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AUTOMATION, SENSOR TECHNOLOGY AND GENOMIC TOOLS FOR IMPROVING NUTRIENT- AND WATER-USE EFFICIENCY IN CROPS: A REVIEW

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ABSTRACT
Enhancing nutrient and water use efficiency is critical to ensuring sustainable crop production amidst growing climate variability, loss of soil fertility, water scarcity, and high input costs of farming. Traditional agriculture usually involves blanket fertilization and irrigation practices that may lead to inefficient nutrient utilization, water utilization, pollution, and reduced yields. Modern developments in automation, sensing, and genomics technologies present possibilities to improve resource utilization through precision farming practices and creation of resource-efficient crops. Automation technologies include variable-rate fertilizers application, automatic irrigation, robotic technology, and artificial intelligence (AI) decision-making support tools that allow for timely and location-specific crop management. The sensing technologies include soil moisture sensors, canopy temperature sensors, chlorophyll sensors, multispectral imaging, remote sensing, and Internet of things (IoT). Alongside this, genomics techniques, which include QTL mapping, GWAS, marker assisted selection, genomic selection, and genome editing using CRISPR-Cas technology aid in the detection and enhancement of traits related to nutrient and water uptake, root physiology, stomata control, and stress tolerance. The integration of these techniques can aid in linking field-based observations with automated decision-making and genetic improvement techniques. However, the use of these techniques is hindered by high costs of initial investments, low digital infrastructure, issues related to interoperable data collection, required skills, and gene-by-environment interactions. This review highlights the principles, applications, opportunities, and limitations of automation, sensors, and genomics technologies for improving nutrient and water use efficiency in crops.

KEYWORDS: Precision agriculture, sensor technology, nutrient-use efficiency, genomic selection and CRISPR-Cas.

1. INTRODUCTION
Increase in agricultural production needs to occur in tandem with minimizing the impact exerted on the limited water resources, soil fertility, and the environment. The plant growth, photosynthesis, biomass development, reproduction, and yield depend on availability of water and mineral nutrients. However, there could be loss of fertilizer input through leaching, volatilization, runoff, and gaseous losses while there could be loss of irrigation water through evaporation, runoff, and deep percolation. Increasing the efficiency with which the plant utilizes these resources is thus an important target in sustainable agriculture, (Ali et al., 2025).

The nutrient-use efficiency (NUE) refers to how efficiently the plants take up nutrients from the soil or fertilizer application and convert the nutrients into biomass and harvestable yield. On the other hand, water use efficiency (WUE) refers to the ratio of crop production to either the consumed or applied water depending on the measurement scale used. The two attributes are dependent on the genetic makeup, soil characteristics, environment, management and growth stage. Thus, increasing NUE and WUE involves an integrated approach towards management of soil, water, nutrients, and crop genotypes and not increased fertilizer and irrigation application alone (Hedley, 2015; Passioura, 2006).

The approach of precision agriculture enables the improvement in resource use efficiency through the combination of spatial information, real-time measurements, decision support system, and site-specific input application. Using sensors, variation in soil moisture, nutrient status of crops, canopy temperature, and stress can be determined and management tailored accordingly to meet the needs of crop plants. Automation enhances the accuracy and timing of

irrigation, fertilization, and other field management. Recent literature emphasizes the use of sensors, remote sensing, machine learning, and variable rate technology to optimize irrigation and fertilization (Xing & Wang, 2024; Chaudhari, 2022).

In addition to these technological innovations, innovations in genomics are paving the way to breed crop plants that utilize water and nutrients in a highly efficient manner. Quantitative trait locus analysis, genome-wide association analysis, genomic selection, and genome editing help in understanding and breeding for root architecture, nutrient uptake, transpiration control, photosynthesis, and tolerance to abiotic stress. However, genetic improvement should be tested under field conditions as the expression of resource utilization traits depends on soil, climatic, and management conditions, (Xing et al., 2024).

The combination of automation, sensors, and genomics is an emerging trend in crop improvement for today's world. Phenotypic information from sensors helps detect the desired genotypes, genomics helps make decisions regarding breeding, while automation creates optimal environmental conditions to fully manifest their genotype potential. The article analyzes these techniques, their synergies, applications, drawbacks, and future perspectives to increase nutrient and water use efficiency.

2. Nutrient and water use efficiencies - concept and measurements

2.1. Nutrient use efficiency

Nutrient use efficiency is a multi-dimensional concept which consists of efficient nutrient uptake, efficient utilization of nutrients within the plant, and their conversion into economic yield. The crop may have high NUE because of efficient nutrient uptake from the nutrient-poor soil, efficient utilization of the absorbed nutrients for biomass production, or both. This concept applies specifically to nitrogen and phosphorous, although potassium and micronutrients also play an important role (Fixen, et al., 2015). Common indicators include:

$$\text{Agronomic NUE} = \frac{\text{Yield in fertilized plot} - \text{Yield in control plot}}{\text{Nutrient applied}}$$

$$\text{Partial factor productivity} = \frac{\text{Crop yield}}{\text{Nutrient applied}}$$

$$\text{Nutrient utilization efficiency} = \frac{\text{Economic yield}}{\text{Nutrient accumulated}}$$

These indicators assess various parameters of nutrient effectiveness and cannot be interchanged. These indicators are interpreted based on factors such as the rate of nutrient applications, fertility status of the soil, nutrient absorption, and yield responses of crops. Fertilizer application with the use of sensors and variable-rate technique will assist in enhancing nutrient management through field variability and not blanket fertilization of the whole field (Hedley, 2015).

2.2. Water-use efficiency

The measure of water-use efficiency can be performed at the leaf, plant, crop, or field level. In the leaf scale, the water-use efficiency is usually considered in terms of the carbon assimilation to transpiration ratio. In the crop scale, the water-use efficiency may be expressed in relation to the biomass, grain yield and crop evapotranspiration, transpiration, or irrigation water, (Sharma et al., 2015).

$$\text{Crop WUE} = \frac{\text{Crop yield or biomass}}{\text{Crop evapotranspiration}}$$

$$\text{Irrigation water productivity} = \frac{\text{Crop yield}}{\text{Irrigation water applied}}$$

A crop may have higher WUE without producing greater total yield if water consumption is substantially reduced. Therefore, WUE should be interpreted alongside yield, crop quality, irrigation productivity, and total water consumption. Sensor-guided irrigation should aim to prevent unnecessary water application while maintaining adequate moisture during critical growth stages, (Antu, et al., 2024).

3. Resource use efficiency technologies automation

3.1. Automated irrigation systems

An automated irrigation system consists of sensors to measure soil moisture, weather forecast, controllers, valves, pumps, and irrigation apparatus which provide irrigation depending on the needs of the crops. The difference between automated systems from the ones with a fixed schedule is that they can adapt to changing soil moisture, weather demand and the stage of development of the crops (Bwambale, and Abagale, 2022).

In the case of a closed loop irrigation system, field conditions are constantly measured, the results are compared with a certain threshold or target values and irrigation is adjusted. Measurements of soil conditions can be coupled with measurements of evapotranspiration based on weather conditions and stress on plants caused by water deficiency.

Drip irrigation and automated fertigation are especially useful as water and fertilizer are applied close to the root system of the plant. However, automation alone cannot improve efficiency the accuracy of measurements, calibration, irrigation uniformity, maintenance, and suitable thresholds play an important role. The reviews of smart irrigation reveal that combining soil, plant and weather measurements is a promising method to increase water-use efficiency (Bwambale et al., 2022).

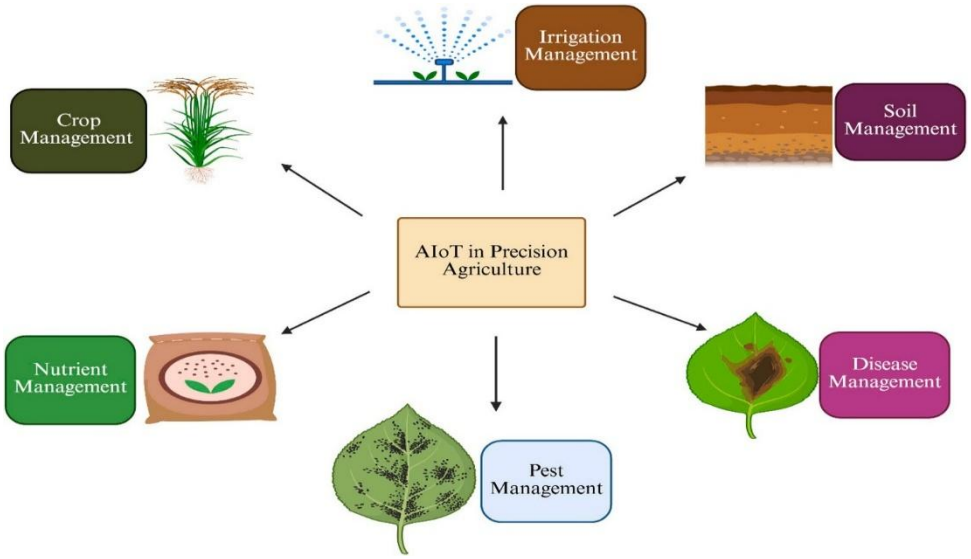
3.2. Variable-rate fertilizer application

The principle of variable-rate technology (VRT) involves varying fertilizer application depending on soil fertility, crop development, nutrient content, or yield potential in the field. Prescription maps can be generated through soil tests, remote sensing, yield maps, and crop sensors. Using equipment installed with controllers and positioning systems, it will be possible to vary the rate of fertilizer application to different field zones.

This method will help to minimize the excessive application of fertilizer where there is enough supply of nutrients and prevent insufficient application of fertilizer in zones with deficient nutrients. The nitrogen application can be best handled using sensors since nitrogen content in crops varies during the season (Mirzakhaninafchi, et al., 2021). However, fertilizer application should take into account mineralization, weather conditions, crop requirements, and nutrient losses. Sensor information should thus be combined with agronomic guidelines for precise fertilizer application (Hedley, 2015).

3.3. Robotics, artificial intelligence, and the Internet of Things

Agricultural robots, self-driving cars, and intelligent machines are capable of assisting in precision seeding, mechanical weed removal, application of chemicals, fertilizers, and monitoring of crops (Thillaiarasu, et al., 2022). These systems, when paired with machine vision, satellite positioning, and computer image recognition, are capable of performing tasks with a minimum of homogenous treatment of fields based on row recognition, stress detection, and other parameters, (Nsoh, et al., 2024).



(Source, Bayar et al., 2025)

Fig. 1. Role of AIoT in enhancing core agricultural practices including soil, irrigation, nutrient and crop disease management.

Field sensors, irrigation systems, weather stations, and cloud platforms are part of the Internet of Things (IoT). Using data from these devices, AI and machine learning algorithms are able to make predictions about plant water needs and deficiencies in nutrients and recommend appropriate actions (Sow, et al., 2024). It should be noted that the validity of the algorithm relies on quality and representativeness of the training dataset. Recommendations should be validated locally prior to large scale adoption. The recent literature review discusses the opportunities of implementing AIoT system for irrigation and nutrients management and identifies key issues related to integration, (Bayar, et al., 2025).

Table-1: Different case studies on AIoT applications in plant disease monitoring with methodologies, technologies and outcomes.

Objective	**Technology used**	**Dataset** 80 leaf samples from 4 groups (diseased/healthy ± mycorrhizal fungus), each with 2150 spectral data points.	**Advantages** Early disease detection before visual symptoms, non-destructive and cost- effective lab method, high accuracy (100 % KNN for binary classification).	**Limitations**	**Crop studied**	**References**
Early detection of *Fusarium* disease in pepper plants using spectral reflectance (350–2500 nm) and classification via ML (KNN, ANN, NB).	Spectroradiometer (FieldSpec 3), ML algorithms (KNN, ANN, NB).			High dimensional data (needed reduction), study limited to lab location not field-tested.	Pepper (*Capsicum annuum*)	Karadağ, et al., 2020)
To develop an AIoT system (RiceTalk) that detects rice blast disease using non-image-based sensors and AI, avoiding delays and manual efforts common with image- based systems.	IoT, CNN and cloud based dashboard.	5267 samples from 158 locations.	Real-time detection without human image capture, reduced labor/ time cost spore germination used as a novel projecting feature, accuracy improved to 89.4 % in positive predictions.	Limited to environmental conditions influencing blast disease, barometric pressure and rain exposed minimal predictive effect, CNN model training requires careful tuning.	Rice (*Oryza sativa*)	(Chen et al., 2019)
To detect chilli crop leaf diseases (leaf spot and leaf curl) using YOLOv5 object detection model trained on in-field RGB images.	YOLOv5 (deep learning object detection model) Google Colab (GPU training).	210 in-field RGB images (160 training, 40 validation, 10 test).	Real-time detection capability, fast inference speed (13 ms/image), lightweight model (13.8 MB), trained on actual field data.	Small dataset size, leaf spot detection is less accurate due to non-uniform symptoms.	Chilli (*Capsicum annuum*)	(Mayalekshmi et al., 2023)

Compare CNN and AlexNet deep learning architectures for classifying healthy and diseased mango and potato leaves using image data.	CNN and AlexNet (a pre-trained deep learning model).	Total 4004 images with 4 classes (2 healthy, 2 diseased).	AlexNet showed higher accuracy (98.33 %) than CNN (90.85 %), can be used on minimal hardware (CPU-based).	AlexNet takes more training time (50 min) than CNN (20 min).	Potato (*Solanum m lycopersicu m*), Mango (*Mangifera indica*)	(Arya, et al., 2019)
Develop a real-time apple leaf disease detection model using an improved CNN (INAR-SSD), incorporating Inception modules and Rainbow concatenation for improved multi-scale feature removal.	Deep learning with INAR-SSD.	Total 26,377 images (from lab and real fields) include 5 disease classes.	High accuracy (78.80 %) and real-time speed (23.13 FPS), robust to small lesions and diverse image conditions, handles multi- disease detection in single images.	Some diseases like *Alternaria* and Grey spot are hard to differentiate due to alike features, model performance declines in low-light or noisy situations.	Apple (*Malus domestica*)	(Jiang, et al., 2019)

Table 2. Comparison of automation, sensor technologies, and genomic tools

Technology	**Examples**	**Primary application**	**Contribution to resource-use efficiency**	**Key limitation**
Automated irrigation	Soil moisture-controlled drip irrigation, smart valves	Irrigation scheduling and control	Reduces unnecessary water application	Calibration and installation costs
Variable-rate technology	GPS-guided fertilizer applicators, prescription maps	Site-specific fertilizer application	Matches nutrient inputs to field variability	Requires reliable spatial data
Soil sensors	Moisture, electrical conductivity and nutrient sensors	Soil and root-zone monitoring	Supports irrigation and nutrient decisions	Indirect measurements may require calibration
Plant sensors	Chlorophyll meters, canopy temperature sensors, plant physiological sensors	Crop nitrogen status and water stress assessment	Enables crop-demand-based management	Responses vary with crop and environment
Remote sensing	UAVs, satellite imagery, thermal and multispectral imaging	Field-scale crop monitoring	Identifies spatial variation and stressed crop zones	Requires ground-truth validation
Artificial intelligence and IoT	Machine-learning models, connected sensor networks	Prediction and decision support	Integrates observations for timely management	Data quality and connectivity constraints
QTL mapping and GWAS	Genetic markers and association analysis	Identification of resource-efficiency traits	Identifies genomic regions associated with useful traits	Environmental interactions and validation requirements
Genomic selection	Genome-wide marker-based breeding-value prediction	Improvement of complex quantitative traits	Accelerates selection of promising genotypes	Requires representative training populations

CRISPR-Cas genome editing	Targeted gene modification	Functional validation and genetic improvement	Enables investigation and modification of relevant pathways	Potential unintended effects and regulatory constraints

Sources: Hedley (2015); Chen et al. (2019); Sharma et al. (2023); Xing and Wang (2024); Biswas Antu et al. (2024); Bukhamsin et al. (2025).

4. Sensor systems to enhance nutrient utilization and water-use efficiency

4.1. Soil Sensors

Soil sensors measure the moisture content, temperature, electrical conductivity, and specific chemical characteristics of soil. These measurements can be used in irrigation scheduling, soil variability mapping, and in making nutrient management decisions, (Thingujam, et al., 2025).

Soil moisture sensors: These include capacitance sensors, frequency domain reflectometry, and time domain reflectometry. They measure soil water content, and can help to determine when irrigation is needed.

Soil water potential sensors: Tensiometers and associated sensors can be used to determine the energy status of soil water, thus determining if soil water remains easily available to plant roots.

Soil electrical conductivity sensors: These determine the ability of soil to transmit an electric current and are useful in assessing salinity and spatial variability in soil characteristics. Electrical conductivity is not a direct measurement of nutrient concentration as it depends on moisture, texture, temperature, and salts.

Soil nutrient sensors: Electrochemical sensors, ion selective electrodes and spectroscopy sensors can be useful in nutrient assessment.

Soil sensing is particularly useful when combined with geographic information systems (GIS), field sampling, and nutrient-response models. Chaudhari (2022) reviewed soil and crop sensing approaches and highlighted their potential for precision farming and agricultural decision support. More recent research also emphasizes the integration of sensor networks, spectroscopy, and IoT platforms for monitoring soil health.

4.2. Sensors made from plants

The sensing based on plants measures the physiological status of the crops instead of soil alone. The reason why this is crucial is that moisture and nutrients in the soil do not always correlate directly with those absorbed by the plants, (Sachin, et al., 2023).

Such methods as chlorophyll meters and optical sensors can be used to measure leaf greenness and nitrogen status. Canopy temperature measures transpiration and water stress of the plants, while stem diameter, leaf thickness, sap flow, and leaf water potential may also give physiological data.

The new optical and electrochemical sensors can also detect some plant metabolites, hormones, and stress markers. It can help in recognizing early plant response when there are no symptoms visible yet. Nevertheless, it is impossible to measure the plant status using one sensor; it needs several indicators as well as proper calibration (Bukhamsin et al., 2025).

4.3. Remote sensing and multispectral imaging

Satellite images, UAVs, and proximal imaging are useful tools to detect the condition of the crops on a large scale. Vegetation indices, thermal imagery, and spectral reflectance analysis give an insight into the development of the canopy, biomass production, chlorophyll health, and possible water stress (Jiang, et al., 2011). The main examples are:

NDVI – normalized difference vegetation index to analyze vegetation greenness and canopy development.

NDRE – normalized difference red edge to analyze canopy properties and possibly chlorophyll variation under certain conditions.

Canopy temperature and thermal indices to detect possible water stress.

Multispectral and hyperspectral reflectance to estimate nutrient content of crops and physiological changes.

Table 3. Sensor technologies for monitoring water and nutrient status in crops

Sensor or platform	Parameter measured or estimated	Potential use	Important consideration
Capacitance soil moisture sensor	Volumetric soil water content	Irrigation scheduling	Calibrate for soil type
Tensiometer	Soil water tension	Identifying irrigation thresholds	Appropriate operating range and installation are important
Chlorophyll meter	Leaf greenness or chlorophyll-related index	Estimating crop nitrogen status	Interpret alongside crop stage and cultivar
Canopy temperature sensor	Canopy surface temperature	Detecting potential water stress	Consider air temperature, humidity and radiation

Electrical conductivity sensor	Electrical conductivity of soil or solution	Salinity and spatial variability assessment	Not a direct measurement of individual nutrients
Ion-selective sensor	Concentration or activity of selected ions	Targeted nutrient monitoring	Selectivity, drift and calibration affect accuracy
UAV multispectral camera	Spectral reflectance and vegetation indices	Crop vigour and nutrient-stress assessment	Ground validation is needed
Thermal camera	Surface temperature distribution	Mapping potential crop water stress	Weather and canopy conditions affect readings
IoT sensor network	Connected soil, crop and weather observations	Automated irrigation and decision support	Reliable power, connectivity and data quality are necessary

Sources: Bukhamsin et al. (2025); Xing and Wang (2024); Biswas Antu et al. (2024); Ghanghas et al. (2026).

Remote sensing is useful for the identification of variability within a field and creating prescription maps for variable rate irrigation and fertilization. However, vegetation indices do not measure directly the level of nitrogen content and water-use efficiency. The interpretation of vegetation indices depends on several factors such as crop type, growth stage, canopy structure, soil background, and atmospheric and sensor conditions.

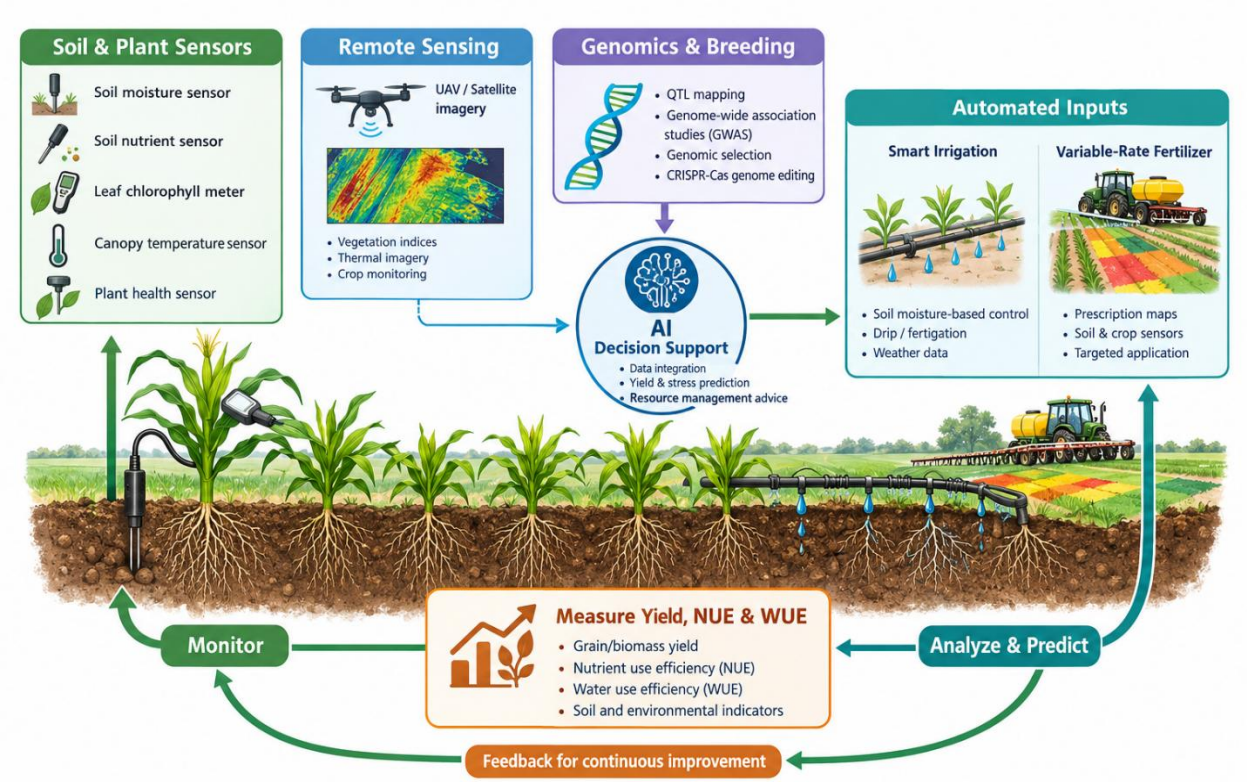


Figure-2: Integrated framework for using automation, sensor technology and genomic tools to improve nutrient and water use efficiency in crops

Table 4. Major sensor technologies and their applications in crop resource management

Sensor technology	Information obtained	Application for NUE or WUE	Major limitation
Soil moisture sensor	Volumetric soil water content	Irrigation scheduling	Requires appropriate placement and calibration
Soil water-potential sensor	Soil water availability	Irrigation timing	Sensitive to soil type and installation
Chlorophyll meter	Leaf greenness or chlorophyll-related index	Nitrogen-status assessment	Influenced by cultivar and leaf characteristics
Electrical conductivity sensor	Soil or solution conductivity	Salinity assessment and spatial mapping	Does not directly quantify individual nutrients

Canopy temperature sensor	Canopy thermal response	Detection of water stress	Influenced by weather and canopy conditions
UAV multispectral imaging	Canopy reflectance and vegetation indices	Nutrient and crop-vigour assessment	Requires ground-truth calibration
Thermal remote sensing	Surface or canopy temperature	Water-stress mapping	Affected by atmospheric and environmental conditions
Ion-selective or electrochemical sensor	Selected ions or chemical analytes	Targeted nutrient monitoring	Selectivity, drift, and matrix effects
IoT sensor network	Connected soil, crop, and weather observations	Automated decision support	Connectivity, maintenance, and interoperability

Sources: Hedley (2015), Chaudhari (2022), Bukhamsin et al. (2025), and Xing and Wang (2024).

5. Genomics for enhancing resource-use efficiency

In addition to sensor technology, genomics allows for identification, characterizations, and optimization of genetic variations that are linked with resource acquisition and usage.

5.1. QTL mapping and GWAS

Quantitative Trait Locus (QTL) mapping helps to identify genomic locations of the genes related to traits based on the segregation analysis of populations produced from genetically different parents. Genome-Wide Association Studies (GWAS) look for associations between the markers and phenotypic variability in various germplasm collections, (Liang, et al., 2025).

Such tools can be used to detect loci that are linked with root depth, root architecture, nutrient uptake, nitrogen-use efficiency, drought tolerance, stomatal function, and yield stability. The applicability of such methods depends on the reliability of phenotyping, presence of genetic diversity, appropriate population structure, and validation in other populations/environments.

The combination of genomics with phenotyping is especially important for resource-use traits, since phenotype observed can be affected by multiple interactions between genotype and environment. A locus that has effect on drought performance in one environment might not have any effect in another soil and environmental conditions.

5.2. Marker-Assisted Selection

Marker-Assisted Selection (MAS) involves the use of molecular markers associated with desired genes or QTLs for selection purposes. MAS can expedite the introgression of well-defined traits into elite breeding backgrounds, (Abah et al., 2026).

For resource efficient breeding of crops, MAS could prove helpful in cases where the desired trait has a reliable marker-trait association and can be measured accurately in the breeding population. However, nutrient and water use efficiency are often quantitative traits that involve several loci, thus making it challenging to use only a few markers for their selection, (Kumar et al., 2026).

5.3. Genomic Selection

Genomic selection (GS) involves the use of genome-wide molecular marker data for calculating the breeding values of an individual. Unlike MAS, genomic selection accounts for the effect of many genomic regions rather than a few loci, (Biswas, et al., 2020).

This can be used for expediting the breeding of crop varieties that have better root system, nutrient acquisition ability, transpiration efficiency and yield stability under varied nutrient and water conditions. Genomic predictions are more effective when high-quality training population data and phenotypic information are available. Genomic selection has become an important framework for improving breeding efficiency for complex traits, although prediction accuracy varies with population structure, genetic relatedness, trait heritability, and environmental conditions, (Tuncel et al., 2025).

5.4. Genome editing with CRISPR-Cas systems

Genome editing using CRISPR-Cas allows specific alteration of desired DNA sequences. Based on the gene targeted and type of editing, it may be applied for studying functions of the gene in question or for altering traits related to root structure, nutrient transport, stomatal movement, photosynthesis control, and plant reactions to stresses, (Chen, et al., 2019).

Genome editing allows studying genetic basis of NUE and WUE through investigation of gene regulation of nutrient transporters, root formation, and plant reactions to drought. It is important to remember that genome editing does not necessarily result in the development of plants with higher resource-use efficiency. Pleiotropy, off-target effects, penalties to yield, genotype by environment interaction should be considered. The ultimate goal of the procedure is to increase efficiency of resource use without reduction in yield potential and crop quality, (Sharma et al., 2023).

Table 5. Genomic tools and their potential role in improving NUE and WUE

Genomic approach	Principle	Relevant traits	Potential application
QTL mapping	Locates genomic regions associated with phenotypic variation	Root architecture, nutrient uptake and drought response	Identifying genomic regions for breeding
GWAS	Identifies marker–trait associations in diverse populations	Nitrogen-use efficiency, root traits and stress tolerance	Discovering candidate loci and alleles
Marker-assisted selection	Selects plants using markers associated with target traits	Traits controlled by major genes or validated QTLs	Introgression of useful alleles
Genomic selection	Predicts breeding values using genome-wide markers	Complex traits with many genetic contributors	Accelerating breeding cycles
Transcriptomics	Examines gene-expression patterns	Nutrient transport and drought-response pathways	Identifying candidate genes and regulatory networks
Functional genomics	Investigates gene functions and biological pathways	Root development, stomatal control and nutrient metabolism	Understanding mechanisms of resource acquisition and use
CRISPR-Cas genome editing	Enables targeted changes in DNA	Candidate genes affecting nutrient transport and water regulation	Functional testing and development of improved genotypes

Sources: Chen et al. (2019); Sathee et al. (2022); Sharma et al. (2023).

5.5. Root architecture and functional genomics

Root architecture is an important factor determining the acquisition of nutrients and water. Factors like root depth, root branching, development of lateral roots, root hairs, and the distribution of the root system affect the access to water and nutrients from various soil layers.

Methods like functional genomics, transcriptomics, and gene expression can provide insight into the biological processes behind these characteristics. Combining them with root phenotyping may uncover genetic variation that can be utilized through breeding, genomic selection, or genome editing.

It is important to note that there is no ideal root architecture for all cases. While deep roots may be beneficial in acquiring water stored in deeper soil layers, dense shallow roots may prove to be more effective in acquiring nutrients available near the soil surface. Therefore, root traits must be chosen depending on the crop and production system.

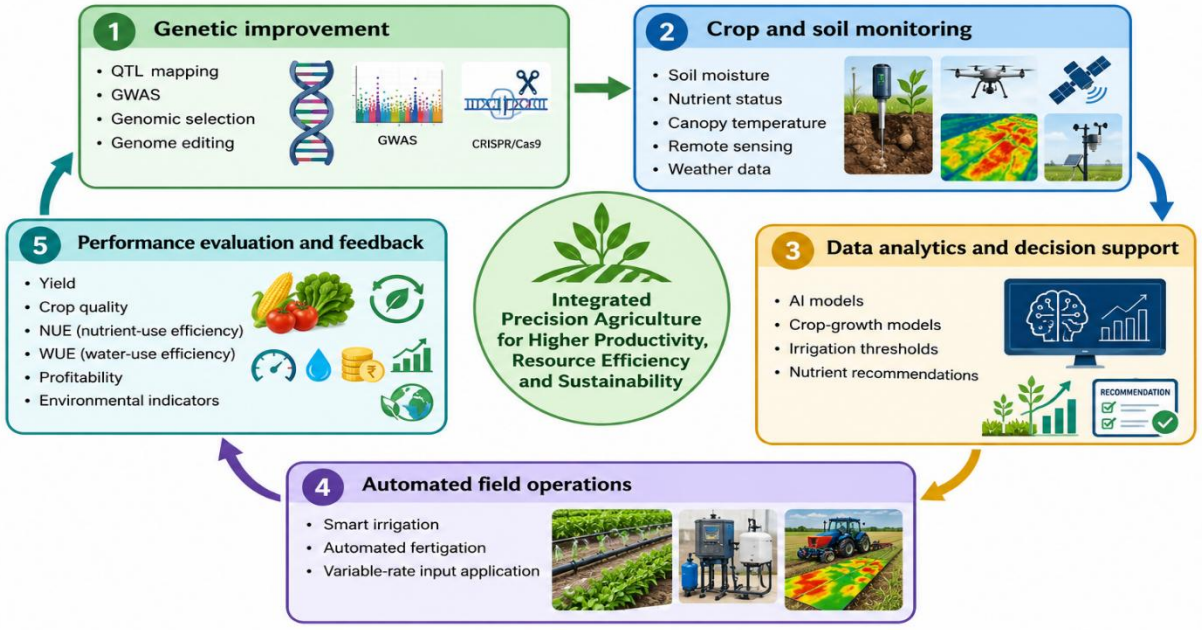


Figure-3: Conceptual framework proposed for integrating genomic improvement, sensor-based monitoring data analysis and automated resource management

6. Integration of automation, sensors, and genomics technologies

The major advantage in increasing nutrient- and water-use efficiency is in integration of these technologies into crop management and breeding programs. Automation and sensors provide environmental information related to current crops, while genomics is responsible for genetic characteristics of crop resource acquisition and use.

6.1. Genomic selection with sensors

A high-throughput phenotyping platform can collect such information as canopy temperature, vegetation indexes, biomass accumulation, and others. All these parameters can be used together with genotypic data to detect promising genotypes and calculate their breeding value.

UAV-based estimation of canopy temperature and spectral information can help analyze drought response of breeding populations. If genotyping information and yield are included into analysis, it will be possible to choose varieties that can be productive in the conditions of water limitation. Such approach is especially helpful for analyzing complicated traits that are difficult to measure manually, (Sharma, et al., 2023).

Data-driven approach in integration of phenotyping, genomics, and machine learning can contribute to detection of genetic variation in relation to drought resistance and water-use efficiency (Data-driven approaches to improve water-use efficiency and drought resistance in crop plants, 2023).

6.2. Precision nutrient management linked with genetic improvement

Genotypes differ in their nutrient acquisition capacity, root architecture, nutrient transport, and internal nutrient utilization. Therefore, fertilizer recommendations developed for one cultivar may not always be optimal for another cultivar under the same environmental conditions, (Ruder, et al., 2026).

Combining nutrient-response experiments with genomic characterization can help identify genotypes that maintain yield under reduced fertilizer availability. Sensor-based nitrogen assessment can subsequently guide the timing and rate of fertilizer application according to crop demand. This integration may reduce unnecessary fertilizer use while maintaining productivity, provided that recommendations are validated for the relevant crop, soil, and environment, (Getahun et al., 2024).

Genome-editing research also offers opportunities to investigate regulatory networks involved in nitrogen, phosphorus, and potassium uptake and utilization. Sathee et al. (2022) reviewed candidate genome-editing targets and strategies for improving nutrient-use efficiency and adaptation to nutrient stress

7. Applications across major crop groups

The relevance of these technologies differs according to crop characteristics, production systems, and the dominant constraints on resource availability.

Table 6. Potential applications of integrated technologies in major crops

Crop group	Priority traits or management targets	Suitable technologies	Expected benefit
Cereals: rice, wheat and maize	Nitrogen-use efficiency, drought tolerance and root development	Canopy sensors, VRT, genomic selection and automated irrigation	Improved fertilizer management and yield stability
Pulses: chickpea, lentil and pigeon pea	Root development, phosphorus acquisition and drought adaptation	Soil sensing, root phenotyping, QTL mapping and genomic selection	Improved nutrient acquisition under variable soil moisture
Oilseeds: mustard and soybean	Water stress, nitrogen nutrition and reproductive stability	Canopy imaging, weather stations, nutrient sensors and genomic tools	More precise input management and stress adaptation
Vegetables: tomato, chilli and cabbage	Fertigation, root-zone moisture, nutrient balance and marketable yield	Drip automation, substrate sensors, optical imaging and marker-assisted breeding	Improved crop quality and more efficient input use
Fruit crops	Irrigation scheduling, root-zone salinity and nutrient management	Soil moisture sensors, canopy temperature monitoring and automated drip irrigation	Reduced water losses and more targeted nutrient delivery
Protected cultivation crops	Precise irrigation, fertigation and microclimate control	IoT sensors, automated fertigation, climate controllers and imaging	Greater control over crop growth and input application

8. Challenges and limitations

Despite considerable potential, the widespread adoption of integrated precision agriculture remains constrained by technical, economic, biological, and institutional barriers.

High initial investment: Sensors, UAVs, automated irrigation equipment, robotics, and data-processing infrastructure can be expensive. Small and marginal farmers may face difficulties adopting these technologies without affordable equipment, custom-hiring services, or institutional support.
Sensor calibration and reliability: Measurements may be influenced by soil texture, moisture, temperature, canopy structure, and environmental conditions. Regular calibration and field validation are essential to avoid inappropriate irrigation or fertilizer recommendations.
Data interoperability and connectivity: Different devices and software platforms may use incompatible data formats. Limited rural connectivity, electricity availability, and technical support can prevent reliable operation of IoT-based systems.
Complexity of resource-use traits: NUE and WUE are influenced by numerous genetic and environmental factors. Improving one component, such as reduced transpiration, does not necessarily increase total yield or overall agricultural water productivity. Similarly, increased nutrient uptake may not translate into higher nutrient utilization efficiency.
Genomic and phenotyping limitations: Genomic selection requires suitable training populations, accurate phenotypic records, and validation across target environments. Genome editing additionally requires effective transformation or delivery methods, regeneration protocols, and evaluation of unintended effects.
Economic and social constraints: Adoption depends on farmer knowledge, equipment availability, perceived benefits, access to credit, and compatibility with existing production practices. Technologies developed for large mechanized farms may require modification for smallholder agriculture.
Environmental and governance concerns: Digital agriculture introduces questions concerning data ownership, cybersecurity, long-term equipment maintenance, and dependence on proprietary platforms. Environmental claims should also be evaluated using field-based evidence rather than assumed from technological adoption alone. A 2026 systematic review by Ruder et al. emphasized the importance of distinguishing demonstrated environmental benefits from benefits that have been asserted without sufficient empirical evidence.

9. Future perspectives

Future developments should aim at the creation of reliable, cost-effective and agronomically tested integrated systems. Some priorities require special attention.
1. Development of affordable sensors: Reliable sensors should be designed for soil moisture, plant water status and crop nutrient deficiency detection under field conditions.
2. Decision making using AI tools: Machine learning algorithms should use data from sensors, weather forecast, soil properties, crop development stage and genotype requirements. Recommendations should be accompanied by an uncertainty level estimation and local validation.
3. High throughput phenotyping: UAV-based systems, thermal cameras, automated root phenotyping and spectral analysis will enhance the speed and accuracy of genetic evaluation for resource-use traits.
4. Integration of genomics and breeding: Genomic selection, marker-assisted breeding, functional genomics and gene editing technologies should be used in combination with field phenotyping to obtain highly productive genotypes resistant to drought and nutrient stress.
5. Testing in multiple environments: Efficient use of resource-efficient genotypes and precise management practices should be tested in different soils, climatic conditions, irrigation and nutrient availability levels.
An important emerging direction is the integration of genomic selection and genome editing for complex, polygenic traits. Rather than expecting a single gene or technology to improve resource-use efficiency, future breeding programmes will need to combine multiple traits and evaluate their interactions under practical production conditions, (Meena et al., 2026).

Table 6. Published studies supporting the integration of precision agriculture and crop improvement

Research focus	Relevance to the present review
Crop productivity under limited water availability	Foundational concepts for improving crop performance under water scarcity
Precision agriculture for nutrient management	Supports sensor-guided and site-specific nutrient management
CRISPR/Cas genome editing in agriculture	Provides a foundation for targeted genetic improvement
Genome-editing targets for NUE and nutrient-stress adaptation	Connects genomic approaches with nutrient-use efficiency
Data-driven approaches for WUE and drought resistance	Connects genomics, phenotyping, omics and machine learning
Precision application of water and fertilizer	Reviews sensing, remote sensing, variable-rate technologies and predictive modelling
Emerging technologies for agricultural water efficiency	Reviews sensors, AI, remote sensing and other water-management technologies

AI for nutrient, water and weed management	Supports the role of AI in optimizing agricultural inputs
Plant sensors for precision farming	Reviews plant physiological monitoring and field deployment
Sensors, imaging, AI, precision irrigation and robotics	Provides a recent synthesis of integrated smart-water-management technologies

10. CONCLUSION

Automation, sensors and genomics each offer complimentary prospects for enhancing the efficiency of nutrient and water use in contemporary agriculture. Irrigation, fertigation and variable rate fertilization make it possible to manage nutrients more precisely, while soil sensors, plant monitoring and remote sensing ensure up-to-date information on the needs of plants and field conditions. Finally, genomics, including QTL mapping, GWAS, genomic selection and CRISPR-Cas genome editing, facilitates the discovery and development of the genetics of nutrient uptake, root systems, water absorption and tolerance of stresses. These technologies may help create a feedback loop where genetic improvement determines the potential of crops, sensors define field conditions, modeling aids decisions and automation realizes them. However, their performance relies on accurate measurements, proper calibration, effective integration of data and verification in production. Efforts to enhance resource use efficiency cannot be evaluated only from the point of reduction of input such as fertilizers or irrigation; crop productivity, product quality, profit and environmental effect must be taken into consideration as well.

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