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Nutrient Management Strategies for Warm-Season Crops in Smart Greenhouses

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Abstract

Warm-season greenhouse crops such as tomato (*Solanum lycopersicum* L.) and paprika (*Capsicum annuum* L.) require nutrient supply strategies that respond dynamically to temperature, solar radiation, vapor pressure deficit (VPD), root zone water status, and electrical conductivity (EC). This systematic review assessed four operational strategies: (1) solar radiation-proportional irrigation; (2) radiation-rate-based volume and EC adjustment; (3) supply–drainage and substrate-feedback control; and (4) temperature, humidity, and VPD-based supervisory correction. Scopus, Web of Science, IEEE Xplore, ScienceDirect, and MDPI were searched on 15 August 2026 for studies published from 2010 onward, yielding 4088 records (2326 after removal of duplicates). Studies were eligible if they addressed a controlled-environment production system, a warm-season crop, a nutrient-management component, and the use of sensing, automated control, models or decision-support systems, or IoT/AI tools. After title/abstract screening and full-text assessment, 90 studies were included: 29 studies from the database search and 61 studies identified by manual searching of publisher platforms, the three other references were from textbooks. Radiation-based approaches provide practical feedforward estimation but incompletely represent humidity and root zone dynamics. Supply–drainage feedback offers stronger closed-loop information, while temperature and VPD-based correction improves responsiveness to atmospheric demand. Tomato requires careful calcium and potassium management during reproductive stages, whereas paprika demands stable substrate moisture, EC, and drainage. A conceptual hierarchical framework is proposed in which solar radiation establishes the baseline nutrient-solution supply, radiation-rate information provides short-term adjustment, root-zone and drainage measurements provide feedback correction, and temperature or VPD serves as a supervisory layer. Ion-specific sensing, mechanistic models, and AI/ML approaches can further support nutrient-specific and predictive management. Few included studies evaluated these strategies under explicitly imposed high-temperature conditions; therefore crop, cultivar, and growth-stage-specific validation under commercial high-temperature greenhouse conditions is required before operational thresholds can be generalized.

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Keywords: smart greenhouse; warm-season crop; nutrient management; vapor pressure deficit; closed-loop control

1. Introduction

Smart greenhouses have become indispensable in intensive crop production, offering year-round cultivation and resource efficiency [1]. The demand for efficient nutrient management in controlled-environment agriculture has grown rapidly with advancements in smart greenhouse technologies amid increasing environmental variability and resource constraints [2,3]. Smart greenhouses integrate sensors, automation, and data-driven control to regulate temperature, humidity, solar radiation, CO_2 concentration, and nutrient conditions, ensuring stable crop production, improved yield quality, and resource-use efficiency [4].

Nutrient management is a central component of greenhouse production. In this review, nutrient management refers to the monitoring and regulation of nutrient solution concentration and composition, nutrient solution delivery, root zone nutrient conditions, drainage, and environmental factors affecting nutrient uptake and transport. Irrigation-related variables are considered only where they directly affect nutrient solution delivery, root zone EC, nutrient availability, plant water status, or nutrient transport. In soilless culture, where the irrigation water is the nutrient solution, irrigation control is therefore treated as part of nutrient-solution management. Thus, the principal focus is nutrient management rather than irrigation as an independent water management process [5].

Conventional nutrient supply schedules are commonly based on predetermined timing, solution concentration, crop-development calendars, and accumulated solar radiation [6]. These approaches are operationally simple but may not adequately respond to rapid environmental fluctuations, changes in crop water use, root zone salt accumulation, or growth-stage-specific nutrient requirements. Consequently, sensor-based and algorithm-assisted nutrient management has received increasing attention as a means of matching nutrient solution supply with actual crop demand [7–9]. Tomato, paprika, cucumber, eggplant, and melon are warm-season crops; however, their growth does not increase continuously with temperature. Temperatures exceeding crop and developmental-stage-specific optimum ranges can alter stomatal behavior, atmospheric evaporative demand, photosynthesis, reproductive development, root respiration, and nutrient uptake [10,11].

Tomato and paprika are high-value greenhouse crops with long production cycles, continuous reproductive development, and strong sensitivity to the balance among water supply, nutrient concentration, and greenhouse microclimate. Their nutrient requirements vary substantially with crop stage. Nitrogen is especially important during vegetative development, whereas potassium and calcium become increasingly important during flowering, fruit set, fruit enlargement, and ripening. In tomato, inadequate calcium transport can contribute to blossom-end rot, while paprika is highly responsive to changes in substrate water content, drainage, and EC [12–15].

Nutrient supply algorithms are computational models that determine nutrient timing, concentration, nutrient ratios, and corrective actions in response to crop and environmental conditions [9–16]. Unlike conventional schedules, these algorithms can dynamically adapt to crop and environmental feedback [17,18], making decisions regarding irrigation timing, volume, concentration, frequency, and nutrient adjustment. Data from nutrient solution sensors, including electrical conductivity (EC) and pH, environmental sensors measuring temperature, relative humidity, CO_2 concentration, and solar radiation, and automated nutrient supply systems provide the information required for responsive nutrient management [8].

Nutrient supply algorithms translate these measurements into operational commands concerning nutrient solution timing, volume, frequency, EC, and corrective action. However, the literature often combines fundamentally different control concepts under broad labels such as automated nutrient management or intelligent greenhouse control. Previous reviews have largely addressed nutrient sensing, hydroponic nutrient monitoring, smart greenhouse technologies, and general nutrient-management systems [19,20], and none have systematically searched and screened the literature on technology-based nutrient-supply control for warm-season crops. The review question was therefore: in the controlled-environment production of warm-season crops, how do sensor-, model-, and algorithm-based nutrient-supply strategies differ in inputs, control logic, performance, crop-specific implications, and suitability for high-temperature conditions? Accordingly, the present review was organized around four operational nutrient supply strategies:

1. Solar radiation-proportional nutrient solution supply;
2. Radiation-rate-based nutrient solution volume and EC adjustment;
3. Supply-drainage and substrate-feedback control; and
4. Temperature-, humidity-, and VPD-based supervisory corrections.

EC/pH feedback control, ion-selective sensing, mechanistic models, AI/ML prediction, and hybrid intelligent systems are examined as supporting technologies capable of improving these four strategies rather than as additional parallel nutrient supply strategies. The specific objectives of this review are to: (i) characterize the physiological and root zone mechanisms linking high-temperature conditions with nutrient demand and transport, (ii) evaluate nutrient, environmental, root zone, and plant sensing technologies supporting nutrient supply control, (iii) examine the operating principles, inputs, outputs, advantages, and limitations of the four nutrient supply strategies, (iv) evaluate their crop- and growth-stage-specific implications for tomato and paprika, (v) synthesize supporting control and prediction technologies, including EC/pH control, ion-specific monitoring, mechanistic modeling, and AI/ML, (vi) compare performance, high-temperature adaptability, implementation requirements, and validation maturity, and (vii) propose an integrated conceptual framework for heat-responsive nutrient management in smart greenhouses.

2. Review Methodology

2.1. Review Scope and Definitions

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement [21] to identify, evaluate, classify, and synthesize research on nutrient management strategies for warm-season crops cultivated in smart greenhouses. This review focused on nutrient management in smart greenhouses and other controlled-environment production systems for warm-season crops, with particular attention to tomato and paprika. Relevant topics included nutrient solution supply, EC and pH management, root zone monitoring, nutrient-specific sensing, environmental sensing, crop-response sensing, drainage control, nutrient-demand estimation, and sensor-based decision support [5,22].

In this review, high-temperature conditions refer to air and/or root zone temperatures exceeding crop, cultivar, and developmental stage-specific optimum ranges reported or defined in the original studies, rather than a single universal numerical threshold. This definition was adopted because thermal sensitivity varies among crops, cultivars, developmental stages, production systems, and greenhouse conditions. Studies performed under naturally warm greenhouse conditions without explicitly imposed thermal treatment were distinguished from those that directly evaluated high-temperature effects. One amend-

ment was made to the eligibility criteria during screening; it is described and justified in Section 2.3.

2.2. Literature Search Strategy

Five bibliographic sources were searched on 15 August 2026 through the Chungnam National University library: Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect (Elsevier), and the MDPI journal platform. These sources cover plant science, greenhouse horticulture, controlled-environment agriculture, sensing technologies, and agricultural engineering. SpringerLink was not used as a database source because its search cannot be restricted to titles and abstracts and its exports are limited to 1000 records. Studies known to the authors from earlier manual title and keyword searching of publisher websites (including SpringerLink and MDPI) that were not retrieved by the database searches were recorded as studies identified through other methods (Figure 1).

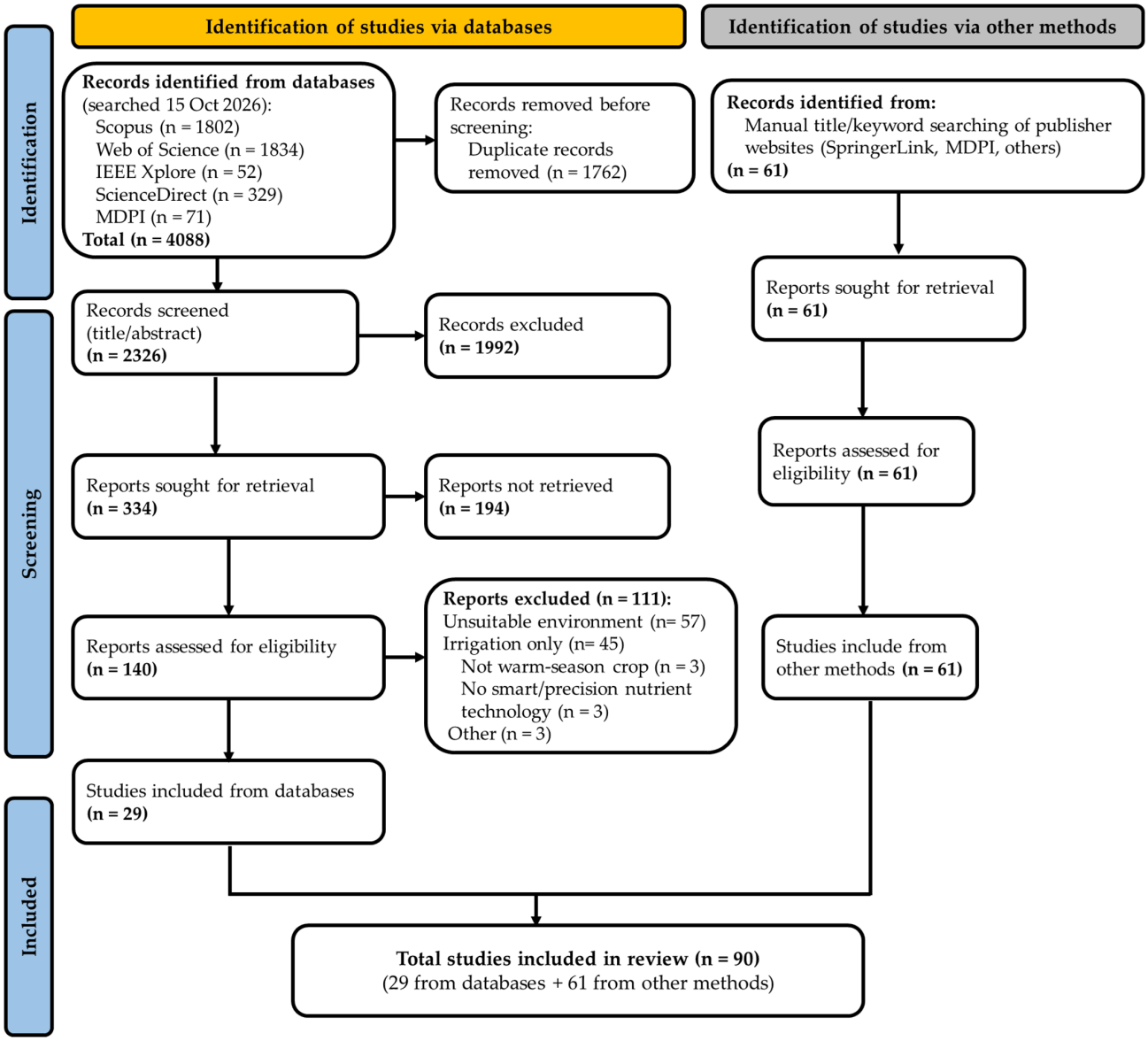


Figure 1. PRISMA-guided study identification, screening, eligibility assessment, and inclusion processes.

All searches covered publications from 1 January 2010 to the search date and were restricted to English-language journal articles, conference papers, and review articles. Search

strings combined three concept groups: the production system (greenhouse, controlled-environment agriculture, hydroponic, soilless, substrate culture, plant factory), nutrient management (nutrient management, nutrient solution, nutrient supply, fertigation, electrical conductivity, pH control, ion-selective electrode, root zone, irrigation control, irrigation scheduling), and the crop (tomato, paprika, sweet pepper, bell pepper, cucumber, eggplant, melon, warm-season crop). Title, abstract, and keyword fields were searched. The Scopus search string was: TITLE-ABS-KEY ((“smart greenhouse” OR “controlled-environment agriculture” OR CEA) AND (“nutrient management” OR “electrical conductivity” OR “pH control” OR “root zone monitoring” OR “ion-selective electrode”) AND (“tomato’’ OR ‘’paprika’’ OR ‘’warm-season crop’’)).

The same concept groups were adapted to the syntax of each platform. Web of Science used the topic field (TS=) with identical terms; IEEE Xplore used the “All Metadata” field; ScienceDirect, which does not support wildcards and allows at most eight Boolean operators per query, was searched with four complementary queries (tomato; pepper/paprika; cucumber/eggplant; sensing and control terms); and MDPI was searched in the title/abstract/keyword field. The searches retrieved 1802 records from Scopus, 1834 from Web of Science, 52 from IEEE Xplore, 329 from ScienceDirect, and 71 from MDPI (4088 in total). In addition, three textbooks on plant mineral nutrition, crop physiology, and numerical methods [23–25] were consulted as background references to support physiological and methodological explanations; these were not part of the systematic search, were not screened, and are not counted among the included studies or shown in Figure 1.

2.3. Inclusion/Exclusion Criteria and Study Selection

Studies were considered relevant when they addressed smart greenhouses or controlled-environment crop production and focused on warm-season crops, included nutrient management, nutrient supply, nutrient-related sensing technologies, nutrient supply control approaches, or algorithm-based decision support. Studies were excluded when they focused on inappropriate production environments, such as uncontrolled glasshouses or open-field conditions, addressed irrigation without a nutrient management component under warm-season conditions, were not available in English or lacked quantitative crop-response data relevant to elevated-temperature environments.

The inclusion criteria involved: (i) smart greenhouse or other controlled-environment crop production; (ii) warm-season crops, with emphasis on tomato and paprika; (iii) focus on nutrient management, nutrient supply, nutrient-related sensing, nutrient supply control or algorithm-based decision support; (iv) use of smart or precision nutrient technology, namely sensing, automated control, models or decision-support systems, or IoT/AI tools; and (v) journal articles, conference papers or review articles published in English between 2010 and 2026. The exclusion criteria corresponded to the reasons reported in Figure 1, such as: (i) unsuitable production environment (uncontrolled glasshouses or open-field production); (ii) irrigation only, without a nutrient-management component under warm-temperature conditions; (iii) crops other than warm-season crops; and (iv) other reasons, such as non-English publications. Three textbooks that were not identified through the database or publisher-website searches were added separately (Section 2.2; Figure 1). Included studies were grouped for synthesis into the five thematic categories described in Section 2.5, according to the main contribution of each study. One amendment was made to the eligibility criteria during screening: the original requirement for quantitative crop-response data under elevated-temperature conditions was replaced by the requirement for smart or precision nutrient technology (inclusion criterion iv) because few studies imposed explicit high-temperature treatments. All records were re-screened against the revised criteria. The database searches identified 4088 records (Scopus, n = 1802; Web of Science,

$n = 1834$; IEEE Xplore, $n = 52$; ScienceDirect, $n = 329$; MDPI, $n = 71$). After 1762 duplicate records were removed, 2326 records were screened by title and abstract, and 1992 were excluded. Full texts were sought for the remaining 334 reports, of which 194 could not be retrieved; the other 140 reports were assessed for eligibility. Of these, 111 were excluded because of an unsuitable production environment ($n = 57$), irrigation only without nutrient management ($n = 45$), a crop other than a warm-season crop ($n = 3$), no smart or precision nutrient technology ($n = 3$), or other reasons ($n = 3$), leaving 29 studies included from the databases. Manual title and keyword searching of publisher websites (SpringerLink, MDPI, and others) identified a further 61 records; all 61 reports were retrieved, assessed for eligibility, and included. Together with three textbooks, 93 studies were included in the review (29 from databases + 61 from other methods) + 3 from textbooks. These figures are arithmetically consistent ($4088 - 1762 = 2326$; $2326 - 1992 = 334$; $334 - 194 = 140$; $140 - 111 = 29$; $29 + 61 = 90$).

Duplicate records were identified and removed before screening. Title/abstract screening and full-text assessment were carried out by one reviewer. The 111 excluded full-text reports, with the specific reasons for each (PRISMA item 16b), are mentioned in Table S1. Databases searched: Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect, and MDPI. Additional studies were identified through manual title and keyword searching of publisher platforms (SpringerLink, MDPI and others).

The complete identification, screening, eligibility, and inclusion procedure is illustrated in Figure 1 according to the PRISMA 2020 framework (also added in Table S2). Of the 90 included studies, 29 were from databases and 61 from publisher websites, in addition to three that were outside textbooks, to make a total of 93 references. Because the MDPI search engine does not apply Boolean operators strictly, non-matching MDPI records were removed at screening.

2.4. Literature Classification, Data Extraction, Comparative Analysis and Evidence Synthesis

Information from the selected studies was extracted using a structured review framework. To ensure data integrity, extraction was performed by one reviewer and cross-checked independently by that same reviewer, with any discrepancies resolved through group discussion. The extracted variables included crop species, cultivation system, environmental conditions, sensing technologies, nutrient-management objectives, input variables, control approaches, measured outputs, performance indicators, advantages, limitations, and future research recommendations. To evaluate the internal validity of the included literature, a risk of bias assessment was independently performed by the reviewer using a customized quality appraisal matrix tailored for agricultural engineering and precision horticulture studies. Each study was evaluated across four core methodological domains: (1) environmental control reporting and microclimate tracking validation; (2) adequacy of control or comparison groups; (3) specification of sensor calibration, accuracy margins, and sampling frequencies; and (4) data completeness and analytical or algorithmic verification rigor. Each domain was graded as having a low, high, or unclear risk of bias, and disagreements were settled by discussion until 100% consensus was achieved.

Data were extracted from each report by one reviewer using a structured extraction form and verified; extraction was therefore not performed fully independently in duplicate. No study investigators were contacted to obtain or confirm data, and no automation tools were used. Outcomes sought were nutrient-use efficiency (NUE), water-use efficiency (WUE), crop yield, crop/fruit quality, nutrient uptake, control accuracy of EC/pH (set-point error, R^2, and RMSE), or nutrient concentration defined in the original studies. All results compatible with each outcome domain (all measures, time points and analyses) were sought and recorded without selecting a single result per study. Other variables

sought were crop species, cultivation system, environmental conditions, sensing technologies, nutrient-management objectives, input variables, control approaches, performance indicators, advantages, and limitations. Where information was missing or unclear, it was recorded as "not reported", and no values were imputed or assumed.

Risk of bias was assessed with the customized four-domain appraisal matrix described above, because established tools such as RoB 2 or ROBINS-I are designed for clinical studies and do not fit engineering and horticultural experiments. The reviewer assessed every study independently, and no automation tools were used.

2.5. Evidence Synthesis and Comparative Analysis

The 90 included studies constituted the primary systematic evidence base for comparative synthesis. To structure the review, the selected studies were classified into five thematic categories for this study.

1. Physiological and nutrient-demand responses under elevated-temperature conditions;
2. Nutrient, root zone, crop, and environmental sensing technologies;
3. Nutrient supply and nutrient supply control algorithms;
4. Crop-specific nutrient-management applications in greenhouse crops; and
5. Intelligent and autonomous nutrient management systems.

Within these categories, nutrient-management approaches were further classified as EC/pH-based control, climate-responsive nutrient-management, radiation-driven control, drainage-feedback systems, ion-specific management, mechanistic nutrient-uptake models, AI/ML-based approaches, and hybrid intelligent systems [16,26–31].

The included studies were comparatively evaluated based on nutrient-use efficiency (NUE), water-use efficiency (WUE), crop yield and quality, sensing requirements, automation level, environmental adaptability, implementation complexity, and commercial applicability. Additional consideration has been given to the responsiveness of algorithms under elevated-temperature conditions, particularly regarding crop water demand, root zone dynamics, nutrient uptake, and greenhouse climate interactions [10,28,30,32]. The 90 selected studies constituted the primary systematic evidence base for the comparative synthesis. Classification reflected the main contribution evaluated in each publication rather than the presence of particular keywords or technologies. Additional references cited throughout the manuscript were included only to provide physiological, methodological, and conceptual backgrounds and were not considered part of the systematic evidence dataset. Figure 2 summarizes the distribution of studies across the major thematic areas included in this review.

No pooled effect measure (e.g., risk ratio or mean difference) was calculated. Outcomes were presented as reported in the original studies (e.g., percentage change in yield, NUE or WUE in the original units).

Studies were eligible for a given synthesis when their main contribution matched one of the five thematic categories above. Data were prepared for presentation by converting units to a common basis (e.g., EC in dS m^{-1}, temperature in °C]; no missing summary statistics were imputed. Results of individual studies and of the syntheses are tabulated in their specific sections and summarized in Figure 2. A structured narrative synthesis was used. A meta-analysis was not performed because the studies differ widely in crops, cultivation systems, temperature treatments, sensing technologies, outcome metrics and designs, and comparable effect estimates with measures of variance were not available; hence no statistical model, heterogeneity statistic or software package applies. Possible sources of heterogeneity (crop, growth stage, cultivation system, control strategy, temperature regime) were explored qualitatively by comparing studies within these groups; no subgroup analysis or meta-regression was performed. No sensitivity analysis was performed.

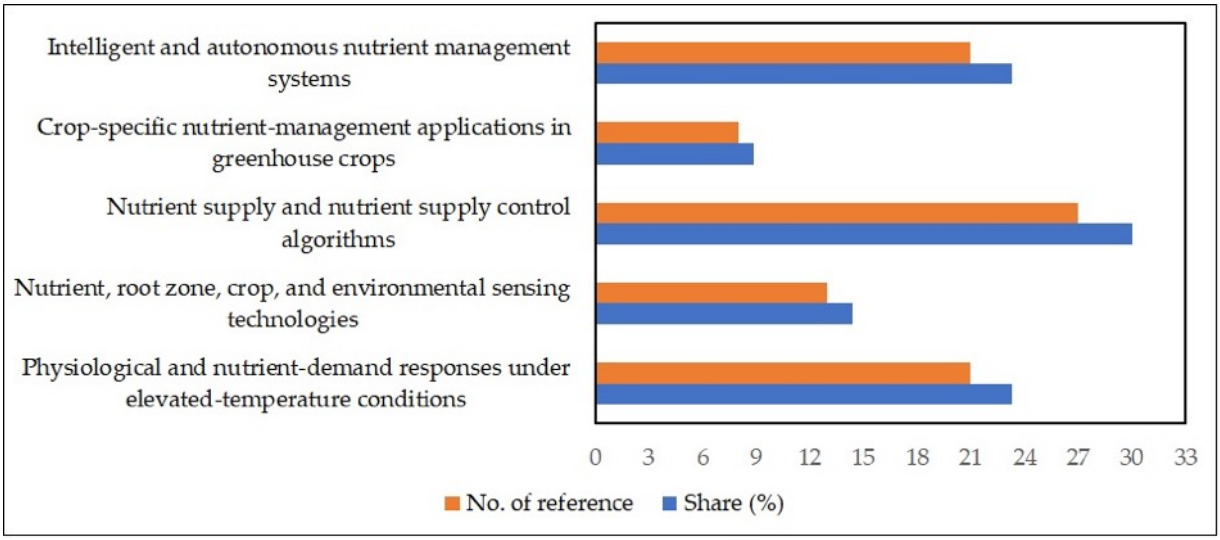


Figure 2. A bar chart showing the number and percentage of included studies across the principal thematic categories.

The risk of bias due to missing results (reporting bias) was not formally assessed (e.g., funnel plots or statistical tests) because no meta-analysis was performed; possible publication bias towards positive results is acknowledged as a limitation of the review. The certainty of the body of evidence was not graded with a formal system such as GRADE; instead, the validation maturity of each strategy (laboratory, greenhouse, commercial) was compared qualitatively (Section 7.2).

3. High-Temperature Effects on Nutrient Demand and Root Zone Dynamics

High temperatures influence greenhouse nutrient management by interacting with atmospheric, plant, and root zone processes. Therefore, temperature alone is an insufficient indicator of nutrient demand. Its effects depend strongly on humidity, solar radiation, ventilation, crop developmental stage, canopy size, substrate characteristics, and root zone conditions.

3.1. Temperature and Transpiration

Increasing air temperature generally increases evaporative demand when sufficient radiation is available and atmospheric humidity does not simultaneously increase. Higher transpiration can increase crop water consumption and accelerate the mass flow of mobile nutrients toward the root surface. Consequently, irrigation frequency or volume may need to increase during warm, high-radiation periods.

However, this response is not linear. Excessive temperatures can reduce stomatal conductance, disrupt photosynthesis, impair pollen development and fruit set, and induce physiological stress. Under such conditions, water demand may remain high while nutrient uptake or biomass production declines. Algorithms should therefore distinguish between increased evaporative demand and increased nutrient requirement rather than increasing nutrient concentration proportionally with temperature.

3.2. VPD and Nutrient Transport

VPD provides a more physiologically informative measure of atmospheric demand than relative humidity alone because it incorporates the combined effects of air temperature and moisture. Moderate increases in VPD promote transpiration and can facilitate

xylem-mediated transport of nutrients such as calcium. Excessively high VPD, however, can promote stomatal closure and reduce photosynthetic activity, whereas very low VPD restricts transpiration and may reduce calcium transport to rapidly developing tissues [33–35]. Calcium is particularly sensitive to these processes because it is transported mainly through the transpiration stream. Developing fruits generally transpire less than leaves and may therefore receive insufficient Ca even when total nutrient solution EC appears adequate. In tomato, manipulation of VPD during different growth stages has been associated with changes in fruit Ca accumulation, yield, water productivity, and fruit quality [33,36]. Therefore, VPD is most useful as a supervisory or corrective variable rather than a direct proportional nutrient-dose command for operational nutrient management.

3.3. Root Zone Temperature, Water Status, and EC Dynamics

Elevated root zone temperature alters root respiration, membrane transport, dissolved oxygen availability, water uptake, and nutrient absorption. At the same time, strong transpiration can rapidly remove water from a limited substrate volume; when water removal exceeds nutrient-ion removal, dissolved salts become concentrated and root zone EC increases. High EC reduces the osmotic potential of the root zone solution and further constrains water uptake.

Increasing the nutrient solution supply frequency can stabilize substrate moisture and moderate short-term EC fluctuations. However, excessive supply may increase drainage, nutrient losses, and the risk of reduced root zone aeration. Root zone temperature, substrate moisture or weight, drainage fraction, and drainage EC provide important complementary information for determining whether high atmospheric demand is producing actual root zone water or nutrient stress [37].

3.4. Decoupling of Water Uptake and Nutrient Uptake

A central challenge in high-temperature nutrient management is that plant water uptake and nutrient-ion uptake do not increase at identical rates. High atmospheric demand can substantially increase water consumption while nutrient demand remains comparatively stable or even declines because of heat-induced reductions in photosynthesis or biomass production. Conversely, nutrient demand may increase during rapid reproductive growth even when short-term atmospheric demand is moderate.

This decoupling means that nutrient solution volume and nutrient concentration should not be adjusted using the same proportional rule. EC provides an overall measure of ionic concentration but cannot determine whether Ca, K, nitrate, or another specific nutrient is deficient or excessive. Thus, maintaining a target EC does not guarantee a balanced nutrient composition.

3.5. Heat-Related Nutrient Imbalance

Heat-related nutrient imbalance results from the fact that water and individual nutrient uptake do not respond identically to environmental conditions. High transpiration may increase water consumption faster than nutrient demand, whereas high humidity may restrict transpiration-dependent calcium movement despite adequate total nutrient concentrations.

EC alone cannot distinguish such conditions because it represents the total ionic concentration rather than individual nutrient availability. Calcium deficiency, for example, may occur even when root zone EC is within the target range. Accordingly, warm-season nutrient supply control requires the coordinated regulation of water volume, irrigation frequency, root zone EC, drainage, and nutrient composition rather than simple proportional adjustment of nutrient concentration [38].

3.6. Tomato and Paprika Responses

Tomato and paprika are both sensitive to interactions among temperature, transpiration, nutrient concentration, and reproductive development. Tomato fruit development requires particularly careful calcium and potassium management, with inadequate calcium transport contributing to blossom-end rot [15]. Paprika similarly requires stable root zone water and nutrient conditions and can respond strongly to fluctuations in substrate EC and irrigation regime [12–14].

These responses establish the physiological basis for the sensing and algorithmic approaches discussed in the next section. Figure 3 shows crop growth stages, nutrient uptake drivers, and crop performance. Table 1 shows environmental drivers, physiological responses, nutrient consequences, and implications for nutrient supply control.

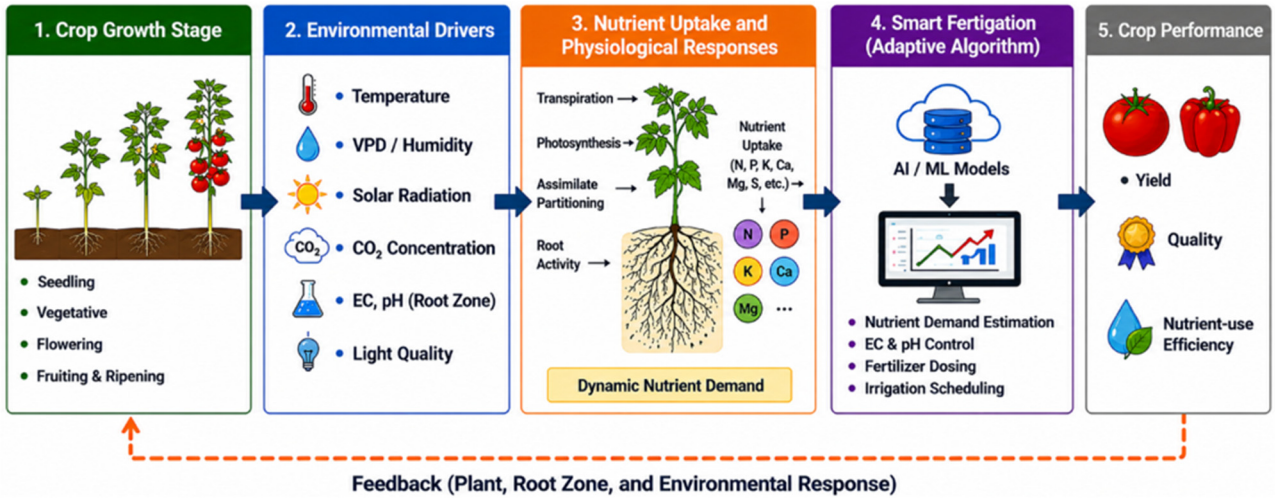


Figure 3. Crop growth stages, environmental drivers, nutrient uptake, and crop performance in a nutrient controlled environment.

Table 1. Environmental drivers, physiological responses, nutrient consequences, and implications for nutrient supply control.

Environmental Driver	Main Physiological Response	Nutrient-Management Consequence	Control Implication	Reference
Increasing air temperature within tolerable range	Increased atmospheric demand and transpiration	Greater solution-volume demand, potentially faster ion transport	Increase supply frequency/volume when confirmed by radiation and root zone status	[34,35]
Excessive air temperature	Stomatal regulation, reduced photosynthesis, reproductive stress	Water demand may become uncoupled from nutrient demand	Avoid proportional increases in nutrient concentration based on temperature alone	[33,39]
Moderate VPD	Supports transpiration and xylem flow	Can facilitate Ca transport	Use as supervisory indicator of atmospheric demand	[33,34]
Excessive VPD	Stomatal restriction and altered Ca partitioning	Potential fruit Ca limitation despite adequate EC	Combine VPD with root zone and crop-stage information	[15,35]
Very low VPD	Low transpiration	Reduced xylem-mediated Ca movement	Avoid excessive nutrient concentration as compensation	[34]

Table 1. *Cont.*

Environmental Driver	Main Physiological Response	Nutrient-Management Consequence	Control Implication	Reference
Elevated root zone temperature	Altered respiration, ion-uptake, and dissolved oxygen	Nutrient uptake imbalance possible	Monitor root zone temperature, EC, moisture, and oxygen risk	[30,37]
Substrate drying	Concentration of dissolved salts	Increased EC and osmotic stress	Increase solution frequency/volume within drainage limits	[14,40]
Excessive substrate moisture	Low aeration and high drainage	Nutrient loss and impaired root function	Reduce volume or extend interval	[41,42]
Salinity accumulation	Reduced water availability and altered nutrient balance	Lower yield and increased physiological disorders	Use EC as a safety constraint with drainage feedback	[43,44]

4. Sensing Technologies for Nutrient Management

The effectiveness of nutrient supply algorithms depends largely on the quality and reliability of data acquired from greenhouse monitoring systems. Modern smart greenhouses employ a wide range of sensors to continuously monitor nutrient solution characteristics, environmental conditions, and crop responses. As greenhouse production systems become increasingly automated, sensing technologies have evolved from simple electrical conductivity (EC) and pH measurements to advanced multi-sensor platforms integrating nutrient monitoring, environmental sensing, machine vision, and Internet of Things (IoT) technologies [45]. Accurate sensing allows nutrient supply algorithms to respond dynamically to environmental fluctuations and physiological changes, thereby improving nutrient-use efficiency, reducing fertilizer losses, and enhancing crop productivity. However, sensor selection, calibration, maintenance requirements, and cost remain critical challenges affecting the implementation of advanced nutrient management systems [20,46].

4.1. EC and pH

Electrical conductivity sensors are among the most widely used tools for nutrient monitoring in greenhouse production systems. EC measurements provide an indirect estimate of the total dissolved salt concentration within the nutrient solution and are commonly used to assess nutrient availability and nutrient management. Because EC sensors are relatively inexpensive, reliable, and easy to integrate into automated control systems, they remain the primary sensing technology used in commercial hydroponic production [27,30]. Calcium deficiency may develop despite adequate EC levels because of the disproportionate uptake of other ions. This limitation has encouraged the development of complementary sensing technologies capable of monitoring specific nutrients [47–49].

Nutrient solution pH significantly influences nutrient availability and uptake efficiency in hydroponic systems. Most greenhouse crops perform optimally within a pH range of approximately 5.5 to 6.5, where essential nutrients remain readily available for absorption. Continuous pH monitoring enables automated correction through acid or alkali dosing systems, helping maintain optimal nutrient uptake conditions [26,50]. Sensor drift and fouling remain common challenges, particularly in recirculating hydroponic systems where nutrient concentrations fluctuate continuously [20,51,52].

4.2. Ion-Selective Electrodes (ISEs)

Ion-selective electrodes represent a significant advancement in nutrient monitoring technology by enabling the direct measurement of specific nutrient ions such as nitrate (NO_3^-), potassium (K^+), calcium (Ca^{2+}), and ammonium (NH_4^+). Unlike EC sensors, ISEs provide nutrient-specific information that allows more precise nutrient management and the correction of individual nutrient deficiencies [47,48,53,54]. The integration of ISEs into nutrient supply algorithms offers considerable potential for improving nutrient-use efficiency and reducing fertilizer wastage. However, widespread adoption remains limited because of high sensor costs, calibration requirements, sensitivity to environmental conditions, and limited long-term stability under commercial greenhouse conditions [20,46,55]. Figure 4 shows ion-selective electrode nutrient monitoring.

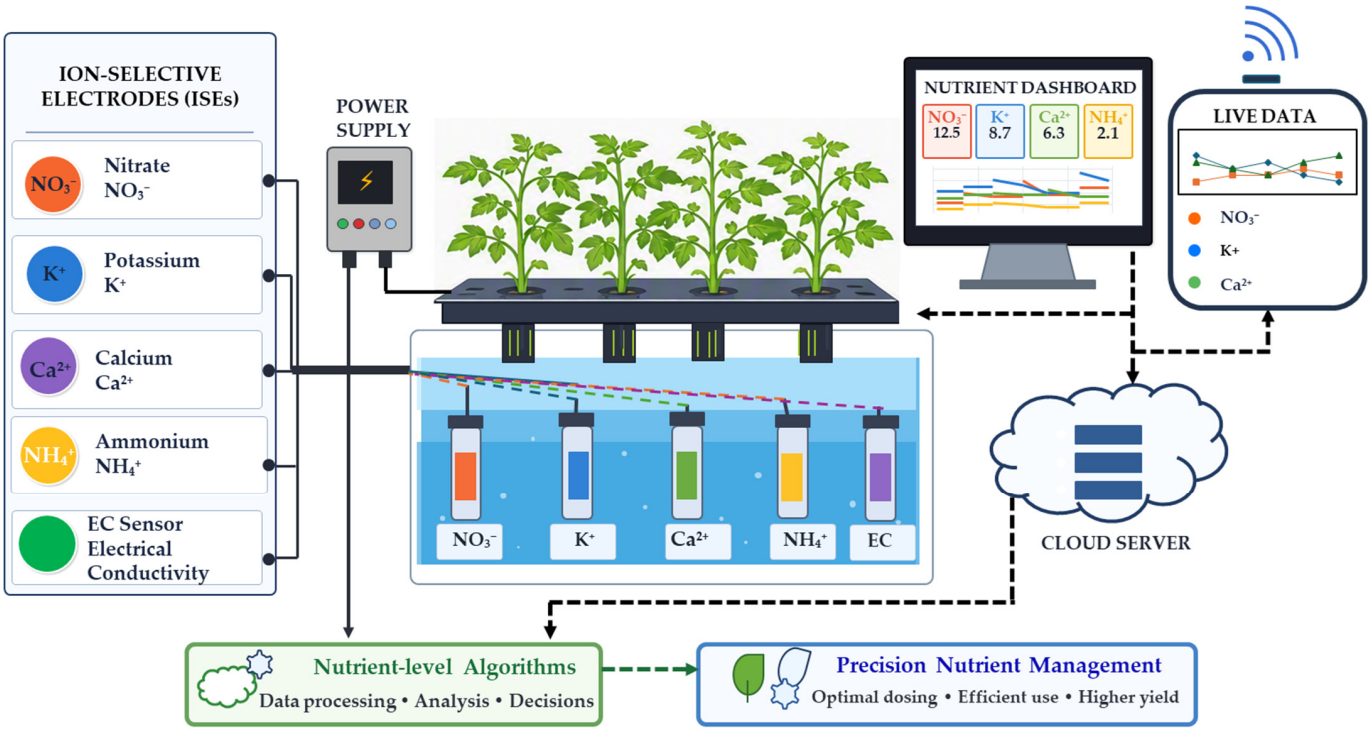


Figure 4. Ion-selective electrode nutrient monitoring for a nutrient management system.

4.3. Environmental Sensors

Environmental conditions strongly influence nutrient uptake and crop performance. Consequently, modern nutrient supply algorithms incorporate environmental sensor data to improve decision-making and nutrient management accuracy. Temperature sensors are typically deployed throughout greenhouses and integrated into climate control systems to maintain optimal growing conditions [28,45,56].

Relative humidity (RH) and vapor pressure deficit (VPD) influence transpiration rates and nutrient transport within plants. Calcium transport, for example, is highly dependent on transpiration and may become limited under conditions of high humidity. VPD-based nutrient-management strategies have therefore gained increasing attention as a means of improving nutrient management and reducing physiological disorders in greenhouse crops [33–35].

Solar radiation is one of the most commonly used variables in greenhouse nutrient supply algorithms. Radiation influences photosynthetic activity, biomass production, and nutrient demand. Several commercial greenhouse systems schedule irrigation events based

on accumulated solar radiation, making radiation sensors a critical component of smart nutrient supply systems [57–59].

CO_2 enrichment is widely used in commercial greenhouse production to increase photosynthetic efficiency and crop productivity. Elevated CO_2 concentrations often increase nutrient demand by stimulating biomass production, highlighting the importance of integrating CO_2 measurements into nutrient management algorithms [60,61]. Table 2 lists the environmental sensor inputs and their roles in nutrient supply algorithms.

Table 2. Environmental sensor inputs and their roles in nutrient supply algorithms.

Sensor Variable	Algorithmic Function	Main Control Output	Important Limitation	References
Air temperature	Estimates metabolic activity, crop development, and heat-stress conditions	Irrigation-volume or irrigation-interval correction	High temperature does not necessarily indicate increased nutrient uptake, particularly under heat stress	[28,45,56,62]
Root zone temperature	Evaluates root activity, nutrient absorption, respiration, and dissolved-oxygen risk	EC constraint, solution cooling, aeration, or warning	Measurements depend strongly on representative sensor placement within the substrate or nutrient solution	[20,30,45]
Relative humidity	Indicates atmospheric moisture conditions affecting crop transpiration and nutrient transport	Supervisory irrigation-volume or interval correction	Relative humidity must be interpreted together with air temperature	[34,45]
VPD	Estimates atmospheric transpiration demand and potential nutrient transport	Irrigation timing, pulse volume, and interval adjustment	Crop- and growth-stage-specific target ranges are required	[33–35]
Solar radiation	Estimates crop energy load, transpiration, and short-term water demand	Irrigation triggering and baseline irrigation-volume calculation	Radiation alone does not fully represent humidity, temperature, canopy size, or crop-stage effects	[57–59]
PPFD	Estimates photosynthetically active radiation and potential photosynthetic demand	Crop-growth and nutrient-demand model adjustment	Measurements are affected by sensor position, canopy shading, and spatial light variability	[45,58,59]
CO_2 concentration	Indicates enrichment conditions affecting photosynthesis, biomass production, and nutrient demand	Nutrient-demand model correction	CO_2 enrichment increases crop demand only when radiation, temperature, water, and other growth factors are suitable	[60,61]

4.4. Plant-Based Sensing

While nutrient and environmental sensors provide indirect information regarding crop status, plant-based sensing technologies offer direct measurements of crop responses. Advances in machine vision, imaging systems, and plant phenotyping platforms have

enabled the real-time monitoring of plant growth, canopy development, stress responses, and nutrient deficiency symptoms [63,64].

RGB cameras, multispectral imaging systems, thermal cameras, and chlorophyll fluorescence sensors have been increasingly applied in greenhouse production systems to monitor plant health and detect nutrient-related stress before the appearance of visible symptoms. These technologies provide valuable information for predictive nutrient management and may improve the responsiveness of nutrient supply algorithms [63–65].

4.5. IoT and Data Acquisition

The Internet of Things (IoT) has transformed greenhouse monitoring by enabling continuous communication among sensors, controllers, cloud-based platforms, and decision support systems [66]. IoT-based greenhouse systems facilitate real-time data acquisition, remote monitoring, automation, and predictive analytics. By integrating nutrient sensors, environmental sensors, and plant-based monitoring technologies into a unified platform, IoT systems provide the data infrastructure required for advanced nutrient supply algorithms [66,67].

Cloud-based data management systems further enable long-term data storage, machine learning model development, and predictive nutrient management strategies [68,69]. Figure 5 shows the sensor architecture for smart greenhouse nutrient management.

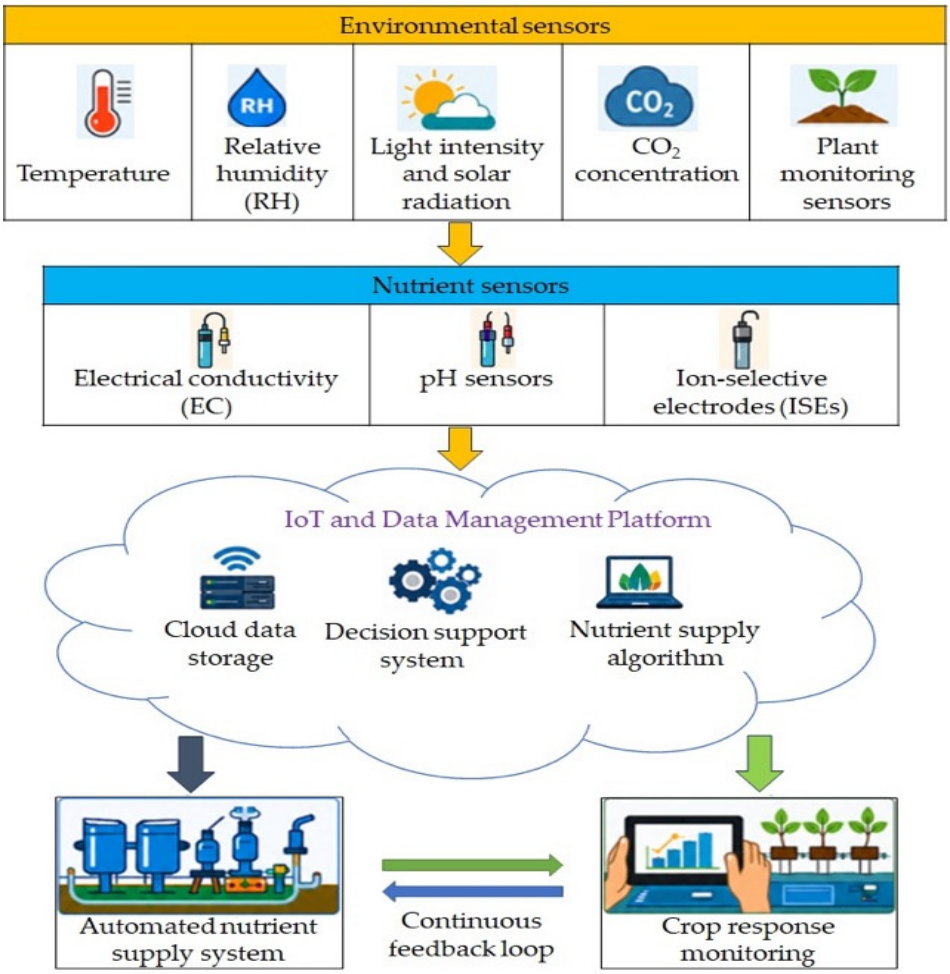


Figure 5. Sensor architecture for smart greenhouse nutrient management depending on environmental condition.

4.6. Sensor Reliability and Fault Detection

Sensor reliability is a fundamental requirement for autonomous control. The failure modes include drift, fouling, disconnected sensors, frozen measurements, communication loss, calibration errors, displaced root zone probes, obstructed drainage measurements, and inconsistent readings among sensors.

Therefore, operational control systems should incorporate range checks, missing data detection, rate-of-change limits, stuck sensor detection, cross-sensor consistency tests, calibration tracking, and fallback control states. Automated drift compensation and machine-learning-based fault detection provide promising methods for maintaining reliable EC and pH measurements [51,70,71].

When a critical measurement fails, the controller should not continue unrestricted autonomous correction. A safer strategy is to hold the most recent validated command, revert to a conservative baseline schedule, or disable the affected correction layer until sensor validity is restored.

5. Operational Nutrient-Supply Control Algorithms

Nutrient supply algorithms form the decision-making core of smart nutrient supply systems, translating sensor inputs into real-time irrigation and nutrient dosing commands. Rather than relying on rigid, time-based schedules, modern operational frameworks integrate environmental energy drivers, root zone feedback, and atmospheric demand. This section addresses solar-radiation scheduling, irrigation and EC adjustment, drainage feedback, substrate moisture or weight sensing, and climate-responsive nutrient management, and compares each algorithm using five criteria: control objective, required inputs, decision variable, feedback timing, and implementation limitations. The primary objective of these algorithms is to synchronize nutrient supply with crop demand while enhancing nutrient use efficiency, reducing fertilizer losses, and sustaining crop productivity and quality. Advances in sensing technologies, computational power, automation, and artificial intelligence have driven the evolution of these algorithms from simple rule-based approaches to advanced machine learning and hybrid intelligent systems [19,30,31,72]. Table 3 summarizes the algorithms, their outputs, and limitations.

Table 3. Nutrient supply algorithms: inputs, controlled outputs, control roles, and limitations.

Algorithm	Primary Inputs	Controlled Outputs	Control Role	Typical Limitation	References
Solar radiation-proportional scheduling	Cumulative radiation, zone volume, dripper capacity, time window	Irrigation timing and pulse volume	Feedforward baseline	Requires crop- and season-specific radiation thresholds	[12,13]
Radiation-rate-based volume and EC control	Radiation accumulated per 30 min, crop response	Irrigation volume and target EC	Dynamic feedforward adjustment	Correlation shift with growth stage and greenhouse climate	[12,42,73]
Supply-drainage and substrate feedback	Supply, drainage, substrate weight or moisture	Percentage correction of irrigation volume	Closed-loop root zone feedback	Drainage response can be delayed, weighing systems require stable installation	[13,42,72]
Temperature humidity correction	Air temperature and RH or VPD deviations	Change in irrigation volume, optional EC correction	Supervisory climate compensation	Rules must avoid overcorrection and condensation risk	[42,73]

5.1. Solar Radiation Nutrient Supply Algorithms

5.1.1. Solar Radiation Proportional Irrigation Scheduling

This algorithm scales daily irrigation delivery in proportion to accumulated solar radiation across defined operational cycles [12,57]. The baseline irrigation volume per event (V_i) is expressed in Equation (1):

$$V_i = V_{zone}\left(1 + k_r \frac{R_{cum}}{R_{ref}}\right) \quad (1)$$

where V_i is the commanded irrigation volume for an event, V_{zone} is the baseline irrigation volume assigned to the irrigation zone, k_r is the irrigation-rate coefficient, R_{cum} is the accumulated solar radiation since the previous reset or event, and R_{ref} is the reference radiation value [12,13]. This anticipatory feedforward approach prevents root zone water stress before it develops, though parameters must be calibrated by crop stage and season [74]. The calculated irrigation volume is converted to valve operating time according to the emitter discharge rate as shown in Equation (2) [75]:

$$T_{open} = \frac{V_i}{Q_d} \quad (2)$$

where T_{open} is the valve opening duration and Q_d is the emitter discharge rate.

Operationally, the controller should (i) identify the current six-hour cycle, (ii) accumulate radiation, (iii) compare the accumulated value with the cycle-specific threshold, (iv) calculate the zone-specific volume, (v) convert volume to valve-open time using dripper capacity, and (vi) apply the waiting period before the next event. The same logic can be applied independently to multiple zones with different crop loads, substrate volumes or emitter characteristics.

The main advantage is anticipatory control: irrigation delivery can increase before measurable root zone water stress develops because the command is linked to incoming radiation. The algorithm is computationally simple, transparent to growers, and compatible with commercial climate computers. Its principal limitation is that radiation is only a proxy for transpiration. Temperature, humidity, leaf area, crop stage, and ventilation can change water demand even when cumulative radiation is similar. Therefore, the reference radiation and proportional coefficient must be calibrated by crop stage and season.

5.1.2. Irrigation Volume and EC Control Based on Cumulative Solar Radiation Rate

The radiation-rate-based algorithm complements accumulated-radiation scheduling by considering how rapidly solar radiation changes over a defined control interval. A rapid increase in radiation indicates a short-term increase in atmospheric energy load and potential transpiration demand that may not be adequately represented by a daily or cycle-based accumulated-radiation threshold. The radiation accumulation rate can therefore be used as a feedforward variable to modify irrigation volume, and where supported by crop- and system-specific calibration, the target nutrient-solution EC [40,74]. A generalized representation of the radiation accumulation rate is shown in Equation (3) [25]:

$$S_r = \frac{SR_t - SR_{t-\Delta t}}{\Delta t} \quad (3)$$

where SR_t and $SR_{t-\Delta t}$ are cumulative solar radiation values measured at consecutive control intervals and Δt is the control interval duration [16,42].

The calculated radiation accumulation rate is used to determine an irrigation-volume correction factor and to update the target nutrient solution electrical conductivity (EC). Irrigation volume is adjusted proportionally to the radiation-driven transpiration demand, while EC is regulated toward a dynamically updated setpoint using feedback control.

This approach enables rapid adaptation to transient environmental fluctuations while maintaining nutrient delivery within crop-specific limits. The target EC is defined using Equation (4):

$$EC_{set,t} = EC_{base} + \Delta EC(Sr) \quad (4)$$

where EC_{base} is the crop stage baseline EC and $\Delta EC(Sr)$ is a calibrated adjustment based on the radiation accumulation rate.

The measured EC is continuously compared with the target EC, and the resulting error is used by the nutrient supply controller to regulate fertilizer injection and maintain a stable solution composition, following feedback-control principles similar to those described by Wu et al. (2019) [16]. Table 4 summarizes the recommended irrigation volume responses and corresponding EC target adjustments under different radiation-rate conditions. These EC adjustments should be regarded as crop- and system-specific calibration parameters rather than universal responses. Because EC dynamics exhibit nonlinear behavior and time delays during mixing and nutrient injection [15], the controller should enforce upper and lower EC limits, use filtered sensor measurements, and suspend EC correction when sensor validation checks fail.

Table 4. Irrigation volume and EC responses under different radiation-rate conditions and their control interpretation.

Radiation Rate Condition	Irrigation Volume Response	EC Response	Control Interpretation	Reference
Low	Maintain or reduce pulse volume according to compensated accumulated radiation and crop water demand	Maintain crop-stage target while monitoring substrate EC	Low short-term demand, avoid excessive drainage	[12,42]
Moderate	Apply baseline pulse volume according to the compensated radiation integral, with substrate moisture used as an additional feedback variable	Maintain target EC while continuously monitoring changes in substrate EC	Normal operating condition, radiation-driven transpiration balanced with nutrient uptake	[12,42]
High	Increase pulse volume according to compensated radiation and measured crop/root-zone demand rather than using a fixed proportional increase	Apply calibrated EC correction according to substrate EC response rather than radiation alone	Rapid increase in transpiration and water uptake, requires dynamic adjustment	[12,42]
Root-zone deviation from target conditions	Modify irrigation timing and/or supply based on substrate moisture together with compensated radiation information	Correct nutrient-solution management when substrate EC deviates from the desired range	Integration radiation enables more adaptive irrigation and nutrient management than radiation-only control	[42]

Since EC response to temperature and irrigation volume is crop- and system-dependent, the EC rule should be treated as a calibrated control relationship rather than a universal direction. The controller should enforce upper and lower EC limits, use filtered sensor values, and suspend EC correction when sensor validity checks fail.

5.2. Autonomous Irrigation Volume Control from Supply Drainage Balance and Substrate Water Status

This closed-loop feedback algorithm estimates crop water use during the control interval from the mass balance among supplied nutrient solution volume (V_{supply}), drainage volume (V_{drain}), and substrate water storage changes (ΔS) using Equation (5) [76]:

$$WU = V_{supply} - V_{drain} - \Delta S \quad (5)$$

where WU is crop water use during the control interval. When evapotranspiration is required on an area and time-normalized basis, the water balance should additionally be divided by the represented cultivation area and measurement interval. This algorithm closes the control loop using the measured response of the root zone, estimating crop absorption and evapotranspiration from the mass balance among supplied nutrient solution, drainage, and changes in substrate water storage [8,77]. In a weighing system, the substrate mass provides a direct estimate of water storage change, whereas in a moisture sensor system, the volumetric water content is converted to an equivalent storage term after calibration. Table 5 shows the recommended corrections for the substrate conditions observed.

Table 5. Recommended corrections for observed substrate conditions.

Observed Condition	Substrate Status	Drainage Status	Recommended Correction	References
Water deficit	Below target moisture or weight	Low	Increase irrigation volume by a bounded percentage	[40]
Balanced root zone	Within target band	Within target ratio	Maintain baseline volume	[41]
Excess water	Above target moisture or weight	High	Reduce irrigation volume or extend interval	[40]
Sensor inconsistency	Moisture and drainage signals conflict	Uncertain	Hold last safe command and request validation	[71]

The drainage feedback is delayed because drainage may occur several minutes after irrigation. Consequently, each correction should be based on a complete response window rather than immediate post-irrigation readings. Load cells require vibration isolation and temperature compensation, whereas moisture sensors require substrate-specific calibration and periodic verifications. Sensor plausibility checks are essential because an obstructed drain line, leaking emitter, or displaced sensor can generate false control signals.

5.3. Irrigation Volume Control Based on Temperature and Humidity

This algorithm compensates for atmospheric conditions that are not fully represented by radiation. It compares measured air temperature and relative humidity with upper and lower control zones, and the irrigation volume is increased or decreased according to the deviation from these zones. Under similar radiation and substrate conditions, a decrease in aboveground humidity generally increases evaporative demand and may justify a larger irrigation volume. High light combined with warm, dry air typically increases transpiration and nutrient transport. The irrigation volume is adjusted according to atmospheric evaporative demand represented by VPD. VPD is computed from air temperature and relative humidity, as shown in Equation (6) [76]:

$$VPD = e_s(T)\left(1 - \frac{RH}{100}\right) \quad (6)$$

where $e_s(T)$ is the saturation vapor pressure calculated using the Tetens equation. VPD integrates the effects of temperature and humidity on crop transpiration, higher VPD values indicate increased water demand and justify higher irrigation volumes.

The EC response must be implemented conservatively. When the selected production protocol requires a lower nutrient concentration or a modified water to nutrient ratio at higher temperatures, the controller may reduce the target EC or adjust the solution concentration within agronomic limits. This action should not be generalized without crop-specific validation because temperature, transpiration, source-water quality, and drainage fraction interact to determine the root zone EC [30]. Table 6 shows temperature and humidity-based irrigation control strategies under different greenhouse climate conditions.

Table 6. Temperature and humidity-based irrigation control strategies under different greenhouse climate conditions.

Temperature Zone	Humidity Zone	Likely Demand	Control Action	References
Within target	Within target	Normal	No climate correction	[38,73]
High	Low	High transpiration demand	Increase volume or shorten interval within limits	[33,73]
High	High	Heat stress with restricted transpiration possible	Use cautious correction, prioritize climate control	[33,38]
Low	High	Low evaporative demand	Reduce volume or extend interval to avoid saturation	[33,73]
Low	Low	Moderate drying but low metabolic demand	Small correction based on substrate feedback	[38,41]

5.4. Integrated Four-Algorithm Control Architecture

Rather than operating in isolation, these four algorithms can be integrated into a cohesive hierarchical control architecture. The solar radiation proportional algorithm establishes the baseline daily volume, the radiation-rate algorithm adapts to rapid microclimatic shifts, the supply drainage feedback loop corrects for root zone dynamics, and the temperature-humidity algorithm applies supervisory atmospheric compensation. Together, this rule-based hierarchy provides a transparent and interpretable framework for autonomous control in warm-season greenhouse crops such as tomatoes and paprika. Its potential lies in combining anticipatory radiation-based control, real-time root zone feedback, and climate-responsive adjustment, though further commercial validation is needed to confirm its robustness across diverse production environments [78].

5.5. Comparison of Nutrient Supply Algorithms

The four nutrient supply algorithms differ mainly in their control inputs and response mechanisms. Solar radiation-proportional scheduling provides a simple feedforward baseline by adjusting irrigation according to accumulated radiation, whereas the radiation-rate-based algorithm responds more dynamically to short-term changes in radiation by modifying both irrigation volume and EC. Supply-drainage and substrate feedback provide closed-loop control based on actual root zone water status, allowing for more precise correction of irrigation but requires reliable sensors and accounting for delayed drainage responses. In contrast, temperature-humidity correction acts as a supervisory layer that compensates for atmospheric demand not fully represented by radiation. Overall, these algorithms are most effective when integrated, combining anticipatory radiation-based control, real-time root zone feedback, and climate-responsive adjustment to achieve stable

and adaptive nutrient management [79,80]. Table 7 shows the control stages and functions of the integrated nutrient supply algorithm for smart greenhouse nutrient management.

Table 7. Control stages and functions of the integrated nutrient supply algorithm for smart greenhouse management.

Control Stage	Function	Reference
Acquire	Solar radiation ($MJ \cdot m^{-2}$), air temperature (°C), relative humidity (%), vapor pressure deficit (kPa), nutrient solution EC ($dS \cdot m^{-1}$), supply volume (mL), drainage volume (mL), substrate weight (g) or volumetric water content (%)	[40,42,71]
Validate	Sensor integrity checks: range validation, missing-data detection, drift compensation, stuck-sensor identification, cross-sensor consistency algorithms	[71]
Baseline	Calculation of cycle-specific radiation threshold and zone irrigation volume	[12,42]
Feedforward correction	Adjustment of irrigation volume and EC based on radiation accumulation rate	[12,42,73]
Feedback correction	Closed-loop correction using substrate storage capacity and drainage fraction to refine irrigation volume	[40–42]
Climate supervision	Supervisory adjustment using bounded temperature, RH, and VPD thresholds, prevents condensation and heat-stress imbalance	[73,81]
Actuate and log	Actuation verification: zone valve operation, delivered volume confirmation, logging of command-response data for traceability and model calibration	[40,42,71]

6. Crop Specific Applications in Tomato and Paprika

The effectiveness of nutrient supply algorithms ultimately depends on their ability to accommodate the physiological characteristics and nutrient requirements of individual crops. Although tomato and paprika share many similarities as high value greenhouse crops, important differences exist in nutrient uptake patterns, sensitivity to environmental conditions, and responses to nutrient management. Consequently, nutrient supply algorithms developed for one crop cannot always be directly transferred to another without calibration and adaptation. Understanding crop-specific nutrient dynamics is therefore essential for developing effective smart nutrient supply systems [14,28,32]. Modern greenhouse nutrient management systems increasingly incorporate crop-specific growth models, nutrient demand profiles, and environmental response functions to improve nutrient-use efficiency and maintain crop productivity.

6.1. Tomato-Specific Nutrient Management

Tomato nutrient management during reproductive development requires particular attention to calcium (Ca) and potassium (K) supply and transport. Electrical conductivity (EC) provides a useful indication of the total ionic strength of the nutrient solution, but it does not directly quantify individual nutrient concentrations, consequently, an apparently acceptable EC can coexist with insufficient or imbalanced availability of specific ions [22,47]. This limitation is particularly relevant for Ca because its delivery to developing fruit depends largely on xylem transport and plant–water relations [82]. Tomato fruit have relatively low transpiration rates and limited xylem transport compared with vegetative tissues, which can restrict Ca delivery during periods of rapid fruit growth [82]. Disturbances in Ca

homeostasis, together with irregular water supply and environmental stress, are strongly associated with blossom-end rot (BER) development [44].

Atmospheric conditions further influence Ca transport. High vapor pressure deficit (VPD) can modify transpiration and Ca partitioning between vegetative tissues and fruit, and recent evidence has demonstrated that VPD regulation during specific tomato growth stages can affect fruit Ca accumulation, yield, and fruit quality [36]. Therefore, radiation-based irrigation scheduling can provide an anticipatory baseline for estimating crop water demand, but radiation alone may not adequately represent the conditions controlling Ca movement to the fruit. Integration of VPD information with root zone moisture, EC, and drainage measurements could provide more responsive correction when atmospheric and substrate conditions deviate from the expected range. Potassium management should similarly be adjusted according to crop development because K uptake increases markedly from flowering through fruit set, while the response to K supply is also influenced by plant water status and irrigation regime [83,84]. Accordingly, nutrient supply algorithms for tomato should emphasize crop-stage-specific calibration of Ca and K management rather than assuming that a single EC target or control strategy is universally robust.

6.2. Paprika Specific Nutrient Management

For paprika, maintaining a stable root zone water and nutrient environment is particularly important during reproductive growth and fruit development. Paprika transpiration responds not only to incoming radiation, but also to atmospheric VPD and substrate moisture conditions. Tai et al. [85] demonstrated that models combining radiation and VPD predicted paprika transpiration more accurately than radiation alone and that substrate moisture affected plant growth and fruit productivity. These findings indicate that atmospheric demand and root zone water status should be considered together when determining irrigation and nutrient solution supply.

Root zone EC and drainage are also important control variables in soilless paprika production. Shin and Son [42] showed that an irrigation strategy incorporating accumulated radiation, drainage rate, and substrate EC provided more precise control of the root zone environment than conventional radiation-based scheduling alone. Maintaining stable substrate conditions is important because increasing EC can reduce plant water availability and modify transpiration, whereas excessive fluctuations in moisture and drainage can produce alternating periods of water and osmotic stress. Consistent with this response, Salinas et al. [43] reported substantial reductions in total and marketable sweet pepper yield and fruit weight as salinity increased, together with deterioration in plant–water relations and increased incidence of BER was reported [19,43]. Irrigation and nutrient supply also interact strongly in determining paprika yield, quality, and resource-use efficiency [13,14,86]. Consequently, EC adjustments in paprika should be conservative and coordinated with substrate moisture and drainage feedback rather than implemented as isolated increases or decreases in nutrient solution concentration [13,42]. Crop cultivar, developmental stage, substrate characteristics, and greenhouse climate should therefore be included when calibrating operational EC and irrigation thresholds.

6.3. Growth Stage-Specific Implications

The relative importance of nutrient and environmental control variables changes throughout crop development, supporting the use of growth-stage-specific rather than fixed nutrient-management strategies. During the vegetative stage, nutrient management should support canopy establishment and adequate nitrogen availability, while radiation-based scheduling can provide a practical baseline for estimating water and nutrient solution demand under relatively stable root zone conditions. However, nutrient uptake patterns

change substantially as plants enter reproductive development. In hydroponically grown tomato, the uptake rates of major ions increased markedly after flowering and during fruit set, with a particularly high uptake of K and Ca compared with earlier developmental stages [74,87]. Thus, the transition from vegetative to reproductive development represents an important point at which nutrient supply algorithms should become more responsive to ion-specific demand and plant water status.

During flowering and fruit set, greater emphasis should be placed on maintaining Ca and K availability while simultaneously avoiding water stress that could restrict nutrient transport. In tomato, this stage-specific approach is particularly relevant because VPD influences Ca distribution and subsequent fruit development [36]. In paprika, the combined influence of radiation, VPD, and substrate moisture on transpiration similarly indicates that both aerial and root zone conditions should be incorporated into irrigation decisions [84]. As fruit enlargement and ripening progress, maintaining stable substrate moisture, EC, and drainage becomes increasingly important for limiting osmotic stress and supporting consistent fruit development and quality [13,43]. These stage-related responses should be interpreted as guidelines for adaptive control rather than fixed prescriptions because optimum set points can vary with cultivar, substrate, greenhouse climate, crop load, and production objective.

6.4. Comparative Algorithm Implications

Comparison of tomato and paprika suggests that radiation-, VPD-, and root zone-based control approaches should be viewed as complementary components of an integrated nutrient-management architecture rather than as competing alternatives. Radiation-based control provides a useful feedforward component because incoming radiation is closely associated with crop transpiration and short-term water demand. However, radiation does not fully account for changes in atmospheric humidity, crop development, or substrate conditions. Incorporating VPD provides an additional supervisory variable representing atmospheric evaporative demand; this is particularly relevant to tomato because of the relationship between transpiration conditions and Ca transport to developing fruit and is also useful for improving transpiration estimation in paprika [36,85,88].

Root zone monitoring can subsequently provide closed-loop correction through measurements of substrate moisture, EC, and drainage. The relative weighting of these inputs should differ between crops. In tomato, the control strategy should place greater emphasis on maintaining conditions favorable for Ca and K transport during fruit set and enlargement, with VPD and root zone information used to correct a radiation-based baseline. In paprika, substrate moisture, EC, and drainage feedback should receive stronger emphasis because changes in root zone water and salinity conditions directly affect transpiration, water status, yield, and fruit quality [13,43]. Therefore, a hierarchical strategy consisting of a radiation-based feedforward baseline, VPD-based supervisory adjustment, and root zone feedback correction represents a promising framework for both crops, while allowing crop- and growth-stage-specific differences in control priorities. Nevertheless, this integrated framework should be regarded as a conceptual basis for adaptive nutrient management rather than a universally validated control strategy. Further validation under commercial greenhouse conditions, different cultivars, substrate types, seasons, and elevated-temperature environments is required before fixed operational thresholds can be recommended [89].

Overall, nutrient supply algorithms have evolved from simple EC and pH threshold-based systems to advanced AI-driven and hybrid frameworks. Conventional algorithms remain important because of their simplicity, reliability, and low implementation cost, but they lack the adaptability and nutrient-specific control required for precision nutri-

ent management. Climate-based, mechanistic, and AI-driven approaches provide greater adaptability and improved accuracy, though they demand more sensors, calibration, computational resources, and technical expertise. Current evidence suggests that hybrid intelligent systems, which integrate physiological models, real-time sensor data, nutrient monitoring, and machine learning, represent the most promising direction for future autonomous nutrient management [90,91]. Figure 6 shows the classification framework of nutrient supply algorithms, and Table 8 shows crop-specific quantitative responses and algorithm implications for tomato and paprika.

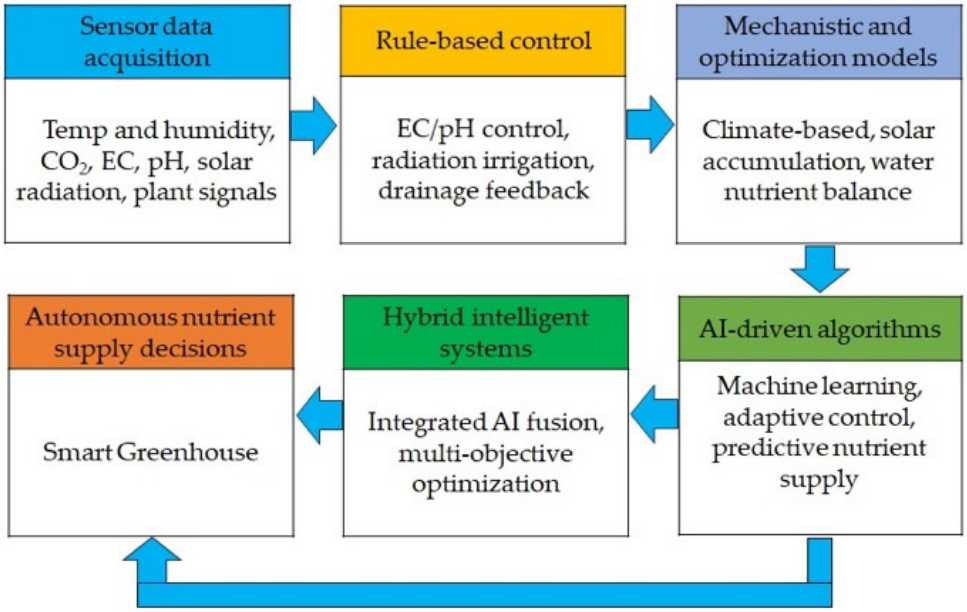


Figure 6. Classification framework of nutrient supply algorithms.

Table 8. Crop-specific quantitative responses and algorithm implications for tomato and paprika.

Feature	Tomato	Paprika	Algorithm Implication	Reference
Major fruit-stage concern	High Ca demand during fruit expansion; Ca deficiency associated with blossom-end rot (BER)	Fruit growth and marketable yield highly sensitive to nutrient and water availability during fruit development	Crop-stage-specific nutrient management	[44,85]
Response to VPD	Elevated VPD increases transpiration and Ca transport demand; excessive VPD may increase BER risk	Fruit growth and transpiration strongly affected by VPD and radiation conditions	VPD-adaptive irrigation with root zone feedback	[36,85]
Radiation control	Solar radiation is a reliable predictor of crop water demand	Radiation-driven irrigation commonly used to estimate transpiration requirements	Radiation-driven feedforward irrigation scheduling	[13,42,85]
Root zone feedback	Substrate moisture and drainage fraction indicate irrigation adequacy and nutrient uptake conditions	Root-zone water content and EC directly affect fruit yield and quality	Closed-loop substrate moisture and EC control	[13,42,85]
EC/salinity response	Excessive EC may restrict Ca uptake and increase physiological disorders	Yield reduction occurs when salinity exceeds crop tolerance limits	EC threshold protection and nutrient-solution adjustment	[43,44]
BER response	BER strongly associated with inadequate Ca transport under water-stress conditions	Salinity and moisture stress can indirectly reduce fruit quality	Calcium-stress mitigation and fruit-quality correction	[43,44]

7. Comparative Evidence Synthesis

7.1. Comparative Performance of Nutrient-Supply Algorithms

EC/pH algorithms generally provide strong regulation of solution concentration and acidity but provide limited information on crop water demand or individual nutrient status. Radiation-based methods improve irrigation timing relative to fixed-time scheduling and require comparatively inexpensive sensors. Root zone and drainage-feedback systems more directly characterize actual system response but require additional sensors and appropriate delay handling. Ion-specific and mechanistic systems provide stronger nutrient-level information but require substantially greater calibration. AI/ML systems can provide high predictive accuracy for specific tasks but are more dependent on data quantity, training conditions, and validation strategy. Quantitative synthesis should therefore report comparable metrics separately rather than combine unrelated indicators into a single performance score.

Control accuracy should be evaluated relative to the principal objective of each algorithm. For EC/pH systems, relevant metrics include set-point error, overshoot, settling time, and concentration stability. For environmental irrigation algorithms, appropriate measures include irrigation timing error, transpiration or ET prediction accuracy, drainage stability, and substrate moisture deviation. For nutrient-specific systems, ion-concentration prediction or control error is more informative than total EC. For AI/ML approaches, RMSE, MAE, R^2, classification accuracy, and prediction horizon should be reported alongside external validation results. This metric specific approach prevents misleading comparisons between fundamentally different control objectives.

Water-use efficiency, nutrient-use efficiency, drainage fraction, fertilizer loss, nutrient discharge, crop yield, and fruit quality are particularly important for evaluating whether improved control performance translates into agronomic benefit. Dynamic nutrient management can reduce unnecessary nutrient discharge by aligning supply more closely with crop uptake. Closed-loop and drainage-feedback systems provide additional opportunities for water and nutrient recycling, while ion-specific control may reduce over-application caused by EC-based replenishment. These resource indicators should be reported together with crop productivity because reductions in water or nutrient supply are beneficial only when yield and quality are maintained.

7.2. Validation Scale and Commercial Readiness

Commercial readiness varies considerably among nutrient and irrigation control approaches because sensing requirements, control complexity, and validation scales differ substantially. Conventional EC/pH control and accumulated-radiation-based irrigation are already compatible with commercial greenhouse climate computers and therefore have comparatively high implementation readiness [19,57]. Root-zone and drainage-feedback strategies have also progressed toward practical application, particularly where substrate moisture, weighing meters, or drainage measurements are available. However, their performance depends strongly on sensor placement, calibration, maintenance, and the representativeness of local measurements. Ion-specific monitoring and control remain less mature because sensor drift, cross-sensitivity, fouling, calibration frequency, and long-term stability continue to restrict reliable operation under commercial conditions.

Mechanistic and AI/ML-based control systems have shown increasing capability for prediction, optimization, and adaptive decision support, but most studies remain limited to individual facilities, crops, seasons, or relatively short experimental periods. Consequently, model transferability, robustness to changing environmental and management conditions, and integration with existing greenhouse control infrastructure remain important barriers to broader adoption. Commercial readiness should therefore be evaluated not only according to predictive accuracy or short-term control performance, but also according to long-term

reliability, maintenance requirements, interoperability, scalability, and economic feasibility. Long-duration, multi-season, and multi-facility validation is therefore essential before research-scale control strategies can be considered commercially mature.

7.3. High Temperature Adaptability

High-temperature adaptability provides an additional criterion that is not captured by general algorithm accuracy. EC/pH control has relatively low intrinsic temperature adaptability because environmental effects are represented only after they alter nutrient solution conditions. Radiation-based feedforward control has moderate adaptability because radiation is associated with transpiration but cannot fully represent heat and humidity interactions. VPD or transpiration-based approaches provide stronger atmospheric responsiveness. Root zone feedback is particularly valuable under heat because it identifies whether increased atmospheric demand has actually produced substrate drying, salt accumulation, or excessive drainage. Ion-specific, mechanistic, and hybrid approaches provide the greatest theoretical capacity to separate water demand from nutrient demand, although their practical advantage depends on sensor reliability. Table 9 shows a comparative synthesis of nutrient-control algorithms.

Table 9. Comparative synthesis of nutrient control algorithms.

Approach	Prediction/Control Target	Quantitative Performance	Comparative Result	Reference
LSTM	Root zone EC prediction, sweet pepper	Good predictive capability for root-zone EC under the evaluated greenhouse conditions	Performed better than the alternative recurrent architectures	[17]
LSTM + multi-task learning	Six root zone macronutrient ions	Moderate-to-good capability for simultaneous nutrient-ion prediction	Potential of multi-task learning for nutrient-specific monitoring	[92]
VegSyst mechanistic model	Dry-matter production	Good agreement between predicted and observed crop growth	Mechanistic modeling can adequately represent crop biomass accumulation	[93]
VegSyst mechanistic model	N uptake	Accurately represented crop nitrogen uptake patterns	Strong potential for estimating crop-specific nutrient demand	[93]
VegSyst mechanistic model	K uptake	Generally reliable prediction of potassium uptake	Mechanistic models can support nutrient-demand estimation	[93]
PID nutrient-mixing control	Target K^+ concentration	Stable regulation of the target potassium concentration	Demonstrated that appropriately tuned PID control can provide effective real-time regulation of nutrient concentration	[7]
PID-flow-rate comparison	K^+ nutrient mixing	Maintained nutrient-concentration control across different flow-rate conditions	Demonstrates speed–accuracy trade-off	[7]
Event-based predictive controller	Tomato substrate–water control	Reduced irrigation water use while maintaining control performance	Predictive event-based control can improve water-use efficiency without substantially compromising root-zone water regulation	[41]
Radiation + root zone feedback	Paprika irrigation	Maintained substrate moisture and EC within a more stable operating range	Provided more effective regulation of substrate conditions	[42]
Radiation + root zone feedback	Paprika productivity/resource use	Improved transpiration efficiency and crop productivity	Potential to improve both resource-use efficiency and crop performance	[42]

7.4. Characteristics and Limitations of the Evidence Base

The 90 included studies were published between 2011 and 2026 and comprised 72 research articles, 2 conference papers, and 16 reviews. Of these, 22 addressed tomatoes, 8 pepper or paprika, 4 lettuce or Chinese chive, and 56 did not specify a single crop. The four lettuce and Chinese chive studies were included for their transferable nutrient-solution sensing, pH control, and fertigation-scheduling methods (Section 2.3) and were not used for crop-specific conclusions. Where the cultivation system was specified, 21 studies involved hydroponic systems, and 20 involved soilless substrate systems. The evidence base has several limitations: outcome metrics were heterogeneous, which prevented quantitative pooling; many control studies reported prediction or control accuracy without crop yield, NUE, or WUE; validation was frequently limited to one facility and one season; and few studies reported sensor calibration intervals or failure rates. These limitations should be considered when interpreting the comparative ratings in Sections 7.1–7.3.

8. Technical Challenges and Research Roadmap

Despite rapid progress, autonomous greenhouse nutrient management remains constrained by sensor reliability, algorithm transferability, data availability, system interoperability, and commercial implementation costs. Sensor performance remains a fundamental bottleneck. EC and pH sensors are inexpensive and mature but provide limited nutrient specificity. Ion-selective electrodes provide more detailed information but remain vulnerable to drift, interference, fouling, and frequent calibration. Plant-based sensors provide valuable physiological information but still require robust interpretation before they can be used routinely for direct control. The second challenge concerns algorithm transferability. Parameters developed for a specific crop, cultivar, greenhouse, substrate, emitter configuration, or climate may not remain valid under different conditions. Radiation thresholds, VPD targets, root zone moisture limits, nutrient ratios, and model coefficients therefore require systematic evaluation across crop stages and seasons.

A third limitation is data fragmentation. Greenhouse datasets are commonly collected using different sensor frequencies, variable definitions, control systems, and experimental protocols. This restricts the development of generalizable AI models and makes quantitative comparison among studies difficult. Standardized datasets and reporting protocols should therefore include environmental variables, root zone conditions, nutrient composition, irrigation commands, drainage, crop stage, crop response, and sensor-quality indicators. Fourth, nutrient, irrigation, climate, lighting, and crop-monitoring systems are often managed through independent controllers. Future systems require interoperable architectures capable of exchanging sensor information and coordinating control decisions. Fifth, AI-based systems require greater interpretability. Explainable AI, physics informed machine learning, constrained optimization, and hybrid modeling may reduce the risk associated with purely black-box control while increasing grower confidence.

Future research should progress toward a hierarchical closed-loop architecture comprising the following functional stages. Figure 7 shows a flow of activities in nutrient management from sensing through to adaptive correction.

At the sensing level, EC/pH measurements should be combined progressively with ion-specific monitoring, environmental sensors, root zone sensing, drainage measurements, and crop-response measurements. At the decision level, rule-based safety constraints should be combined with mechanistic or predictive demand estimation. At the actuation level, controllers should independently regulate irrigation volume, pulse frequency, nutrient concentration, nutrient composition, and drainage targets rather than combining all decisions into a single undifferentiated command [93,94]. At the feedback level, actual solution delivery, root zone response, drainage, and crop response should be compared with

predicted values. Digital twins, reinforcement learning, and hybrid mechanistic–machine-learning models provide promising long-term opportunities, but their implementation should occur within agronomically defined safety boundaries rather than replace established crop-management knowledge.

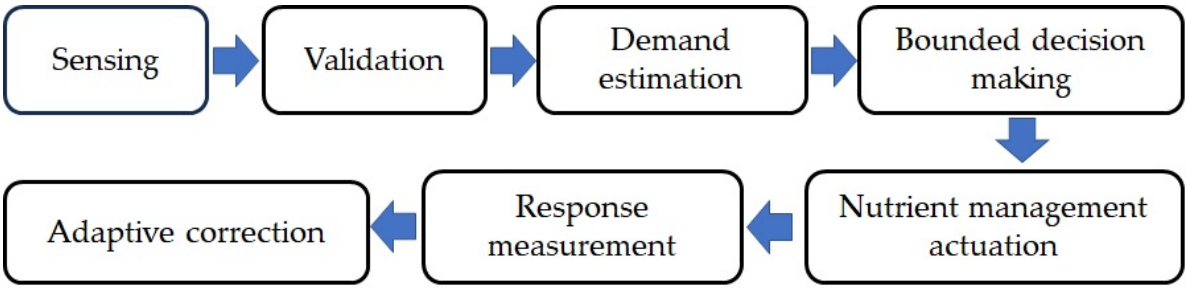


Figure 7. Flow diagram for nutrient management in soilless greenhouses.

A major research priority is experimental validation specifically under elevated-temperature conditions. Future studies should intentionally evaluate combinations of high air temperature, high root zone temperature, varying VPD, and high radiation instead of treating temperature as an incidental environmental variable. Responses should also be evaluated across vegetative, flowering, fruit-set, fruit-development, and ripening stages. Commercial trials should extend across complete production seasons and quantify yield, fruit quality, WUE, NUE, nutrient discharge, sensor failure frequency, maintenance requirements, computational cost, and economic benefit. Figure 8 shows the research roadmap toward heat responsive autonomous greenhouse nutrient management.

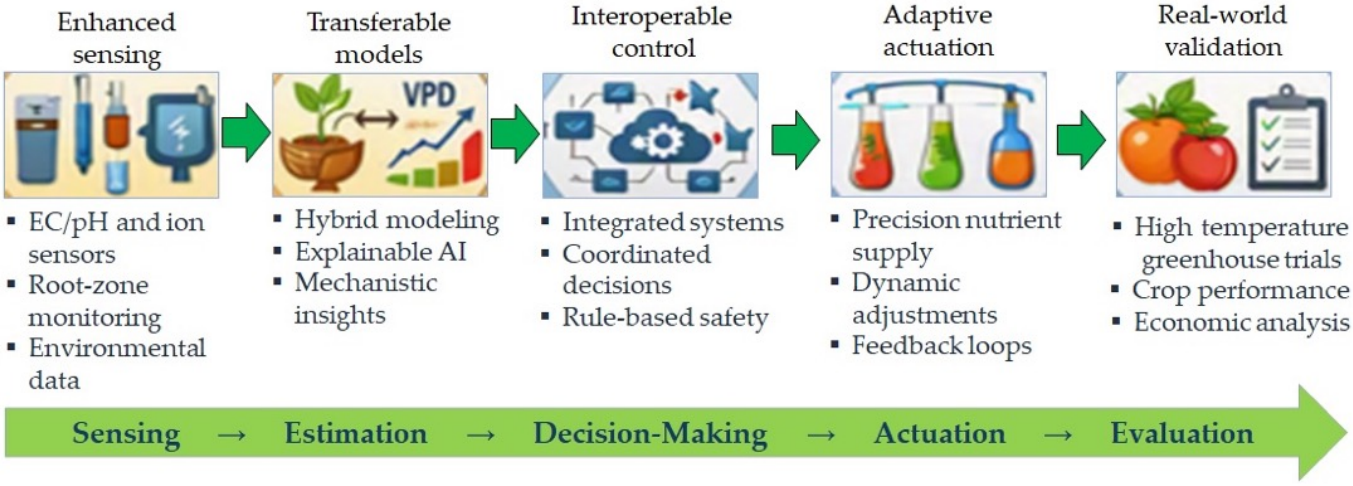


Figure 8. Research roadmap toward heat-responsive autonomous greenhouse nutrient management.

Limitations of This Review

This review has several limitations. The protocol was not registered in advance, and one eligibility criterion was amended during screening (Section 2.3), although all records were re-screened against the revised criteria. The amendment may have influenced which studies were included. Only English-language publications from five sources were searched, and SpringerLink and grey literature were not searched systematically, so relevant studies may have been missed. Title/abstract screening was assisted by keyword rules and a large language model; although every decision was checked manually by a reviewer, automated pre-classification may have introduced systematic errors, and records lacking technology-related terms in their titles and abstracts may have been excluded at that stage. A total of 194

reports could not be retrieved in full text, which may have led to the omission of relevant evidence. Finally, the heterogeneity of crops, systems, and outcome metrics precluded meta-analysis, and the comparative ratings are therefore qualitative.

9. Conclusions

This systematic review synthesized 90 studies and three from textbooks on technology-based nutrient management for warm-season crops in controlled environments. Nutrient management in greenhouse tomato and paprika production is governed by interactions among crop developmental stage, atmospheric demand, solar radiation, root zone conditions, nutrient concentration, and physiological response. These interactions become particularly important under elevated-temperature conditions because increasing temperature may increase transpiration and water demand while excessive heat, high humidity, root zone warming, or crop stress can restrict nutrient uptake. Temperature should therefore not be treated as a simple proportional indicator of nutrient requirement. Greenhouse nutrient-management technologies demonstrate a progression from EC/pH threshold and PID control toward radiation- and transpiration-based feedforward control, root zone and drainage feedback, nutrient-specific monitoring, mechanistic modeling, AI/ML prediction, and hybrid intelligent systems. These approaches provide different and complementary functions rather than representing mutually exclusive alternatives.

EC/pH and radiation-based methods remain attractive because of their simplicity and commercial maturity. Root zone and drainage measurements strengthen closed-loop control by representing actual substrate response. Ion-specific sensing improves nutrient-level regulation, while mechanistic models provide physiological interpretation. AI/ML methods offer greater capacity for representing non-linear interactions but increase requirements for sensor reliability, representative datasets, calibration, computing infrastructure, and external validation. The following are priorities for research, not established findings. The hierarchical closed-loop architecture proposed here is a hypothesis. In it, crop-stage nutrient requirements set baseline targets, radiation or transpiration models estimate short-term demand, root zone and drainage measurements provide feedback correction, ion-specific measurements constrain nutrient composition, and temperature, humidity, VPD and root zone temperature provide supervisory heat-response control. Because few included studies tested these strategies under explicitly imposed high temperatures, the architecture has not been validated as a whole. Four needs follow from this:

1. Ion-specific sensing: long-term reliability under commercial conditions, including drift, cross-sensitivity, fouling and calibration frequency.
2. Mechanistic modelling: parameterization and testing across crop stages, cultivars and explicit high-temperature regimes.
3. AI/ML: independent, external validation across facilities and seasons, with standardized datasets and reported performance metrics.
4. Commercial validation: full-season, multi-facility trials that report yield, quality, WUE, NUE, nutrient discharge, sensor failure, and economic benefit.

Future research should emphasize standardized evaluation metrics, explicit warm-season experiments, sensor fault tolerance, crop- and development stage transferability, independent validation, interoperable control systems, and full-season commercial trials. These developments are necessary for smart greenhouse nutrient management to progress from isolated automated functions toward reliable, interpretable, resource efficient, and self-adaptive nutrient-control systems.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agronomy16212169/s1, Table S1: Full-text reports excluded at the eligibility stage, with reasons for exclusion; Table S2: PRISMA 2020 checklist.

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