



Review

Digital Technologies in Crop Production: A Scoping Review with Transferability Analysis for Central Asia

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Abstract

This scoping review maps 224 empirical studies (205 from a structured Scopus search, 2020–2026, plus 19 from a targeted Central Asia supplement) across four digital technology domains for crop production: IoT and sensor-based systems, UAVs and remote sensing, machine learning and AI, and nanostructured agrochemicals. The review follows the PRISMA-ScR framework and pursues three research questions concerning documented effects and validation limitations (RQ1); cross-cutting barriers in human capital, data governance, and infrastructure (RQ2); and the state of empirical evidence from Central Asia and Kazakhstan relative to international findings (RQ3). Across all four domains, the strongest reported effects occur where the data-to-decision-to-action loop is closed and sustained over multiple seasons, yet most published metrics rest on single-season, single-site, or controlled-environment validation that overstates likely field portability. IoT and selected UAV and ML workflows are closest to operational readiness where maintenance, calibration, and advisory support are sustained. Nanostructured materials remain the least mature domain in agronomic terms. For Central Asia, foundational monitoring and salinity-oriented remote sensing are the most immediately transferable elements; intervention-grade ML and integrated digital systems require local calibration, extension infrastructure, and multi-season field validation that are largely still absent. The review identifies the digital skills gap, incomplete data governance, and underreported total cost of ownership as the principal institutional barriers to scaling. Policy priorities include shifting from technical pilots to multi-season agronomic proof, building intermediary service capacity, and establishing transparent data-governance frameworks before large-scale procurement.

Keywords: digital agriculture; precision farming; IoT; UAV; artificial intelligence; machine learning; agronanotechnology; scoping review; Central Asia; Kazakhstan



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1. Introduction

Crop production is being reshaped by a convergence of digital and material technologies commonly grouped under the banners of Agriculture 4.0 and smart farming. Four domains dominate the current evidence base: Internet-of-Things (IoT) sensing and control, unmanned aerial vehicles (UAVs) and remote sensing, machine learning and artificial intelligence (ML/AI) for agronomic prediction and classification, and nanostructured agrochemicals for controlled delivery. Primary studies report tangible effects in each domain, ranging from multi-year IoT-based decision support that maintained vine water status

under variable climates [1] and UAV- and satellite-derived management zones that reduced nitrogen application in winter wheat [2] to chemical savings under UAV-based prescription spraying [3] and accuracy gains in weed and disease detection with deep-learning architectures [4,5]. These effects, however, are uneven across crops, seasons, and agroecological zones, and most are documented under conditions that differ markedly from the dryland, infrastructure-constrained settings that characterise Central Asia and other transitional agricultural economies. Kazakhstan, with approximately 25 million hectares of cropland, exemplifies this mismatch: policy ambitions for sustainable intensification and digitalisation coexist with a continental, water-limited climate, persistent vulnerabilities in transboundary water governance [6], and a documented digital-skills gap that constrains technology uptake among rural workforces [7].

The recent review literature has consolidated what is known within each technology domain but has not delivered the cross-domain and regional synthesis that such a policy context requires. Recent systematic reviews have mapped IoT and AI in smart sensing [8], UAVs in precision agriculture [9], and nano-enabled inputs for sustainable crop production [10], each with valuable depth within a single technology. What these otherwise rigorous reviews do not jointly provide is the cross-technology comparison that decision-makers need when allocating resources across competing options, nor do they provide an analysis framed by transferability—whether reported effects hold under different soils, seasons, farm sizes, and data infrastructures, rather than peak accuracy or best-case yield gains. A third, more specific gap concerns the evidence base for Central Asia and Kazakhstan, which is sparsely represented in these international syntheses and is not mapped against global findings in a structured way, leaving open the practical question of how much published evidence is actually applicable to regional practice. These three gaps together motivate a synthesis that is broad enough to cover the four dominant technology domains, disciplined enough to apply a consistent transferability and validation lens across them, and regionally explicit.

This review addresses that need. Using the PRISMA extension for Scoping Reviews (PRISMA-ScR) [11], we map 205 empirical studies published between 2020 and 2026 across IoT, UAVs, ML/AI, and nanostructured agrochemicals, complemented by a supplementary regional set of 19 studies with explicit Central Asia or Kazakhstan focus. The review pursues three research questions. RQ1 asks what digital technologies have been applied or tested in crop production and what their documented effects and validation limitations are. RQ2 asks what cross-cutting barriers to technology adoption exist in terms of human capital, data governance, and infrastructure. RQ3 asks what the current state of empirical evidence from Central Asia and Kazakhstan is and what transferability gaps exist relative to international findings. The contribution of the review is threefold: it provides a cross-technology synthesis applying a uniform transferability and validation lens to four domains that are typically reviewed in isolation; it conducts an explicit transferability analysis for Central Asian dryland conditions rather than asserting regional relevance rhetorically; and it integrates a dedicated regional evidence lens that separates internationally generalisable findings from those that require local validation. Sections 2–6 develop the methodology, the mapped evidence for the four technology domains, the human capital and institutional requirements that cut across them, a discussion centred on cross-technology synthesis and transferability, and the conclusions anchored to RQ1–RQ3. The stages of agricultural development toward digital crop production are summarised in Figure 1.

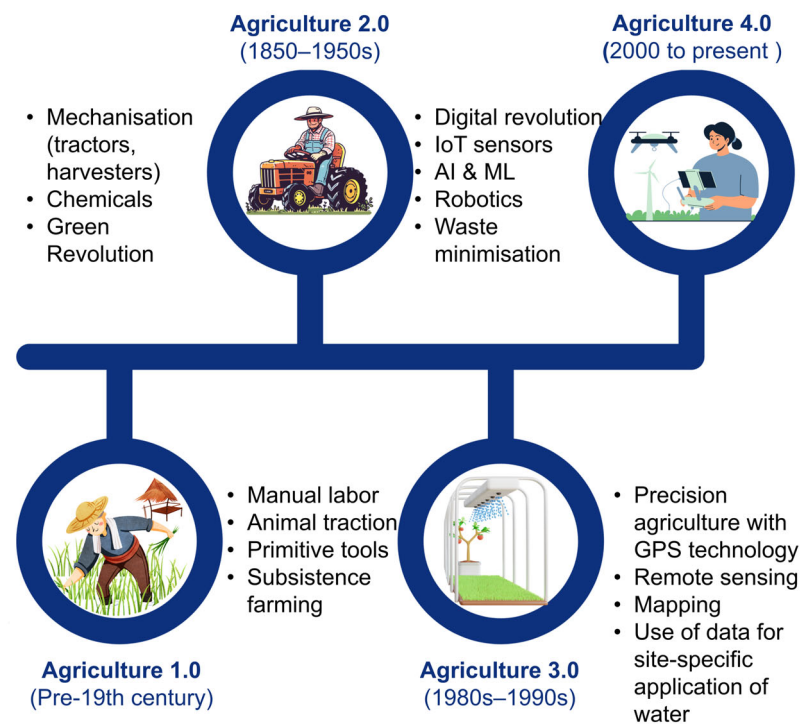


Figure 1. Stages of agricultural development toward digital crop production.

2. Methodology

2.1. Review Design and Research Questions

This study follows the PRISMA extension for Scoping Reviews (PRISMA-ScR) framework [11]. A scoping review was chosen because the objective is to map the breadth and nature of the available evidence across multiple technology domains rather than to evaluate the effectiveness of a single intervention. This design accommodates the heterogeneous evidence base that spans IoT, UAVs, machine learning, and nanostructured agrochemicals without requiring formal quality appraisal or meta-analytic synthesis, which would be premature given the diversity of study designs, metrics, and agroecological contexts encountered. This design was used to address the three research questions stated in the Introduction while allowing the evidence base to be mapped across heterogeneous technologies, crops, validation designs, and regional contexts. The completed PRISMA-ScR checklist is provided in Supplementary Table S1.

2.2. Search Strategy and Eligibility Criteria

A structured search was conducted in the Scopus database using the following query applied to the Title, Abstract, and Keywords fields:

TITLE-ABS-KEY(("Digital agriculture" OR "Digitalization in Agriculture" OR "Smart farming" OR "Agriculture 4.0") AND ("drone" OR "UAV" OR "UAS" OR "unmanned aerial vehicle" OR "sensor" OR "IoT" OR "internet of things" OR "artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "nanofertilize*" OR "nanopesticide*" OR "nanotechnology")).

The search was restricted sequentially: by subject area (Agricultural and Biological Sciences), publication year (2020–2026), document type (Article), and language (English). The filtration sequence and resulting sample sizes are reported in the PRISMA-ScR flow diagram (Figure 2).

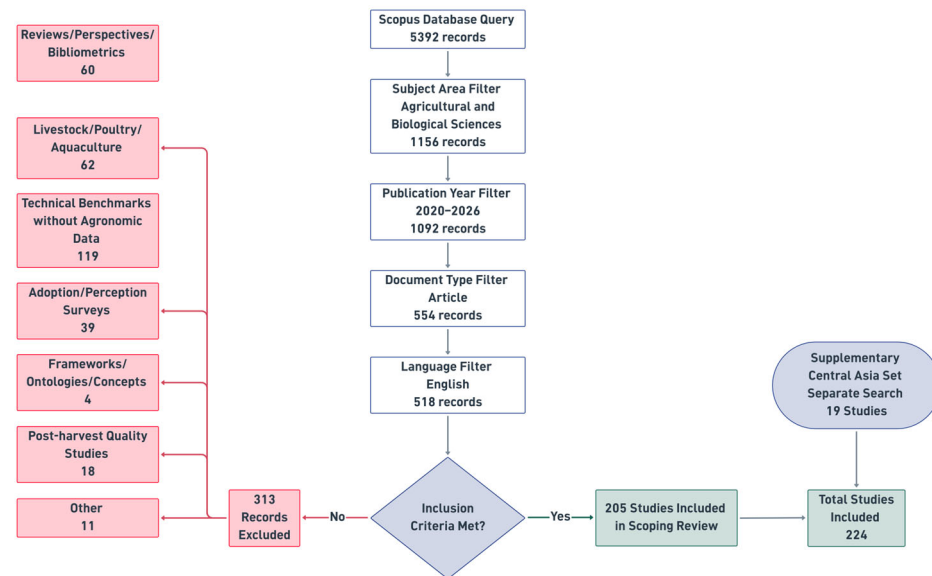


Figure 2. PRISMA-ScR flow diagram of study identification, screening, and inclusion. Database-level filtration reduced the initial 5392 Scopus records to 518 articles for title and abstract screening. Of these, 205 met all inclusion criteria and were charted for synthesis. A supplementary set of 19 unique Central Asia-focused studies was assembled through separate targeted searches outside the primary Scopus query and is not part of the PRISMA denominator. The final evidence base therefore comprised 224 studies: 205 from the primary screen and 19 unique regional studies. The exclusion categories shown on the left sum to the 313 records excluded at the title/abstract screening stage.

Inclusion criteria. Studies were included if they met all four conditions: (1) described a specific protocol, experiment, or field implementation; (2) reported quantitative outcomes related to yield, water use, agrochemical application, cost, or model performance in an agronomic context; (3) specified crop or production system and agroecological setting; and (4) presented transparent data processing or analytical methods.

Exclusion criteria. Studies were excluded if any of the following applied: (a) review, meta-analysis, perspective, editorial, or bibliometric study; (b) conference proceeding or book chapter; (c) focused exclusively on livestock, poultry, aquaculture, or food processing without a crop production component; (d) described a device, algorithm, or benchmark dataset without reporting agronomic outcomes; (e) perception, adoption, or sociological survey without quantitative technology performance data; (f) post-harvest quality assessment, sorting, or grading without connection to in-season crop management; or (g) duplicate record.

2.3. Screening Process and Results

The initial Scopus query returned 5392 records. After applying subject area, year, document type, and language restrictions, 518 articles remained for title and abstract screening. Two authors independently reviewed titles and abstracts against the eligibility criteria. Discrepancies were resolved through discussion. A total of 205 articles met the inclusion criteria and proceeded to full-text charting.

The exclusion breakdown across the 313 removed articles was as follows: technical benchmarks or device descriptions without agronomic results ($n = 119$); livestock, poultry, and aquaculture studies ($n = 62$); reviews, meta-analyses, perspectives, and bibliometrics ($n = 60$); sociological, adoption, or perception surveys ($n = 39$); post-harvest quality studies ($n = 18$); other non-eligible records including security systems, policy analyses, and regulatory studies ($n = 11$); and frameworks, ontologies, or conceptual studies ($n = 4$). The complete screening decisions for all 518 articles are available in Supplementary Table S2.

2.4. Data Charting

Included studies were charted into four primary technology domains based on the principal technology evaluated: (1) IoT, sensing, irrigation, fertigation, and environmental control; (2) UAVs, remote sensing, mapping, and precision spraying; (3) machine learning and AI for agronomic prediction, detection, and classification; and (4) nanostructured materials for agrochemical delivery. A fifth thematic corpus on cross-cutting implementation—covering digital twins, integrated platforms, and farm machinery automation—was assigned to studies addressing multi-technology deployment or system-level integration. Studies were tagged with additional descriptors: FIELD for open-field experiments, ECON for studies reporting economic data, and CA for studies with explicit Central Asia or Kazakhstan context.

For each included study, the following data items were extracted: crop and agroecological context, technology type and components, study design (controlled environment, single-field, multi-site, multi-season), validation protocol (internal split, cross-validation, external test), key performance metrics, reported effects on yield or resource use, and stated limitations.

The charted evidence base and the cited bibliography should therefore be distinguished. The full evidence base includes 224 studies: 205 included studies from the primary screen and 19 unique Central Asian studies from the supplementary search. The reference list contains the subset cited directly in the narrative synthesis, selected because these studies provide distinct evidence for the comparative arguments developed in Sections 3–5. The remaining included studies are retained in the supplementary screening and charting materials rather than repeated as narrative citations.

2.5. Regional Evidence: Central Asia Supplementary Set

The primary Scopus screening yielded only two studies with explicit Central Asia or Kazakhstan relevance among the 205 included: a VNIR hyperspectral wheat-disease study in Kazakhstan [12] and a multi-country AI-based precision agriculture analysis covering Kazakhstan and Uzbekistan [13]. To address RQ3 and provide a meaningful regional analysis, a supplementary set of 19 studies was assembled through targeted searches in Scopus and Google Scholar using queries combining technology terms with “Kazakhstan”, “Central Asia”, “Uzbekistan”, “Kyrgyzstan”, and “Turkmenistan”. This regional set is reported separately and is not included in the primary PRISMA-ScR denominator of 518 records. It serves as a supplementary lens for the transferability analysis in the Discussion. Including the supplementary regional set, a total of 224 studies inform this review (205 from the primary screen and 19 from the regional supplement).

2.6. Deviations from a Full Systematic Review

Consistent with scoping review methodology, this study does not include formal quality appraisal or risk-of-bias assessment of individual studies, nor does it perform meta-analysis. The primary search was limited to a single database (Scopus), which may have excluded relevant studies indexed only in Web of Science, PubMed, or regional databases; the regional supplementary search partially mitigates this for Central Asian evidence but does not close the gap for other underrepresented regions. Screening was conducted by two authors without a third-party arbitrator. These limitations are discussed further in Section 5.5.

3. Innovative Technologies

Agriculture 4.0 is fundamentally based on data-driven management, generated and processed by a system of people, devices, software, and rules. In this section, we criti-

cally examine four core technologies of this system: IoT, UAVs, machine learning, and agronanotechnologies, assessing their capabilities and limitations (see Figure 3).

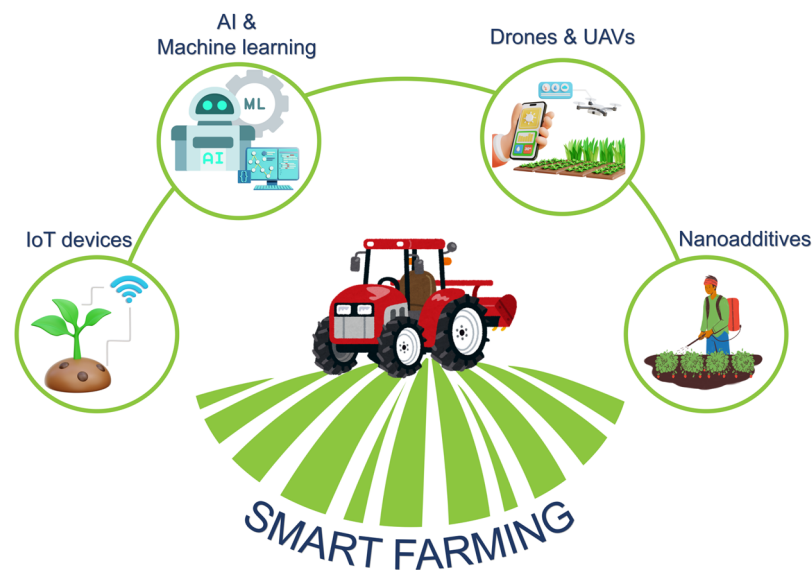


Figure 3. Core technologies of smart farming.

3.1. IoT and Sensor-Based Systems

The Internet of Things provides the foundational data layer of the four technology domains reviewed here. Sensing generates the measurements on which UAV analytics, ML models, and nano-enabled delivery decisions are judged, while actuation closes the loop between data and field operation. Recent systematic reviews have already mapped IoT sensing architectures and their communication protocols [8]. This subsection therefore focuses on transferability: which reported gains persist beyond the original deployment, and which depend on maintenance routines, data correction, and infrastructure commitments that Central Asian dryland operations may find difficult to sustain.

3.1.1. Architectural Components and Their Trade-Offs

Three architectural layers recur across the IoT literature: sensing, connectivity, and control. The published evidence shows that the binding constraint is rarely sensor availability in and of itself. It is the fit between architectural choice and operational context.

Sensing. The core sensor stack is highly consistent across the corpus, air and soil temperature, relative humidity, soil moisture, light intensity, and, where irrigation is central, water-level or flow sensing. Nutrient-oriented systems extend this stack with electrochemical or ion-selective measurements for pH and NPK. Polling cadence ranges from hourly logging to sub-10-min intervals, depending on the control objective. The critical weakness at this layer is not measurement scarcity but measurement reliability. Low-cost sensors are attractive because they make deployment financially plausible, yet they frequently drift under real operating conditions. Studies that combine low-cost sensing with data assimilation, anomaly filtering, or gap-filling routines show that usable records can be preserved, but only by adding a correction layer to the system rather than by trusting raw telemetry at face value [14,15]. This pattern is repeated across sensor classes. Nutrient sensors, environmental probes, and water-level systems all require recalibration, pre-correction, or field-specific adjustment before their outputs can support decisions [16–22]. Cheap sensing, therefore, reduces entry cost but shifts the burden to calibration, correction, and maintenance.

Connectivity. The literature converges on a limited set of viable communication choices whose comparative value depends on geography rather than on abstract technical superiority. LoRaWAN is the dominant option in remote field settings because it is independent of mobile operators, supports kilometre-scale coverage, and allows multi-year battery life in low-data applications [23]. AgriLink in Morocco illustrates this logic well. Its main contribution is not a sharply quantified crop response, but the demonstration that semi-arid orchard monitoring can be organised around LoRaWAN with practical alternatives such as Sigfox and NB-IoT when infrastructure permits [24]. NB-IoT becomes attractive where cellular coverage is stable, but it ties the system to tariff structures and operator dependence. Wi-Fi remains useful as local transport inside node clusters, while higher-bandwidth options enter the picture only where robotics or continuous imaging make latency a primary concern. No architecture dominates universally. Connectivity is a regional design decision with direct implications for recurring cost, autonomy, and service dependence. Empirical comparisons reinforce this conclusion. LoRa and NB-IoT coverage modelling shows that NB-IoT consistently extends range where LTE infrastructure is present, but LoRaWAN supports autonomous deployment where it is not [25]. In field robotic operations, private 5G outperformed public 4G in latency, while local Wi-Fi 6 delivered even lower latency within its coverage footprint [26]. For indoor-farming subsegments, ZigBee mesh networks with improved routing reduce latency and packet loss [27].

Control. The control layer spans a gradient from threshold rules to fuzzy logic, predictive ML, and reinforcement-learning scheduling [28,29]. Recent studies report strong short-horizon forecasting performance for greenhouse microclimate and vineyard soil moisture using attention-based or multi-task neural models [30,31]. Yet these gains do not establish that sophisticated control closes the economic case in ordinary farm operations. Each increase in algorithmic complexity raises demands on sensor cadence, data quality, and supervision. This makes system stability more fragile, not less. For the small and medium farm structures that dominate much of Central Asia, simple, auditable threshold rules paired with well-maintained sensors remain the more operationally stable choice. More recent work adds digital-twin and reinforcement-learning layers to IoT-driven irrigation in both apple-scab and winter-wheat settings, using WOFOST and similar crop models as simulation environments [32]. Such architectures demonstrate architectural sophistication, but they also multiply the data and maintenance dependencies that constrain simpler systems. AI-enabled IoT platforms for chilli production under split-plot field design across two seasons show that economic benefit-cost ratios can be reported alongside yield response, yet even these remain single-crop, single-region designs [33].

3.1.2. Validation Scope and the Dominant Bias

A central limitation of the IoT evidence base is that effect sizes are still dominated by short-horizon deployments in controlled or semi-controlled environments. Greenhouse, hydroponic, and indoor studies remain overrepresented. Examples include edge-computing optimisation of strawberry production in Andean greenhouses, IoT-based hydroponic enhancement of Chinese cabbage, and frost-control systems that combine IoT with ANN and fuzzy control [34–36]. These studies are useful because they show that dense sensor-control loops can work under tight management. They do not show that the same gains persist in open-field conditions with variable weather, irregular maintenance, and heterogeneous soils.

Long-horizon open-field evidence is rare. The clearest counter-example in the cited set is the 10-year maize case from northern Italy, where continuous soil-moisture sensing, Sentinel-2 integration, and variable-rate nitrogen application were associated with approximately 31% higher yield and 23% lower nitrogen input over time [37]. This is one of the few studies in which digital agriculture appears as a sustained management system

rather than as a bounded pilot. By contrast, most open-field IoT cases in the corpus are shorter and narrower. Field studies on sweet corn, coffee, and rice and wheat irrigation report meaningful effects within their own deployment envelopes, but they do not establish stability across independent fields or years [23,38,39]. The dominant bias is therefore not laboratory artificiality alone. It is short-horizon internalism, the tendency to validate within the same field logic, climate window, and maintenance regime that generated the result.

This point matters for interpretation. A system may perform well because sensors are freshly calibrated, because the operator is technically engaged, or because environmental variation remains limited during the trial period. Those conditions are part of the result. They are not background details that disappear when the system is scaled.

3.1.3. Economic Evidence and Total Cost of Ownership

The economic record remains thinner than the technical one. A minority of IoT studies report costs in a form that allows comparison across contexts. Better examples do exist. IoT-supported alternate wetting and drying in the Mekong Delta documented water and irrigation-energy savings alongside agronomic outcomes [40]. A life-cycle assessment and life-cycle cost analysis of smart irrigation in protected zucchini cultivation showed a 38.2% reduction in water and energy use, without yield loss, and a reduction in externalised environmental costs per tonne [41]. More recent fertigation work based on a micro-services architecture reported substantial savings in fertiliser and water use against conventional proportional injection systems, although its assumptions remain highly controlled [42].

What is still largely missing from the broader literature is ongoing cost disclosure for sensor replacement, recalibration labour, firmware maintenance, communications, and data management. Those are the costs that decide whether a system remains operational after the pilot period ends. Farmer-facing adoption studies repeatedly identify uncertainty about realised benefit and total cost as a primary barrier, which is consistent with economic analyses framing digital-agriculture investments under risk rather than under idealised payback assumptions [43,44]. The economic lesson is straightforward. The most persuasive IoT studies are not those with the densest dashboards, but those that connect measured savings to a system that farms could plausibly maintain. The representative IoT deployments discussed in this subsection are summarised in Table 1.

Table 1. Selected IoT and sensor-based deployments in crop production, with documented effects and transferability insights. Studies are ordered by validation scope, from stronger field evidence to narrower prototype or controlled-environment cases.

#	System/Location	Crop	Core Technology	Scale & Duration	Documented Effect	Transferability Key Insight	Reference
1	Digital-agriculture case, northern Italy	Maize	Soil-moisture sensing, Sentinel-2 integration, variable-rate nitrogen application	22 ha field, 10-year record	Approximately 31% higher yield and 23% lower nitrogen input over time	Strong long-horizon evidence, but success depended on decade-scale field history, machinery compatibility, and continuous management commitment	[37]
2	IoT-supported alternate wetting and drying, Mekong Delta, Vietnam	Rice	Water-level sensing with IoT decision support	Multi-site on-farm trial, 2 years	Additional 13 to 20% water saving and about 25% lower irrigation energy cost relative to manual AWD	Stronger-than-usual field evidence, but fit is specific to levelled paddy systems with controlled water access	[40]
3	Autonomous irrigation framework, Punjab, India	Rice and wheat	LoRaWAN-linked soil-moisture monitoring with automated valve control	Field deployment across two cultivation cycles	About 9% water saving in rice and 11% in wheat relative to conventional practice	Useful field-scale evidence, but thresholds remain site-specific and must be recalibrated across soils and crop systems	[39]
4	Smart drip irrigation versus ETc scheduling, India	Sweet corn	Soil-moisture-driven irrigation with solar-powered ESP32 nodes	Field, multi-season	About 12% higher yield and 11% water saving under sensor-driven scheduling	Sensor-based rules can outperform generic scheduling, but only when sensor calibration is actively maintained	[38]

Table 1. Cont.

#	System/Location	Crop	Core Technology	Scale & Duration	Documented Effect	Transferability Key Insight	Reference
5	IoT-Agro platform, Colombia	Coffee	Three-layer IoT architecture with edge analytics, anomaly detection, and yield forecasting	Farm-level deployment with short real-time monitoring and multi-year historical data	Functional web platform, outlier detection with high precision, yield prediction workflow	Shows that platform integration is feasible, but structured management data remain a bottleneck and economic disclosure is still qualitative	[23]
6	AgriLink monitoring platform, Morocco	Orange orchard	LoRaWAN primary, alternative LPWAN pathways, low-cost weather and soil sensing	Orchard-scale deployment	Stable low-power monitoring architecture in semi-arid orchard conditions	Strong infrastructure case, but agronomic performance evidence remains weaker than connectivity evidence	[24]
7	Real-time water-level monitoring, Taraz, Kazakhstan	Irrigation infrastructure	Solar-powered ultrasonic sensing with 4G cloud transmission	Canal-scale field logging over several weeks	Continuous telemetry and dashboard-based monitoring under hot arid conditions	Important regional signal for monitoring feasibility, but not yet evidence of crop-linked decision support or economic return	[45]
8	Smart irrigation under LCA and LCC, southern Italy	Zucchini	Sensor-based cloud irrigation compared with conventional management	Protected cultivation, single 95-day cycle	38.2% lower water and energy use without yield loss	One of the clearer TCO-oriented studies, but protected-cultivation evidence should not be extrapolated directly to open-field dryland systems	[41]

3.1.4. Synthesis

Four conclusions emerge from this subsection, each with direct relevance for transferability to Central Asian conditions.

First, IoT systems transfer only when maintenance and correction routines transfer with them. Reliable operation depends on recalibration, anomaly filtering, gap filling, and periodic supervision, as shown in low-cost sensor-assimilation studies, crop-quality monitoring, and field irrigation or orchard-sensor deployments [14–18]. These tasks are not peripheral to the technology; they are part of the operational system. In regions where field service is thin and technical support is uneven, this becomes a structural adoption constraint rather than a minor inconvenience.

Second, connectivity choice is region-specific rather than best-in-class. LoRaWAN remains the most plausible near-term architecture for remote dryland settings because it combines autonomy, low power demand, and acceptable range [23,24]. Cellular options become viable only where coverage quality and pricing are stable enough to support routine telemetry.

Third, control sophistication does not substitute for operational robustness. Reinforcement learning and advanced predictive control may outperform simple rules under dense, clean, research-grade data streams [28,29]. Yet for medium-scale farms operating under infrastructural constraint, the more credible pathway remains calibrated sensing with transparent decision rules, not algorithmic complexity for its own sake.

Fourth, the regional evidence from Kazakhstan is best read as evidence of foundational monitoring feasibility, not of mature agronomic scalability [45]. The current record shows that low-cost, open-source telemetry can operate under arid field conditions. It does not yet show multi-season crop responses, integrated prediction layers, or stable total-cost-of-ownership performance under routine farm use. The cross-technology implications of this distinction are developed in Section 5.1, while Section 5.2 returns to what it means for transferability to Central Asia.

3.2. UAVs and Remote Sensing

UAV and remote-sensing systems form the observational layer of digital crop production. They convert within-field heterogeneity into spatial products such as stress maps, maturity estimates, growth proxies, and prescription zones, but they do not improve

agronomic performance by observation alone. The recent domain review already cited in the Introduction maps the breadth of platform and sensor configurations in precision agriculture [9]. The narrower task here is transferability. Which reported effects rest on multi-field or multi-season validation, and which remain dependent on calibration routines, site-specific thresholds, or processing burdens that are unlikely to transfer directly to Central Asian dryland systems?

3.2.1. Architectural Components and Their Trade-Offs

In this domain, platform class matters less than the interaction between payload, ground truth, and decision protocol. RGB payloads are often sufficient where the target variable is structural or morphological, as in nutrient-deficiency diagnosis in winter wheat and winter rye [46]. Multispectral imaging adds red-edge and near-infrared sensitivity that supports germination assessment, nitrogen-status estimation, tuberisation timing, maturity classification, and salinity mapping [47–50]. Hyperspectral systems extend discrimination further, as shown in early wheat-disease classification in Kazakhstan [12], but each increase in spectral richness raises calibration, processing, and interpretation demands.

The binding constraint lies downstream in the processing chain. Remote-sensing studies that stop at classification maps and those that close the loop into field action belong to different evidential classes. Low-cost UAV imagery has already been translated into operational weed-management prescription maps in Italian maize, reducing the treated area substantially under threshold-dependent scenarios [3]. Related work on management-zone delineation for variable-rate nitrogen application in wheat reaches the same practical threshold, namely the conversion of image-derived heterogeneity into a machine-readable agronomic instruction [2]. By contrast, integrated monitoring architectures that report high information-product accuracy across satellite, UAV, and ground systems still do not necessarily demonstrate field-level intervention benefit if the chain from detection to machinery or decision is left implicit [51]. The architectural question is therefore not whether imaging is accurate in isolation, but whether capture, georeferencing, calibration, processing, interpretation, and execution can all occur within the agronomic window.

A second trade-off concerns spatial coverage versus agronomic specificity. UAVs and satellite-linked workflows are well suited to salinity gradients, crop zoning, canopy condition, and visible disease signals, but they remain weaker where the relevant process is sub-canopy, root-zone, or strongly management-mediated. The Central Asian evidence illustrates this clearly. The regional subset is concentrated in salinity mapping and early detection workflows in southern Kazakhstan and adjacent arid systems [12,50,52,53]. This focus is agronomically rational because soil salinity is a major production constraint in the region. It also exposes a structural gap. Spatial diagnosis is developing faster than evidence on how those maps alter irrigation, nitrogen, pesticide, or yield decisions over time.

3.2.2. Validation Scope and Its Dominant Bias

High headline metrics are common across the UAV literature. Potato maturity classification reported low mean absolute error under breeding-trial conditions [49]. Soybean germination assessment reported strong plot-level agreement with standing density [47]. UAV-based wheat lodging detection reached 89.23% classification accuracy, yet single-stage models failed once canopy appearance shifted across developmental stages [54]. These studies are useful, but most validate within the same site, season, or phenological envelope that generated the training data.

The stronger counter-examples are more informative than the median study. Peanut studies in Brazil used temporal or spatial hold-out designs rather than relying only on internal splits. One reported model generalisation across independent commercial areas with

mean absolute percentage error around 9.3% for yield prediction [55]. Another showed that pod-maturity estimation transferred more credibly when calibration and testing were separated across areas and dates [56]. A winter wheat and rye nutrient-diagnosis study made the seasonal boundary explicit rather than hiding it behind random partitions, reporting only 18% cross-year transfer despite strong within-season performance [46]. A potato tuberisation study for irrigation timing added a further step toward agronomic relevance by linking UAV-derived plant height to root-depth dynamics over three seasons but still depended on labour-intensive ground truth and constrained experimental conditions [48]. The dominant validation bias is therefore single-season internalism, often reinforced by reliance on manual labels, breeder scores, or site-specific thresholds.

This point is especially important for the Central Asian subset. Regional UAV studies are not only diagnosis-centred. They are also highly local in calibration. Salinity models in southern Kazakhstan required field-specific tuning and remained sensitive to relief, landscape complexity, and limited ground observations [50,52]. Long-term salinity mapping with pseudo-colour composites revealed stable broad patterns but still produced substantial error at low salinity and depended on labour-intensive preprocessing [53]. The wheat hyperspectral study from Kazakhstan is regionally valuable because it demonstrates explicit pathogen-level discrimination under local conditions, yet it still relies on five-fold cross-validation within a limited set of plots rather than on farm-to-farm or year-to-year external testing [12]. The regional evidence base is therefore emerging, but it remains narrow in both intervention scope and validation depth.

3.2.3. Economic, Implementation, and Total-Cost-of-Ownership Evidence

The implementation literature is thinner than the mapping literature. Where UAV systems are linked directly to operations, the reported gains are real but partial. Operational weed prescription mapping reduced the treated area substantially relative to blanket application [3]. Drone plant protection among Chinese maize smallholders was associated with lower operating cost, shorter exposure time, and lower yield loss, but the evidence came from service-based adoption data rather than from full audited cost accounting [57]. These studies suggest economic potential, yet they do not amount to a stable total-cost-of-ownership record across farm types.

What is usually missing is the cost structure after the pilot. Published UAV studies rarely disclose battery replacement schedules, sensor recalibration labour, insurance, software subscriptions, cloud storage, repeat-flight cost under missed weather windows, or the agronomic labour required to interpret imagery quickly enough for action. This omission matters because remote sensing imposes substantial overhead that is easy to ignore during a funded trial and difficult to absorb under routine use. Integrated monitoring systems and crop-model hybrids can report strong product accuracy or simulated profitability, yet the same papers often acknowledge that acquisition cost, model calibration, or machinery compatibility limit practical use beyond large or well-supported farms [51,58].

For Central Asia, service dependence is a material risk. The regional corpus supports the technical feasibility of UAV-based salinity and disease mapping [12,50], but it does not yet document long-run maintenance budgets, replacement cycles, or service-market structures for routine agronomic use. Under dryland conditions with large field extents and uneven local support networks, the decisive economic question is not whether a UAV captures useful imagery. It is whether farms can sustain the full capture-to-decision chain without outsourcing each update, interpretation, and repair. The representative UAV and remote-sensing studies discussed in this subsection are summarised in Table 2.

Table 2. Selected UAV and remote-sensing studies in crop production, with documented effects and transferability insights. Studies are ordered by validation scope, from stronger multi-field or multi-season evidence to narrower or more calibration-bound deployments.

#	System/Location	Crop	Core Technology	Scale & Duration	Documented Effect	Transferability Key Insight	DOI
1	Peanut yield prediction, Brazil	Peanut	PlanetScope imagery plus MLP neural networks	11 commercial fields, 2 seasons	Mean absolute percentage error around 9.3% under generalisation testing	Stronger-than-usual temporal and spatial validation, but performance still depends on management and climatic comparability across areas	[55]
2	Peanut pod-maturity estimation, Brazil	Peanut	Remote sensing plus ANN across multiple platforms	Independent geographic areas, multi-date evaluation	Generalisation maintained at high predictive quality across separated areas	One of the clearer examples of external validation, but still crop-specific and sensitive to scale mismatch between field and regional variables	[56]
3	Nutrient-deficiency diagnosis, Germany	Winter wheat and winter rye	UAV RGB imagery plus deep learning	Long-term field experiment, cross-year testing	Within-season accuracy was strong, but cross-year transfer fell to about 18%	Temporal portability is a stronger constraint than within-season classification performance	[46]
4	Tuberisation timing for irrigation, Québec	Potato	UAV multispectral imagery and structure-from-motion plant-height modelling	3 seasons, 3 experimental fields	UAV-derived height tracked root-depth dynamics closely enough to support irrigation timing	Agronomic linkage is stronger than in breeding-only studies, but the method still depends on labour-intensive ground truth and constrained field conditions	[48]
5	Operational weed prescription mapping, Italy	Maize	Low-cost UAV RGB imagery with ANN, MLC, and OBIA classification	Field operational case	Treated area reduced substantially relative to blanket spraying, depending on decision threshold	One of the clearest action-linked UAV cases, showing that value appears only when imagery becomes executable management	[3]
6	Drone plant protection adoption, China	Maize	Service-based drone spraying	351 households, 2 growing seasons	Lower operating cost and lower yield loss under more frequent spraying access	Economic evidence exists, but it is tied to service models and incentive structures rather than to simple equipment ownership	[57]
7	Salinity mapping, southern Kazakhstan	Agricultural fields	UAV multispectral imaging plus machine-learning salinity models	Regional field case, short campaign with limited ground data	Field-level salinity maps produced, but best performance remained modest and field-specific	Regional capability is real, yet calibration is highly local and model portability remains weak under heterogeneous relief and sparse sampling	[50]
8	Early wheat-disease detection, Kazakhstan	Wheat	VNIR hyperspectral signatures plus machine-learning classification	5 field plots, local survey campaign	Random Forest achieved high class-level F1 scores for early disease discrimination	Valuable regional case for local disease sensing, but external validation across farms and seasons is still absent	[12]

3.2.4. Synthesis

First, observation still outpaces action. The strongest pattern in this subsection is the imbalance between mapping capacity and intervention evidence. UAV systems detect salinity, disease, nutrient status, and weed patches with increasing precision, but only a minority of studies close the loop into an executable management change [2,3]. For Central Asia, imagery acquisition on its own should not be mistaken for digital transformation.

Second, temporal robustness is the main unresolved validation problem. The strongest counter-examples in this subsection show that performance weakens once time is treated as a real boundary rather than as background noise [46,55,56]. This point is especially important for Kazakhstan, where interannual weather variability and irrigation instability are stronger than in many source studies.

Third, the Central Asian evidence base is not only narrow in topic, it is also narrow in calibration. Most regional studies focus on salinity mapping or early disease detection and rely on limited ground samples, field-specific tuning, or cross-validation within a bounded local setting [12,50,52,53]. The result is an emerging sensing capability, not yet a transferable decision-support system under routine farm conditions.

Fourth, the economic case remains incomplete. Where savings or yield protection are reported, they are concentrated in spraying and prescription-map workflows rather than in monitoring-only systems [3,57]. For large, service-thin dryland regions, recurring

interpretation, maintenance, and processing costs are likely to shape feasibility more strongly than the acquisition price of the drone itself.

Section 5.1 returns to these patterns at the cross-technology level, and Section 5.2 examines what they imply for transferability to Central Asia.

3.3. Machine Learning and Artificial Intelligence

Machine learning and artificial intelligence form the inferential layer of digital crop production. Sensors, imagery, and farm records gain agronomic value only when a model converts them into a diagnosis, forecast, ranking, or control signal. The recent reviews cited in the Introduction have already mapped the breadth of AI use in smart farming. The narrower task here is evaluative. Within the ML and AI studies in the present corpus, which applications rest on validation that extends beyond internal accuracy, and which remain tied to narrow label regimes, farm-specific patterns, or decision thresholds that are unlikely to transfer directly to Central Asian dryland systems?

3.3.1. Architectural Components and Their Trade-Offs

Across the included studies, model architecture matters less than the relation between input type, label quality, and decision use. Image-based systems dominate the literature. These range from disease and pest classifiers built on field photographs to crop-state recognition from UAV or satellite imagery [5,59–61]. Their headline performance often appears strong because labels are visually clean, classes are bounded, and the agronomic task is reduced to recognition. Yet this apparent strength masks a central trade-off. As image models become more specialised, they also become more dependent on background regularity, stable lighting, crop stage, and the consistency of the training labels themselves.

A second architectural family combines sensor streams, weather data, or historical records with prediction models for irrigation, yield, growth stage, or time-to-harvest [62–65]. These systems sit closer to farm decision-making because they aim to support management rather than classification alone. Their binding constraint is not image quality but context dependence. Models improve when they absorb site-specific structure, such as farm identity, field history, or local weather sequences, yet the same step often weakens portability outside the source environment [62,63]. In practical terms, the model learns the farm as much as it learns the crop process.

A third group moves beyond prediction into optimisation and control. These studies include reinforcement-learning or decision-time systems for irrigation, crop management, or machine operation [29,66]. They are especially important because they close the loop between inference and action. Yet this is also where the architecture becomes most exposed. Reward functions, calibration assumptions, and out-of-distribution behaviour become decisive. A control model that performs well in the training environment may degrade sharply once soil condition, machine behaviour, or seasonal pattern shifts.

The core trade-off across all three families is therefore consistent. Accuracy rises when the model is trained on dense, homogeneous, and strongly curated data. Transferability weakens when the same model is asked to operate across new farms, years, cultivars, or stress combinations. The strongest ML systems in agriculture are not necessarily those with the most complex backbone but those whose input logic, validation protocol, and decision threshold remain interpretable after the model leaves the paper.

3.3.2. Validation Scope and Its Dominant Bias

The dominant validation bias in this subsection is narrow-scope internalism. Many studies report strong performance on internally split datasets, within a single protected environment, or across a restricted range of visually similar agronomic conditions [4,59,61].

Under those conditions, models often learn stable backgrounds, phenological regularities, or farm-specific patterns rather than transferable agronomic structure.

The more informative counter-examples make this bias visible. Encoding farm identity improved tomato harvest prediction, vineyard water-status models performed better under block-out than date-out validation, and rice-yield models transferred poorly between upland and plains clusters [62–64]. These findings show that time, place, and farm structure are core validity conditions rather than nuisance variables.

Image-based pest and disease systems show the same pattern. A potato pest classifier in Bangladesh remained strong under leave-one-location-out validation yet still dropped on unseen field images, even within a limited four-pest scope [60]. A multimodal apple leaf diagnosis framework reported near-perfect metrics but relied on a very small physiological sensor dataset and lacked cross-dataset testing across unfamiliar orchard conditions [59]. The lesson is not that these studies are weak. The lesson is that their strongest results are conditional on bounded environments.

Uncertainty quantification remains underused relative to the scale of the decisions being supported. A recent conformal-prediction study is important precisely because it does not promise better agronomy through accuracy inflation. Instead, it shows that calibrated prediction sets help signal when model output requires human review [67]. That contribution matters because most agricultural ML papers still treat point prediction as sufficient, even where data drift, label ambiguity, and domain shift are obvious.

For Central Asia, the regional evidence in this subsection remains thin. The Eurasian AI study that includes Kazakhstan and Uzbekistan is useful as a regional signal of policy and pilot activity, yet its evidential basis remains much weaker than the specialised field papers used elsewhere in this section [13]. As a result, the main regional conclusion for ML is negative but important. There is still no dense body of externally validated, farm-level ML evidence from Central Asia comparable to the stronger international cases.

3.3.3. Economic, Implementation, and TCO Evidence

Economic evidence in the ML literature is thinner than the technical rhetoric suggests. Most studies report predictive performance, classification quality, or control success but do not disclose the ongoing costs of annotation, retraining, sensor maintenance, cloud support, label curation, and threshold revision. This silence matters because farms do not adopt models in isolation. They adopt workflows that include data collection, correction, interpretation, and accountability for wrong decisions.

The better exceptions show what more useful evidence looks like. A multi-method assessment of nitrogen recommendations across 21 on-farm wheat and barley trials over four seasons showed that data-rich empirical models outperformed weaker sensor-based heuristics and improved profitability by up to \$47 per hectare [65]. A maize downy mildew forecasting system in India linked Random Forest prediction to a working web application and reported a yield increase from 19.5 to 23.5 q/ha when plant protection followed forecast logic rather than routine timing [68]. AI-assisted tractor control in secondary tillage matched professional human performance while increasing area output by 29.1% and improving fuel efficiency by 8.4% under field trials [66]. These cases are valuable because they tie model use to agronomic or operational outcomes rather than to abstract classification quality alone.

Even in the stronger implementation studies, the hidden cost lines remain substantial. Multi-source smart-farming services for grapevine phenology required major human effort in data transformation and multidisciplinary validation before model output became usable [69]. Conformal prediction points in the same direction from another angle; reliable decision support depends not only on model output but also on an additional calibration

layer that itself requires labelled data [67]. This makes the real implementation burden heavier than inference speed or edge deployment metrics suggest.

For transferability, the practical conclusion is direct. The decisive cost in agricultural ML often lies not in running the model, but in sustaining the surrounding information system. That burden includes labelled local data, periodic recalibration, human review, and the institutional capacity to decide when the model should not be trusted. Where those conditions are weak, the apparent affordability of ML at publication stage becomes misleading. The representative ML and AI studies discussed in this subsection are summarised in Table 3.

Table 3. Representative machine-learning and AI studies in crop production, with emphasis on validation scope, implementation evidence, and transferability.

#	System/Location	Crop	Core Technology	Scale & Duration	Documented Effect	Transferability Key Insight	Reference
1	Multi-method nitrogen recommendation assessment, Australia	Wheat and barley	Data-driven ML recommendation models benchmarked against EONR	21 on-farm trials, 4 seasons	Profitability improvement up to A\$47 ha ⁻¹ over current farmer practice	One of the strongest field-economic ML cases, yet performance weakens under data-limited conditions	[65]
2	Disease forecasting web application, Karnataka, India	Maize	Random Forest forecasting for downy mildew with deployed web tool	48 disease cycles, 2018–2022	Forecast-based management increased yield from 19.5 to 23.5 q ha ⁻¹	Strong action-linked example, but still tied to a single susceptible genotype and one agro-climatic zone	[68]
3	AI-assisted tractor control, Germany	Spring barley establishment	Decision-time planning and reinforcement-learning support for tillage control	5 fields, field trials in 2024	Area output up 29.1%, fuel efficiency up 8.4% relative to baseline	Rare case where AI reaches operational control, yet performance drops outside trained machine and field conditions	[66]
4	Smart-farm survival modelling, South Korea	Tomato	Deep neural survival model with farm-effect encoding	65 farms, 2 cultivation cycles	DNN models with farm identity outperformed RF, XGB, and SVR on harvest prediction	Strong evidence that farm-specific hidden structure matters, but that same dependence limits portability to unseen farms	[62]
5	Spatial-temporal water-status prediction, California	Grapevine	Gradient Boosting Machine on Landsat-derived predictors	10 ha vineyard, 2 seasons	Strong spatial prediction, weak temporal prediction unless anchored by prior field measurement	One of the clearest demonstrations that temporal transfer is harder than spatial interpolation	[64]
6	Real-time block-level yield forecasting, Jammu, India	Basmati rice	Lightweight CNN-LSTM with compressed edge deployment	6 administrative blocks, 2014–2019	Mean RMSE 0.31 with efficient edge execution	Good local forecasting, but domain shift between upland and plains clusters raised error by 50.8%	[63]
7	Edge-oriented pest classification, Bangladesh	Potato	Fine-tuned VGG16 classifier	3000 field images across 2 seasons	96.3% accuracy and 95.9% F1 score, with field-capable inference time	Stronger-than-usual validation through leave-one-location-out design, yet performance still drops on unseen field imagery	[60]
8	Eurasian AI precision-agriculture programme	Mixed regional cropping contexts	AI-enabled precision-agriculture platform with drone and satellite inputs	Regional programme across Kazakhstan and Uzbekistan	Yield and fertiliser-saving claims reported in regional pilot narratives	Useful only as a weak regional signal, because the evidential base is secondary and methodologically thin relative to specialised field studies	[13]

3.3.4. Synthesis

First, the strongest ML failure mode is not low accuracy but narrow validity. Many studies achieve high internal metrics, yet performance weakens sharply once the model crosses a boundary in time, place, farm identity, or stress combination [62–64].

Second, model sophistication does not solve weak agronomic grounding. Deep ensembles, transformers, and multimodal systems often perform well inside curated datasets [59,60]. Yet the studies that matter most for farm use are those that connect model output to an intervention, threshold, or operational change [65,66,68].

Third, uncertainty handling remains underdeveloped relative to the scale of decisions being supported. The conformal-prediction evidence is important because it makes explicit what much of the literature leaves implicit, namely that a usable agricultural model must also indicate when its own output is unsafe to trust [67].

Fourth, the practical cost of ML lies in the surrounding information system rather than in inference speed alone. Data curation, label quality, recalibration, and expert review are recurrent burdens in the better implementation studies [65,69]. This is especially important for Central Asia, where region-specific labelled datasets and long validation series remain scarce.

Fifth, the regional conclusion is still mainly one of absence. Central Asia is visible in policy and pilot narratives, yet robust farm-level ML evidence from the region remains too limited to support confident transfer claims [13].

Section 5.1 returns to this asymmetry at the cross-technology level, and Section 5.2 examines what it means for transferability to Central Asian crop systems.

3.4. Nanostructured Materials

Nanostructured materials occupy a different position in crop production from IoT, UAVs, and ML. They are not the sensing layer, and they are not the inferential layer. They are the delivery layer, where the agronomic claim is that nutrients or pesticides become more selective, more persistent, or less wasteful because the active ingredient is reformulated at the nanoscale. The recent domain review already cited in the Introduction maps the broader promise of nano-enabled agriculture [10]. The narrower task here is stricter. Within the evidence assembled for this review and the manuscript's vetted nanomaterial reference set, which delivery claims are supported by crop-level validation, and which still depend on greenhouse efficacy, short exposure windows, or toxicological fragments that do not yet amount to transferable agronomic evidence?

A second distinction is necessary at the outset. In the regional supplementary set, no Central Asian study tests nano-enabled fertiliser or pesticide delivery in crop production under field conditions. The only clearly regional nanomaterial paper concerns sulfur nanoparticle synthesis with antibacterial screening and acute mammalian toxicity, not crop-performance validation [70]. For RQ3, the regional message of this subsection is therefore not local efficacy but the near absence of region-specific agronomic evidence.

3.4.1. Architectural Components and Their Trade-Offs

The central architectural choice in this subsection is not the active ingredient itself but the relation between carrier, trigger, and agronomic target. Nanofertiliser studies based on amorphous calcium phosphate focus on nutrient loading and slower nitrogen release, with the expectation that better retention translates into comparable crop response at lower input intensity [71–73]. Nanopesticide studies use a wider carrier set, including silica, lignin-based systems, lignin-chitosan hybrids, and other hybrid nanostructures, to stabilise the active ingredient, protect it from degradation, or alter where and when release occurs [74–77].

The binding constraint is the same across these architectures. A release mechanism has agronomic value only when the trigger corresponds to a field condition that is stable enough to predict and common enough to matter. pH-responsive and redox-responsive systems are chemically attractive because they promise selective release in pathogen-affected or physiologically distinct microenvironments [74,75]. Yet each added layer of responsiveness also increases dependence on formulation stability, weather, leaf-surface chemistry, and operator precision. The trade-off is clear. As the release logic becomes more sophisticated, the claim of lower residue or lower dose becomes stronger in principle, while the burden of proving reliable field behaviour also rises.

A second trade-off concerns what the formulation is optimised to do. Some systems are designed for efficacy against a target pest or pathogen. Others prioritise persistence, residue reduction, compatibility with plant tissues, or combined nutritional and protective

action [72,74,75]. These aims are not equivalent. A formulation that performs well in lesion suppression over 48 h is not yet a formulation with proven seasonal value for farmers. Likewise, a material that lowers residue in leaf tissue may still impose unmeasured costs in storage, registration, non-target exposure, or applicator compatibility. The subsection therefore treats nanostructured materials as agronomic systems, not as release-curve demonstrations.

3.4.2. Validation Scope and Its Dominant Bias

The dominant validation bias in this subsection is greenhouse and laboratory concentration. The cited set includes genuine field evidence, but it is the exception rather than the rule. The most useful counter-example is the viticulture study on urea-doped calcium phosphate nanoparticles, which links the formulation to yield and grape-quality outcomes in Pinot Gris rather than to release kinetics alone [72]. A second important counter-example is the strawberry field evaluation of polymer- and silica-based nanopesticides, precisely because the result was restrained rather than promotional. The study did not find clear yield or bioaccumulation advantages over classical formulations, which is methodologically more informative than another greenhouse efficacy claim [78].

Most of the remaining evidence is narrower in scope. Greenhouse and plant-level studies show that pH-responsive silica systems can control rapeseed lesions at lower nominal iprodione doses while also altering tissue Mn and Si status [74]. Mesoporous silica loaded with acetamiprid can reduce leaf residue in faba bean while maintaining aphid control at reduced field rate [75]. These studies are valuable, but they do not yet resolve the central transferability question, namely whether the same formulation remains effective and acceptably safe across soils, seasons, and farm-management regimes.

Safety evidence is mixed and formulation-specific. Some nano-enabled systems report lower residue or acceptable plant compatibility [75,77], while others show material-specific non-target effects on soils and biological communities that cannot be inferred from the active ingredient alone [79,80]. The practical point is that efficacy without matched non-target assessment remains under-validated.

3.4.3. Economic, Implementation, and Total-Cost-of-Ownership Evidence

Economic evidence is weaker here than in any other technology subsection. Nanostructured-material studies usually report loading efficiency, release profile, lesion control, pest mortality, residue reduction, or physiological response. They seldom report application cost, formulation shelf life under farm storage, compatibility with existing spray equipment, or the registration burden associated with new materials. Even the stronger nanofertiliser work that explicitly addresses environmental sustainability and manufacturing cost remains closer to formulation optimisation than to whole-farm economic evaluation [71].

This omission matters because nano-enabled inputs do not enter farms as stand-alone scientific objects. They enter through procurement, handling, regulation, and repeated application. A formulation that lowers active-ingredient dose but requires special storage, narrower environmental conditions, or additional compliance testing may still raise total ownership cost. None of the representative studies in this subsection provides a mature answer to that problem. The absence of economic reporting therefore has to be read as a real evidence gap, not as a neutral omission.

For Central Asia, the implementation gap is wider still. The regional supplementary record shows scientific capacity in nanoparticle synthesis [70], but it does not yet show crop-specific delivery systems tested under water-limited field conditions, nor any evidence on registration pathway, local production feasibility, or grower-side handling costs. In this subsection, the regional transferability problem is therefore sharper than in UAVs or ML.

The issue is not incomplete adaptation of an established tool. It is the absence of a validated regional agronomic evidence base. The representative nanostructured-material studies discussed in this subsection are summarised in Table 4.

Table 4. Representative nanostructured-material studies relevant to crop production and transferability.

#	System/Location	Crop	Core Technology	Scale & Duration	Documented Effect	Transferability Key Insight	DOI
1	Urea-doped calcium phosphate nanoparticles, Italy	Pinot Gris grapevine	Nitrogen nanofertiliser	Field viticulture study	Yield and grape-quality outcomes reported under vineyard conditions	One of the few crop-level field cases, but still limited to one crop and one production system	[72]
2	Polymer- and silica-based nanopesticides, field strawberries	Strawberry	Nanoformulated pesticides	Two-season field evaluation	No clear yield or bioaccumulation advantage over classical formulations	Negative or neutral field evidence is critical because it shows that laboratory promise does not guarantee field superiority	[78]
3	Lignin-chitosan nanocarriers in grapevine endotherapy	Grapevine	Nanocarriers for bioactive natural products	Plant-level agronomic application	No phytotoxicity by chlorophyll-related indicators, with higher yield in treated arms than control	Plant compatibility is useful, yet routine seasonal disease-management value still requires broader validation	[77]
4	Acidity-activated Mn-engineered silicon nanohybrids	Rapeseed	pH-responsive nanopesticide with nutritional co-function	Greenhouse, short lesion-control window	Comparable lesion control at lower nominal dose, with altered tissue Mn and Si status	Dual-function design is promising, but short-window greenhouse success is not yet field transferability	[74]
5	Mesoporous silica nanocarrier loaded with acetamiprid	Faba bean	Nanocarrier pesticide delivery	Plant-level efficacy and residue comparison	Aphid control maintained, leaf residue reduced at half field rate	Residue reduction is agronomically relevant, but durability across seasons and non-target exposure remain unresolved	[75]
6	Long-term nano versus bulk copper exposure	Sugarcane	Nano and bulk copper compounds	Long-term pot exposure	Material form altered crop response and reduced juice yield at high dose	Longer exposure sharpens risk interpretation, but pot evidence still falls short of multi-site field validation	[79]
7	Soil-biota response to copper-based materials	Agricultural soil systems	Nano and bulk copper materials	Controlled soil experiment	Biological response differed by material form	Safety cannot be inferred from the active ingredient alone, which makes formulation-level testing essential	[80]
8	Hydrophilic sulfur nanoparticles, Kazakhstan	No crop system tested	Sulfur nanoparticle synthesis with antibacterial screening	Laboratory study with acute toxicity assay	Antibacterial activity and acute toxicity reported	This is a regional capability signal, not crop-production evidence, which makes the Central Asian gap explicit rather than filled	[70]

3.4.4. Synthesis

First, nanostructured-material studies are strongest when they connect formulation behaviour to crop-level comparison rather than to release kinetics alone. In the present evidence base, those studies are few. Field viticulture and strawberry cases show that agronomic validation can either support or weaken the technological claim, and both outcomes are informative [72,78].

Second, the dominant evidential pattern is still greenhouse or plant-level optimisation. Triggered release, reduced residue, and short-window efficacy are repeatedly demonstrated under controlled conditions, but seasonal robustness across variable soils and management regimes remains under-tested [74–76]. For Central Asian dryland conditions, where soil chemistry, irrigation quality, and climatic stress vary sharply, this makes direct transfer claims premature.

Third, efficacy and safety cannot be separated analytically. Some nano-enabled inputs reduce residue or improve plant compatibility, yet non-target evidence remains formulation-specific and sometimes adverse [75,79,80]. For policy and practice, the relevant question is not whether a nanocarrier works in principle, but whether crop benefit and non-target effects have been evaluated within the same agronomic frame.

Fourth, economic and ownership evidence is still largely absent. Manufacturing optimisation has been discussed, but farm-level cost, shelf-life stability, equipment com-

patibility, and registration burden remain underreported [71]. This silence is a material obstacle for transferability to regions where procurement chains and regulatory support are still uneven.

Fifth, the regional conclusion for Central Asia is negative but important. The supplementary evidence shows nanomaterial research activity in Kazakhstan [70], yet no crop-production field study was identified that would justify regional claims about nano-enabled fertilisers or pesticides.

Sections 5.1 and 5.2 therefore return to this domain not as a mature regional option but as a technology class whose local agronomic evidence base still has to be built.

4. Human Capital and Institutional Requirements

The four technology domains reviewed in Section 3 share a dependency that none of them resolves internally. Each requires human competence to calibrate, interpret, and sustain the data-to-decision loop, and each depends on institutional arrangements, including data standards, access rules, service networks, and advisory structures, that lie outside the technology itself. The evidence assembled in Section 3.1 through Section 3.4 makes this pattern explicit. IoT systems degrade when recalibration and correction routines lapse. UAV workflows lose value when image products do not reach actionable decisions within the agronomic window. ML systems weaken when labelled local data, review capacity, or recalibration logic are absent. Nano-enabled inputs remain largely pre-field objects where registration pathways, handling protocols, and local agronomic validation are missing. This section consolidates these cross-cutting human and institutional requirements, which together define the barrier layer addressed by RQ2.

4.1. The Digital Skills Gap as a Structural Constraint

The most persistent non-technical barrier in the reviewed evidence is not hardware access alone but the shortage of personnel able to convert measurements into defensible management decisions. European small-scale farming surveys document insufficient digital preparation among farmers and agricultural workers, together with a need for sustained, practice-oriented upskilling rather than one-off interface training [81,82]. Adoption studies in precision irrigation point in the same direction. Perceived complexity and uncertainty about realised benefit often deter uptake more strongly than equipment price itself [83]. The implication is that digital agriculture requires more than sensor literacy. It requires the ability to evaluate data quality, interpret model output critically, recognise when thresholds are site-specific, and understand measurement uncertainty.

The reviewed primary studies sharpen this point. Low-cost IoT systems frequently rely on correction layers, anomaly filtering, or data assimilation before their measurements become usable [14,15]. ML workflows become reliable only when someone curates labels, reviews drift, and decides whether the model is operating outside its training envelope [67,69]. This shifts the skills problem from basic device operation toward a wider competence in calibration, data engineering, and agronomic interpretation.

For Kazakhstan, the skills gap has a structural dimension that extends beyond training design. Panel evidence shows that growth in digital literacy coincides with a reduction in the share of hired and self-employed agricultural labour, which is consistent with a redistribution of functions from manual operations toward analytical and data-oriented roles [7]. Formal internet coverage is high, yet urban-rural disparities in connection quality, digital service use, and real-time data capacity remain substantial [84]. National-level analyses of agribusiness digitalisation reinforce the same conclusion. Policy ambition has advanced faster than field-level institutional capacity to implement data-intensive systems at farm scale [85,86].

A three-tier competence structure emerges from the reviewed evidence. At the basic level, farmers and operators need to read dashboards and maps, verify data plausibility, and execute threshold-based recommendations. At the applied level, technicians and agronomists need to calibrate sensors, revise thresholds, export task maps, and interpret model output against field conditions. At the advanced level, analysts, educators, and institutional intermediaries need competence in experimental design, uncertainty assessment, data integration, and the liability implications of algorithmic decisions. The empirical literature suggests that failure at any of these levels weakens adoption, even where the underlying technology is technically mature.

4.2. Data Governance, Interoperability, and Farmer Trust

A second cross-cutting barrier concerns the institutional rules that govern agricultural data once it is collected. This issue surfaced repeatedly in the technology sections. IoT and UAV systems generate farm-level telemetry and spatial records whose value depends on aggregation and reuse, yet the conditions under which such sharing occurs are neither stable nor widely trusted.

Empirical studies of farmer willingness to share data show that concerns about ownership, usage transparency, and the risk of commercial exploitation consistently reduce sharing readiness [87]. Policy discussions in Europe have moved toward combining horizontal governance instruments with sector-specific codes of conduct for agricultural data, but these frameworks remain incomplete and unevenly adopted [88,89]. Interoperability is a related constraint. Where sensor records, prescription maps, and farm-management datasets cannot move across systems without manual reformatting, the practical value of each digital layer declines and vendor dependence deepens [90].

The primary studies reviewed here show that the problem is not only legal. It is also operational. Multi-source smart-farming services and ML systems often require extensive data transformation, expert checking, and repeated calibration before they become usable in practice [23,69]. Pilot architectures built around federated learning, digital twins, or interoperable APIs are moving in the right direction, yet they still rely heavily on manual calibration, local pilot conditions, and incomplete machinery integration [32,91]. Interoperability therefore remains more mature as a design objective than as a stable institutional reality.

For Central Asia, governance development is still more conceptual than empirical. Regional policy literature from Kazakhstan, Kyrgyzstan, and Uzbekistan discusses digital transformation, financing, cyber-regulation, and innovation ecosystems [85,92,93]. What it does not yet provide is a dense farm-level record of how data-sharing rules function in practice, what trust levels farmers place in intermediaries, or how interoperable standards are adopted under real field conditions. In this sense, governance discussion in the region is progressing faster than governance validation.

4.3. Advisory Services and Knowledge Transfer Models

Advisory systems connect technological possibility with farm-level action. The international evidence shows that delivery format matters as much as informational content. Field experiments in Ethiopia, Uganda, Mali, and Bangladesh demonstrate that video-mediated extension, interactive voice response, SMS prompts, and behaviour-sensitive recommendation design can improve uptake and, in some cases, yield and income outcomes [94–97]. These studies matter because they show that advisory effectiveness depends on local relevance, communication channel, and timing, not on information volume alone.

The primary digital-agriculture studies reviewed in this manuscript point to an analogous pattern. AI and IoT systems become usable only when intermediary structures

exist to interpret outputs, update datasets, and convert model signals into crop-specific decisions. This is visible in deployed forecasting systems, web-based disease tools, and multi-source decision services, all of which depend on a layer of human mediation beyond the algorithm itself [23,68,69]. Even in technically strong deployments, farmers and field staff rarely interact with raw model logic. They interact with an advisory translation of that logic.

For Kazakhstan and the broader Central Asian context, this point is especially important because the regional literature still documents a thin advisory infrastructure for digital agriculture at farm scale. Existing analyses emphasise regulatory design, investment need, and innovation ecosystems [85,93] but provide little direct evidence on how extension systems, universities, input suppliers, and service providers jointly support adoption in crop production. The practical implication is that scaling digital agriculture in the region will depend not only on training farmers directly but also on building intermediary competence in agronomic consulting, calibration support, and field-level troubleshooting.

4.4. Synthesis

First, the skills gap is not a narrow training deficit. It is a structural constraint produced by the shift from manual operations toward calibration, interpretation, and data-management work. Digital agriculture changes the labour profile of farming, and the competence response must match that shift rather than treating digitalisation as a matter of interface familiarity.

Second, data governance is a binding institutional bottleneck that technology does not solve internally. Trust, interoperability, transparent access rules, and standardised exchange formats are preconditions for scaling. In Central Asia, these foundations remain less developed than in the North American and European settings from which most empirical evidence still originates.

Third, advisory systems are effective when they combine accessible delivery with local agronomic translation. The evidence from both extension studies and digital-agriculture deployments shows that model output becomes actionable only when it is embedded in an intermediary layer capable of adaptation, interpretation, and follow-up.

Fourth, the regional literature from Central Asia is still weighted toward policy framing, regulatory aspiration, and national-level transformation narratives rather than toward farm-level empirical evidence on adoption, interoperability, and digital trust. This asymmetry is itself a substantive result of the review and becomes important in the transferability analysis developed in Section 5.2.

5. Discussion

Sections 3 and 4 show that digital agriculture in crop production depends less on invention alone than on whether measurement, interpretation, and action remain connected over time. Across IoT, UAVs, ML, and nanostructured materials, the strongest reported gains occur when a technical system is embedded in a sustained agronomic workflow rather than evaluated as an isolated device, model, or formulation.

5.1. Cross-Technology Synthesis

A first cross-technology pattern is that the most credible effects arise when the data-to-decision-to-action loop is closed. In IoT, the strongest evidence comes from long-horizon field systems in which sensing is linked directly to irrigation or nutrient management over multiple seasons or years [37,40]. In UAV studies, the most policy-relevant cases are not imaging demonstrations but workflows that convert imagery into executable prescription maps or operational spraying decisions [3,57]. In ML, the more useful evidence comes from

systems tied to advisory recommendations, field control, or measurable economic outcomes rather than from image classification alone [65,66,68]. In nanostructured materials, by contrast, the loop is rarely closed beyond controlled crop or plant-level tests, which explains why the domain remains less mature from an agronomic point of view [72,78].

A second pattern is that headline performance systematically overstates transferability when validation boundaries remain narrow. The form of that bias differs by technology, but the direction is consistent. IoT literature is still weighted toward short-horizon or protected-environment deployments [34,35]. UAV studies often validate within a single season, crop stage, or local threshold regime [47,49]. ML studies often retain high internal performance while weakening across farms, years, or environmental clusters [62–64]. Nano-enabled formulations remain dominated by greenhouse efficacy and short exposure windows [74,75]. The common implication is that many published metrics describe bounded validity rather than stable agronomic generality.

A third pattern is the asymmetry between technical reporting and implementation reporting. Technical performance is usually described in detail. Total cost of ownership, maintenance labour, retraining burden, service dependence, and replacement cycles are much less often disclosed. This gap appears in IoT, where calibration and correction routines are rarely costed fully [14,41]. It appears in UAV systems, where processing delay, operator skill, repeat flights, and software costs are often omitted [3,57]. It appears even more sharply in ML, where the hidden costs lie in labelled data, recalibration, and review capacity rather than in inference speed [67,79]. It is strongest of all in nanostructured materials, where shelf life, registration cost, and application compatibility are rarely treated as part of the agronomic system [71].

Taken together, these patterns suggest a maturity gradient across the four domains. IoT and selected UAV and ML workflows are already close to operational relevance where field validation is sustained and the action chain is explicit. Nanostructured materials remain the least mature in agronomic terms because the literature is still dominated by formulation performance rather than field-proofed delivery systems.

5.2. Transferability to Central Asia

The transferability problem is especially important for Central Asia because the region combines large land areas, water stress, soil salinisation, uneven connectivity, and a still-developing support infrastructure for digital agriculture [98,99]. In this setting, a technology is transferable only if its core assumptions remain plausible under dryland variability, fragmented service support, and limited local calibration capacity. The regional supplementary corpus makes it clear that the current evidence base is uneven across domains.

The most immediately transferable elements are foundational monitoring and targeted sensing architectures. Low-cost water-level and environmental telemetry can already operate under arid regional conditions, even if crop-linked outcome evidence remains limited [45]. UAV and satellite workflows for salinity detection and landscape diagnosis are also regionally relevant because salinity is a first-order production constraint in southern Kazakhstan and adjacent oasis systems [50,52,53,100]. These technologies fit the regional problem structure better than greenhouse-optimised control systems or highly curated multimodal AI stacks.

A second group is conditionally transferable rather than immediately transferable. This includes UAV-based disease sensing, crop-status classification, and ML decision support. The wheat hyperspectral work from Kazakhstan is important because it demonstrates that local disease discrimination is feasible under regional conditions [12]. Yet the broader regional evidence in UAV and ML remains narrow in both scale and validation depth. Salinity studies often require field-specific tuning, local ground sampling, and bounded

calibration domains [50,52]. Early soybean detection workflows remain specific to one crop stage and one training setting [101]. These systems are therefore best viewed as regionally promising but still conditional on local recalibration, agronomic extension, and external testing across farms and seasons.

A third group remains premature from the perspective of regional deployment. Nano-enabled fertilisers and pesticides fall into this category because no crop-production field study from Central Asia was identified that validates agronomic benefit under local conditions [70]. Large integrated architectures, such as federated hybrid platforms, satellite-air-ground services, or digital twins, also remain premature as regional defaults unless service infrastructure, interoperability, and calibration support are built in parallel [32,51,91]. Under current Central Asian conditions, the transferability ladder is therefore asymmetric. Foundational monitoring and constrained sensing tasks are plausible now. Intervention-grade ML and integrated orchestration are plausible only with adaptation. Nano-enabled delivery remains largely pre-transfer.

This unevenness also changes how regional relevance should be judged. The mere presence of local pilot activity does not amount to regional proof. The relevant standard is not whether a technology has been demonstrated once in Kazakhstan or Uzbekistan, but whether it has been validated across enough agronomic variation to inform routine practice. By that standard, the regional evidence base is still strongest in diagnosis and weakest in sustained intervention.

5.3. Data Governance and Scaling

Scaling in digital agriculture depends on more than technical performance because the value of digital systems rises only when data move across devices, seasons, farms, and advisory layers without losing meaning. Existing evidence shows that farmer willingness to share data remains sensitive to ownership, transparency, and perceived risk of external exploitation [87]. At the same time, practical interoperability between platforms remains incomplete even where standards are discussed extensively [88–90]. This means that the scaling problem is simultaneously institutional and technical.

The reviewed primary studies show how this constraint appears operationally. IoT and platform papers often require extensive data transformation, outlier filtering, and manual checking before information becomes usable for agronomic decisions [23,69]. Digital-twin and hybrid AI architectures move toward syntactic and semantic interoperability but still depend on manual calibration, pilot-scale integration, or incomplete machinery connectivity [32,91]. Reinforcement-learning systems add a further scaling barrier because recommendation quality becomes harder for users to audit when model logic is opaque. In practice, weak transparency and high calibration demand reinforce each other.

This problem is magnified in regions where service ecosystems are thin. Central Asia is not constrained only by equipment supply or connectivity. It is constrained by the limited availability of intermediary actors who can calibrate systems, manage data pipelines, maintain standards, and translate output into field practice. In such settings, scaling may stall even when a technology performs well in a pilot. The central governance issue is therefore not data collection alone but the institutional capacity to preserve meaning, trust, and actionability once data leave the field.

Scale also affects the distribution of benefits. A recent meta-analysis of precision agriculture reports positive average returns globally but also shows that benefits are stronger and more stable on larger farms than in smallholder settings because capital intensity, service access, and management overhead matter [102]. This finding aligns with the evidence in the present review. Many digital systems are technically feasible for smaller farms, but their economics remain less stable once full implementation burdens are counted.

5.4. Policy Recommendations and Future Research

A first policy priority is to shift demonstration design from technical pilots toward agronomic proof. Multi-season, multi-site field trials with pre-specified external validation are more informative than single-cycle high-accuracy studies. For IoT, this means reporting recalibration cadence, maintenance overhead, and fallback behaviour. For UAV and ML systems, this means testing across years, farms, and decision windows rather than relying on random splits alone. For nanostructured materials, this means pairing crop benefit with non-target assessment and basic implementation metrics in the same field frame.

A second priority is to build intermediary capacity rather than treating adoption as a direct transaction between vendor and farmer. The reviewed evidence supports a competence ladder that includes operators, technicians, agronomists, analysts, and extension intermediaries. In practical terms, this implies investment in calibration support, labelled local datasets, advisory translation, and troubleshooting networks rather than in hardware alone. For Central Asia, this point is critical because the main barrier is often not first acquisition but the absence of institutions able to sustain use after acquisition.

A third priority is governance infrastructure. Standardised exchange formats, transparent data-rights rules, interoperability requirements in public procurement, and auditable change logs should be treated as enabling infrastructure rather than as secondary legal detail [88,90]. In regions with budget constraints, such as Kazakhstan, blended public-private financing models may be necessary, but they will only improve adoption if institutional trust and accountability mechanisms develop in parallel [85].

A fourth priority concerns future research design by technology class. IoT research should move toward long-horizon field performance with explicit ownership costs. UAV research should prioritise intervention-linked studies over new mapping metrics. ML research should foreground uncertainty quantification, domain shift, and recalibration burden rather than accuracy alone [67]. Nano research should move from greenhouse efficacy to field-tested delivery systems with integrated economic and safety reporting. Across all domains, the strongest missing evidence is not another proof of possibility but rather clearer knowledge of when digital systems remain reliable after local novelty has worn off.

5.5. Limitations of This Review

This review has several limitations that follow directly from its design. The main corpus was derived from a Scopus search restricted to articles in English published between 2020 and 2026. After database-level filtering, 518 records entered screening, and 205 studies were included. A supplementary Central Asia set of 21 studies was assembled separately, of which 19 made a unique contribution after overlap removal, yielding 224 unique studies overall. This design was appropriate for mapping the field, but it inevitably excludes some grey literature, non-English regional studies, and operational reports that may matter for local practice.

A second limitation is methodological. As a scoping review, the study was designed to map breadth, evidence structure, and transferability constraints rather than to conduct formal effect-size synthesis or quality appraisal [11]. The included studies differ too widely in crop, scale, metric, and validation design to support meta-analysis across the four technology domains. This means that the review can compare evidential patterns and implementation logic, but it cannot claim pooled quantitative effects across the field.

A third limitation concerns regional asymmetry. The international evidence base is substantially richer than the Central Asian evidence base, especially for long-horizon intervention studies. In the regional set, salinity sensing, policy framing, and macro-level transformation narratives are better represented than farm-level comparative trials. The

review therefore provides a structured picture of regional gaps, but it cannot fully resolve them from published evidence alone.

These limitations do not weaken the main conclusion of the review; they clarify its scope. The study does not claim to identify a universally optimal technology pathway. It identifies where the strongest evidence lies, where transferability breaks down, and where Central Asian agriculture is currently closest to adoption versus where it still lacks a credible empirical base.

6. Conclusions

This scoping review shows that digital technologies already influence crop production in measurable ways, but their agronomic value differs sharply by technology class and by validation depth. For RQ1, three conclusions follow. First, IoT systems, UAV workflows, and selected ML applications show the strongest practical value when they are linked to explicit management actions such as irrigation scheduling, variable-rate application, disease forecasting, or machine control rather than to monitoring or classification alone. Second, many reported effects remain bounded by narrow validation designs, especially single-season trials, internally split datasets, and controlled environments, which means that published performance often exceeds likely field portability. Third, nanostructured materials remain the least mature of the four domains from an agronomic perspective, because the evidence base is still dominated by greenhouse efficacy, residue studies, and formulation performance rather than by multi-season crop-level field validation with economic and safety evidence.

For RQ2, the main barriers to adoption are human and institutional rather than purely technical. First, digital agriculture depends on skills in calibration, correction, interpretation, and threshold revision, not only on basic device use, which means that workforce preparation must extend beyond short digital-literacy courses. Second, scaling is constrained by weak data governance, incomplete interoperability, and limited trust in data-sharing arrangements, which reduce the value of otherwise strong sensing and modelling systems. Third, implementation costs remain underreported across the literature, especially where maintenance labour, model updating, software dependence, and service provision determine whether a system remains viable after the pilot stage. As a result, adoption depends on advisory structures, support networks, and governance design as much as on the underlying technology.

For RQ3, the current evidence base from Central Asia and Kazakhstan is real but uneven, and its main strength lies in diagnosis rather than sustained intervention. The regional literature shows emerging capacity in foundational monitoring, salinity mapping, and local disease sensing, particularly through UAV, hyperspectral, and low-cost telemetry studies. At the same time, the region still lacks a dense body of multi-season field evidence showing that these tools improve crop management, profitability, or resource efficiency under routine farm conditions. The most plausible regional pathway is therefore sequential rather than simultaneous: first strengthen foundational monitoring, local calibration, and service support, then expand toward intervention-grade ML and integrated decision systems, while treating nano-enabled inputs as a longer-term research domain until field-valid regional evidence becomes available.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agriengineering8050199/s1>, Table S1: PRISMA-ScR checklist; Table S2: complete screening decisions for the 518 records assessed in the primary Scopus screening.

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