Review

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Bridging Magnetic Field Agriculture and UAV-Based Precision Monitoring: A Systematic Review and Framework for Field-Scale Validation

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Abstract

Magnetic field (MF) technologies have been applied in agriculture for decades. However, they have not achieved mainstream adoption, partly because no validated methodology exists for evaluating their effects under realistic field conditions. UAV-based multispectral sensing represents a potential pathway to address this limitation: by providing spatially explicit, non-destructive estimates of key canopy physiological variables at field scale, it could provide the monitoring infrastructure through which MF treatment responses are, for the first time, systematically evaluated and validated under open-field conditions. To exploit this complementarity, however, a common evidential ground must first be established, identifying which crop physiological variables are both consistently modulated by MF treatments and reliably detectable by UAV remote sensing. This study addressed this challenge through a dual-stream systematic review of 216 peer-reviewed publications, comprising 102 studies on MF treatments in agricultural crops and 114 studies on UAV-based multispectral monitoring. Evidence from both research domains was synthesised to identify physiological variables that are simultaneously responsive to MF treatments and detectable through UAV remote sensing. Five direct bridge variables were identified: chlorophyll content, nitrogen use efficiency/nitrogen assimilation, above-ground biomass, leaf area index, and yield. Chlorophyll content emerged as the strongest bridge variable, combining consistent MF responsiveness with UAV estimation accuracies of up to $R^2 = 0.90$. Based on these findings, a conceptual framework was developed linking MF treatments, UAV-derived vegetation indices, ground-truth measurements, and machine-learning approaches for field-scale validation. The results reveal a complete absence of integration between the two research domains despite their strong biological and methodological compatibility. The proposed framework provides the first operational pathway for evaluating MF technologies under realistic farming conditions and may support future research on sustainable and digitally enabled crop production systems.

Keywords: magnetic field treatments; magnetopriming; UAV multispectral sensing; precision agriculture; nitrogen use efficiency; digital agriculture; sustainable agriculture; vegetation indices; crop monitoring

1. Introduction

Global food systems are under increasing pressure to expand production while simultaneously reducing their environmental footprint. This challenge is particularly evident in the context of nitrogen (N) fertilisation. The EU Farm to Fork Strategy [1], a key component of the European Green Deal, aims to reduce nutrient losses by 50% and fertiliser use by at least 20% by 2030 [1,2]. These targets reflect growing recognition that decades of intensive nitrogen application have contributed to widespread aquatic eutrophication, nitrate contamination, and biodiversity loss. However, in conventional farming systems, nitrogen use efficiency (NUE), defined as the proportion of applied N assimilated by the crop, routinely remains below 50%, meaning that more than half of the applied nitrogen is lost to the environment [3]. Improving NUE without compromising productivity requires not only agronomic optimisation but also the development of complementary physical technologies capable of enhancing plant nitrogen assimilation without additional chemical inputs. Within this context, the application of magnetic fields (MFs) to seeds, irrigation water, or growing crops has re-emerged as a scientifically credible and policy-relevant area of research.

Magnetic field treatments in agriculture are generally applied through three principal approaches. The first is magnetopriming, in which seeds are exposed to a controlled static or pulsed magnetic field before sowing. The second is magnetised water irrigation (MWI), where irrigation water passes through a permanent magnetic device installed on the supply line. The third involves direct and continuous exposure of growing crops through in-field electromagnetic systems. Although these approaches differ in their mode of application, they share a common biological basis, namely the interaction of externally applied magnetic flux with cellular processes involved in ion transport, enzyme activity, and reactive oxygen species (ROS) signalling [4]. A wide range of field intensities has been investigated, from weak static homogeneous fields (0–100 μT) to stronger milliTesla- and Tesla-level fields, as well as extremely low-frequency (ELF) configurations. Reported responses vary according to crop species, developmental stage, and exposure duration [4]. At the cellular level, MF treatments alter ion fluxes, enzyme activity, and gene expression, improving water and solute transport while enhancing chlorophyll and carotenoid synthesis and increasing the quantum efficiency of Photosystem II [5,6].

The agronomic potential of MF technology is supported by a growing body of evidence. In controlled germination experiments, magnetopriming of flax (Linum usitatissimum L.) at 350 mT for 100–120 min resulted in 100% germination, a 26.81-fold increase in seedling vigour index I, and a 2.63-fold increase in catalase activity compared with untreated controls [7]. The benefits of MF treatment extend beyond germination and persist through subsequent crop development. Field experiments on common bean (Phaseolus vulgaris L.) under MF treatment recorded increases of 13%, 21%, and 26% in chlorophyll a, chlorophyll b, and carotenoid content, respectively [8]. Of particular relevance to sustainable agriculture, MF treatments have been associated with improved NUE through the upregulation of nitrate reductase activity, a key enzyme in plant nitrogen assimilation [5]. A systematic review of magnetopriming effects on photosynthetic performance confirmed that static MF treatments consistently improve PSII efficiency, photosynthetic pigment concentrations, and leaf gas exchange parameters across multiple crop species [5]. These physiological benefits are also attracting commercial interest: magnetic water treatment devices are already commercially available and increasingly adopted by farmers, with reported fertiliser use reductions of 15–25%, while the Asia-Pacific region represents 48% of the global market, supported by governmental incentives in countries such as China and India [6]. In parallel, magnetically treated brackish water is gradually being incorporated into agricultural production systems, particularly in water-limited and saline environments where conventional irrigation management is costly [6].

Despite this convergence of scientific evidence and commercial adoption, an important methodological gap continues to limit the broader validation and agronomic credibility of MF technologies. Most studies have been conducted under controlled laboratory or greenhouse conditions, including pot experiments, small uniform plots, and simplified monoculture systems in which spatial variability, microclimatic gradients, and field heterogeneity are intentionally minimised [4,6]. Consequently, the translation of these findings to open-field agriculture at hectare scale remains largely unexplored. Farmers deploying MF technologies currently have no validated

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methodology for determining whether treatments produce measurable physiological responses under their specific field conditions, at which spatial locations those responses occur, or at which growth stages they are most pronounced. Inconsistencies among experimental protocols, exposure conditions, and proposed mechanisms of action further hinder the interpretation and comparison of results [6,9], limitations that are compounded by the absence of non-destructive monitoring tools capable of assessing treatment effects at field scale. It is precisely this absence of field-scale monitoring capacity that UAV-based multispectral remote sensing is positioned to fill.

UAV-based multispectral remote sensing has meanwhile matured into a widely deployed precision agriculture technology capable of estimating canopy physiological status non-destructively across entire fields [10]. The critical observation for the present argument is not that UAV technology exists, but that the specific variables it measures with greatest accuracy, chlorophyll content, nitrogen nutrition index (NNI), above-ground biomass, and leaf area index, are precisely the variables that MF treatments consistently improve. NDRE-based indices achieve $R^2 = 0.90$ for chlorophyll content estimation; NNI mapping from UAV imagery has been validated across wheat, rice, and maize at field scale [10,11]. This biological coincidence creates a closed monitoring cycle: MF treatment is applied, a physiological response is induced, the canopy spectral signature changes, and a UAV detects that change. A researcher applying MF treatment to a wheat field therefore already has access to the instrument needed to answer the question MF research has never been able to answer at scale: did the treatment work, where in the field did it work, and at which growth stage was the effect strongest? Exploiting this opportunity, however, requires first identifying which variables both systems share, the common ground that makes integrated monitoring possible. That identification is what the present review provides. In this sense, UAV technologies are not simply a monitoring tool for MF research, they may represent the enabling mechanism required to translate MF technologies from controlled experimental settings into scalable, evidence-based agronomic practices.

This review establishes the evidential basis for that monitoring cycle by synthesising evidence from two previously unconnected domains: MF-induced physiological responses in agricultural crops (Stream A) and UAV multispectral detection of those same variables at field scale (Stream B). The proposed framework translates this synthesis into a concrete operational protocol: MF treatment parameters are selected based on Stream A evidence, UAV flight plans and vegetation indices are matched to confirmed bridge variables, and machine learning models distinguish treatment-induced spectral signatures from background field variability. In doing so, the review responds directly to the Farm to Fork Strategy's emphasis on digital precision fertilisation and sustainable agricultural practices [1,12]. By identifying the existing research gap, integrating evidence across disciplines, and proposing a standardised protocol for future multi-site field experiments, this review aims to support the transition of MF technologies from controlled experimental settings to practical field-scale applications.

2. Materials and Methods

2.1. Study Design and Rationale

This paper is structured as a dual-stream systematic review and framework synthesis following the PRISMA 2020 guidelines for systematic evidence synthesis [13]. Rather than adopting a conventional single-domain approach, the study was designed to address a cross-disciplinary research gap: the absence of a validated methodology for monitoring the in-field physiological responses of crops to magnetic field (MF) treatments at agronomically relevant scales.

To develop a scientifically grounded monitoring framework, evidence was synthesised from two previously unconnected research domains. The first documents the physiological effects of MF treatments on agricultural crops, while the second demonstrates the capability of UAV-based multispectral remote sensing to estimate the same physiological variables non-destructively at field scale. The review focuses specifically on UAV multispectral sensing because it represents the most widely adopted, commercially mature, and operationally scalable remote sensing platform currently available for precision agriculture applications. Although other sensing approaches, including hyperspectral, thermal, fluorescence, and proximal sensing technologies, may provide complementary information, multispectral UAV systems currently offer the greatest potential for practical field-scale deployment.

The two streams therefore serve complementary roles within a single evidentiary framework rather than constituting independent reviews. Stream A identifies the physiological responses most consistently associated with MF treatments, whereas Stream B evaluates the capacity of UAV multispectral sensing to detect and quantify those responses under field conditions. The integration of evidence from both streams forms the basis of the conceptual monitoring framework proposed in this study.

The review was not registered in PROSPERO because its objective is methodological and technological integration rather than the evaluation of a clinical, biomedical, or epidemiological research question. The PRISMA flow diagram summarising the screening process for both streams is presented in Figure 1.

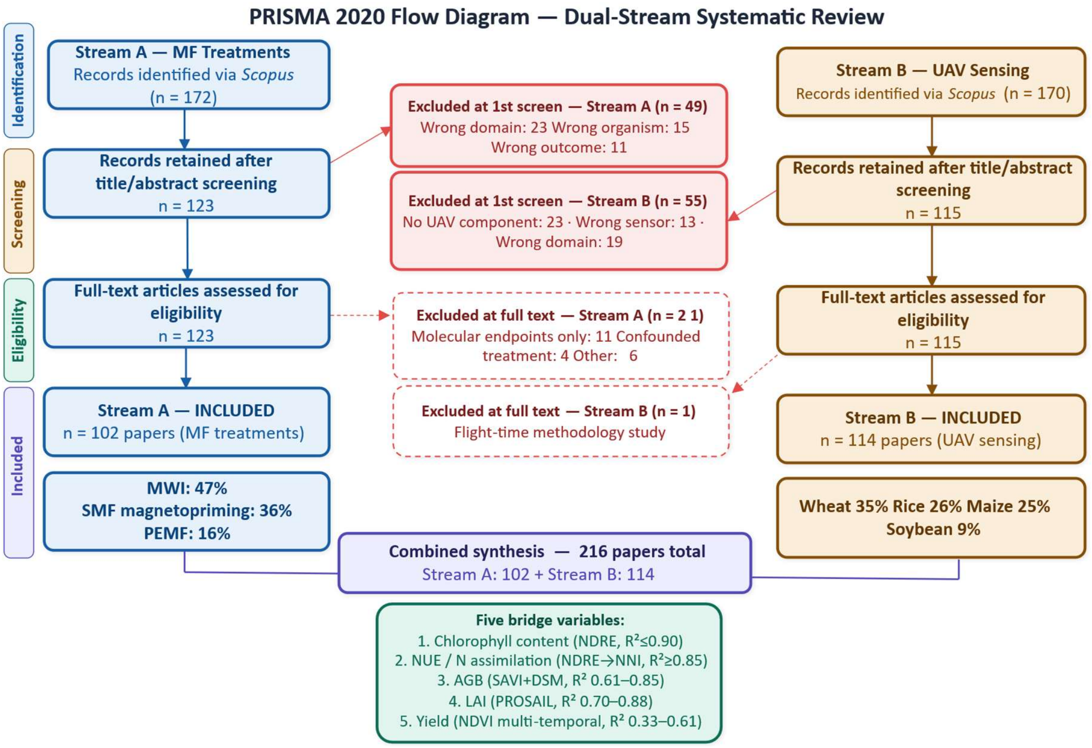

Figure 1. PRISMA 2020 flow diagram of the dual-stream systematic review. Stream A (MF treatments, blue) and Stream B (UAV multispectral sensing, amber).

2.2. Research Questions

Two complementary research questions structured the literature search and data extraction:

RQ1 (Stream A): Which physiological variables are consistently and significantly modulated by magnetic field treatments in agricultural crops, and at what experimental scales have these effects been documented?

RQ2 (Stream B): Can UAV-mounted multispectral sensors, through validated vegetation indices, detect and quantify the same physiological variables identified in RQ1, and with what level of reported accuracy?

The synthesis of answers to RQ1 and RQ2 directly informs the construction of the proposed monitoring framework: variables identified in Stream A as MF-responsive are cross-referenced against variables for which Stream B demonstrates remote-sensing detectability, yielding a set of index-variable pairs that form the operational basis of the framework.

2.3. Search Strategy

A systematic literature search was conducted in Scopus (www.scopus.com) in May 2026. Two independent queries were constructed, one per stream, using Boolean operators and field-code restrictions (TITLE-ABS-KEY). Search terms were selected to maximize precision rather than recall, reflecting the targeted nature of the cross-domain synthesis. The full queries are presented in Table 1. Stream A was restricted to publications from 2016 onwards to capture the period of significant growth in magnetopriming and magnetized water irrigation research. Stream B was restricted to publications from 2019 onwards to reflect the maturation of affordable UAV multispectral platforms (e.g., DJI Phantom 4 Multispectral, MicaSense RedEdge) in precision agriculture applications.

Table 1. Scopus search queries for Stream A (MF treatments) and Stream B (UAV remote sensing), with associated research questions.

Stream	Research Question	Scopus Query (TITLE-ABS-KEY) — abbreviated
Stream A *MF Treatments*	Which physiological variables do MF treatments consistently modulate?	**TITLE-ABS-KEY**(("static magnetic field" OR "pulsed magnetic field" OR "electro-magnetic field" OR "magnetopriming" OR "magnetized water" OR "magnetically treated water" OR "magnetic water treatment") AND ("seed germination" OR "plant growth" OR "chlorophyll" OR "nitrogen use efficiency" OR "NUE" OR "biomass" OR "photosyn-thesis" OR "nitrogen uptake" OR "crop yield" OR "antioxidant enzyme" OR "reactive oxygen species") AND ("agriculture" OR "agronomy" OR "crop" OR "wheat" OR "maize" OR "soybean" OR "tomato" OR "lettuce" OR "rice" OR "sunflower" OR "barley")) AND NOT TITLE-ABS-KEY("cancer" OR "tumor" OR "MRI" OR "medical" OR "animal" OR "livestock" OR "poultry" OR "fish" OR "scale inhibition" OR "pipe" OR "industrial" OR "wastewater treatment" OR "heavy metal removal") AND PUBYEAR > 2015 AND DOCTYPE (ar OR re) AND LANGUAGE (english)
Stream B *UAV Sensing*	Can UAV multispectral indices detect those same variables with validated accuracy?	**TITLE-ABS-KEY**(("UAV" OR "unmanned aerial vehicle" OR "drone" OR "UAS") AND ("multispectral" OR "NDVI" OR "NDRE" OR "vegetation index") AND ("chloro-phyll" OR "nitrogen use efficiency" OR "NUE" OR "nitrogen nutrition index" OR "NNI" OR "leaf nitrogen content" OR "nitrogen status" OR "photosynthetic pigment" OR "bio-mass estimation") AND ("wheat" OR "maize" OR "rice" OR "soybean" OR "barley" OR "cereal" OR "field crop")) AND NOT TITLE-ABS-KEY("satellite" OR "Sentinel" OR "Landsat" OR "MODIS" OR "hyperspectral" OR "greenhouse" OR "indoor" OR "forest" OR "vineyard" OR "fruit tree") AND PUBYEAR > 2018 AND DOCTYPE (ar OR re) AND LANGUAGE (english)

2.4. Study Selection and Screening

Following the database search, retrieved records were screened following the four-phase PRISMA 2020 structure: Identification, Screening, Eligibility, and Inclusion. First-pass screening was conducted at the title and abstract level applying the exclusion criteria in Table 2. Papers were retained in cases of ambiguity and subjected to full-text eligibility review. Second-pass full-text screening applied additional exclusion criteria focused on methodological relevance to the framework objective: papers were excluded if they measured only molecular or intracellular endpoints with no canopy-level physiological outcome detectable by remote sensing (Stream A), or if the reported spectral data lacked quantified accuracy metrics and did not estimate a variable relevant to MF treatment response (Stream B).

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Table 2. Inclusion and exclusion criteria applied at title/abstract and full-text screening stages.

Stream	Category	Stream A — Exclude if:	Stream B — Exclude if:
Both	Publication type	Conference abstract, book chapter, or non-peer-reviewed	Conference abstract, book chapter, or non-peer-reviewed
A only	Wrong organism	Animals, humans, bacteria, cell cultures, trees, ornamentals	—
A only	Wrong domain	Water purification, scale inhibition, medical, veterinary, industrial, post-harvest preservation	—
B only	Wrong platform	—	Satellite-only (Sentinel, Landsat, MODIS); manned aircraft; ground sensors with no UAV component
B only	Wrong sensor	—	RGB-only (no NIR band); hyperspectral; thermal-only imaging
B only	Wrong target variable	—	Disease/pest/weed detection; soil mapping without canopy measurement; fruit quality; no N/chlorophyll/biomass link
B only	No quantified accuracy	—	No R^2, RMSE, or correlation metric between VI and physiological variable

2.5. Data Extraction

Data extraction was performed independently for each stream using a standardized extraction sheet developed a priori (Table 3). Extraction was designed specifically to serve the framework construction objective: fields were selected to generate the evidence base required to match MF-responsive physiological variables (Stream A) against UAV-detectable physiological variables (Stream B). The critical operational field in each stream is the 'framework bridge flag': for Stream A, this records whether the physiological outcome measured is, in principle, detectable by UAV multispectral imaging; for Stream B, it records whether the target variable estimated corresponds to a variable consistently modulated by MF treatment. Papers flagged YES in both streams at the same variable form the direct evidentiary basis for each node in the proposed framework.

Table 3. Data extraction fields for Stream A (MF treatment papers) and Stream B (UAV remote sensing papers).

Field	Stream A — MF Papers	Stream B — UAV Papers
Technology type	SMF / PEMF / magnetized water / direct exposure	UAV platform (DJI Phantom / Matrice / Parrot / other)
Physical parameters	MF intensity (mT/μT/T); exposure duration; application mode	Sensor type; spectral bands available
Application stage	Pre-sowing / seedling / vegetative / reproductive / full season	Growth stage(s) at which UAV flights conducted
Target variable	Chlorophyll / NUE / NNI / biomass / N uptake / PSII / yield	Chlorophyll / NUE / NNI / leaf N / biomass / LAI / PSII / yield
Quantified accuracy	% change from control (direction and magnitude)	R^2 and/or RMSE; ML algorithm if used
Framework bridge flag	Does the paper measure any variable detectable by UAV? (YES / NO / PARTIAL)	Does the paper estimate a variable directly modulated by MF? (YES / NO)

2.6. Framework Construction Approach

The dual-stream systematic review was designed not only to characterise the existing literature in each domain but to identify where it can be operationally connected. Following extraction of all Stream A and Stream B data, a cross-domain variable mapping procedure was applied to determine which physiological variables simultaneously satisfy three evidence-based inclusion criteria: (i) the variable is reported with a consistent positive directional effect in at least two independent Stream A studies using MF treatment; (ii) at least one Stream B study has demonstrated that the same variable can be estimated from UAV multispectral imagery at canopy scale with a reported $R^2 \geq 0.60$, this threshold was selected as a minimum level of moderate predictive performance suitable for exploratory field-scale monitoring; and (iii) the biological quantity is physically measurable at canopy scale by passive optical remote sensing, without requiring contact instrumentation or destructive sampling.

Variables meeting all three criteria were assigned a bridge status of YES (direct connection confirmed). Variables meeting criterion (i) but only partially meeting (ii) or failing (iii) — specifically, variables not directly estimable by passive multispectral UAV but accessible via an indirect proxy or an emerging active sensing technique — were assigned a PARTIAL flag. Variables present in Stream A but absent from Stream B at the required accuracy threshold were excluded from the bridge table and recorded as monitoring gaps. Antioxidant enzyme activity (SOD, CAT, APX), for example, is consistently reported as a significant MF treatment response in Stream A but has no validated canopy-scale UAV detection method in Stream B and was therefore excluded.

The confirmed bridge connections formed the basis for a three-stage conceptual framework for scalable agronomic validation of MF treatments, presented in Section 3.3 and illustrated in Figure 2. The framework proceeds as follows. **Stage 1 (Treatment Design)** uses the Stream A evidence base to define experimental parameters — crop species, MF treatment type, intensity, and application timing — informed by the physiological responses most consistently documented for the target crop. **Stage 2 (UAV Monitoring Protocol)** specifies the UAV multispectral flight plan and the vegetation index corresponding to each confirmed bridge variable: NDRE for chlorophyll content and nitrogen nutrition index, SAVI combined with DSM-derived canopy height for above-ground biomass, NDVI and NDRE with PROSAIL radiative transfer model inversion for LAI, and multi-temporal NDVI with machine learning for yield, generating spatially explicit canopy maps of treatment response at each critical growth stage. **Stage 3 (ML Validation)** applies machine learning architectures validated in Stream B to help distinguish treatment-related spectral patterns from background spatial variability attributable to soil heterogeneity and microclimatic conditions. Within the proposed framework, this approach can support a more robust interpretation of canopy responses observed in MF-treated fields while reducing the influence of potential confounding factors. The cross-domain variable mapping that underpins this framework, together with the supporting evidence from both streams, is presented and discussed in Section 3.3.

2.7. Quality Assessment

Given the cross-disciplinary and framework-oriented nature of this review, formal risk-of-bias assessment tools designed for clinical studies (e.g., GRADE, Cochrane RoB) were not applicable. Methodological quality was assessed using two criteria applied during full-text screening: (i) whether the study reported quantified outcomes (% change from control, R^2, RMSE) rather than only qualitative descriptions, and (ii) whether the experimental design included a true control group. Papers meeting both criteria were prioritized in framework construction; papers meeting only one were included in the narrative synthesis but flagged. This approach is consistent with quality assessment practice in agricultural technology reviews of comparable scope [14].

3. Results

3.1. Stream A: Systematic Evidence on Magnetic Field Treatment Effects in Agricultural Crops

3.1.1. Screening Outcomes and Study Characteristics

The dual-stream PRISMA screening process is summarised in Table 4 and Figure 1. For Stream A, the Scopus query returned 172 records. First-pass title and abstract screening excluded 49 papers:

23 fell outside the agricultural MF domain (food processing, pseudoscience, non-MF electromagnetic applications, or engineering papers); 15 studied non-target organisms (tree crops, medicinal herbs, model plants, fungi, or human cell lines); and 11 addressed wrong outcome variables (heavy metal phytoremediation, herbicide management, or soil engineering). Second-pass full-text screening of the remaining 123 papers excluded a further 21 papers: 11 reported exclusively molecular or cellular endpoints with no canopy-level physiological outcome; 4 used treatments confounded by a second physical agent with no MF-only control; and 6 were excluded for other methodological or crop-context reasons, including hydroponic indoor systems, germination- or water-quality-only outcomes, and off-topic crop contexts. The final Stream A corpus comprised 102 included papers.

Table 4. PRISMA screening outcomes for Stream A (MF treatments) and Stream B (UAV remote sensing).

PRISMA Phase	Stream A — MF	Stream B — UAV
Records identified via Scopus	172	170
Excluded at 1st screening (title/abstract)	49	55
Retained after 1st screening	123	115
Excluded at 2nd screening (full abstract/text eligibility review)	21	1
FINAL INCLUDED for synthesis	102	114

Of the 102 papers, 93 were original research articles and 9 were review articles. Of the 93 original research articles, 89 provided extractable treatment data and were therefore used for the descriptive characterisation of study scale, crop distribution, and MF treatment categories. Among the 89 empirical studies, study scale distribution reflects the lab-to-field gap central to this paper: 23 papers (26%) used purely laboratory or controlled-chamber conditions; 21 papers (24%) employed pot or greenhouse experiments; and 45 papers (51%) reported results from small field plots or open-field conditions. Soybean (Glycine max L.) was the most studied species (16 papers), followed by wheat (Triticum spp., 13 papers), tomato (Solanum lycopersicum L., 10 papers), maize (Zea mays L., 10 papers), lettuce (Lactuca sativa L., 5 papers), and rice (Oryza sativa L., 2 papers). By MF treatment type, calculated from the 89 non-review empirical papers and recorded as non-mutually exclusive categories, magnetised water irrigation was reported in 47% of studies (n = 42), static magnetic field magnetopriming in 36% (n = 32), pulsed electromagnetic field treatments in 16% (n = 14), and combined or direct in-season exposure in 7% (n = 6). Of the 102 papers, 52 (51%) received a framework bridge flag of YES and 50 (49%) received a PARTIAL flag. Critically, zero of the 102 Stream A papers employed remote sensing of any kind to monitor treatment response, a finding that directly quantifies the research gap this review addresses.

3.1.2. MF Treatment Types and Application Modes

Three principal MF delivery modes are represented in the Stream A corpus: magnetopriming, magnetized water irrigation (MWI), and direct in-season MF exposure. These approaches differ in their mode of application and duration of exposure but share the common objective of modulating plant physiological processes through magnetic field intervention.

Magnetopriming involves exposing seeds to a static or pulsed magnetic field prior to sowing, typically for 30–120 min at field intensities ranging from 50 mT to 1000 mT [4,5,15]. As a pre-sowing treatment, magnetopriming is applied only once before crop establishment. The proposed mode of action includes modifications in seed membrane permeability, enzyme activity, and water absorption kinetics, resulting in enhanced germination, accelerated emergence, and improved seedling vigour. Importantly, several studies report carry-over effects that extend beyond early development, including improvements in chlorophyll content and nitrogen metabolism that persist through later growth stages.

Magnetized water irrigation (MWI) involves passing irrigation water through a device containing permanent magnets before application to the crop [16–18]. The treatment is proposed to alter physicochemical water properties, particularly hydrogen bonding angle, surface tension, and dissolved oxygen content. Unlike magnetopriming, MWI can be applied continuously throughout the growing season and is currently the only MF treatment mode with established commercial deployment at farm scale. Commercial systems are available for integration into drip and sprinkler irrigation infrastructure, making MWI the most operationally mature MF technology represented in the corpus.

Direct in-season MF exposure applies continuous or periodic electromagnetic fields to actively growing crops through dedicated in-field equipment [19–21]. Although it is the least frequently studied approach in the reviewed literature, largely because of its infrastructure requirements, it provides the most direct means of influencing physiological processes during critical developmental stages such as anthesis and grain filling. As a result, it offers the potential for targeted intervention during periods of high physiological sensitivity.

3.1.3. Synthesis of MF Effects on UAV-Detectable Physiological Variables

Chlorophyll Content and Photosynthetic Pigments

Enhanced chlorophyll accumulation is the most consistently reported MF effect across the Stream A corpus, appearing in approximately 43 of the 102 included papers and spanning all three treatment modes as well as all major crop species. This response is therefore not restricted to a particular crop or MF application strategy, but represents a broadly documented physiological outcome of MF treatment.

Evidence of enhanced chlorophyll content has been reported across multiple crop species and treatment configurations. SMF magnetopriming of soybean improved PSII efficiency (Fv/Fm) together with chlorophyll a and chlorophyll b concentrations under both UV-B stress conditions [22,23] and natural growing conditions [24]. Similarly, magnetopriming of tomato seeds enhanced chlorophyll content and leaf area during vegetative development [25], while magnetized water irrigation increased chlorophyll a, chlorophyll b, and carotenoid concentrations in tomato [26,27]. In addition, PEMF treatment of durum wheat during the growing season produced significant improvements in chlorophyll content alongside increases in yield and enzyme activity [28]. Field-scale magnetized water experiments have also reported enhanced chlorophyll pigment concentrations in bean [29] and tomato [26], including increases in chlorophyll a, chlorophyll b, and carotenoids.

The mechanistic basis for these responses has been documented across multiple crop species. Proposed mechanisms include enhanced Mg^{2+} availability for chlorophyll synthesis, reduced photo-oxidative damage, and improved thylakoid membrane integrity, all of which contribute to greater photosynthetic capacity and pigment accumulation [4–6]. From a framework perspective, chlorophyll content represents the strongest bridge variable identified in this review. Among all physiological variables evaluated, chlorophyll exhibits the highest reported UAV estimation accuracy in the Stream B corpus, with NDRE-based models achieving R^2 values of up to 0.90 [30]. This combination of consistent MF responsiveness and highly accurate remote sensing detectability establishes chlorophyll content as the primary and most robust connection between MF treatment physiology and field-scale UAV monitoring.

Nitrogen Assimilation and Nitrogen Use Efficiency

Approximately 15 papers in the Stream A corpus report direct effects of MF treatment on plant nitrogen metabolism, making nitrogen assimilation one of the most consistently documented physiological responses relevant to sustainable crop production. Across these studies, improvements in nitrogen uptake, assimilation, and utilisation have been reported under both SMF and magnetized water treatments, indicating that the effect is not restricted to a single MF application strategy. The primary mechanistic pathway involves the upregulation of nitrate reductase (NR) activity, the enzyme catalysing the first and rate-limiting step of nitrate reduction ($NO_3^- \rightarrow NO_2^-$), thereby enabling subsequent ammonium assimilation into amino acids. Enhanced NR activity under SMF and magnetopriming conditions has been reported across multiple studies [31,32], providing a physiological basis for the observed improvements in nitrogen-related parameters.

Representative evidence has been documented across several crop species and experimental conditions. Static magnetic field treatment in wheat significantly enhanced nitrate reductase activity, nitrogen assimilation efficiency, and canopy chlorophyll content, with effects confirmed under both controlled and open-field conditions [33]. In legumes, magnetized water irrigation combined with root MF exposure increased nodule formation and biological nitrogen fixation in bean crops [34]. Similarly, magnetized water irrigation improved nitrogen absorption in rice seedlings grown under saline-alkaline stress conditions [35]. Additional improvements in nitrogen-related parameters, including nitrogen content, protein accumulation, and water and radiation use efficiency, have been reported in chickpea under both SMF magnetopriming [36] and magnetized water irrigation [37], as well as in winter wheat under magnetized water irrigation [38,39].

From a framework perspective, nitrogen assimilation represents one of the most important bridge variables identified in this review. The biochemical responses documented in Stream A are directly linked to canopy-level indicators of crop nitrogen status that can be estimated non-destructively using UAV multispectral imagery. In particular, nitrogen nutrition index (NNI) mapping, validated extensively in Stream B, provides a practical means of monitoring the spatial expression of MF-induced improvements in nitrogen assimilation and NUE under field conditions.

Above-Ground Biomass and Yield

Improvements in biomass accumulation and final yield represent some of the most agronomically significant outcomes reported in the Stream A corpus. Field-scale yield increases are documented in approximately 47 papers, while explicit measurements of above-ground biomass (AGB) are reported in approximately 10 studies. Evidence of positive biomass and yield responses spans a wide range of crop species, including wheat [38–43], maize [21,44–46], sunflower [20,47,48], and various legume species [49–52].

Yield improvements have been reported across all major MF treatment types and under diverse environmental conditions. The strongest responses are generally associated with magnetized water irrigation, particularly under water-stressed conditions where improvements in water uptake and physiological efficiency may confer a greater agronomic advantage. In field-grown soybean, magnetopriming produced significant yield gains accompanied by enhanced gas exchange and PSII efficiency [50]. Similarly, PEMF seed treatment in buckwheat and maize resulted in measurable increases in photosynthetic performance, biomass accumulation, and final yield in replicated field trials [53,54].

These findings suggest that biomass and yield improvements are not isolated responses but rather downstream manifestations of the enhanced physiological performance documented throughout the Stream A literature, including improvements in chlorophyll content, photosynthetic activity, and nitrogen assimilation. From a framework perspective, above-ground biomass represents a particularly valuable bridge variable because it can be estimated reliably at field scale using UAV multispectral imagery. In the Stream B corpus, SAVI and DSM-integrated approaches consistently achieve AGB estimation accuracies ranging from $R^2 = 0.61$ to 0.85 [55,56], providing a practical means of assessing MF-induced growth responses under real farming conditions.

Leaf Area Index and Canopy Development.

Increases in leaf area index (LAI) and canopy development are reported less frequently than chlorophyll or biomass responses but nevertheless appear consistently across approximately six studies in the Stream A corpus. These responses are generally associated with improved leaf expansion, enhanced stomatal conductance, and accelerated canopy closure, all of which contribute to greater light interception and photosynthetic capacity.

Representative examples include magnetized water irrigation of bean [57] and magnetopriming of maize [44], both of which resulted in significant increases in leaf area and LAI under field conditions. In addition, downstream improvements in radiation use efficiency associated with enhanced canopy development have been documented in chickpea and sunflower under SMF treatment [20,36]. Although the number of studies is smaller than for other physiological variables, the consistency of the reported responses suggests that canopy structural development is a recurring outcome of MF treatment.

From a framework perspective, LAI represents an important bridge variable because it can be estimated directly from UAV multispectral imagery with validated accuracy across multiple crop species. Studies included in Stream B report LAI estimation accuracies ranging from $R^2 = 0.70$ to 0.88 using NDVI-, NDRE-, and PROSAIL-based approaches (see Section 3.2.2). Furthermore, UAV-derived LAI maps can be generated at sub-metre spatial resolutions, reaching ground sampling distances as low as 0.015 m [58]. This combination of biological relevance and reliable remote sensing detectability makes LAI a valuable component of the proposed monitoring framework.

3.2. Stream B: UAV Multispectral Remote Sensing for Physiological Variable Estimation

3.2.1. Screening Outcomes and Study Characteristics

The Stream B Scopus query returned 170 records. First-pass title and abstract screening excluded 55 papers across three categories: 23 studies lacked an operational UAV monitoring component, relying instead on satellite remote sensing platforms (e.g., Sentinel-2, Landsat, MODIS), ground-based proximal or handheld spectroscopy, or general radiative transfer modelling without drone-acquired imagery; 13 studies used sensor configurations incompatible with the multispectral framework — predominantly RGB-only cameras or thermal-only sensors without near-infrared spectral bands; and 19 studies targeted application domains with no link to N status, chlorophyll, or biomass estimation, including crop disease and pest detection, herbicide tolerance screening, evapotranspiration mapping, grain maturity identification, radiometric correction methodology, and UAV spraying system design. Second-pass full-text screening excluded one additional paper [59] whose primary output was a flight-time methodology study without any estimation of agronomic physiological variables. The final Stream B corpus comprised 114 papers from which all data were extracted.

The corpus spans publications from 2019 to 2026, reflecting the rapid growth of UAV multispectral applications following the commercialisation of affordable consumer-grade platforms. The most commonly studied crops are wheat (Triticum aestivum and T. durum, approximately 40 papers, 35%), rice (Oryza sativa, approximately 30 papers, 26%), maize (Zea mays, approximately 28 papers, 25%), and soybean (Glycine max, approximately 10 papers, 9%). UAV platforms are dominated by multirotor DJI systems, including the DJI Phantom 4 Multispectral (P4M) [60,61], alongside fixed-wing platforms such as the senseFly eBee equipped with the Parrot Sequoia+ multispectral sensor [62]. Sensor configurations are predominantly 5-band multispectral (Blue, Green, Red, Red-Edge, NIR), with some studies combining multispectral with RGB imagery for feature fusion [63–66]; a subset of studies augmented spectral data with LiDAR for explicit 3D canopy structure mapping [67–69], while several others derived canopy height estimates from UAV photogrammetry-based digital surface models (DSMs) without LiDAR [55,56]. Of 114 papers, 111 (97%) received a framework bridge flag of YES, confirming that the estimated variable corresponds to a physiological parameter consistently modulated by MF treatment in Stream A. Zero of the 114 Stream B papers studied magnetically treated crops, confirming the complete absence of cross-domain application that this review addresses.

3.2.2. Vegetation Index Performance for MF-Relevant Variables

Chlorophyll Content Estimation

Chlorophyll estimation from UAV multispectral imagery is the most extensively validated application identified in the Stream B corpus, appearing as the primary target variable in approximately 43 studies. Across a wide range of crop species and management conditions, chlorophyll content consistently emerges as one of the physiological variables that can be estimated with the highest accuracy using UAV-derived vegetation indices.

Among the evaluated indices, the normalized difference red-edge index (NDRE) consistently outperforms NDVI and other broadband vegetation indices due to its sensitivity to chlorophyll absorption in the red-edge spectral region (700–730 nm). Across multiple cereal and field crop systems, NDRE-based approaches achieved the highest reported accuracies, reaching $R^2 = 0.90$ for chlorophyll estimation in triticale and sunflower under varying nitrogen amendment levels [30].

Similarly, two-year UAV monitoring of winter wheat demonstrated stable and reliable chlorophyll estimation across growing seasons [70].

Alternative vegetation indices also demonstrated strong performance under specific conditions. The green normalized difference vegetation index (GNDVI) was identified as the most effective green-band index for chlorophyll estimation in smallholder maize systems subjected to varying nitrogen fertilisation regimes [71]. These findings suggest that although NDRE is generally the most robust indicator, alternative indices may provide advantages depending on crop type, management practices, and sensor configuration.

Recent studies have further improved chlorophyll estimation through the integration of machine learning and physically based modelling approaches. Physics-informed transfer learning frameworks combining UAV multispectral imagery with radiative transfer models (RTM) achieved high accuracy for leaf chlorophyll content (LCC) and canopy chlorophyll content (CCC) estimation in winter wheat [72], while improving model transferability across environments. Similarly, a double-layer physical-statistical modelling approach successfully estimated canopy photosynthetic pigments, including chlorophyll a, chlorophyll b, and carotenoids, together with canopy nitrogen content in winter wheat [73].

Collectively, these findings establish chlorophyll content as the most robust and consistently validated physiological variable within the Stream B corpus. Combined with the strong evidence for MF-induced chlorophyll enhancement identified in Stream A, this high level of remote sensing detectability reinforces chlorophyll as the strongest bridge variable linking MF treatment responses with field-scale UAV monitoring.

Nitrogen Nutrition Index and NUE Estimation

The nitrogen nutrition index (NNI), defined as the ratio of actual crop nitrogen concentration to the critical nitrogen concentration at a given biomass level, is one of the most agronomically relevant indicators of crop nitrogen status and is directly linked to nitrogen use efficiency (NUE). Reflecting its importance for nutrient management and precision agriculture, approximately 41 papers in the Stream B corpus address the estimation of NNI or NUE using UAV multispectral imagery. Across these studies, NDRE emerged as the dominant vegetation index for nitrogen status assessment. Its sensitivity to changes in leaf nitrogen content within the red-edge spectral region enables the detection of nitrogen-related variation before visible deficiency symptoms become apparent. As a result, NDRE-based approaches have become a central component of UAV-assisted nitrogen management strategies.

The capability of UAV systems to estimate NNI and NUE has been demonstrated across a wide range of crops, environmental conditions, and management scenarios. High-accuracy NNI estimation was reported in rice at the critical early panicle initiation stage using a combination of spectral, texture, and discrete wavelet transform (DWT) features evaluated across three growing seasons and ten varieties [74]. UAV-based NNI estimation has also been successfully applied in smallholder winter wheat systems at the village scale using an eBee fixed-wing platform equipped with a Parrot Sequoia+ multispectral sensor, demonstrating applicability beyond large experimental research stations [62]. Direct UAV-based NUE phenotyping has been reported across full growing seasons in rice [75], spring wheat [76], wheat under varying soil mineral nitrogen conditions [77], and winter wheat [61,78–81].

Recent studies further demonstrate the value of advanced analytical approaches for improving nitrogen status estimation. Stacking ensemble machine learning models integrating UAV-derived spectral information with environmental and management variables achieved enhanced NNI prediction accuracy across diverse rice-growing environments [82]. These developments illustrate the increasing maturity of UAV-based nitrogen monitoring and its capacity to support field-scale assessment of crop nitrogen dynamics under heterogeneous conditions.

From a framework perspective, NNI and NUE represent the most operationally valuable bridge variables identified in this review. The improvements in nitrogen assimilation and nitrate reductase activity documented in Stream A can be translated into spatially explicit indicators of crop nitrogen status through UAV-derived NNI mapping. Consequently, UAV multispectral sensing provides a practical and non-destructive approach for evaluating whether MF-induced improvements in nitrogen metabolism are expressed at canopy scale under real field conditions.

Above-Ground Biomass and LAI Estimation

Above-ground biomass (AGB) estimation from UAV multispectral imagery is addressed in approximately 29 papers within the Stream B corpus. Unlike chlorophyll estimation, which can often be achieved using a single vegetation index, accurate biomass estimation generally requires the integration of both spectral and structural crop information. Consequently, the best-performing approaches combine vegetation indices with canopy height metrics derived from digital surface models (DSMs) generated through UAV photogrammetry, consistently improving prediction accuracy compared with VI-only regression approaches [56,83].

Several studies demonstrate the effectiveness of this integrated approach across diverse crop systems and management conditions. The photosynthetic accumulation model (PAM), which combines vegetation indices and canopy height information, achieved improved AGB estimation performance in rice across multiple cultivars and growing seasons [55]. Biomass estimation has also been successfully evaluated under varying irrigation and nitrogen management regimes in corn [84] and in maize-based smallholder farming systems [85]. In addition, soil-adjusted vegetation indices such as SAVI have been incorporated to minimise the influence of soil background effects under partial canopy cover conditions commonly encountered in grain crops [86].

Leaf area index (LAI) estimation is addressed in approximately 15 papers and represents a complementary measure of canopy development and crop growth. Several studies demonstrate that UAV multispectral imagery can provide reliable LAI retrievals through both empirical and physically based approaches. Among these, PROSAIL radiative transfer model inversion enabled physically interpretable LAI estimation at a spatial resolution of 0.015 m in maize [58]. Similarly, physics-informed transfer learning frameworks estimated LAI together with leaf chlorophyll content (LCC) and canopy chlorophyll content (CCC) with high accuracy across multiple growing seasons in winter wheat [72].

From a framework perspective, both AGB and LAI represent valuable indicators of the cumulative physiological effects of MF treatments. Whereas chlorophyll and NNI provide insight into specific physiological processes, biomass accumulation and canopy development integrate the combined effects of enhanced photosynthetic performance, nitrogen assimilation, and crop growth over time. The demonstrated capability of UAV systems to estimate these variables at field scale therefore provides an important mechanism for evaluating whether MF-induced physiological improvements translate into measurable agronomic outcomes under real production conditions.

Yield Prediction

Yield prediction is addressed in approximately 33 papers within the Stream B corpus and represents one of the most practically relevant applications of UAV multispectral remote sensing. Unlike chlorophyll content, NNI, or LAI, yield is not a directly measurable physiological variable but rather the cumulative outcome of multiple interacting processes occurring throughout the growing season. Consequently, yield prediction presents a greater modelling challenge and typically exhibits lower prediction accuracies than intermediate physiological indicators.

Despite this complexity, UAV-based yield estimation has been successfully demonstrated across several cereal systems using commercially available platforms. Consumer-grade DJI Phantom 4 Multispectral (P4M) systems have been validated for grain yield prediction in both barley [60] and winter wheat [61], highlighting the accessibility of the approach for both research and practical applications. Reported grain yield prediction accuracies range from $R^2 = 0.33$ to 0.61 in barley breeding trials employing nonparametric modelling across multiple measurement dates [60].

Although these accuracies are lower than those reported for chlorophyll content, NNI, or LAI estimation, they remain sufficient for detecting treatment-level differences at field scale. From a framework perspective, this is particularly important because yield represents the ultimate agronomic outcome of the physiological responses induced by MF treatments. As such, UAV-based yield prediction provides a means of evaluating whether improvements in chlorophyll content, nitrogen assimilation, biomass accumulation, and canopy development ultimately translate into measurable productivity gains under field conditions.

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3.2.3. Machine Learning Integration for Predictive Validation

Approximately 34 papers in the Stream B corpus employ machine learning (ML) approaches beyond conventional regression techniques for the estimation of physiological variables from UAV-derived spectral information. The reported methods span a broad range of algorithms, including Random Forest (RF), support vector machines (SVM), convolutional neural networks (CNN), deep learning architectures, and ensemble learning approaches. Collectively, these studies demonstrate the increasing role of ML in improving prediction accuracy, handling complex non-linear relationships, and integrating multiple sources of agronomic information.

Several studies highlight the advantages of advanced ML frameworks over traditional modelling approaches. A CNN-LSTM-XGBoost hybrid architecture applied to multimodal UAV imagery achieved robust performance for field-scale nitrogen stress classification while providing interpretable, feature-level insights into nitrogen status decisions [87]. Similarly, PSO-optimised ensemble learning combined with spectral feature selection significantly outperformed individual models for chlorophyll content estimation in rice under varying nitrogen application regimes [88]. Ensemble learning approaches have also improved the estimation of maize leaf chlorophyll content (LCC) and fractional vegetation cover (FVC) across multiple growth stages, addressing variations in model performance throughout the growing season [89].

The increasing adoption of ML-based approaches reflects a broader shift from simple vegetation index regression towards data-driven predictive modelling capable of integrating spectral, structural, environmental, and management-related information. This development is particularly relevant for field-scale applications, where crop responses are influenced by multiple interacting factors and where traditional linear relationships may not fully capture observed variability.

From a framework perspective, these ML architectures provide a potential mechanism for strengthening the interpretation of UAV-derived physiological responses in MF-treated fields. Once baseline spatial maps of chlorophyll content, nitrogen status, biomass, or canopy development have been generated, ML models may help identify treatment-related spectral patterns while accounting for background variability associated with soil heterogeneity, management history, and microclimatic conditions. Although these approaches have not yet been specifically validated for MF-treated cropping systems, the evidence presented in Stream B suggests that they offer a promising pathway for future field-scale assessment and validation of MF treatment responses.

3.3. Cross-Domain Evidence Synthesis: The Framework Bridge Table

The central analytical output of this dual-stream review is the cross-domain variable mapping presented in Table 5. The purpose of this mapping is not simply to list variables reported in the two corpora, but to identify which MF-modulated physiological responses can realistically be monitored at field scale using UAV-based multispectral sensing. Each row therefore represents either a confirmed or partially confirmed bridge connection between Stream A and Stream B.

A bridge connection was classified as direct when the same physiological variable was consistently modulated by MF treatment in Stream A and could be estimated non-destructively at canopy scale by UAV multispectral imaging with validated accuracy in Stream B. These connections were assigned a YES flag. Variables were classified as partial when the MF-responsive trait could not be directly measured by standard passive multispectral UAV sensors but could potentially be inferred through a proxy variable or an emerging sensing approach. These connections were assigned a PARTIAL flag. In this way, the bridge table provides the operational basis for the proposed monitoring framework by distinguishing variables that are immediately suitable for field-scale validation from those requiring additional methodological development.

Table 5. Cross-domain bridge table: MF-modulated physiological variables (Stream A) mapped against UAV-detectable variables with best-performing vegetation index and reported accuracy (Stream B). Bridge status indicates whether the same variable is directly detectable (YES) or via proxy/indirect method (PARTIAL).

MF-Modulated Variable	Stream A (n papers)	MF Effect — Direction & Evidence	Best UAV Index	Best R^2	Bridge
Chlorophyll content (Chl a+b, carotenoids)	43	Consistent improvement across SMF, PEMF, and MWI in wheat, maize, soybean, tomato, lettuce, and cotton. Mechanism: Mg^{2+} channel activation → enhanced chlorophyll synthesis; reduced photo-oxidative damage to thylakoid membranes [22–24,26–28,33,46]	NDRE, GNDVI	0.90 [30]	YES
NUE / Nitrate reductase / N assimilation	15	SMF and magnetopriming upregulate nitrate reductase (NR: $NO_3^- \rightarrow NO_2^-$), the first and rate-limiting step of N reduction. NUE and canopy N content improvements in soybean, wheat, chickpea, rice field experiments [31–35]	NDRE → NNI model	≥0.85 [62,74,82]	YES
Above-ground biomass (AGB)	10	Positive AGB and canopy growth across all MF types in field experiments — wheat, maize, sunflower, legumes. Enhanced dry matter via photosynthate translocation [20,21,39,40,44,45]	SAVI; NDVI + DSM (canopy height)	0.61–0.85 [55,56]	YES
Leaf Area Index (LAI)	6	MWI and magnetopriming increase leaf expansion via improved stomatal conductance and cell division. Field-scale LAI increases in bean and maize [44,46,51,57]	NDVI, NDRE; PROSAIL RTM inversion	0.70–0.88 [58,72]	YES
Grain / fruit yield	47	Aggregate downstream outcome of improved photosynthesis, NUE, and biomass. Documented across wheat, maize, soybean, chickpea, and bean in open-field trials [28,37,39,40,46–48,50]	NDVI at heading/grain-fill; RF/ANN (multi-stage)	0.33–0.61 [60,61]	YES
PSII efficiency (Fv/Fm)	23	SMF preserves PSII reaction centres; consistent Fv/Fm improvements in magnetopriming studies under stress [22–24,46,50]	Indirect: GNDVI (Chl proxy); CF+UAV emerging [90]	Indirect	PARTIAL
Water use efficiency (WUE)	11	MWI reduces surface tension → improved water uptake and stomatal regulation. Documented in chickpea, watermelon, sunflower, cotton under deficit irrigation [36,48,91]	CWSI (thermal+MS); Gs via PROSAIL [92–94]	Indirect	PARTIAL

Five of the seven mapped variables received a YES bridge flag, confirming direct methodological connections between MF treatment outcomes and UAV monitoring capability. Chlorophyll content represents the strongest bridge node. It is the most consistently reported MF-responsive variable in Stream A, with 43 papers documenting improvements in chlorophyll a, chlorophyll b, and carotenoid concentrations across all MF treatment modes and several major crop species [22–28]. At the same time, Stream B demonstrates very high UAV-based detectability for chlorophyll, with NDRE-based models reaching $R^2 = 0.90$ in a multi-crop, multi-season field study [30]. This makes chlorophyll the most robust entry point for field-scale validation of MF treatment responses, because it combines strong biological responsiveness with high remote sensing accuracy.

Nitrogen nutrition index and NUE form the second critical bridge node and are particularly important from a sustainability perspective. Stream A provides evidence that MF treatments can influence nitrogen metabolism through nitrate reductase upregulation and improvements in canopy nitrogen status [31–33]. Stream B, in turn, demonstrates that NNI can be estimated using NDRE-based UAV approaches across wheat, rice, and maize systems [62,74,82]. This bridge matters because it links the biochemical mechanism most relevant to NUE improvement with a practical field-scale monitoring method. It therefore provides a direct pathway for assessing whether MF treatments contribute to more efficient nitrogen use under real agronomic conditions.

Above-ground biomass, LAI, and yield complete the five confirmed direct bridge connections [39–41,44–46,55,56,58,60,61,83]. These variables are important because they represent progressively more integrated expressions of crop performance. AGB and LAI reflect the cumulative effects of improved photosynthesis, nitrogen assimilation, and canopy development, while yield represents the final agronomic outcome of these physiological processes. Although UAV-based yield prediction shows lower accuracy than chlorophyll or LAI estimation, with reported values ranging from R^2 = 0.33 to 0.61, it remains relevant for detecting treatment-level productivity differences at field scale. In contrast, LAI estimation reaches higher accuracies of R^2 = 0.70–0.88, supporting its use as a reliable canopy development indicator within the proposed framework.

Collectively, the five confirmed bridge variables represent different levels of crop response to MF treatment. Chlorophyll content and nitrogen assimilation reflect primary physiological processes directly associated with photosynthetic performance and nutrient metabolism. Above-ground biomass and LAI represent structural canopy responses that integrate these physiological effects over time, while yield constitutes the final agronomic outcome of their cumulative expression. Together, these variables provide a hierarchical framework for evaluating MF treatment effects from mechanism to productivity under field conditions. In parallel, PSII efficiency and WUE remain physiologically important partial bridge variables, but their direct field-scale estimation requires sensing approaches beyond standard passive multispectral UAV platforms.

Two variables received a PARTIAL bridge flag. PSII efficiency (Fv/Fm), documented in 23 Stream A papers [22–24,46,50], is physiologically important because it reflects the functional status of Photosystem II and is frequently improved by MF treatment, particularly under stress conditions. However, direct Fv/Fm measurement requires active pulse-amplitude modulation (PAM) fluorometry, which is not available through standard passive multispectral UAV platforms. Only one Stream B paper linked chlorophyll fluorescence measurements with UAV canopy imagery [90], leaving direct field-scale spatial mapping of Fv/Fm unvalidated. Similarly, water use efficiency, reported in 11 Stream A papers [36,38,48,91], can currently be estimated only indirectly through thermal-derived Crop Water Stress Index (CWSI) or PROSAIL-coupled stomatal conductance modelling [92–94]. These approaches require sensor configurations beyond standard five-band multispectral UAV payloads. Therefore, PSII efficiency and WUE remain promising but methodologically less mature bridge variables.

The most important finding of this synthesis is not contained within either corpus independently but emerges from their comparison. None of the 102 Stream A papers used remote sensing to monitor MF treatment responses in the field, and none of the 114 Stream B papers examined magnetically treated crops. The bridge identified in Table 5 therefore represents a first-time connection between two established bodies of agricultural research rather than a simple methodological refinement. This absence of direct overlap confirms the central research gap addressed by the review and provides the rationale for the conceptual monitoring framework proposed in the following section.

4. Discussion

4.1. Bridging Two Previously Disconnected Research Domains

The central finding of this review is neither the evidence for MF treatment effects on crop physiology nor the established capability of UAV multispectral sensing to detect those effects [4,6,10]. The central finding is that 102 papers documenting MF-induced physiological responses and 114 papers demonstrating UAV-based detection of those same physiological variables were identified, published and cited across the same ten-year period (2016–2026) without any documented intersection between them. None of the Stream A papers used remote sensing of any kind to monitor treatment responses in the field, and none of the Stream B papers studied crops subjected to magnetic field treatment. This complete absence of cross-domain integration, across a combined corpus of 216

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peer-reviewed papers spanning 2016–2026, is the observation on which the scientific novelty of this work rests.

Perhaps the most telling indicator of the depth of this separation is the directionality of the bridge connections identified in Table 5. When the 114 Stream B papers were systematically assessed against the physiological variables most consistently modulated by MF treatments, 111 (97.4%) were found to be studying variables that Stream A confirms are MF-responsive—principally chlorophyll content, nitrogen nutrition index, above-ground biomass, and leaf area index. The two domains were, in effect, investigating the same biological phenomena: one through experimental intervention and contact measurement, the other through spatially resolved, non-destructive remote sensing. The separation therefore appears to reflect disciplinary fragmentation and limited methodological integration rather than a lack of subject matter compatibility.

The crop species studied in the two corpora reinforce this observation. Wheat (Triticum spp.) featured in 13 Stream A papers and 40 Stream B papers. Maize (Zea mays) appeared in 10 Stream A and 28 Stream B studies, while soybean (Glycine max) was examined in 16 Stream A and 10 Stream B papers. In each case, the same crop species was being investigated by both research communities during the same publication period, under conditions that would in principle have supported methodological integration. Nevertheless, no evidence of such integration was identified.

Several factors likely contributed to this structural separation. The most directly observable is disciplinary fragmentation, which is evident within the corpus data of this review itself. Stream A papers were concentrated in journals such as Bioelectromagnetics, Plants, Horticulturae, Plant Signaling & Behavior, and the International Journal of Molecular Sciences, reflecting a focus on plant physiology, agronomy, and biophysics. In contrast, Stream B papers were concentrated in journals such as Remote Sensing, Precision Agriculture, Computers and Electronics in Agriculture, and Smart Agricultural Technology, reflecting expertise in remote sensing, engineering, and digital agriculture. These research areas have largely evolved within different disciplinary communities, which appears to have limited opportunities for methodological cross-referencing.

A second contributing factor is the measurement paradigm established within MF research. By the time UAV multispectral platforms became widely accessible, MF studies had already adopted a standard toolkit based on contact and destructive measurements, including SPAD meters, portable fluorimeters, gas-exchange analysers, and gravimetric biomass determination. Consequently, few studies in the MF literature drew upon or referenced the rapidly expanding UAV sensing literature, as confirmed by the complete absence of remote sensing applications identified in Stream A. A third factor is the mechanistic heterogeneity that has characterised MF research. Variability in experimental protocols and proposed mechanisms across studies [6,9] may have limited engagement from the precision agriculture community, where methodological reproducibility and operational transferability are often prioritised [10].

The consequences of this separation have been substantial. Of the 89 empirical Stream A studies, 45 (51%) were conducted under open-field or field-plot conditions, yet all relied exclusively on contact-based or destructive measurements to assess treatment outcomes. As a result, the spatial distribution of physiological responses, within-field variability in treatment expression, and temporal dynamics across growth stages remained largely unexplored throughout the field-scale MF literature—not because these dimensions were scientifically unimportant, but because the monitoring methodology capable of capturing them at agronomic scale had matured in a parallel literature that MF researchers had not incorporated. The 45 Stream A field experiments therefore represent a body of research in which spatial expression, temporal trajectory, and within-field heterogeneity of MF treatment response have received comparatively limited attention.

From the perspective of digital agriculture, the findings carry an equally significant implication. The 111 Stream B papers identified as directly relevant to MF treatment monitoring had already validated spectral indices, estimation approaches, and species-specific protocols for variables known to respond to MF treatment. This accumulated methodological evidence provides a readily available foundation for the design of UAV-based MF validation trials. Spectral indices validated extensively in wheat, maize, and rice systems—such as NDRE for chlorophyll content and NNI estimation, SAVI and DSM-integrated approaches for above-ground biomass assessment, and PROSAIL-based

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methods for LAI retrieval—could be applied to MF treatment experiments without requiring fundamental methodological redevelopment.

Beyond its specific implications for MF research and UAV precision agriculture, the findings of this review suggest that similar opportunities for cross-domain integration may exist elsewhere in agricultural research, where technological and biological disciplines often evolve in parallel despite addressing closely related agronomic questions. The dual-stream PRISMA approach adopted here—combining independent systematic evidence synthesis with structured cross-domain variable mapping—may therefore provide a useful methodology for identifying and formalising such connections in future studies.

4.2. From Physiological Responses to Field-Scale Validation

The bridge variables identified in Table 5 describe more than a technical correspondence between MF-responsive traits and UAV-detectable indicators. They represent a biologically coherent sequence of crop responses, progressing from primary physiological processes to canopy development and finally to agronomic performance. This hierarchy is important because it reflects how treatment effects are expected to emerge in the crop: first through changes in photosynthetic and nutritional processes, then through canopy growth, and ultimately through biomass accumulation and yield formation. Importantly, it also provides a mechanistic framework for interpreting MF treatment responses under field conditions. If changes are detected only at the physiological level but fail to propagate to canopy development or yield, this may indicate that the treatment effect is transient or environmentally constrained. Conversely, consistent responses across all three biological levels would provide stronger evidence that MF treatments generate agronomically meaningful benefits.

The identification of bridge variables across these biological scales is particularly important because it transforms the challenge of MF validation from a single end-point assessment into a process-based monitoring strategy. Rather than evaluating MF treatments solely through final yield measurements, researchers can monitor the progression of treatment responses throughout the growing season, thereby improving both mechanistic understanding and field-scale validation.

At the physiological level, chlorophyll content, nitrogen assimilation, NUE, and PSII efficiency represent some of the earliest and most mechanistically informative indicators of MF treatment response. These variables are directly associated with the plant’s capacity to capture light, assimilate carbon, and use nitrogen efficiently. Leaf nitrogen, chlorophyll content, photosynthetic capacity, and radiation use efficiency are closely linked to biomass accumulation and crop productivity in the broader crop physiology literature[95,96], and these relationships underpin the biological coherence of the proposed bridge connections. In the context of this review, this is particularly important because the most consistently reported MF responses in Stream A correspond to the physiological variables most reliably estimated by UAV multispectral sensing in Stream B.

The second level of the response pathway is represented by structural canopy traits, particularly LAI and above-ground biomass. These variables integrate physiological changes over time and provide a more spatially explicit expression of crop growth. Both LAI and above-ground biomass are widely recognised as key indicators of crop development, reflecting canopy expansion, radiation interception capacity, and overall crop productivity potential [97]. While chlorophyll and nitrogen status indicate whether physiological activity has been altered, LAI and biomass show whether these changes are translated into canopy expansion, light interception, and dry matter production. This intermediate level is essential for field validation because it connects early physiological responses with whole-crop performance. It also fits the practical strengths of UAV monitoring, which can repeatedly map canopy development and biomass-related indicators across entire field plots without destructive sampling.

Yield represents the final agronomic level of the hierarchy. Unlike chlorophyll, NNI, LAI, or biomass, yield is not a direct physiological trait but the cumulative outcome of many interacting processes occurring across the growing season. For this reason, yield prediction is expected to show lower accuracy than intermediate indicators. However, this does not reduce its relevance within the framework. Instead, it clarifies its role: yield should be treated as the final validation endpoint, while chlorophyll, nitrogen status, LAI, and biomass provide earlier diagnostic indicators explaining how and when treatment effects develop.

This hierarchical organisation strengthens the proposed framework because it avoids reliance on any single variable as proof of MF treatment effectiveness. A yield-only assessment would be too late and too integrative to explain treatment mechanisms, while a chlorophyll-only assessment would be insufficient to demonstrate agronomic relevance. By combining physiological, structural, and agronomic indicators, the framework enables MF treatment effects to be evaluated across multiple biological scales. This creates a more robust validation pathway, where early physiological responses can be linked to canopy development and then examined in relation to final productivity.

Therefore, the value of UAV-based monitoring in this context is not only its capacity to estimate individual variables, but its ability to follow the progression of MF-induced responses through time and space. This is particularly relevant for MF technologies, where treatment effects may depend on crop species, application method, growth stage, and environmental conditions. A multi-level monitoring strategy can help determine whether observed physiological responses remain localised, whether they develop into measurable canopy-level changes, and whether they ultimately contribute to agronomic performance under field conditions.

4.3. The Proposed Framework as a Pathway Towards Scalable Validation of MF Technologies

One of the most persistent challenges in MF agriculture research is not the demonstration of treatment effects, but their validation under realistic farming conditions. Although the Stream A corpus provides substantial evidence that MF treatments can influence chlorophyll content, nitrogen metabolism, biomass accumulation, and yield-related traits, the majority of studies have relied on measurement approaches that inherently constrain experimental scale and monitoring intensity. Among the 89 empirical studies included in this review, 23 were conducted under laboratory or controlled-environment conditions and a further 21 under greenhouse or pot-based conditions. Even among the 45 studies performed under field conditions, treatment responses were assessed exclusively through contact-based or destructive measurements. Consequently, most evidence regarding MF effectiveness remains derived from observations collected at individual plants, small plots, or limited sampling locations rather than from continuous field-scale assessments.

This methodological limitation has important implications for the interpretation and transferability of existing findings. Agricultural fields are inherently heterogeneous environments characterised by spatial variability in soil properties, nutrient availability, water status, microclimate, and crop development. Under such conditions, treatment responses may not be spatially uniform. However, traditional monitoring approaches such as SPAD measurements, chlorophyll extraction, biomass harvesting, gas exchange analysis, and fluorometry provide information only at discrete sampling points. While these methods remain essential for physiological validation, they cannot readily characterise the spatial distribution of treatment effects across entire fields or capture how responses evolve through time at agronomically relevant scales.

The framework proposed in this review addresses this scalability bottleneck by shifting the focus from point-based assessment to spatially explicit monitoring. Rather than replacing conventional physiological measurements, UAV multispectral sensing complements them by extending observations from individual sampling locations to complete field parcels at agronomically meaningful spatial resolution. This capability is particularly relevant because the variables most consistently affected by MF treatments, including chlorophyll content, nitrogen status, LAI, biomass, and yield-related traits, correspond closely to the variables most extensively validated for UAV-based estimation in Stream B. The framework therefore builds on an existing evidence base rather than requiring the development of entirely new sensing methodologies.

An additional advantage of the proposed approach lies in its temporal dimension. Many MF studies evaluate treatment responses at a limited number of growth stages or rely on end-of-season assessments. Such measurements provide valuable information regarding treatment outcomes but reveal little about how responses emerge, persist, or diminish during crop development. By enabling repeated observations throughout the growing season, UAV-based monitoring creates opportunities to investigate treatment dynamics rather than treatment outcomes alone. This distinction is important because MF-induced responses may vary according to crop species, environmental conditions, developmental stage, and treatment method. Monitoring these dynamics could improve understanding of when treatment effects are strongest and which physiological pathways are most closely associated with subsequent canopy development and productivity.

The framework may also contribute to improving the reproducibility and comparability of future MF studies. One of the recurring challenges identified in the MF literature is the diversity of treatment protocols, field strengths, exposure durations, crop species, and measured response variables. This heterogeneity complicates comparisons among studies and makes meta-analysis difficult. The use of a common monitoring approach based on validated UAV-derived indicators could facilitate more standardised assessment of treatment responses across sites, crops, and growing conditions. While such standardisation would not eliminate biological variability, it could improve the consistency with which treatment outcomes are quantified and reported.

Importantly, the framework should not be viewed as evidence that MF technologies are agronomically effective under all conditions. Rather, its value lies in providing a practical pathway through which such effectiveness can be evaluated at field scale. By integrating physiological indicators, canopy-level measurements, and agronomic outcomes within a single monitoring strategy, the framework offers a means of testing whether responses observed under controlled conditions can be reproduced under the spatial and environmental complexity of commercial agricultural systems. In this respect, the framework should be understood as a hypothesis-driven pathway for field-scale validation rather than an experimentally verified monitoring system, a distinction that the limitations discussed in Section 4.6 address directly.

4.4. Implications for Sustainable Agriculture and Precision Nutrient Management

The methodological integration proposed in this review has direct relevance to sustainable agriculture and precision nutrient management, two domains explicitly addressed by current EU agricultural policy. Current agricultural policy increasingly emphasises the need to improve resource-use efficiency while reducing the environmental impacts associated with crop production. Within the European Union, the Farm to Fork Strategy identifies nutrient losses, excessive fertiliser use, and declining environmental sustainability as major challenges requiring the adoption of innovative and evidence-based agricultural practices [1,98].

Among the physiological responses most consistently associated with MF treatments in Stream A, improvements in chlorophyll content, nitrogen assimilation, nitrate reductase activity, and nitrogen use efficiency are particularly relevant in this context. These responses suggest a potential capacity of MF technologies to influence crop nutrient utilisation and physiological performance without requiring additional chemical inputs. However, despite the promising evidence reported across controlled-environment and field studies, the absence of a standardised field-scale monitoring methodology has limited the ability to evaluate whether these benefits remain consistent under commercial farming conditions.

The framework proposed in this review addresses this challenge by linking MF-responsive physiological variables with UAV-derived indicators already established within precision agriculture. In doing so, it creates a pathway through which MF technologies can be assessed using the same monitoring approaches currently employed for nitrogen management, crop status assessment, and decision support. Rather than introducing a completely new monitoring paradigm, the framework builds upon existing digital agriculture infrastructure and validated multispectral sensing workflows that are already widely used in research and commercial farming [99].

This connection is particularly relevant for precision nutrient management. Nitrogen use efficiency is widely recognised as a critical indicator of both economic and environmental sustainability because inefficient nitrogen use contributes simultaneously to production costs, greenhouse gas emissions, nitrate leaching, and water quality degradation [12]. UAV-based estimation of chlorophyll content and nitrogen nutrition status has become an established approach for supporting site-specific nutrient management and reducing unnecessary fertiliser inputs [100]. The identification of direct bridge connections between MF-induced improvements in nitrogen-related processes and UAV-derived NNI estimation therefore creates opportunities to evaluate whether MF technologies could contribute to more efficient nutrient use under field conditions.

More broadly, the framework aligns with the principles of sustainable intensification and digital agriculture. Sustainable intensification seeks to increase agricultural productivity while minimising environmental impacts and maintaining ecosystem services [101]. Achieving this objective requires technologies that can be evaluated using robust, transparent, and scalable monitoring systems. By integrating physiological indicators, canopy development metrics, and agronomic outcomes within a single monitoring pathway, the proposed framework provides a mechanism through which the performance of MF technologies can be assessed objectively across diverse production environments.

Importantly, the framework should not be interpreted as evidence that MF technologies are inherently sustainable or agronomically beneficial. If future field validation confirms the physiological and agronomic benefits reported in controlled studies, the proposed framework could provide the monitoring infrastructure required to evaluate MF technologies under practical farming conditions. Such evidence would be essential before any conclusions could be drawn regarding their contribution to sustainable crop production, nutrient management, or future precision agriculture strategies.

Ultimately, the value of the framework lies not only in its potential application to MF technologies but also in its demonstration of how digital agriculture tools can accelerate the evaluation of emerging agronomic innovations. As agriculture increasingly moves towards data-driven and sustainability-oriented management systems, approaches capable of linking physiological processes with field-scale monitoring will become increasingly important for translating experimental findings into practical agricultural solutions.

4.5. Future Research Priorities

The most immediate research priority emerging from this review is the implementation of dedicated field experiments integrating MF treatments with UAV multispectral monitoring. While the bridge connections identified in this study demonstrate that several MF-responsive physiological variables can be estimated using established UAV methodologies, no study identified within the literature corpus included in the present review combined MF treatments with UAV multispectral monitoring within a single experimental framework. Consequently, the proposed framework remains a hypothesis-driven pathway requiring empirical validation under real agronomic conditions. Such experiments should include both conventional physiological measurements and UAV-derived indicators to assess whether treatment responses observed at plant level can also be detected consistently at canopy scale. Additionally, given that Stream A identified three distinct MF delivery modes, magnetized water irrigation (MWI, 47% of empirical papers), static magnetic field magnetopriming (SMF, 36%), and pulsed electromagnetic field treatment (PEMF, 16%), future field experiments should evaluate whether the strength and spatial pattern of canopy-level responses detectable by UAV monitoring differ systematically among these treatment types. MWI, as the only mode with established commercial deployment at farm scale, represents the highest-priority candidate for field-scale UAV validation trials.

A second priority is the evaluation of the framework across multiple crops, management systems, and environmental conditions. The current evidence base is dominated by soybean, wheat, tomato, and maize, while several economically important crop species remain underrepresented. Furthermore, environmental factors such as soil characteristics, climatic conditions, irrigation management, and nutrient availability may influence both MF treatment responses and UAV-based estimation performance. Future multi-site studies spanning contrasting pedoclimatic regions would therefore provide a more robust assessment of framework transferability and practical applicability [98]. Such validation is particularly relevant within Europe, where Mediterranean, Continental, Atlantic, and Boreal production systems differ substantially in both environmental constraints and crop management practices.

A third priority concerns the integration of complementary sensing technologies. While hyperspectral, thermal, fluorescence, and proximal sensing technologies may provide additional information on MF-induced crop responses, multispectral UAV systems were selected in the present framework because they currently offer the best balance between cost, operational simplicity, sensor availability, and large-scale deployment potential [10,102]. Future studies should evaluate whether the integration of complementary sensing modalities can further improve the detection and interpretation of MF treatment effects. In particular, thermal sensing may provide additional information on crop water relations, while hyperspectral and fluorescence approaches could improve the monitoring of physiological processes that are only indirectly detectable using standard multispectral systems — a limitation that is further discussed in Section 4.6.

Finally, future research should investigate the potential role of advanced machine-learning and sensor-fusion approaches within MF monitoring frameworks. Recent developments in artificial intelligence, deep learning, and multi-source data integration have demonstrated considerable potential for improving crop status assessment and predictive modelling from UAV data [103]. Applying these approaches to dedicated MF datasets may enhance the ability to identify treatment-related patterns, distinguish them from background environmental variability, and improve the interpretation of treatment responses across different spatial and temporal scales. Together, these research priorities define a structured pathway from conceptual framework development towards comprehensive field-scale validation and operational implementation.

4.6. Limitations

It should be emphasised that the framework proposed in this review is conceptual and derives from the synthesis of evidence across two independent research domains. Although the individual bridge connections are supported by published evidence, the complete framework has not yet been validated through dedicated field experiments involving MF-treated crops monitored using UAV multispectral systems. This limitation reflects the central research gap identified by the review itself: none of the 102 Stream A studies employed UAV-based monitoring, while none of the 114 Stream B studies investigated magnetically treated crops. Consequently, the proposed framework should be viewed as a hypothesis-driven pathway for field-scale validation rather than as an experimentally verified monitoring system. Future research should prioritise dedicated validation trials that combine MF treatments with UAV multispectral monitoring under real agronomic conditions to assess the practical applicability of the framework.

A second limitation relates to the evidence base underpinning the framework. The strongest evidence is currently available for soybean, wheat, tomato, and maize, whereas several other crop species remain underrepresented. As a result, the strength of evidence supporting individual bridge connections is not uniform across all crop systems. In addition, the estimation accuracies reported in Stream B varied among target variables and study contexts. For example, chlorophyll estimation achieved accuracies of up to $R^2 = 0.90$, whereas yield prediction generally produced lower accuracies ($R^2 = 0.33$–0.61). These differences reflect the variability reported in the underlying UAV literature and highlight that the reliability of individual monitoring components may depend on the target variable, crop species, sensor configuration, growth stage, and environmental conditions. Future multi-site experiments encompassing diverse crop species, management systems, and pedoclimatic conditions will therefore be required to assess the robustness and transferability of the proposed framework.

Finally, several methodological boundaries should be acknowledged. The review was intentionally restricted to UAV multispectral sensing because this technology currently offers the most practical combination of operational simplicity, commercial availability, and field-scale deployment potential. Consequently, hyperspectral, thermal, fluorescence, and proximal sensing approaches were not included in the framework, despite their potential to provide complementary information on MF-induced crop responses. Similarly, the literature search was limited to the Scopus database and English-language peer-reviewed publications, which may have resulted in the exclusion of relevant studies indexed elsewhere or published in other languages. Furthermore, although machine learning approaches were incorporated into the conceptual framework based on extensive evidence from Stream B, these models have not yet been specifically validated for MF-treated cropping systems. Future research should therefore investigate the integration of complementary sensing modalities and evaluate the performance of machine learning approaches using dedicated MF datasets collected across a range of environmental and agronomic conditions.

5. Conclusions

This review addressed a previously unexplored gap between two mature but disconnected areas of agricultural research: MF technologies for crop enhancement and UAV-based multispectral monitoring for crop assessment. Through a dual-stream systematic review of 102 MF-related studies and 114 UAV multispectral studies, it was demonstrated that these research domains have evolved largely independently despite focusing on many of the same crop species and physiological processes. No study identified in the MF literature employed UAV-based monitoring, while no study in the UAV literature investigated magnetically treated crops.

The cross-domain evidence synthesis identified five direct bridge variables linking the two domains: chlorophyll content, nitrogen use efficiency/nitrogen assimilation, above-ground biomass, leaf area index, and yield. These variables were consistently reported as MF-responsive in the agricultural literature and have also been validated for field-scale estimation using UAV multispectral sensing. Together, these bridge connections provide the scientific basis for integrating MF treatments with non-destructive, spatially explicit crop monitoring. The cross-domain variable mapping further demonstrates that MF treatment responses can be evaluated across multiple biological levels, from primary physiological processes and structural canopy development to final agronomic performance.

Based on these findings, a conceptual framework was proposed as the first operational pathway for field-scale monitoring and validation of MF treatments using UAV multispectral sensing. Although the framework remains to be validated experimentally, it provides a structured approach for linking physiological responses to canopy-scale observations and agronomic outcomes under real farming conditions. Future empirical validation across crops, environments, and management systems will determine whether this framework can support the transition of MF technologies from promising experimental interventions to evidence-based tools for sustainable and digitally enabled agriculture.

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Abbreviations

MF	Magnetic Field
PEMF	Pulsed Electromagnetic Field
ELF	Extremely low-frequency
NR	Nitrate Reductase
Fv/Fm	PSII maximum quantum efficiency
CAT	Catalase
SMF	Static Magnetic Field
MWI	Magnetised Water Irrigation
ROS	Reactive Oxygen Species

PSII	Photosystem II
SOD	Superoxide Dismutase
APX	Ascorbate Peroxidase
N	Nitrogen
NNI	Nitrogen Nutrition Index
LAI	Leaf Area Index
CCC	Canopy Chlorophyll Content
WUE	Water Use Efficiency
NUE	Nitrogen Use Efficiency
AGB	Above-ground Biomass
LCC	Leaf Chlorophyll Content
FVC	Fractional Vegetation Cover
UAV	Unmanned Aerial Vehicle
DJI	DJI (brand name, platform manufacturer)
RGB	red-green-blue (sensor/imagery type)
DSM	Digital Surface Model
UAS	Unmanned Aerial System
P4M	DJI Phantom 4 Multispectral
NIR	Near-infrared (spectral band)
LiDAR	Light detection and ranging
NDVI	Normalised difference vegetation index
GNDVI	Green normalised difference vegetation index
VI	Vegetation Index
NDRE	Normalised difference red-edge index
SAVI	Soil-adjusted vegetation index
CWSI	Crop Water Stress Index
PAM	Photosynthetic Accumulation Model
DWT	Discrete Wavelet Transform
RTM	Radiative Transfer Model
RMSE	Root Mean Square Error
ML	Machine Learning
SVM	Support Vector Machine
LSTM	Long short-term memory
PSO	Particle Swarm Optimisation
RF	Random Forest
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
XGBoost	Extreme Gradient Boosting
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
EU	European Union
CAP	Common Agricultural Policy
MODIS	Moderate Resolution Imaging Spectroradiometer

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