimation of drip-irrigated citrus orchard based on UAV images and machine learning algorithm in Southwest China.
N17	Monitoring opencast mine restorations using Unmanned Aerial System (UAS) imagery.
N22	Integrating UAV hyperspectral data and radiative transfer model simulation to quantitatively estimate maize leaf and canopy nitrogen content.
N24	Regional-scale precision mapping of cotton suitability using UAV and satellite data in arid environments.
N27	Modelling of the trade-off between the deep soil moisture and vegetation restoration in the hilly area of the Loess Plateau, China.
N28	Grapevine and cover crop spectral response to evaluate vineyard spatio-temporal variability.
N30	Spatial-temporal heterogeneity of yield, protein concentration, and leaf area index in grassland agroforestry systems can be modeled from UAV-borne imagery.
N32	Mapping tillage direction and contour farming by object-based analysis of UAV images.
N34	Optimization of soil background removal to improve the prediction of wheat traits with UAV imagery.
N36	Multi-scale remote sensing for sustainable citrus farming: Predicting canopy nitrogen content using UAV-satellite data fusion.
N38	Spatial mapping of soil moisture content using very-high resolution UAV-based multispectral image analytics.
N39	Inversion of citrus SPAD value and leaf water content by combining feature selection and ensemble learning algorithm using UAV remote sensing images.
N40	Monitoring soil salinization in Arid cotton fields using Unmanned Aerial Vehicle hyperspectral imagery.
N41	Cover crop impacts on soil organic matter dynamics and its quantification using UAV and proximal sensing.
N51	Estimation of corn nitrogen demand under different irrigation conditions based on UAV multispectral technology.
N62	Enhancing maize above-ground biomass estimation through multispectral, digital and LiDAR fusion on UAV platforms.
N68	Assessing plant pigmentation impacts: A novel approach integrating UAV and multispectral data to analyze atrazine metabolite effects from soil contamination.

3.3 Comparative analysis by topic

The comparative analysis presented here is based on the breakdown of articles by topic as previously reported in Table 3. Given the narrative nature of this review, no meta-analytical pooling of data was performed. For each outcome considered (soil moisture, nitrogen content, salinity, and organic matter), results are synthesised by comparing the effect measures reported in the individual studies. The certainty of evidence for each finding was assessed based on the degree of convergence across the included studies. Statements supported by a higher number of independent studies were considered more robust and were given greater weight in the synthesis. The coefficient of determination (R^2) and root mean square error (RMSE) were the predominant metrics used across studies for evaluating predictive model performance and are used consistently throughout this review for cross-study comparison. Where individual studies reported Pearson's correlation coefficient (r) or percentage accuracy gains, these are specified explicitly in the text.

3.3.1 Soil moisture and water stress

The monitoring of soil water content (SMC) by means of UAV represents the most extensively studied application, with seven dedicated articles (N5, N14, N24, N27, N38, N39, N51). Most approaches rely on indirect estimation through the

Table 2. Articles divided by type of land use.

N° of Articles	Crops	Other use
3	Vineyard	
3	Corn	
3	Orange	
2	Wheat	
2	Agroforestry systems	
2	Cotton	
2	Vegetables	
2	Mixed crops	
1	Actinidia	
1		Former Quarries

vegetation response (N14, N24, N27, N39, N51), whereas only study N38 directly analyses bare soil, revealing an inverse relationship between reflectance and moisture that is particularly robust down to a depth of 5 cm.

Random Forest emerges as the dominant algorithm, used in four of the seven studies (N14, N24, N27, N38), with GA-RF models achieving the best performance by combining vegetation indices and SPAD values for estimates at variable depths (5–40 cm). The multidimensional thermal indices TDDI and TVDI demonstrate superiority over traditional vegetation indices (N5, N14, N39), with study N5 reaching R^2=0.966 by combining CatBoost with TDDI for SMC estimation in the root zone.

Multi-sensor UAV+Satellite integration proves to be an effective strategy for regional upscaling (N14, N24, N38), with study N24 achieving significant correlations (R^2=0.498–0.745) by combining UAV and satellite data (Sentinel-2°). GLCM texture features, integrated with spectral indices, improve the accuracy of SMC estimates compared to using vegetation indices alone (N14, N38, N39).

Investigation depth requires differentiated strategies: maximum accuracy is achieved for surface layers (0–10 cm), while for greater depths (>60 cm), multi-source integrations are necessary (N5, N14, N24, N27). The temporal resolution of UAVs proves crucial for phenological monitoring, enabling acquisitions synchronised with critical crop stages and revealing the dynamic variability of soil properties across different growth phases (N5, N24, N39, N51).

3.3.2 Soil fertility and nitrogen content

UAV-based nitrogen monitoring relies on indirect approaches that exploit the relationship between soil nitrogen availability and vegetation development. The comparative analysis of six studies (N2, N22, N28, N36, N51, N62) reveals distinctive methodological strategies.

The spatial variability of mineral nitrogen available in the soil (Nmin) directly influences the structural characteristics of the *canopy*, enabling indirect estimation through vegetation indices (N2). The NDRE (Normalized Difference Red Edge) index emerges as the highest-performing index relative to the traditional NDVI in estimating canopy nitrogen content (CNC), being less susceptible to chlorophyll saturation effects (N51). The effectiveness of NDRE is confirmed by its ability to link nitrogen dynamics to biomass accumulation and yield (N2, N36, N51).

Hybrid approaches integrating mechanistic models with remotely sensed vegetation indices produce lower root mean square errors compared to individual empirical approaches, enabling accurate estimation of leaf nitrogen content (LNC) and canopy nitrogen content (CNC) (N22). Multi-level approaches integrating UAV data with Sentinel-2 satellite imagery and ground-based measurements achieve superior performance compared to the exclusive use of vegetation indices or terrestrial data (N22, N36, N62).

The incorporation of topographic factors such as slope significantly improves the accuracy of above-ground biomass estimates (N62). Study N28 highlights the role of cover crops in fertility management, showing higher soil organic carbon (SOC) and total nitrogen (TN) contents in areas with high NDVI values for both the main crop and the cover crop.

Table 3. Articles sorted by topic.

N° of Articles	Topic covered
8	Moisture, Water stress
6	Fertility, Nutrients
2	Soil compaction
2	Soil contamination
2	Spatial variability
2	Erosion
2	Salinity
1	Background noise
1	Organic matter

The partial factor productivity of nitrogen (PFPN), defined as the grain yield produced per unit of nitrogen fertiliser applied, can be estimated with good precision using UAV data (N51, N2). All of the studies analysed use indirect approaches based on vegetation monitoring, highlighting how the quantification of nitrogen in the soil requires mediation through the vegetative response.

It is important to emphasise a limitation shared by all the studies analysed: the approach used for the quantification of nitrogen in the soil is indirect and relies exclusively on vegetation monitoring, confirming the different value attributed to products rather than to the substrates that generate them. This fact also entails a series of operational implications in terms of acquisition timing (linked to phenological stages) and interpretation of results (it is more difficult to obtain accurate estimates using only indirect remotely sensed data).

3.3.3 Soil salinization

UAV-based salinization monitoring involves two studies conducted in arid environments (N24, N40) employing complementary approaches based on indirect estimation through the analysis of vegetative stress. A first finding indicates that increases in total soil salinity generate water and nutritional stress in plants, causing a reduction in chlorophyll content that translates into alterations in the spectral pattern in the 444–510 nm and 565–675 nm bands (N40). Hyperspectral sensors mounted on UAVs allow the indirect estimation of salinity with R^2=0.92 using the PSO-GPR model, with a strong correlation (r=0.79–0.99) between total soil salinity and electrical conductivity EC1:5 (N40).

An innovative finding concerns monitoring under plastic mulch (N40), where capillary rise concentrates salt in surface layers, a condition otherwise inaccessible to direct remote sensing. The response of the surrounding vegetation provides an effective proxy indicator, enabling the indirect monitoring of salinization.

The integrated UAV+Sentinel-2A approach combines the joint monitoring of moisture and salinity by means of Random Forest, generating a dual-factor suitability index for cotton cultivation suitability maps at municipal scale. The integration of high-resolution UAV data with Sentinel-2A significantly improves the accuracy of the RF model, with R^2 gains ranging from 0.114 to 0.384 when reflectivity corrections are applied to the satellite data (N24).

The co-limitation of salinity and water stress in arid environments requires integrated monitoring strategies that consider both factors simultaneously. Estimation accuracy is superior for surface layers (0–10 cm) compared to greater depths (10–20 cm), highlighting the need for targeted management of irrigation and drainage to support sustainable production in arid climates.

3.3.4 Soil organic matter and soil dynamics

Article N41 provides an in-depth analysis of the potential of UAV remote sensing in monitoring soil organic matter (SOM), with particular emphasis on the role of cover crops in counteracting the decline of SOM in intensive agricultural systems. The study documents a mean reduction of 2.3 g SOM/kg of soil after six years from the start of the experiment, highlighting how cover crops can effectively counteract this decline. In particular, cover radish and the radish-oat mixture significantly reduced SOM losses compared to bare fallow. The use of hyperspectral cameras mounted on UAVs enabled

the mapping of spatial variability in SOM content, with the Random Forest model achieving R^2=0.69. The remote sensing approach improved data collection efficiency in a non-destructive manner, increasing the spatial and temporal resolution of intra-field SOM quantification. However, a critical result emerges: the natural variability of SOM within the field is often greater than the differences induced by cover crop management practices. This underlines the importance of temporal mapping of SOM variations at field level to understand the actual dynamics and distinguish management effects from the intrinsic variability of the soil. The combination of UAV data with proximal sensing allowed greater accuracy in SOM estimation, suggesting that the integration of different acquisition platforms and investigation scales represents the optimal strategy for monitoring organic carbon dynamics in agricultural systems. The capacity to quantify SOM through non-destructive, high spatial and temporal resolution approaches opens up significant prospects for evaluating the impacts of conservation practices and for monitoring ecosystem services related to soil carbon sequestration.

3.4 Cross-cutting methodological issues

3.4.1 Spectral mixing and background noise

The discontinuity of the canopy in row crops generates spectral mixing between vegetation and the inter-row space, a problem that is particularly severe in Sentinel-2 data at 10 m resolution. Study N10 develops a spectral unmixing method based on local least squares with a moving window, achieving relative errors of 16% in separating the NDVI signal of vines from that of the inter-row. The method uses a two-endmember linear model with UAV-derived cover fractions but requires high precision (~3%) since the conditioning index (K2=14) amplifies errors by approximately 14 times. Complementary to unmixing, study N34 develops a threshold value optimization (TVO) methodology for wheat, identifying optimal thresholds between 0.1 and 0.3 for the sequential removal of bare soil pixels. The effectiveness of TVO is evident in early stages (GS32), significantly improving yield and nitrogen output estimates, while at anthesis (GS65) it provides limited improvements, highlighting the phase-dependent impact of soil background removal.

3.4.2 Vegetative vigour and spatio-temporal variability

Study N8 on vineyards documents how NDVI and NDRE show the highest correlations with yield during the berry growth stage, while GNDVI emerges as the optimal index for the accumulation of total soluble sugars (TSS). Acquisition timing proves critical: for vegetative vigour (shoot pruning weight), pre-veréaison acquisitions show the most robust correlations with NDVI, whereas during the late stages of chlorophyll senescence, correlations decrease significantly. Study N28 reveals a positive spatial autocorrelation (Moran's I=0.54) between the vigour of winter cover crops and summer vineyard growth, with high-NDVI areas in both crops associated with higher SOC and total soil nitrogen contents. The high temporal resolution of UAVs enables phenological monitoring synchronised with critical growth stages, distinguishing transient effects of water stress from permanent ones linked to pedological characteristics.

3.4.3 Bare soil applications

UAV monitoring of bare soil opens up innovative application prospects. Study N32 develops an object-based approach for mapping tillage directions and contour farming through the analysis of spatial patterns in high-resolution RGB images, enabling the discrimination of different tillage techniques and the evaluation of conservation practices for erosion control. In the context of contaminant monitoring, study N68 demonstrates that the NDVI, GNDVI, and CCCI indices show significant correlations (R^2=0.85–0.93) with levels of atrazine and metabolites (DEA, DIA, DDA) in the soil. Atrazine interferes with photosystem II, causing the degradation of chlorophyll pigments (a phenomenon that is spectrally detectable). This enables non-destructive monitoring of the spatial distribution of contamination and the identification of hotspots requiring priority remediation interventions.

3.5 Comparative synthesis of approaches

The comparative analysis of machine learning algorithms highlights the systematic superiority of Random Forest, which achieves R^2=0.84–0.88 in calibration and validation for above-ground biomass estimation (N62), outperforming SVM and PLSR by 3–15% in accuracy. Alternative ensemble learning algorithms nonetheless demonstrate excellent robustness: CatBoost achieves R^2=0.966 for water content estimation (N5), while PSO-GPR achieves R^2=0.92 for soil salinity (N40). SVM and neural networks demonstrate moderate but more variable performance, while linear models show systematically inferior performance ($R^2 \leq 0.78$). UAV-Satellite integration combines the high spatial resolution of UAVs with regional satellite coverage. Study N24 develops a “ratio averaging” UAV-Sentinel-2A method, whereby enable correlations of R^2=0.498–0.745 to be obtained, with accuracy gains of 0.114–0.384 (measured as variation in R^2). Multi-level approaches simultaneously integrate UAV, satellite, and terrestrial data, achieving reliable estimates down to 5 m depth for soil water content (N14). The direct approach offers the absolute quantification of moisture for bare soil down to 5 cm depth (N38), showing an inverse relationship between reflectance and moisture. The majority of studies adopt

indirect approaches through the vegetative response, which are preferable when the target parameter generates spectrally detectable stress (salinity in the 444–510 nm and 565–675 nm bands, N40; nitrogen in the red-edge, N51) or under conditions inaccessible to direct remote sensing (plastic mulch). The direct approach retains advantages for bare soil, for shallow depths (<10 cm), and for absolute quantification. The optimal strategy emerging from this comparison appears to be one that involves integrating proximal sensors with UAV remote monitoring (N41).

4. Conclusions

4.1 Main results

The main finding is the clear predominance of indirect approaches based on the vegetative response, which are effective for nitrogen, moisture, and salinity when these generate spectrally detectable stress. Vegetation indices show differentiated performance: NDRE proves superior to NDVI for leaf nitrogen due to lower chlorophyll saturation, while the thermal indices TDDI and TVDI reach R^2=0.966 for soil water content. Accuracy varies with depth, being optimal for surface layers (0–10 cm), although multi-source approaches have demonstrated estimation capacity down to 5 metres. The comparative analysis highlights the superiority of Random Forest and ensemble methods (CatBoost, PSO-GPR) with gains of 3–15% over SVM and linear models, while UAV-Satellite integration produces R^2 gains of up to 0.384. Spectral mixing problems in row crops require unmixing or threshold optimization techniques, which are particularly effective in early growth stages, while acquisition timing proves critical for maximising correlations with target agronomic parameters.

4.2 Operational recommendations

The operational implementation of UAV monitoring requires strategic planning at various technical and decision-making levels. For nitrogen monitoring, the use of mechanistic-empirical hybrid approaches is recommended, with acquisitions during the phases of maximum vegetative activity and incorporating topographic factors such as slope in non-flat terrain. For soil water content, particular attention must be paid to the synchronisation of acquisitions with critical growth stages and to the consideration of co-limitation with salinity in arid environments. For row crops, it is essential to ensure cover fraction maps of very high precision (~3%) derived from UAV photogrammetric surveys, given the high error amplification factor (K2=14) in unmixing procedures. Multi-scale UAV-Satellite integration should be systematically planned for regional applications, using targeted UAV acquisitions for the calibration and validation of satellite estimates and exploiting the temporal frequency of Sentinel-2 for routine monitoring. Operational management should also take into account that the natural spatial variability of soil properties can exceed the differences induced by management practices, making repeated temporal mapping necessary to distinguish transient effects from permanent trends and to effectively assess the impact of conservation agricultural practices.

4.3 Future directions

The future developments of UAV monitoring address current methodological limitations along several research trajectories. The main gap concerns the limited capacity for direct quantification at depths relevant for root processes, requiring the development of sensors capable of greater penetration depth or the refinement of predictive models that integrate proximal and remote information to infer the conditions of deeper layers. A further desirable advancement concerns the integration of emerging technologies such as LiDAR and hyperspectral sensors with deep learning techniques and convolutional neural networks, which could overcome the current limitations in discriminating parameters with similar spectral signatures and improve the automatic extraction of complex features from multi-source imagery. Furthermore, temporal scalability represents an open challenge, requiring standardised protocols for multi-temporal monitoring that separate permanent and transient components of spatial variability and quantitatively assess the effectiveness of management practices over the long term. Finally, the extension of validated methodologies to different pedoclimatic contexts and uninvestigated crops requires independent validation and the development of adaptive models that account for local specificities, ensuring the robustness and transferability of approaches at global scale.

Author contributions

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Ethics consent

Ethical approval and consent were not required.

Data availability

This article is a narrative review; no primary datasets were generated by the authors. All data discussed in the text are derived from previously published studies cited in the reference list. The data underlying the figures and tables produced by the authors (including extracted values from the reviewed literature used to build comparative analyses) are available in Zenodo in the following repository: https://doi.org/10.5281/zenodo.20138581 (Moser, 2026a). The completed PRISMA 2020 checklist has been deposited in Zenodo and is available at: 10.5281/zenodo.20374642 (Moser, 2026b). Both are licensed under a CC0 1.0 Universal Public Domain Dedication.

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