Article

AI- and Nano-Enabled Precision Agriculture: Frontier Approaches for Stress Tolerance in Plants

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Abstract

Increasing climatic variability and the intensifying biotic and abiotic stresses pose major challenges to global crop productivity, emphasising the urgent need for resource-efficient and sustainable agricultural strategies. Artificial intelligence (AI) and nanotechnology have emerged as complementary technologies capable of enhancing precision agriculture through early stress detection, predictive analytics, and targeted agro-input delivery. This review uniquely integrates recent advances in AI-driven predictive analytics and nano-enabled delivery systems within an agricultural framework of closed-loop precision. It highlights their synergistic role in improving plant stress tolerance and climate-resilient crop production. AI approaches to integrating machine learning, deep learning, and multimodal data fusion enable real-time stress monitoring, hotspot detection, and prediction of stress–risk windows for timely site-specific interventions. Concurrently, nano-engineered formulations enhance the efficiency of the use of nutrients, stabilise bioactive compounds,

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UNISA university of south africa PRESS
Nano-Horizons
Volume 5 | 2026 | #21827 | 25 pages
Nano-Horizons
https://doi.org/10.25159/3005-2602/21827
ISSN 3005-2602 (Online)

and enable controlled release mechanisms while reducing environmental losses. The convergence of these technologies supports adaptive crop management systems that integrate stress sensing, predictive decision-making, targeted delivery, and response verification. Despite significant progress, challenges remain regarding field-scale validation, nanoparticle environmental fate, AI model generalisation, and regulatory governance. Future priorities include biodegradable nano formulations, uncertainty-aware AI systems, standardised dosimetry, and adaptive multimodal AI platforms for diverse agroecosystems. Overall, the integration of AI and nanotechnology offers a scalable and sustainable pathway towards climate-resilient agriculture by improving yield stability, optimising resource usage, and minimising ecological impacts.

Keywords: artificial intelligence; nanotechnology; precision agriculture; tolerance to plant stress; smart crop management; nanosensors; sustainable agriculture; climate-resilient farming

1 Introduction

In the 21st century, agricultural productivity is constrained to the extent of becoming a limiting factor by complex and interconnected biotic and abiotic stresses, which are exacerbated by climate variability, environmental degradation, and more intensive cultivation systems and management [1]. Plants rarely experience isolated stress conditions; drought and heat stress frequently occur simultaneously, salinity often interacts with nutrient imbalance, and pathogen outbreaks are more severe in physiologically weakened hosts. Accordingly, plant stress tolerance depends not only on resistance to individual stressors, but also on the plant's ability to maintain physiological homeostasis [2]. From an agronomic point of view, the dynamics of stress is temporal and spatial–acute stresses such as heat at the reproductive stages can produce irreversible yield penalties in short periods, while chronic stresses such as salinity, heavy metals, and nutrient deficiencies progressively reduce plant vigour during growth cycles [3]. These characteristics make early detection, spatial precision, and intervention efficiency critical components of modern crop management. Conceptually, the management of plant stress may be viewed in the context of a decision-based approach which includes the hazard (environmental or biological stress drivers), exposure (the extent and duration of plant interaction with stress) and vulnerability (crop genotype and developmental stage) [4]. Precision agriculture attempts to largely overcome the mitigation of exposure by allowing for site-specific monitoring and intervening, while the advanced technologies related to inputs aim to overcome the vulnerability through improved physiological protection.

However, conventional agricultural practices are still generally based on generalised field averages, pesticide or fertilisation systems based on the calendar, and reactionary pesticide applications [5]. These approaches will often result in poor usage of resources, a delayed response to the onset of stress, accelerated development of resistance, nutrient losses and impacts on helpful soil microbiota. In addition, episodic visual scouting limits the detection of pre-symptomatic physiological disturbances that allow irreversible damage before corrective measures can be taken.

The convergence of artificial intelligence (AI) and nanotechnology offers a fundamental change to overcome such artificial systemic limitations. Nano-enabled agricultural inputs increase the efficiency of delivery through enhancing solubility, adhesion, stability, and controlled release of nutrients, bioactive compounds and protective agents to increase the dose use efficiency and decrease environmental loading [6]. Concurrently, AI-enabled analytics integrates multisource datasets such as remote sensing imagery and hyperspectral signals, the internet of things (IoT) networks including temperature, humidity and weather sensors, and climatic forecast for preliminary stress diagnosis, predictive potential risk assessment and adaptive decision-making. Integrated in a synergistic way, the concepts of AI and nanotechnology support a closed-loop approach to precision agri-food systems that can detect the presence of stress early, intervene spatially optimised, check constantly to see if plants indeed respond, and dynamically change management strategies [7]. This integrated framework is a transition from input-intensive protection of agriculture to intelligence-driven resource-efficient crop resilience for supporting sustainable productivity in the face of increasing environmental stress scenarios. The integrated workflow of AI and nanotechnology in precision agriculture is illustrated in Figure 1.

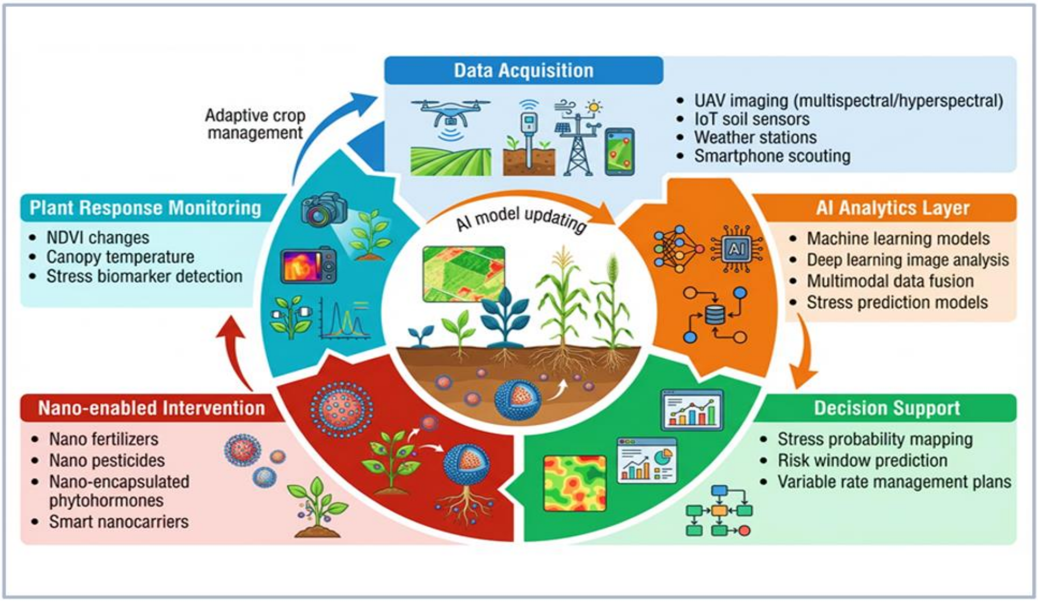

Figure 1: Schematic representation of integrated framework of AI and nano-enabled precision agriculture for plant stress management

This review provides a comprehensive and critical evaluation of recent advances in AI-driven stress diagnostics and nano-enabled delivery systems for improving plant tolerance against biotic and abiotic stresses. This article uniquely emphasises their synergistic integration within agricultural frameworks of closed-loop precision. The review specifically highlights how intelligent sensing, predictive analytics, adaptive decision-making, and nano-engineered interventions collectively contribute to real-time stress management, resource-use optimisation, and climate-resilient crop production. In addition, the article critically discusses technological readiness, environmental safety considerations, scalability challenges, and future directions for the responsible implementation of AI–nano integrated agricultural systems.

2 Overview of Biotic and Abiotic Stress in Plants

2.1 Biotic Stresses

Biotic stresses come from a wide range of living organisms, which can be biotic pathogens such as fungi, bacteria, viruses and oomycetes, and also insect pests, mites, nematodes or competitive weeds that indirectly worsen the limitations on water, nutrients and light availability [8]. Plant defence responses are triggered by highly elaborate systems of immune recognition that can recognise conserved pathogen-associated molecular patterns, and trigger rapid and complex intracellular signalling events including calcium influx, mitogen-activated protein kinase cascades and reactive oxygen species bursts [9]. These early responses suppress pathogens by strengthening cell walls, activating antimicrobial metabolites, and reprogramming transcription to limit pathogen establishment. When primary defences are insufficient, plants respond with more robust approaches to defending themselves, such as signalling and coordinated assault all the way down to a preventive position that involves the deliberate death of cells in areas where the parasite is likely to spread. Although effective, these defences represent large metabolic endowments in the form of allocation of carbon and nitrogen resources away from growth and reproduction into defence-related processes [10].

The epidemiology of biotic stress is much affected by the environmental variability and spatial heterogeneity. Disease epidemics are often linked to short duration microclimatic windows characterised by the right conditions of humidity, temperature and leaf wetness, but pest infestation tends to develop as localised hot spots, rather than homogeneous events on a field scale. Climate change is also increasing these risks by increasing the survival of the vectors that transmit them, increasing the time an infection can last, and altering host and pathogen interactions. Simultaneously, plant-associated microbiomes play a decisive role in either the suppressing or facilitating the disease progression. Intensive chemical incidence, especially repeated exposures of broad-spectrum pesticides or antibiotics can give immediate control but will often damage beneficial microbial communities that contribute to the long-term resilience of plants [11]. Consequently, precision-based monitoring and targeted intervention strategies become more and more recognised as economic tools rather than ecological approaches that protect the functional agroecosystem biodiversity while minimising the evolution of resistance.

2.2 Abiotic Stresses

Abiotic stresses, such as drought, salinity, temperature extremes, flooding, heavy metal toxicity and nutrient imbalance, are among the major constraints to worldwide crop productivity and may often occur in combination [12]. Despite their diversity, these stresses share a common response framework in which (i) stress perception occurs primarily at the cellular membrane, (ii) hormones regulate cellular responses through abscisic acid, salicylic acid, jasmonates and ethylene, and (iii) redox signalling downstream of these hormones controls transcriptional and metabolic reprogramming [13]. Resulting adaptive responses include stomatal regulation, osmolyte accumulation, activation of antioxidant defence systems, alteration of root architecture and maintenance of cellular ion homeostasis. Drought stress limits cell turgor and the main reason for this limitation is stomatal closure, which limits CO_2 assimilation and increases oxidative stress. Salinity induces dual problems in the form of osmotic disturbance and ion toxicity, especially accumulation of Na^+, Cl^- effects on ion uptake of essential nutrients such as K^+, Ca^{2+} [14], [15]. Heat stress destabilises protein structure and membrane integrity and impairs reproductive development by decreasing pollen viability, while heavy metals disrupt enzyme activity and promote excessive reactive oxygen species (ROS) production through redox imbalance [16].

Importantly, non-linear physiological responses occur under the influence of combined stresses because of extensive cross talk in signalling between hormonal and oxidative pathways. For example, abscisic acid (ABA)-mediated drought responses can suppress immune signalling, whereas ROS, although required for defence signalling, can become cytotoxic during simultaneous thermal or water stress. These interactions indicate that successful stress-mitigation strategies should prioritise physiological buffering and adaptive priming rather than maximal stimulation of defence pathways [17]. Overactivation of protective responses may limit growth, while high ROS levels may interfere with major signalling networks. Therefore, modern intervention strategies tend to focus on controlled and low-dose priming combined with continuous monitoring systems and scalable responses in line with the real-time plant stress status; an approach that aligns well with AI-guided and nano-enabled precision agriculture frameworks.

3 Nanotechnology in Plant Stress Management

3.1 Nanomaterials and Their Properties

The agronomic value of using nanotechnology in the agricultural sector is, in large part, in increasing delivery efficiency, ensuring stability of inputs and as a way of optimising resource usage and not based on the inherent toxicity of nanoparticles. Contemporary agriculture nanotechnology focuses on a design of functional materials that can reduce losses of nutrients, improve the bioavailability and under the condition of variable field the targeted deployment of functional materials [18]. Major classes of nanomaterial include metal and metal-oxide nanoparticles such as zinc oxide and iron oxides which are among the most common nanomaterials used for micronutrient delivery [19]. Nanostructures are composed of silica base materials for high carrier capacity and structural reinforcement, carbon-based nanomaterials that are mostly used in sensing applications, and biodegradable polymeric or lipid-based nanocarriers which are engineered for the encapsulation of agrochemicals and bioactive compounds [20]. For example, eco-friendly synthesised CuO–Ag bimetallic nanoparticles prepared using *Withania coagulans* extract have demonstrated stable crystallinity (~22.81 nm) and characteristic functional surface groups confirmed through UV–Vis, XRD, FTIR, and Raman analyses, highlighting their potential for antimicrobial protection and sustainable agricultural applications [19]. Plant exposure to nano-enabled formulations occurs through multiple pathways, including root absorption from soil or a fertigation system and the uptake of nano-enabled technologies through foliar applications from spray systems or seed-priming or coating technologies that affect early phases of development [21].

Nanoparticle performance in real-world agricultural environments is highly influenced by interactions with soil colloids and dissolved salts and organic matter, as well as some environmental variables, such as pH and ionic strength, and environmental variables, such as ultraviolet radiation and precipitation events [22]. These interactions result in modification of aggregation behaviour, surface reactivity, release dynamics giving formulation engineering, and not only particle composition, a key deciding factor in doing robustly in the field. A crucial conceptual difference is to be made between nanomaterials being active agents and nanomaterials being delivery platforms. Although some metallic particles (nanoparticles) have antimicrobial properties, some concerns about persistence, accumulation and non-target toxicity prohibit their sustainability at a large scale. Conversely, biodegradable nanocarriers made from biopolymers, lipids or porous silica become more and more popular as they optimise the delivery efficiency of standard nutrients, botanical compounds or protective agents and they can be degraded in an environmentally compatible way [23]. Importantly, occasionally the agronomic benefits are not provided by excessive internalisation of the nanoparticles, but by better surface retention, longer time availability in the rhizosphere and better timing of active ingredients release. Consequently, the behaviour of nanoparticles during progression through the plant–soil interface and not the maximum nanoparticles penetrate in plant tissues is of the utmost importance in defining successful relocation in the soil.

3.2 Mechanism of Action

Nano-enabled agricultural systems reduce plant stress by five mechanisms that work together to improve physiological resilience. The first mechanism involves improving nutrient-use efficiency through controlled-release nano-fertilisers and nano-chelated micronutrients that maintain nutrient availability in conditions of stress-induced uptake limitations [24]. Second, by nano-encapsulation, sensitive bioactive compounds such as phytohormones, botanicals and crop protectants are stabilised against degradation by ultraviolet, oxidation and volatilisation losses. Third, the use of controlled-release mechanisms, which are based on moisture, pH or matrix degradation, synchronises the active delivery with stress occurrence or pathogen infection windows (improving the timing of intervention) [25]. A fourth mechanism is redox modulation and physiological priming, whereby the selected formulations create enhanced antioxidant capacity or prime defence-signalling mechanisms, without constitutive activation, thereby enabling a faster response when stress intensifies. Fifth, improved adhesion and rain fastness increase retention to target sites so that leaves are protected effectively on leaf surfaces or in the rhizosphere for longer periods [26].

Strict dose characterisation is also essential; application metrics must give proper measure of concentration, mass loading and field-scale application rates to identify the difference between beneficial responses and possible phytotoxic effects. Field realism is a major determinant of technology success. Nanoparticles can form aggregates in solutions of salines or hard water sprays, and by adsorption to the soil organic matter can be surface coronated, which will affect mobility and releasing kinetics. Environmental stressors such as fluctuation of the temperature and the action of solar radiation also contribute to the acceleration of degradation processes for both carrier and encapsulated actives [27]. The latter situation accounts for discrepancies that are often found between controlled-environment experiments and field trials. Therefore, parameters formulation specific such as particle size distribution, carrier composition, release profiles in realistic environmental conditions and preliminary ecotoxicity based on non-target soil microorganisms and beneficial organisms should be reported through high impact studies so that both reproducibility and regulatory confidence are established [28]. The underlying mechanisms of nanomaterial-mediated stress alleviation are shown in Figure 2.

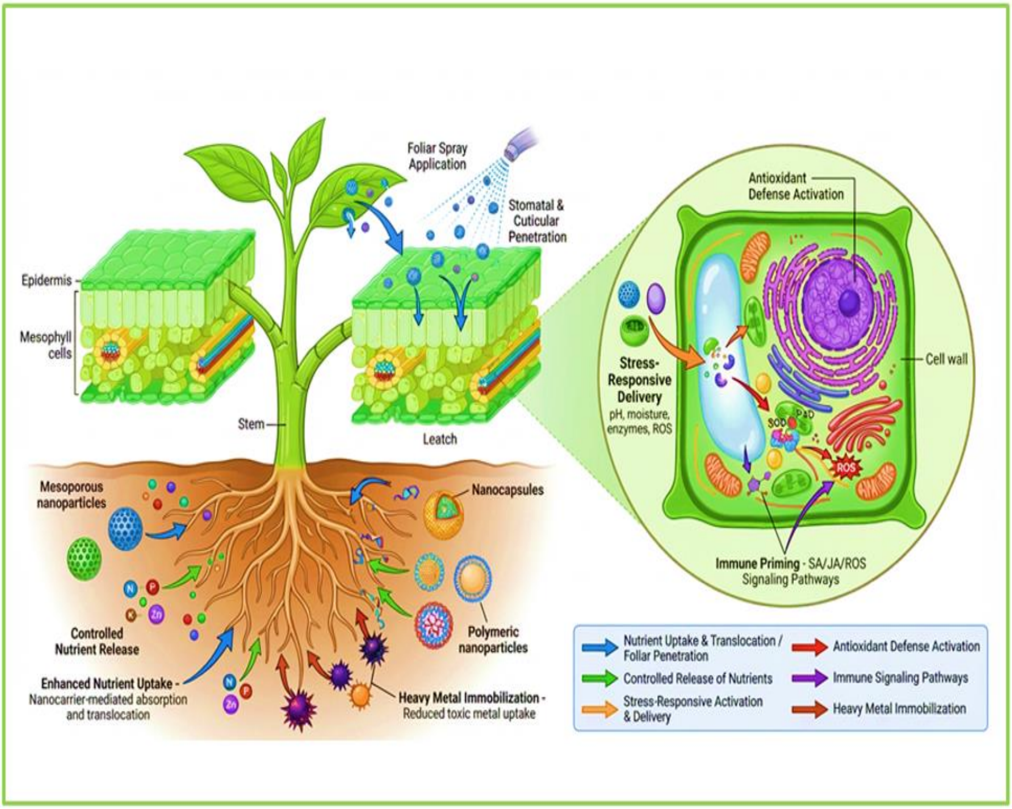

Figure 2: Illustration of the physiological, biochemical and molecular mechanisms by which nanomaterials enhance plant stress tolerance, including antioxidant defence activation, nutrient uptake enhancement, gene expression modulation, and pathogen inhibition

3.3 Application in Stress Mitigation

Nano-enabled interventions hold great promise in a wide range of plant stress situations provided that they are in line with physiological needs and temporal environmental conditions. Under drought and heat stress, nano formulates micronutrients and protective carriers function to maintain photosynthetic functioning, membrane stability and antioxidant balance situations, especially when implemented in preventive mode before predictable stress situations or during critical stages of development [29]. In saline environments, stable agronomic benefits are mostly associated with maintenance of the nutrient homeostasis and oxidative-stress buffering in favour of direct salt removal mechanisms. Similarly, under heavy-metal stress, nano assisted immobilisation strategies and tolerance supporting nutrient delivery strategies can lessen toxicity and damage of plants although long-term soil interaction and environmental fate need to be scrutinised. For biotic stressors, nanotechnology is largely used for improved management by increasing the efficiency of delivering crop protection agents. Nano-encapsulation enhances foliar retention, ultraviolet protection and controls release of doses of active ingredients to be lowered while still protecting against pathogen or pest risk windows [30].

Nanocarriers that contain elicitors or resistance-inducing compounds can be used to prime plant immune responses and therefore reduce disease severity. Excessive or sustained priming should be avoided because it may intensify growth–defence trade-offs and compromise yield. The technology readiness level for different applications of nano-encapsulated crop protection products currently has the greatest pathway to being in the field, as they build on well-established active ingredients and enhance formulation performance that is compatible with existing agricultural equipment [31]. Nano-fertilisers also offer opportunities from scalability, but must show increased nutrient used efficiency in heterogeneous field conditions under consistent conditions to be economically adopted. Stress-priming nano formulations are also still promising but have to be carefully calibrated to avoid constant metabolic costs. Overall, biodegradable nanocarriers offering a reduction in frequency of applications, reduced total input dosage and integration with the AI-guided variable rate delivery systems are the most viable candidates for near-term adaptation and will combine agronomic productivity with the environmental sustainability goals [32]. Different classes of nanomaterial and their functional roles in plant stress mitigation are summarised in Table 1.

Table 1: Nano-enabled inputs for stress tolerance: functions and cautions

Material/ formulation	Typical role	Best-fit stress uses	Key cautions	References
Biopolymer nanocarriers (eg chitosan, alginate)	Encapsulate bioactives; improve adhesion; occasional immune priming	Disease suppression; priming under combined stress	Batch reproducibility; avoid over-priming, growth-defence trade-offs	[33], [34]
Lipid-based carriers (liposomes, solid lipid nanoparticles (NPs))	Deliver hydrophobic actives; improve foliar penetration	Botanical protectants; elicitors	Temperature stability and shelf life	[35]
Metal-oxide micronutrient NPs (Zn/Fe/Mn oxides)	Micronutrient supply; support enzymes/ antioxidants	Drought/salinity support; recovery after stress	Dose-dependent phytotoxicity; soil aggregation; non-target effects	[36], [37]
Silica-based carriers	High loading capacity; carrier for actives	Drought/salinity adjunct; controlled delivery	Variable field responses; formulation dependent	[38], [39]

Material/ formulation	Typical role	Best-fit stress uses	Key cautions	References
Nano-fertilisers (coated N/P/K, nano-chelates)	Controlled release; reduced loss pathways	Stress periods with reduced uptake efficiency	Need field-validated nutrient use efficiency; risk of over-claims	[40], [41]
Nano-encapsulated pesticides	UV protection; controlled release; rainfastness	Hotspot treatment; risk-window protection	Resistance management still required; exposure assessment	[42]
Nano-biosensors/ functional films	Early detection of ions/metabolites; real-time signals	Early warning; scouting prioritisation	Calibration drift; integration cost	[43]

4 Artificial Intelligence in Precision Agriculture

4.1 AI Tools and Techniques

Artificial intelligence has emerged as a key technological backbone of precision agriculture combining machine learning approaches to the processing of structured sensor data, deep-learning approaches to image and time-series data analysis, and more multimodal approaches, combining remote-sensing imagery, spectral signatures and in-field sensor data flows as well as meteorological data. Within plant stress-management systems, AI provides the supreme agronomic value in three ways with regard to operational capability: (i) detecting plant stress before appearance of visible symptoms, (ii) pinpointing stress hotspots in space, and (iii) predicting windows for risk management, therefore predicting opportunities for proactive rather than reactive intervention [44]. Such capabilities aid in making timely management decisions on site which minimise wastage of input while maintaining the productivity of the crop under dynamic environmental conditions. Effective AI deployment depends on robust data ecosystems which include factors such as standardised data acquisition, pre-processing and quality control, cross-environment validation and interpretable outputs that include estimates of uncertainty or confidence estimates.

Importantly, AI systems are most effective when used as decision-support systems that augment agronomic knowledge rather than replacing it, especially in the case of stress management where false negative predictions from these narrow domain AI systems, ie missing a disease outbreak, may lead to significant economic losses [45]. Model selection must therefore be in line with management objectives; irrigation optimisation is well suited to time-series forecasting and predictive control algorithms, while disease surveillance will rely much more on image segmentation, classification and anomaly detection approaches. In large-scale cropping systems, however, it is not uncommon that operational robustness and scalability tend to favour computationally efficient implementations on some highly complex looking pipeline model that might fail under real-field constraints [46]. Performance evaluation should go beyond the level of accuracy of predictions to encompass the level of robustness across cultivars and seasons, lighting environment and agroecological zone as well as the level of inference latency and cost of the deployment. Validation in at least one independent growing season and geographical location is essential for assessing practical generalisability. Where it is not possible to avoid extrapolation, it is essential to report prediction uncertainty transparently for responsible deployment to take place [47].

4.2 AI Stress Detection and Monitoring

AI-driven monitoring systems provide a way to continuously and without destruction evaluate the condition of the crop by using advanced sensing technologies. Nanoparticle-based immunoassays and rapid diagnostic platforms enable early detection of pathogens, toxins, and stress biomarkers in agriculture through enhanced signal amplification and portable sensing systems. Functionalised nanomaterials such as gold nanoparticles, quantum dots, magnetic particles, and carbon nanostructures are widely used in biosensors and field-deployable diagnostic tools [48]. Computer vision platforms using smartphones, fixed field cameras or unmanned aerial vehicles (UAVs) can be used to accurately classify symptoms such as disease, nutrient deficiency and pest damage and object detection and semantic segmentation techniques to spatially delineate the affected zones to be intervened in [49]. Multispectral versus hyperspectral imaging is an added value for analysing the sensitivity of early physiological disturbance such as pigment degradation, chlorophyll variation, or water status before visual stress manifestation. Thermal imaging has shown great success in drought monitoring because lead time to observable wilting symptoms is incurred by decreased transpiration, which results in elevated canopy temperature.

Complementary IoT sensor networks that measure the key parameters of soil moisture, electrical conductivity, microclimate variables and leaf wetness duration supply continuous temporal datasets that enable AI systems to predict stress-progression trajectories [50]. A persistent challenge to deployment, though, is domain shift where models for data analysis that have been trained under certain environmental conditions would perform poorly if transferred to differences in cultivars or regions. Addressing this limitation introduces a need for training datasets with a variety of examples, periodic recalibration needs and uncertainty-aware inference systems which can signal declining confidence [51].

Operational experience shows that often reliable early detection is a product combining several different complementary signals instead of one sensing modality. For example, by combining data from thermal anomalies across the canopy with soil moisture behaviour and predictions of evapotranspiration, the accuracy of drought risk prediction increases significantly. Similarly, multimodal fusion reduces the impact of confounding effects from, for example, shadows, dust deposition, sensor calibration variation or diurnal temperature changes. Continuous updating of the models in domain adaptation, localised labelling and on-farm calibration datasets is however required to ensure no performance drift [52]. In areas with limited digital connectivity, edge-computing strategies that enable on-device inference provide practical support for real-time decision-making without relying on cloud infrastructure. An overview of AI-based stress detection and predictive modelling is presented in Figure 3.

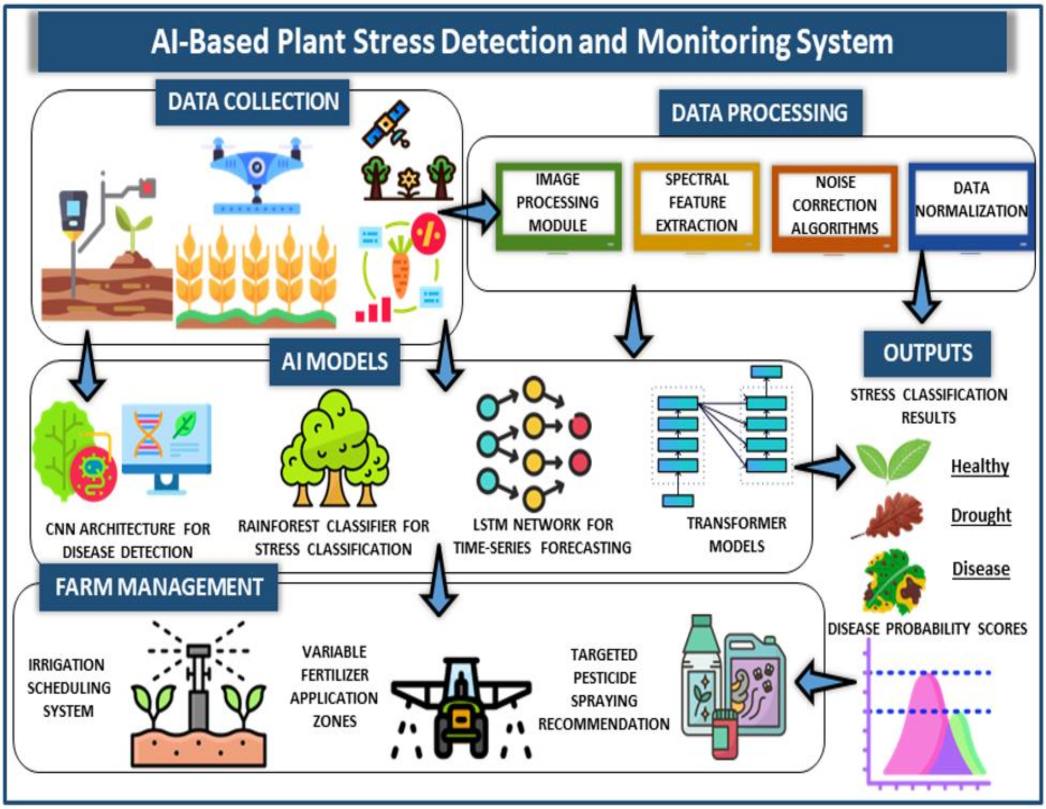

Figure 3: Workflow showing AI integration in agriculture, including data collection (sensors, drones, imaging), preprocessing, model training (ML/DL), stress classification, and decision-support systems for precision crop management

4.3 AI for Decision-making and Crop Management

Beyond effective monitoring, AI plays a significant role in enhancing decision-making in agriculture using complex datasets and translating them into doable crop management recommendations. Some of the major applications are predictive irrigation scheduling using the combination of soil moisture and evapotranspiration forecast, variable-rate fertilisation using the spatial variability of nutrients, and risk-based strategic crop protection strategies using risk maps and focusing on spray timing and hot spots. AI-enabled decision support systems have real value when this type of recommendations is directly tied to control management activities of short span, and then proven through follow-up sensing, UAV-based disease hot-spot mapping and microclimate-driven risk forecasting models [53]. Importantly, agricultural decision environments are faced with logistical constraints such as labour availability, irrigation capacity, regulatory compliance and equipment limitations. AI systems that do not consider these operational facts will tend to have poor rates of adoption despite becoming technically accurate.

Consequently, effective platforms make the outputs of the uncertainty a set of ranked management options such as a prioritisation of irrigation zones based on projected risk of yield loss, or the recommendation of localised treatment instead of whole field application when the probability of disease occurrence is still spatially confined. Verification mechanisms are a vital part of wise management of crops. Post criteria (sensing) from the intervention of the effects of stress management allows for confirmation of the outcomes of the stress mitigation, and builds in place the causal feedback loops to prevent redundant treatments and fine tune the farm-specific decision thresholds over time [54]. This closed-loop learning process enables AI systems to transform from static advisory systems to sensitive systems for adaptive management that can continuously enlarge the resilience of stress management and optimise the use of resources in precision management systems of agricultural industry. A comprehensive summary of AI techniques and their applications in plant stress management is presented in Table 2.

Table 2: AI data streams for stress detection and management: outputs and pitfalls

Data stream	AI task	Farm output	Common pitfall	Reference
RGB images (phone/camera)	Classification/ segmentation	Symptom ID; lesion maps	Lighting/ background bias; mixed stress confusion	[55]
UAV (multi/ hyperspectral)	Early stress mapping	Zone maps (pigment/ water proxies)	Calibration and transfer across sensors	[56]
Thermal imagery	Water-stress inference	Canopy temperature hotspots	Weather confounding; timing of flights	[57]
Soil moisture + microclimate IoT	Time-series forecasting	Irrigation timing; disease risk windows	Sensor drift; missing data/connectivity	[58]
Soil EC/salinity sensors	Zone delineation	Salinity maps; management zones	Spatial heterogeneity; installation depth effects	[59]
Yield history + management logs	Optimisation/ benchmarking	Variable-rate plans; tracking of return on investment	Incomplete records; hidden confounders	[60]

5 Integration of AI and Nanotechnology

5.1 AI-Assisted Design and Optimisation of Nano-Enabled Inputs

Artificial intelligence can boost the development of nano formulations in which formulation is treated as a multi-objective optimisation problem that includes the inclusion of efficacy under stress, stability in real ionic and ultraviolet conditions, release kinetics, cost and safety. By gaining experience on experimental datasets, resources are saved from trial-and-error cycles and formulations are identified to be robust in different soil types and weather regimes [61].

5.2 AI-Guided Development and Response Monitoring

The immediate synergy can be found in AI-guided deployment. Stress maps and risk forecasts help to identify where and when the inputs enabled with nanotechnology should be applied, whether maximising the benefit of the input against minimal off-target effect rates. Response monitoring then closes the loop by guiding reapplication, switching treatments, or adjusting dosage when temperature, spectral indices, or lesion growth do not improve as expected [62]. Integration requires interoperability, ie geo-referenced maps and variable rate equipment and consistent logging of applied inputs. Even in low technology settings, a simplified loop can be brought to fruition with the use of smartphone scouting, coupled with a few low-cost sensors. The key here is to make the connection between measurement and implementing an intervention and then documenting outcomes. In addition, responsible integration includes factors such as governance. For AI, uncertainty reporting and audit trails improve accountability. For nano-enabled inputs, a safe-by-design checklist consists of biodegradability, minimum non-target toxicity and clear disposal and handling advice [63]. These elements reduce regulatory barriers and strengthen trust in adoption.

5.3 Closed-Loop Framework and Implementation Vignettes

The closed-loop framework follows five steps: (i) sense through imagery and sensors; (ii) infer stress probability and severity; (iii) select localised actions under operational constraints; (iv) deliver dose-sparing nano-enabled inputs; and (v) verify the response to update decision rules. Vignette 1 (drought/heat): thermal maps identify rising canopy temperature in a sandy zone, and AI predicts a four-day heat event. Targeted irrigation is combined with a foliar micronutrient carrier. After the heat event, thermal and normalised difference vegetation index (NDVI) maps indicate recovery, avoiding field-wide treatment. Vignette 2 (disease): UAV imagery identifies a disease hotspot, while humidity and leaf-wetness data indicate a favourable infection window. A nano-encapsulated protectant is applied only to the hotspot and buffer rows; lesion expansion slows, reducing the need for whole-field spraying [64]. The synergistic integration of AI and nanotechnology in plant stress management is illustrated in Figure 4.

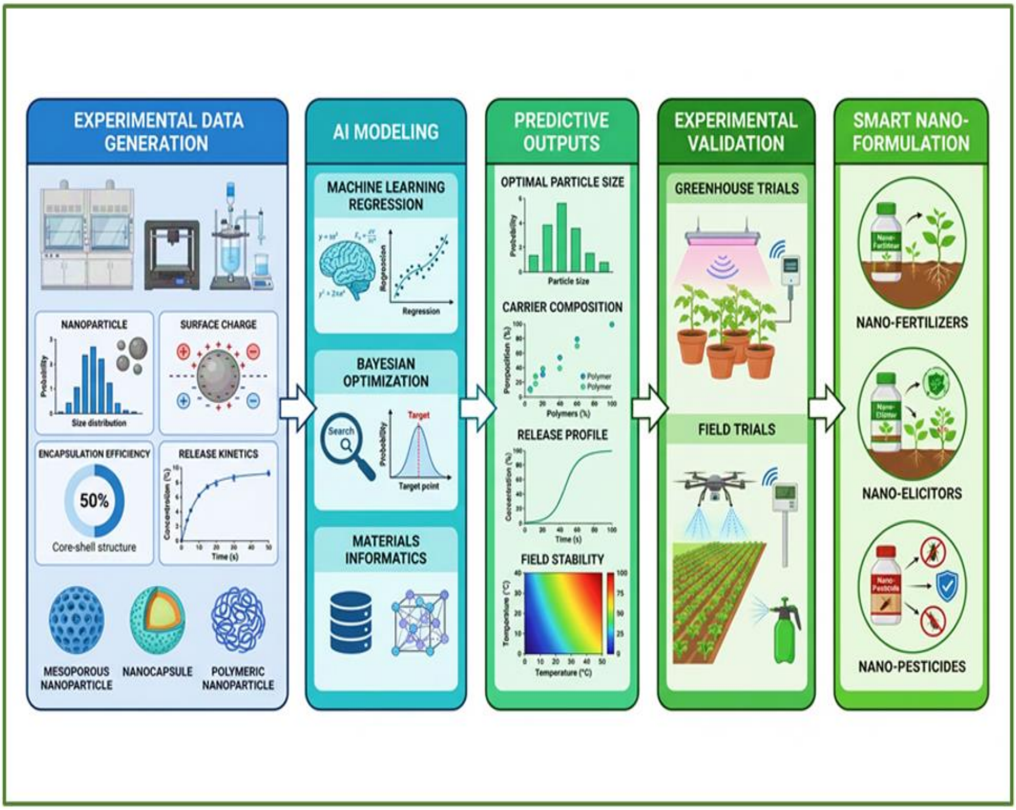

Figure 4: Conceptual diagram illustrating how AI supports nanomaterial design, optimisation and application, while nanotechnology enhances data acquisition and plant responses, forming a feedback-driven smart agricultural system

6 Advantages and Limitations

6.1 Agronomic and Sustainability Benefits

The merging of AI and technologies enabled by the nano-scale world is a transformational advancement to attempt to improve yield stability and maximise the efficiency of use of resources. By combining detection of early stress with targeted interventions in the form of nano formulations, such AI–nano systems allow for targeted spatial and temporal management of crop stress to reduce unnecessary input applications and maintain or increase productivity [65]. Early diagnostic capabilities allow for intervention when irreversible physiological damage cannot occur but nano-enabled deliverable platforms guarantee sustained availability and efficient use of nutrients or protective agents to the requirement site. Collectively, these mechanisms generate more output with less input and consequent strengthening of economic returns and minimal environmental externalities.

Sustainability gains mainly come from dose sparing approaches and localised treatment approaches. AI hotspot identification allows selective application of fertilisers or crop protection agents, and also reduces the problem of leaching of nutrients, or pesticides flow and non-target entity exposure. Continuous monitoring also serves to further deter the repetitive prophylactic applications with regard to confirming treatment efficacy and knowing the size of return on investment regarding empirically measurable crop responses [66]. Integrated systems have been especially beneficial in situations that are marked by high levels of within-field heterogeneity, episodic stress events that require timely application of stress, or low availability of water and agrochemical resources. In such circumstances precision-guided nano interventions can forestall yield losses at the critical stages of growth while conserving inputs. In addition, the spatially limited applications develop agroecological resilience by protecting beneficial soil microbiota and pollinators such as bees and natural predators that are otherwise under potential impact under blanket management practices.

6.2 Limitations and Challenges

Despite their great potential, integrated AI–nano agriculture systems face significant technical, environmental and governance-related issues which have an impact on large-scale adoption. A key limiting factor is model generalisation, in that, during their deployment, AI algorithms tend to lose some of their performance when applied across new cultivars, sensor platforms, climatic conditions or agroecological regions – commonly termed domain shift. Accordingly, long-term effectiveness requires continuous re-calibration, and periodic retraining and validation in different field environments [67]. From the viewpoint of nanotechnology, the issues of proper dosimetry, persistence in the environment, transformation pathways and their effects on beneficial microbial communities and ecosystem functions remain raised. Responsible deployment will require safe-by-design development of materials with biodegradable carriers that have predictable profiles of degrading, labelling and standardising deployment guidelines and monitoring frameworks after application.

Equally important is the combination of uncertainty-aware AI decision systems with human agronomic decision information expertise to prevent automated risk signal misinterpretation [68]. Common operational failure modes are lack of adequate calibration in a sensor, brittle AI under unknown conditions, inconsistency in nano-formulation quality and exaggerated performance results of AI that were tested in controlled greenhouse conditions lacking field realism. Socio-economic barriers such as high upfront investment requirements, ingenious technical extension services and changing regulatory frameworks regarding the use of agricultural nanomaterials also limit the adoption. Mitigation strategies focused on smart systems engineering: limited number of strong sensing signals, multi-environment validation, and the use of biodegradable delivery platform and decision support systems that have the ability for graceful degradation, ie uncertainty refocused on complementary scouting or verification instead of overexploitation [69]. Such approaches provide improved reliability and trust among farmers as well as long-term sustainability of AI–nano enabled precision agriculture systems.

7 Research Gap and Future Direction

Although technological advancement has been fast-paced, there are large gaps in research preventing the large-scale implementation of AI–nano enabled precision agriculture in resilient field environments. Current evidence is limited because of the lack of multi-location, multi-season field experiments to validate nano formulations under conditions of realistic agronomic variability, and the irregular reporting of nanoparticle dosimetry, application rates, and formulation characteristics that come with lack of reproducibility and comparative evaluation. Long-term interactions of nanomaterials and soil systems, and plant-associated microbiomes across cropping cycles have up to now been poorly understood, which adds to the level of uncertainty in ecological persistence and cumulative effects. In addition, AI-based stress detection models are usually trained on controlled datasets that do not represent mixed stress environments, the diversity of cultivars and imaging noise in real-world conditions, which result in a loss of performance when put to use.

Notably, studies aimed at integration are still few; most studies assess sensing technologies or nano-delivery platforms in isolation and not in adaptive closed-loop management systems. Therefore, near-term priorities (0–3 years) should include standardised dosimetry frameworks, multi-season validation of biodegradable or safe-by-design carriers, development of diverse and stress-realistic AI datasets, and integration of uncertainty-aware outputs into decision-support tools. Over the medium term (3–10 years), advances are expected in stimuli-responsive nanoformulations triggered by environmental cues such as humidity, pH or enzymatic activity, and in multimodal AI that combines spectral, environmental and historical management data. Progress in edge computing should enable low-connectivity, on-device inference in resource-limited regions, while governance frameworks must clarify data ownership, accountability, environmental responsibility and data stewardship to support responsible adoption.

A credible innovation pathway to address sustainable agriculture should include observability of performance with on-board benchmarks of performance (ie demonstrable dose sparing with no yield penalty, quantified environmental fate of nano-enabled inputs; AI robustness in the face of domain shift with an open reporting of uncertainty; and integrated system level impacts including earlier stress detection and decreased treated area fraction and verified crop recovery and enhanced season level yield stability, not singly measuring technological capabilities). Key challenges and future research directions in AI–nano-enabled agriculture are summarised in Figure 5.

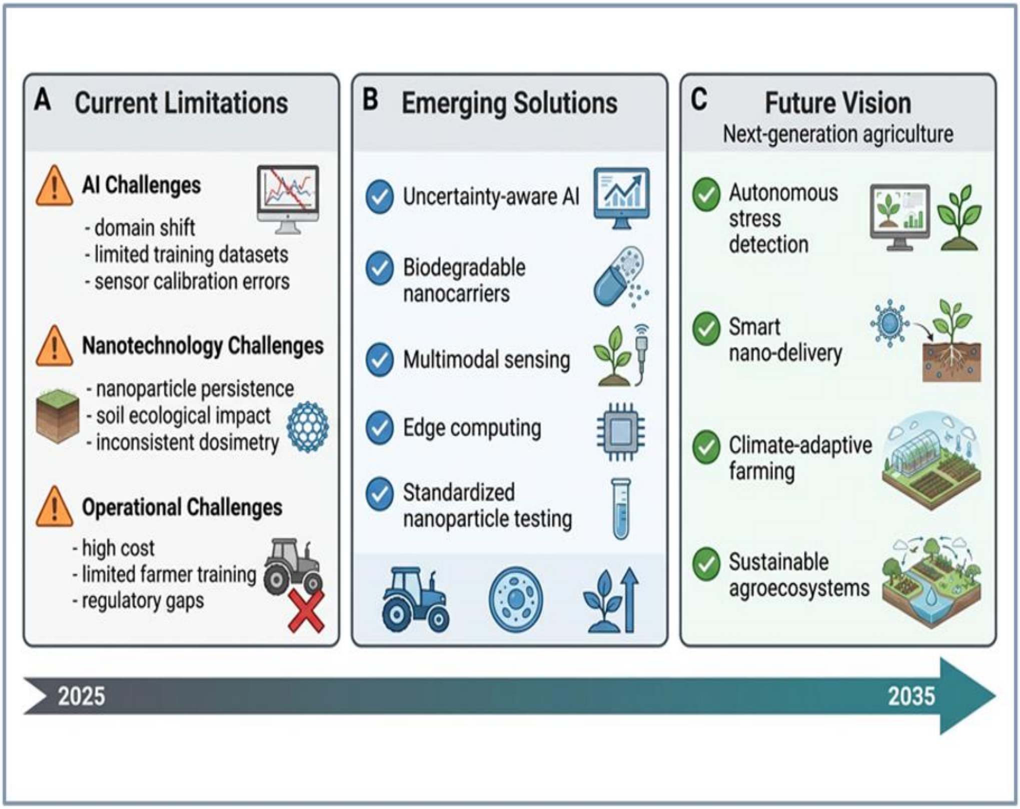

Figure 5: Graphical summary of key challenges (eg cost, scalability, environmental risks, data limitations) and future directions such as smart nanoplatforms, autonomous systems, and climate-resilient agriculture

8 Conclusion

AI and nano-enabled precision agriculture represent a convergent technological framework capable of fundamentally transforming plant stress management from reactive input-intensive practices towards predictive, adaptive and resource-efficient systems. Across biotic and abiotic stress contexts, the integration of intelligent sensing, data-driven decision support and nano-engineered delivery platforms enables early stress detection, spatially targeted intervention, and optimised timing of management actions. Such closed-loop approaches improve yield stability while reducing excessive fertiliser and pesticide use, thereby aligning agricultural productivity with environmental sustainability goals.

The primary advantage of nanotechnology lies not in increased chemical potency but in enhanced delivery efficiency, controlled release, and dose minimisation, while AI strengthens decision accuracy through continuous monitoring and forecasting.

However, successful field translation depends on overcoming critical challenges related to model generalisation, formulation stability, environmental safety, and regulatory governance. Future progress requires standardised reporting practices, multi-location validation, biodegradable carrier development, and uncertainty-aware AI systems supported by agronomic expertise. Moving forward, the greatest impact will arise from integrated platforms that verify outcomes through feedback-driven learning, enabling adaptive crop management across seasons and environments. By shifting emphasis from maximum input application to intelligent delivery and evidence-based intervention, AI–nano integration provides a practical pathway towards climate-resilient, sustainable and precision-driven agricultural systems capable of meeting future food security demands under increasing environmental stress.

9 Author Contributions

Saima Iqbal and Ayesha Fazal conducted the review of literature, prepared the initial draft and refined it for the scientific rigour and clarity. Ammarah Riaz, Nirma Mubeen, Abdul Wahab, Urooj Farid, Sana Azeem Kiani and Mujtaba ul Hassan contributed to the critical analysis, and provided additional references and manuscript editing. Rida Batool contributed to the drawing of the illustrations. Zeeshan Ahmad supervised the whole project and administration, reviewed the manuscript for coherence and quality and gave final approval for submission. All authors reviewed and approved the final version of the manuscript.

10 Acknowledgements

The authors acknowledge the Department of Biosciences at COMSATS University Islamabad for its research support, valuable collaboration and technical input.

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