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Review

Precision Agriculture for Nutraceutical Crops: A Comprehensive Scientific Review

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Abstract

Precision Agriculture (PA) is increasingly applied to nutraceutical cropping systems, where agronomic productivity must be integrated with the stabilization of phytochemical quality and environmental sustainability. This structured narrative review synthesizes scientific evidence (primarily 2010–2025) on the use of Unmanned Aerial Vehicle (UAV)-based multispectral and thermal sensing, LiDAR-derived canopy characterization, Internet of Things (IoT) monitoring, and artificial intelligence (AI)-driven analytics in medicinal, aromatic, and functional crops. The literature indicates that PA enhances high-resolution monitoring of crop–environment interactions, supporting site-specific irrigation, nutrient management, and stress detection. Under validated conditions, these interventions are associated with improved yield stability, resource-use efficiency, and modulation of secondary metabolite accumulation. However, reported outcomes vary substantially across species, agroecological contexts, and experimental scales, and most studies remain plot-scale or pilot-scale, limiting large-scale generalization. *Moringa oleifera* Lam. is examined as a model species for Mediterranean and semi-arid systems. Evidence suggests that integrated spectral, structural, and environmental monitoring can support optimized irrigation scheduling, canopy uniformity, and phytochemical consistency. Nonetheless, genotype-specific calibration, multi-season validation, standardized metabolomic benchmarking, and cross-regional transferability remain significant research gaps. Overall, PA represents a scientifically promising but still maturing framework for nutraceutical agriculture. Future progress will require rigorous multi-site validation, improved model robustness, standardized sustainability metrics, and comprehensive economic assessments to ensure scalability and long-term impact.

Keywords: smart farming; UAV remote sensing; multispectral and hyperspectral imaging; thermal imaging; LiDAR canopy characterization; Internet of Things (IoT); artificial intelligence and machine learning; decision-support systems; digital agriculture; climate-smart agriculture

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1. Introduction

Nutraceutical crops—including medicinal and aromatic plants (MAPs), functional vegetables, and bioactive-rich species—represent one of the fastest-growing segments of global agriculture [1–5]. Their expansion is primarily driven by increasing consumer demand for natural health-promoting compounds and functional foods. Unlike commodity crops, whose economic value is largely determined by yield and biomass, the competitiveness of nutraceutical species is intrinsically linked to phytochemical composition. The concentration, stability, and spatial uniformity of secondary metabolites—such as phenolics, flavonoids, carotenoids, essential oils, vitamins, terpenes, and other bioactive compounds—determine product functionality, extract standardization, regulatory compliance, and acceptance within nutraceutical, pharmaceutical, and cosmetic value chains [6–9].

A defining characteristic of nutraceutical crops is the high physiological plasticity of secondary metabolite biosynthesis. The accumulation of bioactive compounds responds nonlinearly to environmental and agronomic drivers, including water availability, nutrient status, temperature, radiation, and microclimatic heterogeneity. Even moderate fluctuations in plant water status, soil fertility, or thermal regimes can shift metabolic pathways and alter the balance among phenolics, pigments, and other functional compounds [10–12]. Consequently, spatial and temporal variability at field scale directly affects product quality, extract standardization, and market value. Ensuring consistent phytochemical profiles across heterogeneous environments therefore represents a central agronomic and technological challenge.

In Mediterranean regions such as Sicily—where production systems are often characterized by environmental heterogeneity, marginal soils, and increasing climate stress—the stabilization of quality parameters is particularly complex. At the same time, the higher added value of nutraceutical products creates greater economic tolerance for technological investment compared with bulk commodity crops. These features position nutraceutical systems as promising yet underexplored candidates for Precision Agriculture (PA) [13–20].

Precision Agriculture is defined as a data-driven, site-specific management approach that integrates advanced sensing technologies, spatial analytics, and decision-support systems (DSSs) to quantify and regulate within-field variability [21]. By continuously monitoring crop status, soil properties, and microclimatic conditions, PA enables adaptive interventions in irrigation, fertilization, pest control, and harvest timing. In nutraceutical crops, this capability extends beyond yield optimization to the stabilization of biochemical composition [1,3,10,11,21–23].

Recent advances in unmanned aerial vehicle (UAV)-based remote sensing have significantly expanded monitoring capabilities in MAP cultivation [15–20]. Multispectral and thermal imaging allow high-resolution assessment of canopy vigor, chlorophyll status, and water stress, supporting optimized irrigation scheduling and early detection of biotic and abiotic constraints [13,14,24]. Complementary Internet of Things (IoT) sensor networks enable continuous measurement of soil moisture, temperature, and microclimatic variables, reinforcing adaptive management strategies. In Mediterranean environments, photovoltaic-powered IoT systems have demonstrated improved control of post-harvest processes such as solar drying, enhancing quality retention and energy efficiency [1,3,14,22,23,25–34].

Beyond spectral and thermal approaches, Light Detection and Ranging (LiDAR) has emerged as a transformative technology for high-resolution three-dimensional (3D) canopy characterization [35,36]. By generating dense point clouds through laser pulse return-time measurements, LiDAR enables accurate quantification of structural traits such as canopy height, volume, density, porosity, and vertical foliage distribution [35,36]. These parameters are closely linked to photosynthetic efficiency, biomass accumulation, microclimate regulation, and resource-use dynamics [37–42]. Compared with conventional RGB or multispectral imagery, LiDAR provides superior structural resolution and captures both intra- and inter-plant variability, which is particularly relevant for perennial and woody nutraceutical crops [43–53]. When integrated with spectral, thermal, and IoT-derived physiological indicators, LiDAR strengthens DSS frameworks by linking structural, physiological, and biochemical dimensions within a unified data-driven system (Figure 1).

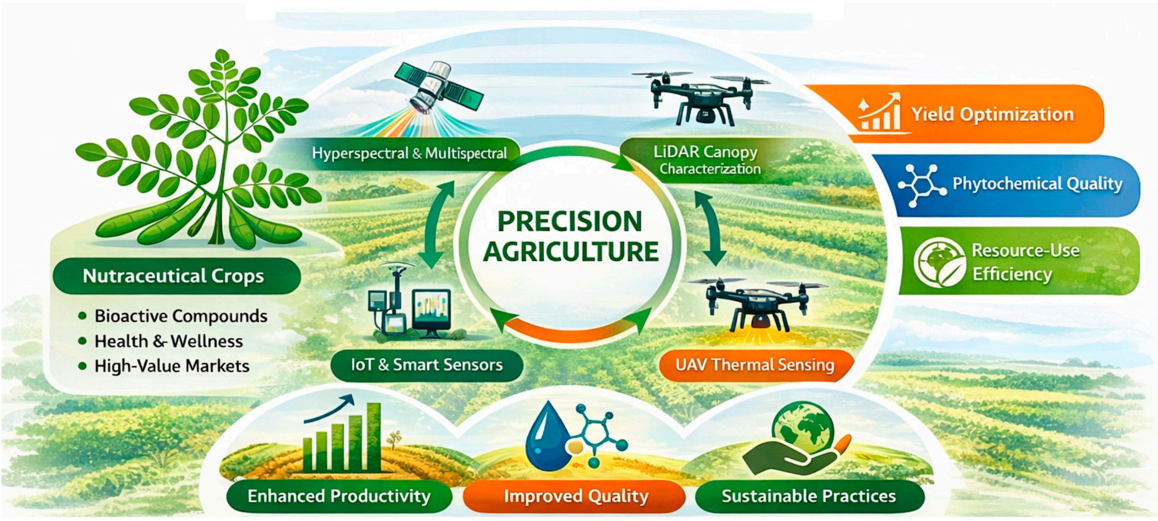

Figure 1. Conceptual overview of Precision Agriculture applied to nutraceutical crops. The figure illustrates the integration of advanced sensing technologies (UAV imaging and proximal sensors), IoT-based monitoring, and AI-driven data analytics within a data-driven precision agriculture framework. This integrated ecosystem supports yield optimization, stabilization of phytochemical quality, and environmental sustainability, enabling smart farming strategies for high-value nutraceutical production and health-oriented agri-food systems.

Despite these technological advances, most PA literature remains focused on high-acreage commodity crops such as cereals, maize, and soybean. Nutraceutical systems present distinct and largely underexplored challenges:

(i) Greater biochemical sensitivity to environmental drivers;
(ii) Stronger need for quality stabilization rather than yield maximization alone;
(iii) Increased variability across genotypes and cultivation systems;
(iv) Higher economic margins that may justify advanced technological integration.

This mismatch between technological potential and crop-specific research depth reveals a clear knowledge gap.

Among emerging nutraceutical species, *Moringa oleifera* Lam. has attracted increasing attention as a multifunctional crop combining nutritional, medicinal, and socio-economic relevance. Its rapid growth, drought tolerance, and versatility for food, feed, pharmaceutical, and bioenergy applications make it particularly suitable for Mediterranean diversification strategies [54–61]. Field-scale studies conducted under semi-arid conditions have demonstrated the effectiveness of UAV-based multispectral and thermal monitoring combined with precision irrigation and nutrient management workflows for optimizing canopy vigor, water-use efficiency, and harvest timing [3,13,14,61–63]. The integration of LiDAR-derived canopy metrics further enhances biomass estimation, structural monitoring, and resilience assessment under climate stressors such as drought and heat waves [42,44,64–70].

Collectively, these advances position nutraceutical crops—and particularly M. oleifera—as valuable model systems for demonstrating how integrated PA frameworks can stabilize phytochemical quality, enhance traceability, and improve climate resilience.

Although individual technologies have been widely investigated, a comprehensive synthesis addressing their coordinated application in nutraceutical systems remains limited. Existing reviews often lack differentiation between predictive monitoring tools and prescriptive decision-making systems, and rarely assess environmental and economic performance alongside agronomic outcomes.

This review aims to address these limitations by:

1. Providing a structured narrative synthesis of Precision Agriculture applications in nutraceutical crops.
2. Critically comparing sensing technologies (UAV multispectral/thermal, LiDAR, proximal sensing, IoT) and associated modeling approaches.
3. Distinguishing predictive systems (monitoring and variability mapping) from prescriptive systems (variable-rate and adaptive management workflows).
4. Evaluating environmental sustainability and economic feasibility dimensions.
5. Identifying methodological gaps and defining future research priorities for climate-sensitive and high-value cropping systems.

By reframing Precision Agriculture from a yield-centered paradigm toward a quality-stabilization and resilience-oriented framework, this review contributes to advancing climate-smart, data-driven nutraceutical farming in Mediterranean and comparable agroecological contexts.

2. Review Methodology and Evidence Synthesis Framework

This study was designed as a structured narrative review supported by systematic search procedures, rather than as a formal quantitative meta-analysis. Although a systematic search strategy was implemented to ensure transparency and reproducibility, statistical meta-analysis was not considered methodologically appropriate due to the pronounced heterogeneity across crop species, sensing platforms, biochemical targets, validation designs, and reported outcome metrics. The reviewed studies differ substantially in experimental scale, analytical methods, environmental context, and performance indicators, making statistical aggregation potentially misleading. Therefore, a qualitative and semi-quantitative evidence synthesis approach was adopted to critically compare technologies, analytical frameworks, and agronomic, biochemical, and sustainability outcomes across nutraceutical cropping systems.

2.1. Literature Search Strategy

The scientific literature included in this review was identified through a structured and systematic search aimed at selecting the most relevant studies on Precision Agriculture applied to nutraceutical crops. The search was conducted between November 2025 and February 2026 using the Scopus, Web of Science, PubMed, and Google Scholar databases. Only peer-reviewed articles published in English were considered.

The primary time window covered publications from 2012 to 2025 in order to capture recent developments in digital agriculture, remote sensing technologies, and AI-based decision-support systems. Earlier foundational studies, dating back to approximately 2002, were selectively included where necessary to contextualize technological evolution and conceptual frameworks.

Search queries were constructed using combinations of keywords and Boolean operators integrating technological and crop-specific dimensions. Representative search strings included combinations of terms such as “Precision Agriculture,” “smart farming,” “UAV remote sensing,” “hyperspectral imaging,” “LiDAR agriculture,” “machine learning,” “Internet of Things,” and “decision support systems,” combined with “nutraceutical crops,” “medicinal plants,” “aromatic plants,” “functional crops,” or “Moringa oleifera,” and further linked to biochemical or quality-related descriptors such as “phytochemical,” “secondary metabolites,” “bioactive compounds,” and “quality stabilization.” Additional targeted searches were performed to ensure adequate coverage of specific intersections between remote sensing technologies and phytochemical monitoring. Search strings were iteratively refined to balance breadth and specificity and to ensure comprehensive coverage of both technological components and crop-specific applications.

2.2. Inclusion and Exclusion Criteria

Studies were included if they were peer-reviewed journal articles published in English and focused on precision or digital technologies applied to medicinal, aromatic, functional, or nutraceutical crops. Eligible studies reported agronomic, biochemical, environmental, or sustainability-related outcomes and provided sufficient methodological transparency regarding sensing technologies, data processing, and validation protocols. Preference was given to studies including field-scale or farm-scale validation, although well-designed experimental trials and pilot-scale studies were also considered when scientifically robust.

Studies were excluded if they were non-peer-reviewed sources, purely engineering or algorithmic contributions lacking agronomic validation, or focused exclusively on staple commodity crops unless their findings were clearly transferable to nutraceutical systems. Articles lacking adequate methodological detail or not aligned with sustainable and precision crop management objectives were also excluded.

2.3. Study Selection and Synthesis

The initial database search identified 312 records across Scopus, Web of Science, PubMed, and Google Scholar. After the removal of duplicate entries ($n = 58$), 254 records remained for the screening phase (Figure 2). Titles and abstracts were subsequently evaluated to assess relevance to the scope of Precision Agriculture applications in nutraceutical cropping systems. Following this preliminary screening, 196 articles were retained for full-text assessment.

During the eligibility evaluation, studies that did not meet the inclusion criteria—such as those lacking agronomic validation, focusing exclusively on algorithm development without field application, or addressing commodity crops without clear transferability to nutraceutical systems—were excluded. After this filtering process, a final set of 167 peer-reviewed studies was retained and included in the qualitative evidence synthesis.

Given the substantial heterogeneity in crop species, sensing technologies, analytical methods, experimental designs, and reported performance indicators, the evidence was synthesized thematically rather than through quantitative meta-analysis. The selected studies were categorized according to three main dimensions:

(i) Sensing technology, including UAV-based multispectral, hyperspectral, and thermal imaging, LiDAR systems, proximal sensing, and IoT sensor networks;
(ii) Crop category, encompassing medicinal and aromatic plants, functional vegetables, and emerging nutraceutical species;
(iii) Primary outcome domain, such as biomass and yield estimation, phytochemical composition, stress detection, or sustainability-related indicators.

An additional analytical distinction was introduced between predictive systems, which primarily generate variability maps or estimate crop physiological or biochemical traits, and prescriptive systems, which support or automate management interventions such as variable-rate irrigation, nutrient application, or adaptive crop management strategies. The synthesis also considered experimental scale, distinguishing plot-level experiments, pilot-scale trials, farm-scale studies, and commercial implementations.

Particular attention was given to studies conducted in Mediterranean and semi-arid agroecosystems, where climatic constraints and environmental heterogeneity strongly influence nutraceutical crop performance. Within this framework, Moringa oleifera Lam. was treated as a representative model species due to its physiological plasticity, measurable phytochemical variability, and growing relevance in high-value agricultural diversification strategies.

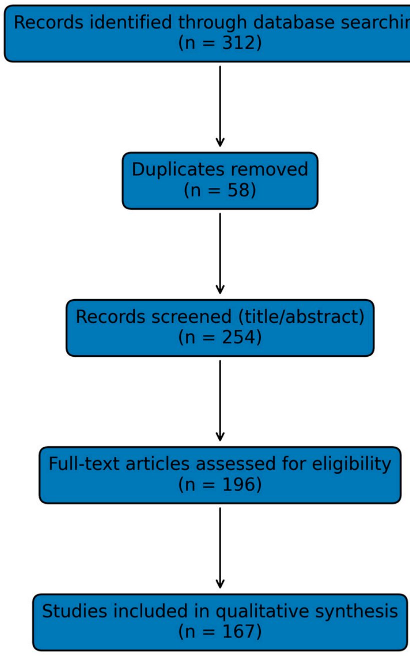

Figure 2. PRISMA flow diagram illustrating the literature identification, screening, eligibility assessment, and final inclusion process adopted in this structured narrative review on Precision Agriculture applications in nutraceutical cropping systems. A total of 312 records were initially identified through database searching (Scopus, Web of Science, PubMed, and Google Scholar). After the removal of duplicates (n = 58), 254 records were screened based on titles and abstracts. Following full-text eligibility assessment (n = 196), a final set of 167 peer-reviewed studies was included in the qualitative evidence synthesis.

2.4. Evidence Quality Assessment

Although no formal risk-of-bias scoring instrument was applied, due to the heterogeneity of study designs, evidence quality was assessed qualitatively according to structured criteria. These criteria included experimental scale, temporal robustness (single-season versus multi-season validation), statistical transparency (including reporting of R^2, RMSE, MAE, coefficients of variation, confidence intervals, and p-values), sensor calibration procedures, validation design, and overall methodological clarity.

Studies demonstrating multi-season validation, field-scale implementation, and transparent statistical reporting were considered to provide stronger inferential value. Conversely, findings derived from single-season experiments, limited calibration datasets, or insufficiently documented validation protocols were interpreted cautiously. Particular attention was paid to distinguishing correlation-based findings from experimentally supported causal interpretations.

Overall, this structured narrative methodology combines systematic search procedures with critical qualitative synthesis, ensuring transparency and reproducibility while maintaining flexibility appropriate to the interdisciplinary and heterogeneous nature of Precision Agriculture applications in nutraceutical cropping systems.

3. Theoretical Foundations

3.1. Precision Agriculture as a Data-Driven Management Framework

Precision Agriculture (PA) is conceptualized here as a data-driven, adaptive management framework integrating remote and proximal sensing, geospatial analytics, Internet of Things (IoT) monitoring networks, and machine-learning-based modeling within a continuous decision-support system (DSS) architecture [71,72]. Rather than representing a collection of isolated technologies, PA operates as a systemic workflow linking data acquisition, interpretation, and site-specific intervention.

Through the coordinated integration of heterogeneous datasets—multispectral and hyperspectral imagery, UAV observations, soil and crop sensors, structural canopy metrics, and environmental IoT measurements—PA enables high-resolution characterization of plant–soil–atmosphere interactions across spatial and temporal scales [25,73]. This integration supports both:

- Predictive functions (variability mapping, stress detection, yield or quality estimation);
- Prescriptive functions (variable-rate irrigation, nutrient optimization, pruning, and harvest timing adjustments).

This dual predictive–prescriptive dimension is particularly relevant for nutraceutical cropping systems. Unlike commodity crops, whose economic performance is primarily yield-driven, nutraceutical systems depend on the concentration, uniformity, and stability of bioactive compounds. Secondary metabolite biosynthesis responds nonlinearly to temperature, radiation, plant water status, and nutrient availability, often generating pronounced within-field heterogeneity in phytochemical profiles [74,75].

Conventional uniform-input strategies lack the spatial resolution and temporal continuity required to manage such biochemical sensitivity. PA, by contrast, enables fine-scale monitoring and adaptive correction, thereby aligning agronomic management with quality stabilization objectives rather than biomass maximization alone.

Recent field-scale applications in Mediterranean aromatic species demonstrate that UAV-based RGB and multispectral fusion can accurately estimate canopy structure and biomass proxies, supporting improved agronomic decision-making [14]. However, evidence remains uneven across nutraceutical species, and multi-season validation is still limited—highlighting the need for systematic synthesis rather than isolated case reporting.

Among emerging species, *Moringa oleifera* has been proposed as a model crop for Mediterranean PA applications due to its rapid growth, environmental plasticity, and bioactive-rich leaf biomass [62]. Nevertheless, in this review it is treated as a representative case within broader nutraceutical systems, not as the exclusive focus, thereby maintaining conceptual coherence.

3.2. Nutraceutical Crops and Phytochemical Optimization

The nutraceutical value of crops is governed by complex metabolic networks producing phenolics, flavonoids, carotenoids, terpenes, essential oils, alkaloids, and glucosinolates [9,76]. These compounds are highly sensitive to micro-environmental drivers and plant physiological status, making spatial and temporal variability a central determinant of product quality.

Precision Agriculture provides a structured framework for phytochemical optimization, but its effectiveness depends on distinguishing between monitoring capacity and intervention capacity. Monitoring tools (e.g., hyperspectral imaging, NIR spectroscopy, chlorophyll fluorescence sensing, IoT-based physiological tracking) allow early detection of metabolic shifts associated with water stress, nutrient imbalance, or phenological transitions [77–80]. However, optimization requires translating these signals into calibrated management actions.

Key prescriptive interventions supported by PA include:

- Precision irrigation, where controlled moderate water deficits may stimulate phenolic and antioxidant synthesis without compromising yield [11,81].

- Site-specific nutrient management, particularly nitrogen and potassium modulation, influencing phenylpropanoid metabolism and essential oil biosynthesis [82,83].
- Light-spectrum management in semi-controlled systems to modulate carotenoid and anthocyanin accumulation [84].

Importantly, responses are genotype- and environment-dependent. Reported improvements in vitamin C concentration, carotenoid content, or antioxidant capacity under precision irrigation regimes (e.g., in *Moringa oleifera*) demonstrate potential but cannot be universally generalized without multi-season and multi-location validation.

Thus, PA in nutraceutical crops should be interpreted not as a deterministic quality-enhancement tool, but as a probabilistic variability-management framework aimed at reducing uncertainty in phytochemical outcomes.

3.3. Spatial Variability Management in Nutraceutical Systems

Spatial heterogeneity in soil depth, texture, water-holding capacity, nutrient distribution, microclimate, and biotic pressure exerts strong influence on both yield and phytochemical uniformity in nutraceutical crops [85–88]. Given the sensitivity of secondary metabolite biosynthesis to micro-environmental fluctuations, managing within-field variability is essential for achieving consistent functional quality.

Within PA frameworks, spatial variability analysis increasingly relies on multi-layer sensing integration:

- Spectral data (multispectral, hyperspectral) for canopy vigor, chlorophyll status, and biochemical proxies;
- Thermal imaging for plant water stress mapping;
- Structural sensing (LiDAR) for three-dimensional canopy architecture assessment;
- IoT networks for continuous environmental and soil monitoring.

Spectral and thermal indices primarily capture physiological surface responses. However, they provide limited insight into canopy architecture, which strongly mediates light interception, transpiration, and microclimate formation [89–92].

Light Detection and Ranging (LiDAR) addresses this limitation by enabling non-destructive quantification of canopy height, volume, density, porosity, and vertical biomass distribution. These structural traits influence photosynthetic performance and secondary metabolite dynamics, particularly in perennial and semi-woody nutraceutical crops. When integrated with spectral and thermal data, LiDAR reduces ambiguity in stress interpretation by embedding physiological signals within their structural context [89–93].

UAV-based platforms offer operational flexibility for acquiring high-resolution RGB, multispectral, thermal, and LiDAR data in heterogeneous Mediterranean agroecosystems [3,14,23,94–98]. However, despite promising results, large-scale commercial validation remains limited, and cost–benefit analyses are still insufficiently documented.

IoT sensor networks further enhance spatial interpretation by providing continuous measurements of soil moisture, nutrient dynamics, pH, electrical conductivity, temperature, and radiation. When fused with structural and spectral datasets, these data streams support machine-learning models (e.g., Random Forest, SVM, CNN, XGBoost) for stress hotspot detection and predictive phytochemical modeling [99–101]. Yet model performance is highly dependent on calibration quality, training dataset representativeness, and statistical transparency.

In Mediterranean *Moringa oleifera* systems characterized by heterogeneous soils and microclimates, integrated UAV multispectral–thermal mapping combined with structural canopy metrics has improved interpretation of spatial gradients in water demand and nutrient sufficiency. While reported improvements in biomass uniformity and quality stabilization are promising, broader replication is needed to confirm robustness.

3.4. Conceptual Implication

The integration of structural (LiDAR), physiological (spectral/thermal), and environmental (IoT) data within adaptive DSS architectures represents a transition from yield-centered PA toward quality-oriented variability management.

For nutraceutical crops, where market value depends on phytochemical consistency, this multidimensional framework offers conceptual advantages. However, empirical validation remains uneven, and future research must prioritize multi-season datasets, standardized reporting metrics, and explicit differentiation between predictive monitoring and prescriptive management effectiveness.

4. Technologies and Methodologies in Precision Nutraceutical Farming

Precision Agriculture (PA) applied to nutraceutical crops operates within an integrated technological ecosystem aimed at detecting, interpreting, and managing spatial and temporal variability in crop physiology, structure, and phytochemical composition. Consistent with the data-driven framework outlined earlier, PA combines advanced sensing platforms, geospatial analytics, IoT-based environmental monitoring, and artificial intelligence (AI)–supported decision systems to enable adaptive, site-specific management strategies.

4.1. Evidence Synthesis Across Nutraceutical Crops

In nutraceutical systems, this integration extends beyond yield optimization to include stabilization of bioactive compound profiles and reduction in environmental variability effects. Given the biochemical sensitivity of secondary metabolite pathways, the effectiveness of PA must be evaluated not only by biomass gains but also by improvements in predictive accuracy, management precision, and quality uniformity.

To support a structured comparison, the reviewed evidence was synthesized across crop types, sensor configurations, intervention strategies, and study scales (Tables 1–3). Tables 2 and 3 are providing methodological granularity, including sample size, experimental duration, validation design, and model performance metrics (e.g., RMSE, MAE, and AUC) where available.

Table 1. Comparative overview of multispectral, thermal, and LiDAR sensing technologies for Precision Agriculture applications in *Moringa oleifera*.

Technology	Main Measured Variables	Key Agronomic Information	Strengths	Limitations	Main Applications in *Moringa oleifera*
Multispectral imaging (UAV)	Spectral reflectance (VIS–NIR), vegetation indices (NDVI, NDRE, GNDVI, VARI)	Canopy vigor, chlorophyll content, photosynthetic activity, spatial variability	High spatial coverage; operational scalability; cost-effective; strong link with physiological status	Indirect estimation of biomass; limited sensitivity to canopy internal structure	Monitoring canopy vigor and uniformity; detection of nutrient and water stress; harvest timing optimization; mapping phytochemical maturity
Thermal imaging (UAV)	Canopy temperature, thermal indices (e.g., CWSI)	Plant water status, transpiration efficiency, heat stress	Early detection of water stress; strong support for irrigation scheduling; rapid response to stress	Sensitive to atmospheric conditions; lower structural detail; requires calibration	Precision irrigation management; water-use efficiency improvement; stress prevention under semi-arid Mediterranean conditions
LiDAR (UAV/terrestrial)	3D point clouds, canopy height, volume, density, porosity, vertical foliage distribution	Structural architecture, biomass estimation, pruning response, spatial heterogeneity	Direct measurement of canopy structure; high accuracy; non-destructive; robust biomass estimation	Higher costs; data processing complexity; limited spectral information	Canopy architecture analysis; biomass and volume estimation; assessment of pruning strategies; integration with multispectral/thermal data for DSS

Table 2. Representative applications of Precision Agriculture in nutraceutical systems.

Crop	Location	Sensor Platform	Management Intervention	Study Scale	Sample Size/Seasons	Key Outcome	Reference Type
Moringa oleifera	Sicily (Italy)	UAV multispectral + thermal	Precision irrigation scheduling	Farm-scale	2 seasons	+12–18% biomass increase and improved canopy uniformity	Field trial
Rosemary (*Rosmarinus officinalis*)	Mediterranean region	UAV RGB + multispectral	Site-specific nitrogen management	Plot-scale	1 season	Improved biomass prediction accuracy (NDVI-based models)	Experimental
Saffron (*Crocus sativus*)	Iran/Spain	Hyperspectral imaging	Early stress detection	Experimental	2 seasons	Improved flowering prediction and stress mapping	Controlled trial
Lavender (*Lavandula* spp.)	Southern Europe	Multispectral UAV	Variable irrigation management	Plot-scale	1 season	Improved essential oil yield stability	Experimental
Medicinal herbs (mixed MAPs)	Mediterranean basin	Multispectral + IoT sensors	Integrated irrigation and nutrient control	Pilot-scale	Multi-site trials	Improved resource-use efficiency and canopy uniformity	Field validation

Table 3. AI-based modeling performance in nutraceutical crop monitoring.

Target Variable	Input Data	Algorithm	Dataset Size	Validation Design	Performance Metrics	Key Notes
Phenolic content	Hyperspectral imagery	PLSR	120–180 samples	Cross-validation	R^2 = 0.72–0.89, RMSE = 5–12%	High sensitivity to spectral preprocessing
Biomass estimation	Multispectral + LiDAR	Random Forest	200–300 plots	Hold-out validation	R^2 = 0.75–0.90, RMSE = 0.15–0.32 kg m^{-2}	Multisensor fusion improves accuracy
Water stress detection	Thermal imaging (CWSI)	Support Vector Machine	150–220 samples	Cross-validation	AUC = 0.82–0.91	Effective for irrigation decision support
Chlorophyll/vigor	Multispectral indices (NDVI, NDRE)	Gradient Boosting	100–160 samples	K-fold cross-validation	R^2 = 0.70–0.85	Robust across MAP species
Phytochemical prediction	Hyperspectral + environmental data	CNN/Deep Learning	250–400 observations	Independent test dataset	R^2 = 0.78–0.88, MAE = 6–10%	Transferability remains limited

The comparative analysis highlights several methodological patterns:

- Most validated applications remain at plot or experimental scale; farm-scale evidence is limited but emerging.
- Multispectral sensing is predominantly used for vigor and biomass estimation, while hyperspectral systems are more frequently applied to biochemical or phenological detection.
- Intervention studies (e.g., precision irrigation) are less common than monitoring studies, indicating a gap between predictive capability and prescriptive validation.

Within this landscape, *Moringa oleifera* cultivated under Mediterranean conditions serves as a representative case study rather than a singular focus. Its physiological plasticity and measurable phytochemical variability make it suitable for evaluating the linkage between remote sensing indicators and downstream nutraceutical quality outcomes. However, broader cross-crop validation remains necessary to generalize findings.

4.2. Modeling Approaches and AI Performance

The effectiveness of PA in nutraceutical crops depends heavily on modeling frameworks that translate sensor data into actionable variables. Table 3 summarizes reported algorithm performance across target outcomes.

Several trends emerge:

1. Multimodal data fusion (e.g., multispectral + LiDAR) generally improves predictive accuracy compared with single-sensor approaches.
2. Hyperspectral data demonstrate strong potential for biochemical estimation, though computational complexity and cost may limit scalability.
3. Reported performance metrics (Coefficient of Determination, R^2; Area Under the Curve, AUC) vary depending on validation protocol; cross-validation dominates, while independent multi-season validation remains limited.
4. In some studies, full statistical transparency (e.g., Root Mean Square Error, RMSE, confidence intervals) was not consistently reported, constraining comparability.

These findings indicate that while predictive modeling accuracy is often high under controlled conditions, translation into robust prescriptive systems requires further methodological standardization.

4.3. Conceptual Integration

Precision nutraceutical farming therefore relies on the coordinated interaction of:

- Monitoring technologies (UAV multispectral, hyperspectral, thermal, LiDAR, IoT).
- Analytical frameworks (machine learning, regression models, data fusion techniques).
- Prescriptive interventions (precision irrigation, nutrient modulation, canopy management).

The comparative synthesis suggests that technological capacity for monitoring now exceeds validated evidence for long-term quality stabilization and economic scalability. Future research should prioritize multi-season datasets, standardized reporting of statistical metrics, and integrated evaluation of agronomic, biochemical, and sustainability outcomes.

Within this structured framework, nutraceutical crops—including but not limited to *Moringa oleifera*—represent high-value systems where PA can potentially shift from yield-centric optimization toward quality-oriented variability management under climate-sensitive Mediterranean conditions.

Across sensing modalities and modeling approaches, monitoring capacity appears substantially more mature than prescriptive validation. While high-resolution spectral, thermal, and structural datasets enable increasingly accurate detection of variability and stress patterns, robust multi-season evidence demonstrating consistent agronomic and phytochemical improvements following site-specific interventions remains comparatively limited. Bridging this gap between predictive capability and validated prescriptive performance represents a key research priority for advancing precision nutraceutical farming beyond observational analytics toward outcome-driven management.

4.4. Hyperspectral and Multispectral Imaging

Hyperspectral imaging (HSI) is widely regarded as a powerful non-destructive technique for monitoring plant biochemical and structural properties due to its acquisition of hundreds of contiguous spectral bands. In nutraceutical crops, several studies have demonstrated statistically significant correlations between hyperspectral signatures and biochemical traits such as total phenolic content, flavonoid concentration, chlorophyll levels, carotenoids, and antioxidant capacity [25,102–104]. Reported coefficients of determination (R^2) for phytochemical prediction typically range between 0.65 and 0.90, depending on crop species, spectral preprocessing, and calibration design [105–107].

However, predictive accuracy is highly dependent on species-specific calibration, seasonal variability, and environmental context. Model robustness often declines when transferred across genotypes, growing conditions, or geographic regions. Most available studies rely on plot-scale experiments or single-season validation, limiting generalizability at commercial scale.

At the operational level, multispectral imaging provides a more scalable and economically accessible alternative. Vegetation indices such as NDVI, NDRE, GNDVI, and VARI have been applied in Mediterranean nutraceutical systems—including *Moringa oleifera*—to assess canopy vigor, chlorophyll status, and stress signals across spatially heterogeneous fields. These indices enable indirect proxies of physiological condition rather than direct biochemical quantification.

Evidence indicates that multispectral monitoring improves stress detection and harvest timing optimization; however, its capacity to predict specific phytochemical concentrations remains indirect and context-dependent. Thus, hyperspectral approaches offer higher biochemical sensitivity, while multispectral systems provide greater scalability and operational feasibility. The integration of both modalities on UAV platforms represents a promising but still calibration-sensitive strategy requiring multi-season validation [108–110].

4.5. UAV-Based Thermal Imaging

Thermal infrared imaging provides spatially explicit assessment of canopy temperature and has been extensively used to estimate plant water status through indices such as the Crop Water Stress Index (CWSI). In nutraceutical crops, plant water status plays a critical regulatory role in secondary metabolite biosynthesis, influencing phenolic accumulation, antioxidant activity, and pigment synthesis [111–115].

Field studies in Mediterranean systems have reported water savings between 20–40% under CWSI-guided irrigation scheduling, with associated increases in phenolic concentration under moderate deficit regimes [3,14]. However, effect sizes vary considerably across environments, irrigation strategies, and genotypes. Importantly, excessive water stress may reduce total biomass and dilute overall metabolite yield per hectare, even when concentration increases.

Therefore, while precision irrigation appears beneficial in many nutraceutical contexts, optimal thresholds are genotype- and climate-dependent. Most studies remain limited to experimental or pilot scale, and long-term resilience effects require further evaluation. Thermal sensing is thus validated for stress detection but requires careful calibration to balance yield–quality trade-offs.

4.6. IoT Soil–Plant–Atmosphere Sensor Networks

IoT-based sensor networks enable continuous monitoring of soil moisture, electrical conductivity, nutrient availability (NPK), temperature, and pH, alongside atmospheric variables such as air temperature, relative humidity, radiation (PAR), and CO_2 concentration [116]. At the plant level, sap flow, leaf temperature, and chlorophyll fluorescence sensors provide physiological indicators of stress and metabolic adjustment.

Evidence suggests that IoT-driven irrigation and fertigation strategies improve water-use efficiency (WUE) by 15–35% in Mediterranean nutraceutical systems, with improved canopy uniformity and reduced input waste [61,117]. In some cases, increased vitamin C and carotenoid accumulation have been observed under stabilized water regimes.

Nevertheless, infrastructure dependency, maintenance costs, data interoperability challenges, and connectivity limitations represent barriers to large-scale adoption. Furthermore, few studies provide multi-year economic assessments or evaluate sensor degradation effects over time.

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IoT systems therefore offer strong potential for quality stabilization in high-value crops, but broader validation under commercial conditions and structured cost–benefit analyses remain limited.

4.7. LiDAR-Based Canopy Characterization

LiDAR technology enables three-dimensional canopy reconstruction through dense point-cloud generation, allowing direct measurement of structural traits including canopy height, volume, density, porosity, and vertical foliage distribution. These structural attributes influence light interception, microclimate buffering, biomass accumulation, and potentially secondary metabolite regulation.

In *Moringa oleifera* and other semi-woody nutraceutical crops, LiDAR has demonstrated high accuracy for biomass estimation (R^2 often exceeding 0.80 in plot-scale studies) and objective assessment of pruning intensity and canopy heterogeneity. Ground-based LiDAR provides superior structural resolution, whereas UAV-mounted systems improve spatial scalability at slightly reduced detail.

However, direct mechanistic links between LiDAR-derived structural metrics and phytochemical concentration remain underexplored. Most studies infer quality improvements indirectly through biomass uniformity or stress reduction rather than direct metabolite quantification. Additionally, LiDAR systems involve higher equipment costs and computational complexity compared to multispectral platforms.

Thus, LiDAR contributes substantially to structural monitoring and yield modeling but requires deeper integration with biochemical datasets to validate its role in phytochemical stabilization.

4.8. Machine Learning, Artificial Intelligence, and Decision-Support Systems

The integration of multisource datasets (spectral, thermal, LiDAR, IoT) necessitates advanced analytical frameworks capable of handling high-dimensional and time-series data. Machine learning (ML) models—including PLSR, support vector machines (SVM), random forest (RF), gradient boosting (e.g., XGBoost), and convolutional neural networks (CNNs)—have been applied for stress classification, biomass prediction, and phytochemical estimation [118–120].

Reported model performance varies widely depending on dataset size and validation design. For phytochemical prediction, R^2 values commonly range between 0.70–0.90 in cross-validation settings, but external validation performance is often lower. Model transferability across seasons and genotypes remains a major challenge.

It is important to distinguish between:

- Predictive models, which forecast stress, yield, or metabolite levels;
- Prescriptive decision-support systems (DSS), which provide optimized management recommendations.

Most published systems remain primarily predictive rather than fully prescriptive. AI-enabled DSS frameworks integrating sensor inputs for irrigation and nutrient scheduling show promising results in experimental settings, including improved phenolic stabilization in *Moringa oleifera* [61]. However, commercial-scale, multi-season validation is still limited.

Emerging concepts such as digital twins and blockchain-based traceability platforms are under pilot evaluation. Their maturity level should be considered developmental rather than fully operational at scale.

Overall, AI enhances analytical capacity but depends critically on large training datasets, standardized calibration protocols, and multi-year validation to ensure robustness and scalability.

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4.9. Precision Irrigation Technologies

Water availability is a primary physiological regulator of secondary metabolite biosynthesis in nutraceutical crops, influencing phenolic pathways, antioxidant activity, and pigment accumulation. Consequently, precision irrigation represents a key intervention within quality-oriented PA systems.

Soil moisture-based smart irrigation platforms integrate capacitance sensors, tensiometers, and IoT-controlled drip systems to regulate water delivery in near real time. Several experimental and farm-scale studies report water savings between 20% and 40% compared to conventional scheduling, depending on crop type and climatic context [121]. However, the magnitude of savings varies significantly across agroecological zones and irrigation infrastructure.

Regulated deficit irrigation (RDI) strategies have been shown in medicinal and specialty crops to increase phenolic and flavonoid concentrations under moderate stress regimes [122]. Importantly, concentration increases do not necessarily translate into higher total metabolite yield per hectare if biomass is reduced. Therefore, quality gains must be evaluated alongside yield stability.

Thermal UAV imaging complements soil-based measurements by enabling spatially explicit canopy temperature mapping and early stress detection [123]. In Mediterranean *Moringa oleifera* systems, IoT-controlled drip irrigation combined with moderate RDI has demonstrated approximately 25–35% water reduction with improved phenolic concentration under experimental conditions. Nevertheless, most available studies are single-season or limited-scale trials, and multi-year resilience indicators remain insufficiently documented.

Overall, precision irrigation is supported by robust physiological rationale and moderate empirical validation. However, optimal thresholds are crop- and genotype-specific, and over-stress risks compromising both biomass and economic return.

4.10. Precision Nutrient Management Systems

Nutrient availability exerts strong influence on both biomass production and secondary metabolite synthesis in nutraceutical crops. Precision nutrient management integrates soil mapping, spectral diagnostics, and variable-rate application technologies (VRT) to align nutrient inputs with spatially differentiated crop demand.

Diagnostic tools such as SPAD chlorophyll meters, portable leaf spectroscopy, and multispectral vegetation indices provide indirect indicators of nitrogen status and nutrient imbalance [124]. Reported improvements in nutrient-use efficiency typically range from 10% to 35% under variable-rate management, depending on soil heterogeneity and crop response.

In leaf-harvested nutraceutical crops such as *Moringa oleifera*, nitrogen and potassium availability are particularly influential in regulating vitamin C content, carotenoid accumulation, and antioxidant activity [60]. Field-scale experiments in Mediterranean environments suggest that site-specific fertilization improves canopy uniformity and stabilizes biochemical composition relative to uniform fertilization practices. However, direct causal quantification between nutrient mapping and phytochemical stabilization remains limited in the literature.

Moreover, many studies rely on short-term experimental plots rather than commercial-scale deployment. Longitudinal assessments of soil health, nutrient carryover effects, and environmental externalities (e.g., nitrate leaching reduction) are still underrepresented.

Precision nutrient management therefore demonstrates agronomic and efficiency benefits, but stronger multi-season and cross-site validation is required to substantiate claims of consistent phytochemical stabilization.

4.11. Low-Cost Precision Tools for Smallholders

Although PA technologies have demonstrated agronomic and quality benefits, adoption barriers persist, particularly for smallholder nutraceutical producers. High upfront costs, technical complexity, and infrastructure requirements constrain scalability in fragmented Mediterranean farming systems.

Recent technological developments have introduced lower-cost alternatives aimed at improving accessibility. Smartphone-based imaging applications combined with machine learning models enable detection of nutrient deficiencies and foliar diseases with moderate classification accuracy (often 75–90% under controlled validation datasets) [125]. However, performance declines under heterogeneous field lighting conditions and when transferred across crop species.

Portable near-infrared (NIR) devices allow rapid in-field estimation of phenolic content and antioxidant capacity, though calibration robustness remains species-specific and sensitive to moisture variation [25]. Open-source IoT platforms (e.g., ESP32, Arduino, Raspberry Pi) facilitate affordable environmental monitoring networks; yet, long-term durability and maintenance costs must be considered.

Consumer-grade UAVs equipped with low-cost multispectral sensors provide canopy vigor assessment at reduced investment cost compared to research-grade hyperspectral systems [126]. While spatial resolution and spectral depth are lower, these systems may offer favorable cost–benefit ratios in high-value nutraceutical crops.

For Mediterranean systems dominated by small and medium-scale farms—including *Moringa oleifera*, aromatic herbs, and specialty crops—cost-effective PA solutions can enhance economic viability if integrated within cooperative frameworks or shared-service models. However, empirical evidence on long-term profitability, adoption behavior, and institutional support mechanisms remains limited.

Thus, low-cost precision tools represent promising enablers of democratized digital agriculture, but their agronomic reliability, economic sustainability, and scalability require further structured evaluation (Figure 3).

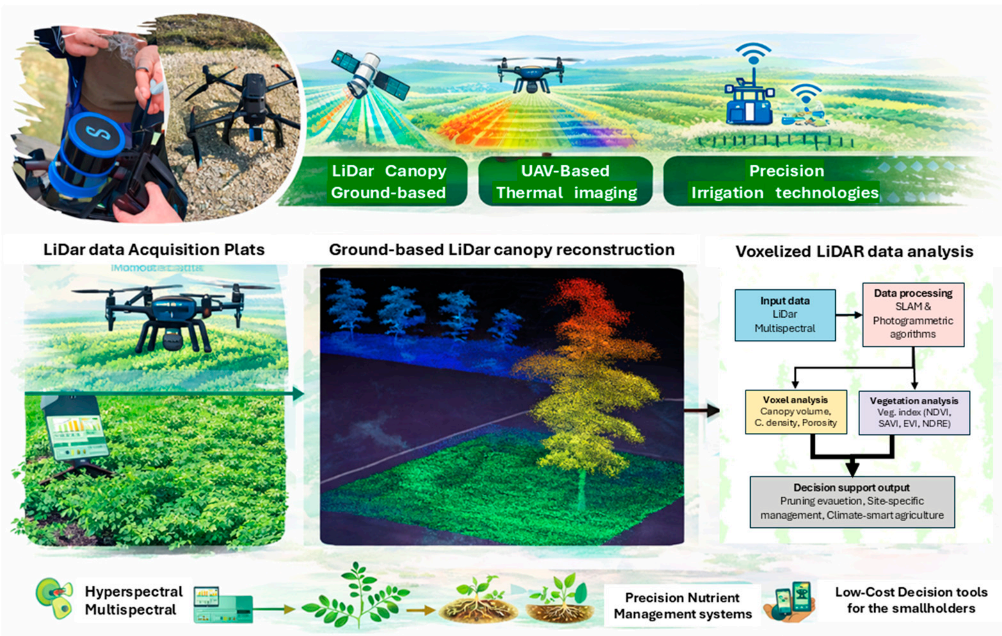

Figure 3. Conceptual representation of Precision Agriculture as a data-driven ecosystem for managing spatial variability in nutraceutical cropping systems, with application to Moringa oleifera. The figure integrates hyperspectral and multispectral imaging, LiDAR-based three-dimensional canopy characterization (ground-based and UAV-mounted), UAV thermal sensing, IoT soil–plant–atmosphere

monitoring, precision irrigation and nutrient management, and low-cost tools for smallholders. LiDAR-derived point clouds and voxel-based metrics quantify canopy structure, volume, density, and porosity. These multi-source data are processed through machine learning and artificial intelligence within decision-support systems, enabling site-specific, climate-smart management aimed at optimizing yield, stabilizing phytochemical quality, and improving resource-use efficiency under heterogeneous field conditions.

5. Impacts on Yield, Quality, and Sustainability

Precision Agriculture (PA) influences nutraceutical cropping systems across three interrelated domains: biomass productivity, phytochemical quality stabilization, and resource-use efficiency. Unlike commodity crops—where yield is the primary performance metric—nutraceutical systems require simultaneous optimization of biomass and biochemical uniformity.

Available evidence indicates that PA can contribute to improved agronomic performance and resource efficiency. However, reported effect sizes vary substantially across crops, agroecological conditions, technological configurations, and validation scales. Many studies remain plot-based or single-season experiments, and long-term commercial-scale validation is still limited.

The following subsections critically evaluate yield, quality, and sustainability impacts while distinguishing empirically demonstrated outcomes from expected or context-dependent benefits.

5.1. Yield Improvements

Yield enhancement represents one of the most frequently reported outcomes of PA adoption. Across specialty and medicinal crops, reported biomass increases typically range from 5% to 30%, depending on species, irrigation regime, nutrient management strategy, and environmental variability [127–129].

High-resolution multispectral indices (e.g., NDVI, NDRE, GNDVI) and UAV-based thermal imagery enable early detection of stress conditions affecting canopy development. These technologies support timely corrective interventions, which may preserve photosynthetic activity and canopy uniformity [93,130,131]. However, improvements are not uniform across environments; yield responses are strongly influenced by baseline management efficiency and climatic constraints.

LiDAR-derived structural metrics contribute indirectly to yield optimization by improving biomass estimation and pruning assessment. While structural uniformity correlates with improved radiation-use efficiency, direct causal links between LiDAR-based structural correction and yield increases remain limited in the literature.

Machine-learning models (CNNs, random forest, LSTM) have demonstrated high predictive accuracy for biomass estimation under cross-validation conditions (R^2 often > 0.80) [132–135]. Nevertheless, model performance frequently declines when applied across seasons or sites without recalibration. Thus, predictive capability does not automatically translate into prescriptive yield optimization.

In Mediterranean *Moringa oleifera* systems, precision irrigation combined with multispectral monitoring has resulted in reported leaf biomass increases of approximately 12–18% under experimental and pilot-scale conditions [61,136]. While promising, these results derive primarily from controlled or semi-controlled studies, and multi-year commercial replication remains limited.

Overall, yield improvements under PA are supported by moderate evidence but exhibit context dependency and require genotype- and environment-specific calibration.

These results should be interpreted cautiously due to the heterogeneity in experimental design, spatial scale, and validation protocols across studies. In several cases, evidence derives from single-season or plot-scale trials, limiting the generalizability of reported agronomic gains to broader commercial and multi-environment contexts.

5.2. Enhancement and Stabilization of Nutraceutical Quality

For nutraceutical crops, quality stabilization is arguably more critical than absolute yield increase. Bioactive compounds—including phenolics, flavonoids, carotenoids, essential oils, and vitamins—are highly responsive to environmental stress, nutrient status, and microclimatic variability [13,137–142].

Precision Agriculture contributes to quality stabilization primarily through:

- Regulated water management;
- Site-specific nutrient adjustment;
- Early stress detection.

Moderate regulated deficit irrigation (RDI) has been associated with increased phenolic and antioxidant concentrations in several nutraceutical crops [143–145]. However, concentration increases do not always correspond to higher total metabolite yield per hectare if biomass is reduced. Therefore, quality enhancement must be evaluated using both concentration and total production metrics.

Precision nutrient management, particularly nitrogen and potassium optimization, influences chlorophyll density, carotenoid synthesis, and secondary metabolite pathways [6,146–148]. Yet direct mechanistic quantification of nutrient–metabolite coupling under field-scale PA remains limited.

Hyperspectral and multispectral sensing provide indirect proxies for biochemical monitoring. While predictive models report R^2 values between 0.70 and 0.90 under calibration datasets, external validation performance is more variable [7,60,149–152]. Measurement uncertainty, spectral overlap, and genotype variability remain critical challenges.

In Mediterranean *Moringa oleifera* systems, improvements in vitamin C concentration, carotenoid content, and antioxidant activity have been observed under precision irrigation and fertilization regimes [61]. However, most studies are limited to single-season or regional trials, and generalization to other nutraceutical crops requires caution.

Thus, PA shows potential for reducing within-field biochemical variability and improving harvest timing precision. Nonetheless, the literature often reports correlational relationships, and causality between specific PA interventions and metabolite stabilization requires further controlled validation.

These modeling performances should be interpreted cautiously, as validation strategies often rely on internal cross-validation rather than independent multi-season datasets. Furthermore, inconsistent reporting of error metrics (e.g., RMSE, confidence intervals) constrains direct comparability and may overestimate real-world predictive robustness.

5.3. Environmental Sustainability and Resource Efficiency

Environmental sustainability in PA-based nutraceutical systems is typically evaluated through resource-use efficiency indicators, including:

- Water-use efficiency (WUE);
- Nutrient-use efficiency (NUE);
- Reduction in chemical inputs;
- Yield stability under stress.

Precision irrigation studies report water savings between 20% and 40% relative to conventional scheduling [71,123,153–157]. These savings are primarily attributable to improved synchronization between plant demand and irrigation delivery. However, climatic variability and infrastructure constraints influence achievable reductions.

Variable-rate fertilization and spatial nutrient mapping contribute to improved NUE, often reducing fertilizer application by 10–35% while maintaining crop performance [158–161]. This may reduce nitrate leaching and environmental contamination, although long-term soil health impacts remain underexplored.

Early stress detection via spectral and thermal sensing can reduce prophylactic pesticide applications by enabling targeted interventions [162–164]. Nevertheless, empirical quantification of pesticide reduction rates in nutraceutical systems remains limited.

The manuscript defines "climate-smart" nutraceutical systems as those demonstrating:

- Stable yield under climatic variability;
- Reduced resource intensity per unit of output;
- Maintained phytochemical uniformity across stress gradients.

While *Moringa oleifera* exhibits inherent drought tolerance, PA interventions appear to enhance yield stability and resource efficiency under Mediterranean semi-arid conditions [3,62]. However, resilience indicators (e.g., multi-season coefficient of variation, recovery time after stress) are rarely reported explicitly in existing studies.

Additionally, the environmental footprint of digital infrastructure—including sensor production, UAV energy use, and data-processing energy consumption—remains insufficiently assessed in the literature. Sustainability claims should therefore be interpreted within a broader lifecycle framework.

In summary, PA contributes to measurable improvements in water and nutrient efficiency and shows potential for enhancing environmental sustainability in nutraceutical crops. However, long-term ecological validation, lifecycle assessment, and economic sustainability analyses remain areas requiring further research.

Collectively, the available evidence indicates that the integration of multispectral, thermal, LiDAR, IoT, and AI-driven technologies within a Precision Agriculture framework can support improvements in yield performance, stabilization of nutraceutical quality, and enhanced resource-use efficiency in *Moringa oleifera* systems. As summarized in Table 4, these outcomes are context-dependent and vary according to environmental conditions, management intensity, and experimental scale. The convergence of structural, physiological, and biochemical monitoring facilitates a shift from uniform, input-intensive practices toward more adaptive and quality-oriented production strategies. In Mediterranean and semi-arid regions, such integrative approaches show particular promise for advancing climate-smart nutraceutical agriculture, although long-term, multi-season validation remains necessary to confirm resilience and sustainability gains under commercial conditions.

Table 4. Mapping of Precision Agriculture technologies to yield, nutraceutical quality, and sustainability outcomes in *Moringa oleifera* cropping systems.

PA Technology	Key Variables Monitored	Yield-Related Outcomes	Nutraceutical Quality Outcomes	Environmental & Sustainability Impacts
UAV Multispectral Imaging (NDVI, NDRE, GNDVI, VARI)	Canopy vigor, chlorophyll content, nutrient status, spatial heterogeneity	+12–18% leaf biomass increase; improved canopy uniformity; optimized harvest timing	Stabilization and enhancement of vitamin C, carotenoids, chlorophyll density, antioxidant capacity	Reduced fertilizer overuse; site-specific interventions; lower input waste
UAV Thermal Imaging (CWSI)	Canopy temperature, plant water stress	Yield stabilization under water-limited conditions; reduced stress-induced biomass losses	Increased phenolic content and antioxidant activity via controlled water stress	25–40% water savings; improved irrigation efficiency; climate adaptation

Table 4. *Cont.*

PA Technology	Key Variables Monitored	Yield-Related Outcomes	Nutraceutical Quality Outcomes	Environmental & Sustainability Impacts
LiDAR-Based 3D Canopy Characterization (UAV & Terrestrial)	Canopy height, volume, density, porosity, structural heterogeneity	Improved biomass estimation accuracy; optimized pruning and canopy management	Indirect enhancement of phytochemical uniformity through optimized light interception and microclimate	Reduced unnecessary pruning; improved resource-use efficiency; structural resilience
IoT Soil–Plant–Atmosphere Sensor Networks	Soil moisture, NPK, EC, pH, microclimate, plant physiological signals	Stable growth trajectories; reduced yield variability across management zones	Enhanced vitamin C, carotenoids, antioxidant capacity via continuous physiological regulation	Water and nutrient savings; reduced leaching; lower environmental footprint
Machine Learning & AI-Based DSS (CNN, RF, LSTM)	Multisource data integration; growth and stress prediction	Accurate biomass forecasting; optimized harvest timing	Prediction of phytochemical accumulation peaks; quality standardization	Reduced trial-and-error inputs; data-driven efficiency gains
Precision Irrigation (RDI + Smart Drip Systems)	Soil moisture thresholds; plant water demand	Yield maintenance under deficit irrigation; improved water productivity	Increased phenolics, flavonoids, antioxidant compounds	Water conservation; improved drought resilience
Precision Nutrient Management (VRA, Spectral Diagnostics)	Nitrogen, potassium, micronutrient status	Improved leaf biomass production; nutrient-use efficiency	Enhanced carotenoid synthesis, vitamin C stability, antioxidant capacity	Reduced fertilizer losses; lower GHG emissions
Low-Cost PA Tools (Smartphone imaging, Open-source IoT)	Visual stress indicators; basic spectral/physiological signals	Yield protection in smallholder systems	Acceptable nutraceutical quality consistency at low cost	Democratization of PA; economic and environmental sustainability

5.4. Economic Competitiveness and Market Value

The economic implications of Precision Agriculture (PA) in nutraceutical cropping systems derive from its potential to improve resource-use efficiency, reduce input variability, and enhance product quality consistency [165–167]. However, while agronomic and environmental benefits are increasingly documented, structured economic evaluations remain comparatively limited, particularly at commercial scale.

Cost reductions associated with PA adoption are primarily linked to:

- Improved water-use efficiency;
- Reduced fertilizer over-application;
- Targeted crop protection interventions;
- Decreased yield variability.

Reported water savings (20–40%) and fertilizer reductions (10–35%) may translate into measurable variable-cost reductions under favorable infrastructure conditions. Nevertheless, the economic return depends strongly on farm size, initial capital investment, technology maintenance costs, and market structure.

For nutraceutical crops, economic competitiveness is closely tied to biochemical standardization and traceability. Markets for pharmaceutical, cosmetic, and functional food ingredients often require compliance with quality specifications related to phenolic content, antioxidant capacity, essential oil composition, or vitamin concentration [7]. In this context, PA-enabled monitoring may reduce batch variability and support access to premium market segments.

However, it is important to distinguish between:

- Demonstrated input savings (moderately supported by field studies);
- Quantified price premiums directly attributable to PA-based quality stabilization (less systematically documented).

Few peer-reviewed studies provide full return-on-investment (ROI) calculations over multiple seasons. Economic analyses frequently focus on agronomic performance rather than integrated profitability metrics that include depreciation, energy consumption, data-processing costs, and training requirements.

In *Moringa oleifera*, improvements in antioxidant capacity, vitamin C concentration, and carotenoid profiles under precision irrigation and nutrient management have been reported [61]. While these biochemical enhancements may increase market value for leaf powders, extracts, and functional ingredients, structured price-differentiation analyses are limited. The magnitude of economic gain therefore remains context-dependent and influenced by certification schemes, export markets, and value-chain organization.

Digital traceability systems integrating UAV data, IoT monitoring, and decision-support platforms may enhance transparency and regulatory compliance. However, technologies such as blockchain-based traceability and digital twins remain in pilot or early-adoption stages within nutraceutical agriculture. Their scalability, interoperability, and cost-effectiveness require further validation before being considered mature economic drivers.

Overall, PA shows potential to strengthen the economic resilience of high-value nutraceutical systems, particularly in regions where product differentiation and sustainability certification command price premiums. Nonetheless, long-term commercial validation, lifecycle cost analysis, and structured ROI frameworks are necessary to fully quantify its economic competitiveness relative to conventional management systems.

6. Challenges and Barriers to Precision Nutraceutical Farming

Although Precision Agriculture (PA) demonstrates measurable agronomic and efficiency benefits, its adoption in nutraceutical cropping systems remains uneven. Barriers arise from technological, economic, infrastructural, biological, and socio-institutional constraints. These factors collectively influence scalability, transferability, and long-term sustainability—particularly in Mediterranean and semi-arid regions characterized by smallholder structures and fragmented landholdings.

The challenges discussed below should be interpreted not as intrinsic limitations of PA technologies, but as systemic constraints affecting their effective implementation in quality-oriented nutraceutical systems.

6.1. Capital Investment and Cost Uncertainty

The implementation of advanced PA systems may require substantial initial investments in UAV platforms, hyperspectral or thermal sensors, LiDAR equipment, IoT infrastructure, data-processing software, and technical services. For small and medium-scale nutraceutical producers, these upfront costs represent a significant adoption barrier.

While reported reductions in water and fertilizer use can partially offset operational costs, structured multi-year return-on-investment (ROI) analyses remain scarce in the nutraceutical sector. Most economic evaluations are short-term or crop-specific, limiting generalization.

Lower-cost alternatives—such as consumer-grade UAVs, smartphone-based diagnostics, and open-source IoT systems—improve accessibility but often involve trade-offs in spectral resolution, data accuracy, or durability. Moreover, recurring costs (maintenance, calibration, cloud storage, software licensing, and training) are frequently underestimated in adoption scenarios.

Thus, economic feasibility is highly context-dependent and influenced by crop value, market structure, and cooperative frameworks.

6.2. Technical Complexity and Digital Skill Requirements

PA systems generate high-dimensional, heterogeneous datasets that require processing and interpretation across agronomic, physiological, and data-science domains. Effective deployment depends on competencies in:

- Remote sensing interpretation;
- Geospatial analysis;
- Sensor calibration;
- Data analytics;
- Machine learning.

In many nutraceutical systems—particularly emerging crops such as *Moringa oleifera*—standardized operational thresholds and validated decision rules remain under development. As a result, producers often depend on external service providers, which may increase costs and reduce operational autonomy.

Additionally, most available decision-support systems (DSS) remain predictive rather than fully prescriptive. The translation of predictive outputs into actionable irrigation or nutrient adjustments requires additional agronomic interpretation.

6.3. Data Interoperability and Standardization Gaps

A major structural barrier within the PA ecosystem is limited interoperability among sensors, platforms, and software solutions. Proprietary architectures and inconsistent data formats restrict cross-platform integration and hinder the development of unified decision-support frameworks.

In nutraceutical crops, quality optimization requires integration of:

- Structural metrics (LiDAR);
- Spectral signatures (multispectral/hyperspectral);
- Thermal stress indicators;
- Soil–plant–atmosphere data.

Here, fragmentation reduces analytical robustness and complicates model validation.

The absence of harmonized metadata standards, open APIs, and standardized calibration protocols constrains reproducibility and cross-regional transferability. This issue is particularly relevant for phytochemical prediction models, which often require species- and genotype-specific recalibration.

6.4. Infrastructure and Connectivity Constraints

IoT-based monitoring and cloud-driven analytics depend on stable broadband connectivity and reliable power supply. However, nutraceutical cropping systems are frequently located in rural, hilly, or semi-arid Mediterranean regions with limited digital infrastructure.

Connectivity interruptions can:

- Delay data transmission;
- Disrupt real-time analytics;
- Compromise model updates;
- Reduce decision timeliness.

Similarly, sensor network durability under harsh field conditions (heat, dust, humidity) affects long-term data continuity. Infrastructure constraints therefore remain a practical limitation for fully integrated PA systems.

6.5. Policy and Institutional Alignment

Adoption of digital agriculture technologies is strongly influenced by policy frameworks, financial incentives, and extension services. In many regions, regulatory structures for data ownership, digital traceability, and sensor-based certification remain underdeveloped.

For emerging nutraceutical crops such as *Moringa oleifera*, additional institutional gaps include:

- Limited standardized agronomic protocols;
- Absence of unified phytochemical quality benchmarks;
- Incomplete integration into certification schemes.

Without coordinated public–private partnerships, training programs, and targeted subsidies, technology diffusion may remain uneven and concentrated among larger producers.

6.6. Biological Variability and Calibration Challenges

Nutraceutical crops exhibit substantial genotypic and phenotypic variability. This biological heterogeneity complicates spectral modeling, stress detection thresholds, and predictive accuracy.

PA algorithms developed for commodity crops cannot be directly transferred to nutraceutical species without recalibration. In *Moringa oleifera*, genotype-specific differences (e.g., African, Indian, PKM1, PKM2 lines) influence:

- Spectral reflectance patterns;
- Canopy architecture;
- Water-use efficiency;
- Secondary metabolite profiles.

Consequently, genotype-specific and site-specific calibration is required to ensure model robustness. Limited multi-genotype, multi-site datasets represent a major research gap.

6.7. Limited Multi-Season and Commercial-Scale Validation

Many PA technologies demonstrate promising performance under experimental or pilot-scale conditions. However, long-term validation across multiple seasons and commercial-scale operations remains limited.

Key underexplored aspects include:

- Interannual yield stability;
- Multi-year phytochemical consistency;
- Lifecycle environmental footprint;
- Long-term ROI;
- Resilience under extreme climatic variability.

For nutraceutical systems, sustained validation is essential because quality metrics may fluctuate across seasons even when biomass remains stable.

6.8. Socioeconomic and Behavioral Factors

Technology adoption is influenced not only by technical feasibility but also by farmer perceptions, cultural practices, and risk tolerance. As illustrated in Figure 4, adoption dynamics in nutraceutical systems are shaped by:

- Risk aversion;
- Trust in digital tools;
- Perceived complexity;
- Uncertainty regarding economic return;
- Attachment to traditional management practices.

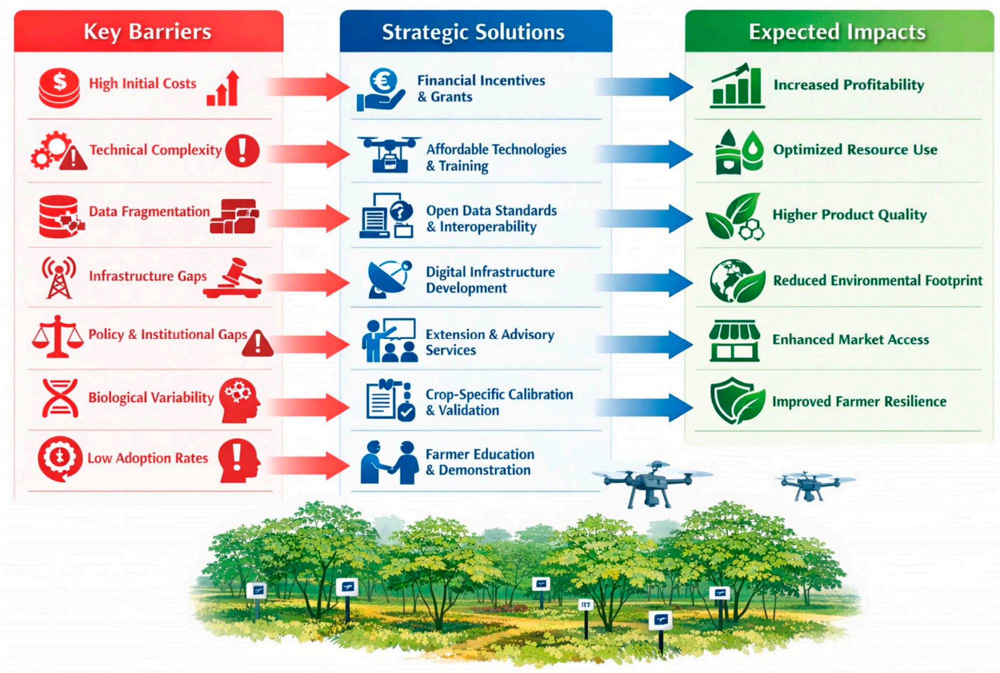

Figure 4. Conceptual framework linking barriers, solutions, and impacts in Precision Nutraceutical Farming. The figure synthesizes the main constraints limiting the adoption of Precision Agriculture (PA) in nutraceutical cropping systems—including high initial costs, technical complexity, data interoperability gaps, infrastructure limitations, biological variability, and socio-institutional barriers—and maps them to corresponding technological, organizational, and policy-oriented solutions. Proposed solutions include low-cost and open-source sensing tools, user-friendly decision-support systems, standardized data architectures, capacity-building initiatives, and supportive policy frameworks. The resulting impacts highlight improved yield stability, enhanced phytochemical quality, increased resource-use efficiency, climate resilience, and strengthened economic competitiveness, with specific relevance to Moringa oleifera-based nutraceutical value chains under Mediterranean conditions.

In artisanal and specialty crop systems, experiential knowledge often plays a central role. Bridging conventional practices with data-driven management requires participatory research, demonstration farms, cooperative digital services, and structured training programs.

Addressing these behavioral and institutional dimensions is essential for realizing the transformative potential of PA in nutraceutical cropping systems.

6.9. Concluding Perspective on Barriers

Collectively, these challenges indicate that the transition toward precision nutraceutical farming depends not only on technological innovation but also on:

- Calibration robustness;
- Economic validation;
- Interoperability standards;
- Infrastructure development;
- Institutional support;
- Social acceptance.

While *Moringa oleifera* provides a valuable model for evaluating integrative PA systems in Mediterranean environments, the scalability of such approaches requires coordinated advances across technological, economic, and governance domains.

7. Future Perspectives

The future evolution of Precision Agriculture (PA) in nutraceutical cropping systems will be shaped by the convergence of rapid technological innovation, expanding global demand for functional and health-promoting foods, and increasing pressures associated with climate change, resource scarcity, and environmental regulation (Figure 5). Demographic growth and rising climate variability require agricultural production systems capable of ensuring high efficiency, adaptive capacity, and operational responsiveness while maintaining environmental sustainability and consistent product quality [94]. Within this context, PA is expected to transition from predominantly experimental or pilot-scale implementations toward mature, scalable, and commercially viable production paradigms.

Figure 5. Future perspectives of Precision Agriculture in nutraceutical cropping systems. The figure illustrates how advances in sensing technologies, UAV-based phenotyping, artificial intelligence, and digital twins—together with controlled-environment agriculture, blockchain-enabled traceability, and low-cost precision tools—are expected to drive the transition from pilot-scale applications to widespread deployment. These innovations support climate-resilient, resource-efficient, and quality-driven production systems, with Moringa oleifera highlighted as a representative nutraceutical crop for Mediterranean and semi-arid agroecosystems.

As sensing technologies, artificial intelligence (AI), automation, and digital infrastructures continue to improve in accuracy, affordability, and interoperability, PA will increasingly enable integrated, end-to-end management of nutraceutical value chains. For environmentally responsive and phytochemically rich species such as *Moringa oleifera*, data-driven management will play a strategic role in scaling production, stabilizing quality attributes, and strengthening resilience across Mediterranean and other climate-sensitive agroecosystems. Emerging evidence demonstrates that the integration of UAV platforms, advanced sensing systems, and AI-based analytics is transforming medicinal and nutraceutical plant cultivation by enhancing productivity, sustainability, and quality consistency, although persistent challenges related to data governance, market integration, infrastructure, and farmer training must still be addressed [21].

7.1. Advances in Sensor Technologies and High-Resolution Phenotyping

Next-generation hyperspectral, multispectral, thermal, and LiDAR sensors are expected to deliver progressively higher spatial, spectral, and temporal resolution while becoming more compact, energy-efficient, and cost-effective. Ultra-light UAV-mounted hyperspectral sensors, combined with low-cost proximal, wearable, and in-canopy sensing devices, will enable continuous, real-time monitoring of physiological, biochemical, and structural traits throughout the growing season.

In *Moringa oleifera*, future phenotyping research is likely to refine robust spectral and structural markers associated with vitamin C concentration, carotenoid accumulation, chlorophyll density, antioxidant capacity, and canopy architecture. The integration of three-dimensional plant modeling with LiDAR-based canopy reconstruction will further enhance biomass estimation, structural characterization, and spatial variability analysis under heterogeneous Mediterranean soil and microclimatic conditions. These developments will facilitate a transition from empirical proxy-based assessment toward mechanistically informed structure–function phenotyping frameworks capable of linking canopy architecture, physiological status, and phytochemical expression.

7.2. Artificial Intelligence, Predictive Analytics, and Digital Twins

Artificial intelligence is poised to drive a fundamental shift in PA from descriptive and reactive management toward predictive, prescriptive, and anticipatory decision-making. Advanced machine-learning and deep-learning architectures will increasingly enable early stress detection, forecasting of phytochemical accumulation, and dynamic optimization of irrigation and nutrient regimes under variable environmental conditions.

Within nutraceutical systems, digital twins—virtual, data-driven replicas of crops, fields, or entire production systems—represent a particularly promising frontier. These models will allow simulation of plant growth, canopy development, and biochemical responses across genotype $\times$ environment $\times$ management scenarios. In *M. oleifera*, digital twins could support genotype-specific simulations of water stress response, nutrient-use dynamics, and microclimatic variability, enabling tailored management strategies that maximize both yield and phytochemical quality. Such tools will be particularly valuable in semi-arid Mediterranean regions, where climate variability and extreme events are projected to intensify.

7.3. Integration of Controlled-Environment Agriculture and Vertical Systems

The convergence of PA with controlled-environment agriculture (CEA), including greenhouses, plant factories, and vertical farming systems, offers new opportunities for year-round nutraceutical crop production with unprecedented control over microclimate, light spectrum, and nutrient delivery. LED-based spectral tuning technologies enable targeted modulation of carotenoid, flavonoid, phenolic, and vitamin biosynthesis, allowing precise regulation of functional quality attributes.

Although *Moringa oleifera* has traditionally been cultivated in open-field systems, growing interest in high-density and protected cultivation suggests alternative pathways for standardized leaf biomass and extract production. Precision climate control, fertigation systems, and programmable spectral lighting could support the production of moringa leaf powders and extracts with highly consistent nutraceutical profiles, meeting stringent pharmaceutical, cosmetic, and functional food industry standards.

7.4. Blockchain and Advanced Traceability Systems

Transparency, traceability, and quality certification are increasingly central requirements in global nutraceutical markets. PA provides the digital infrastructure necessary to support blockchain-enabled traceability systems capable of documenting cultivation practices, environmental conditions, management interventions, and phytochemical attributes throughout the production cycle.

For *Moringa oleifera*-derived products, including leaf powders, teas, and extracts, blockchain-based digital passports could certify geographic origin, production methods, sustainability indicators, and biochemical quality parameters. Such systems have the potential to enhance consumer trust, facilitate regulatory compliance, and improve access to high-value international markets. The strong nutraceutical profile of moringa further reinforces its strategic relevance in the development of traceable and commercially competitive functional food products [56,60].

7.5. Low-Cost and Open-Source PA Tools for Smallholders

Equitable and widespread adoption of PA requires the development of accessible and scalable solutions tailored to small and medium-sized producers, who dominate many nutraceutical and medicinal plant sectors. Advances in low-cost sensors, open-source IoT platforms, smartphone-based diagnostic tools, and cloud-enabled analytics are expected to democratize access to precision technologies.

The parallel development of simplified, user-centered decision-support systems will be essential to reduce technical and cognitive barriers. In Sicily and across the Mediterranean basin, smallholder *M. oleifera* producers may particularly benefit from modular, low-cost PA kits capable of delivering real-time information on soil moisture, nutrient dynamics, canopy status, and stress indicators. Such systems can enable effective precision management without prohibitive capital investment, thereby improving economic viability, environmental sustainability, and product quality.

7.6. Climate Resilience and Adaptation Strategies

Climate change will impose increasing constraints on nutraceutical crop production through rising temperatures, altered precipitation regimes, and more frequent extreme events. PA will be central to the development of adaptive strategies that enhance climate resilience through optimized irrigation management, stress forecasting, and genotype–environment interaction modeling.

Moringa oleifera is inherently drought tolerant and well adapted to warm climates; however, PA tools can further enhance resilience by stabilizing plant water status, mitigating heat stress, and optimizing harvest timing to capture peak phytochemical expression. These characteristics position moringa as a strategic species for climate-smart nutraceutical agriculture in Mediterranean and semi-arid regions.

7.7. Expansion of Genotype-Specific PA Models for Emerging Crops

Most existing PA tools and spectral models have been developed for major staple crops such as cereals, maize, and soybean. The advancement of nutraceutical agriculture will therefore depend on the development of genotype-specific and species-specific PA models tailored to emerging crops. Multi-year and multi-site field experiments, expanded spectral libraries, and integrated biochemical databases will be essential for calibrating sensors and AI models for species such as *Moringa oleifera*, saffron, rosemary, oregano, lavender, and berry crops.

These efforts will improve the prediction of phytochemical dynamics, refine irrigation and nutrient scheduling, and strengthen long-term agronomic planning. In particular, future investigations aimed at identifying species-specific vegetation index thresholds, such as NDVI-based decision rules for integration into decision-support systems, will be critical for implementing targeted fertilization, irrigation, and harvesting strategies in aromatic and nutraceutical crop systems [13] (Figure 6).

Figure 6. Future roadmap for Precision Agriculture (PA) in nutraceutical cropping systems. Conceptual overview of the technological and methodological trajectories shaping next-generation PA for nutraceutical crops, with a focus on Moringa oleifera. The roadmap integrates advances in high-resolution sensing and 3D phenotyping (multispectral, hyperspectral, thermal, and LiDAR), artificial intelligence and digital twins for predictive and prescriptive management, controlled-environment and vertical systems, blockchain-enabled traceability, and low-cost open-source tools for smallholders. These components converge toward climate-resilient, quality-oriented, and resource-efficient production systems, enabling genotype-specific management, standardized phytochemical profiles, and enhanced sustainability across Mediterranean and semi-arid agroecosystems.

8. Conclusions and Outlook

Precision Agriculture (PA) represents a technologically advanced and conceptually coherent framework for managing spatial and temporal variability in nutraceutical cropping systems. Its integration of multispectral and thermal UAV sensing, LiDAR-based structural analytics, IoT-enabled soil–plant–atmosphere monitoring, and AI-driven modeling offers unprecedented data density and decision-support potential. However, while the technological ecosystem is rapidly evolving, the scientific consolidation of PA specifically for nutraceutical crops remains incomplete.

The evidence synthesized in this review indicates that PA can be associated with improvements in yield stability, canopy uniformity, and resource-use efficiency under controlled and well-calibrated conditions. In several studies, precision irrigation and site-specific nutrient management were linked to enhanced secondary metabolite accumulation and reduced input intensity. Nonetheless, effect sizes are highly context-dependent, influenced by crop species, genotype, agroecological conditions, sensor configuration, and validation protocols. The heterogeneity of methodologies—ranging from single-season pilot trials to small plot-scale experiments—limits direct cross-study comparability and precludes robust meta-analytical generalization. Long-term, multi-site, and commercial-scale validations remain scarce, particularly for minor and emerging nutraceutical crops.

A central methodological gap concerns the biochemical validation of remote sensing proxies. Although vegetation indices and spectral models are frequently correlated with phytochemical traits, calibration drift, genotype specificity, and environmental confounders introduce uncertainty in predictive reliability. Few studies report multi-season recalibration, cross-regional transferability testing, or uncertainty quantification for phytochemical predictions. Consequently, many current PA applications in nutraceutical systems remain predictive rather than prescriptive, and correlations should not be interpreted as mechanistic causality.

Within this framework, *Moringa oleifera* is discussed as a model crop to illustrate PA implementation in climate-sensitive Mediterranean environments. Evidence from semi-arid Sicilian systems demonstrates that moringa responds to precision irrigation and nutrient optimization with measurable changes in biomass distribution and phytochemical indicators. However, genotype-specific spectral calibration, standardized metabolomic validation, and multi-year stress-response datasets are still required to substantiate model robustness. Extrapolation to other nutraceutical species—such as saffron, rosemary, oregano, lavender, or berry crops—should therefore be approached cautiously until species-specific spectral libraries and biochemical benchmarks are established.

Structural and operational barriers further constrain large-scale adoption. High initial investment costs, fragmented data ecosystems, limited interoperability between platforms, and insufficient rural digital infrastructure continue to restrict scalability. In addition, the majority of AI-based systems currently function as forecasting or classification tools rather than closed-loop, autonomous management platforms. The absence of standardized data architectures and harmonized validation protocols further complicates integration across technologies. Addressing these limitations will require coordinated efforts in open-data standards, sensor cross-calibration frameworks, and transparent algorithm validation.

Environmental claims associated with PA must also be critically contextualized. While reductions in water and fertilizer use are frequently reported, comprehensive life-cycle assessments accounting for the energy consumption of sensors, UAVs, cloud computing, and data storage are largely absent from the literature. Without full-system environmental accounting, the net sustainability benefit of digital intensification cannot be conclusively determined. Future research should therefore integrate agronomic performance metrics with energy-use and carbon-footprint analyses to avoid unintended rebound effects.

Several emerging trajectories—including digital twins, blockchain-enabled traceability, wearable sensors, controlled-environment integration, and autonomous robotics—are conceptually promising but remain at early maturity stages. Empirical validation of these technologies in nutraceutical systems is limited, and economic return-on-investment analyses are particularly underrepresented. Demonstration projects at commercial scale, coupled with longitudinal cost–benefit assessments, are essential before these innovations can be considered operationally transformative.

Advancement of PA in nutraceutical agriculture will depend on addressing four priority research gaps. First, multi-season and multi-site experimental validation is required to assess model stability under climatic variability. Second, genotype-specific calibration frameworks must be developed to reduce spectral prediction uncertainty. Third, integration of metabolomics with high-resolution sensing is needed to strengthen structure–biochemistry coupling. Fourth, standardized economic and environmental performance indicators should be incorporated into PA evaluation protocols.

The development of species-specific decision thresholds—such as calibrated NDVI or NDRE values linked to irrigation, fertilization, or harvest timing—represents a particularly relevant research direction. Such thresholds must be derived from statistically robust datasets and validated across agroecological zones to support transferability and reproducibility.

In conclusion, Precision Agriculture provides a technologically sophisticated platform for improving the management of nutraceutical cropping systems, but its scientific maturation for this sector is still in progress. Current evidence supports its potential to enhance productivity, stabilize phytochemical profiles, and improve resource-use efficiency under defined conditions. However, broader generalization requires methodological rigor, cross-regional validation, biochemical standardization, economic transparency, and comprehensive sustainability assessment. For *Moringa oleifera* and analogous emerging crops, PA offers valuable tools, yet its consolidation as a scalable, climate-resilient paradigm in nutraceutical agriculture will ultimately depend on addressing these unresolved scientific and operational challenges.

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