Review Article

Multispectral Imagery Remote Sensing for Monitoring Nutrient Deficiency of Onion *(Allium cepa)* under Automated Drip Fertigation System in Greenhouse: A Review

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DOI: 10.14416/j.asep.2026.03.005
Received: 1 October 2025; Revised: 9 November 2025; Accepted: 9 February 2026; Published online: 31 March 2026

Abstract
Onion (Allium cepa) is a globally significant crop; however, its productivity is often constrained by inefficient water delivery and poor nutrient management. Advances in precision agriculture technologies, including multispectral remote sensing (MRS) and automated drip fertigation systems, offer promising solutions for sustainable onion cultivation. This review synthesizes current research on the principles, applications, and challenges associated with integrating MRS and fertigation systems in greenhouse environments, with particular emphasis on Israeli-type protected structures, which are known for their high water-use efficiency. Spectral indices such as NDVI, NDRE, GNDVI, and PRI can detect nutrient deficiencies and water stress up to two weeks before visual symptoms appear, thereby enabling timely corrective actions. MRS-guided automated fertigation has been shown to reduce water consumption by up to 25% and improve nutrient-use efficiency by approximately 18% under controlled conditions. However, several challenges remain, including high capital costs, complex data-processing requirements, signal interference due to greenhouse structures, and limited farmer training. This review also highlights key research gaps, such as the need for onion-specific spectral calibration models, robust multimodal data fusion frameworks, and cost-effective precision technologies tailored for developing countries. Overall, precision agriculture holds significant potential to enhance the sustainability and profitability of onion production while contributing to climate-smart agricultural practices.

Keywords: Automated drip fertigation, Climate-smart agriculture, Israeli-type greenhouse, Onion, Multispectral remote sensing, Precision agriculture, Spectral indices

1 Introduction

Onion *(Allium cepa)* is one of the most economically important vegetable crops worldwide, valued not only as a culinary staple but also for its nutritional and medicinal properties [1]. Global onion production has steadily increased, with Asia, particularly India and China, dominating cultivation. At the same time, Israel and other Mediterranean countries have developed advanced greenhouse systems to stabilize supply and improve bulb quality [2], [3]. Despite the crop's significance, onion production remains vulnerable to water scarcity, nutrient imbalances, and pest and disease outbreaks, which collectively reduce yields and quality [4], [5].

Precision agriculture (PA) offers a suite of tools to address these constraints by integrating sensing technologies, data analytics, and automated control systems for site–specific management [6]. Among these technologies, multispectral remote sensing has emerged as a cost–effective method to monitor crop vigor, nutrient status, and water stress at both field and greenhouse scales [7], [8]. In onion, recent remote sensing work using multispectral and Sentinel–2 data has shown that vegetation indices can effectively estimate canopy chlorophyll content, leaf area index, and overall plant vigor, allowing nutrient deficiencies to be detected [9], Multispectral indices such as Normalized Difference Vegetation Index (NDVI), Green NDVI (GNDVI), and Soil Adjusted Vegetation Index (SAVI) have been widely correlated with leaf chlorophyll, nitrogen (N), and sulfur (S) content in onion, enabling early detection of deficiencies before visual symptoms appear [10].

In parallel, automated drip fertigation systems are increasingly adopted in controlled environments, Israeli–type greenhouses, a structural design characterized by tall sidewalls, roof ventilation, and UV–stabilized polyethylene covering that allows high light transmission and durability under tropical conditions, where precise irrigation and nutrient delivery are critical under conditions of water scarcity [11], [12]. These systems allow dynamic adjustment of water and nutrient inputs, and automated fertigation creates, where spectral signals directly inform irrigation and nutrient scheduling [13], [14]. However, the integration of multispectral and automated drip fertigation in onion production is still in its early stages. While significant progress has been reported in crops such as tomato, potato, and cereals [15], [16], onion–specific studies remain limited. Moreover, challenges such as greenhouse spectral distortions, calibration of spectral threshold, and the high cost of deployment constrain wider adoption of the integrated multispectral and automated drip fertigation system.

Consequently, this review aims to critically synthesize existing literature on the integration of multispectral remote sensing and automated drip fertigation systems for onion production under a protected environment. This review first examines the fundamental concepts and principles of multispectral sensing platforms; then explores the application of spectral indices for detecting nutrient and water stress in onion; subsequently analyses the integration of automated drip fertigation and sensing technologies with emphasis on economic feasibility, data management, and calibration challenges; and finally identifies key research gaps, socio–economic barriers, and opportunities for sustainable adoption among smallholder farmers in the Philippine context.

2 Applications of Remote Sensing Tools in Onion Production

2.1 *Remote sensing tools*

Remote sensing technologies have advanced rapidly in recent years, offering powerful tools for monitoring crop status, diagnosing nutrient deficiencies, and optimizing resource use in precision agriculture. In onion production, remote sensing platforms have been applied successfully in studies of related crops such as maize, wheat, and other vegetables [17]. Table 1 shows the key applications of these tools.

Table 1: Remote sensing tools.

Remote Sensing Tool	**Spectral Index**	***Application in Onion***	**References**
RGB drone imagery	Object–based image analysis	Weed and crop vigor mapping, 85% classification accuracy in spatial variability detection	[18]
Multispectral UAV	NDVI, GNDVI	Nutrient Monitoring in the early detection of deficiencies before visible symptoms	[19]
Hyperspectral imaging	550–700 bands	Sulfur and Nitrogen stress for a strong correlation with leaf nutrient status	[20]
Thermal Imaging	Canopy temperature	Water stress detection in 2–3 days before wilting	[21]
Satellite imagery	MODIS Sentinel–2	Large–scale crop monitoring for regional onion production forecasting	[22], [23]

2.2 *Multispectral UAVs*

The multispectral camera is equipped with vegetation indices, including NDVI and GNDVI, which are widely applied for nutrient monitoring. In onion production, these indices enable early detection of nitrogen and sulfur deficiencies [19]. Vegetation indices such as NDVI, GNDVI, SAVI, and more specialized chlorophyll indices exploit differences in red and NIR reflectance that correlate with chlorophyll content and canopy structure. The underlying physiology is well established: chlorophyll absorbs visible red and blue light. Stress that alters leaf structure changes reflectance patterns, which are detectable by vegetation indices tuned to often correlate better with N status. Similar applications in cereals and leafy vegetables confirm the strong indices for detecting chlorophyll–related stress. Vegetation indices are indirect proxies to capture canopy chlorophyll and structure, not nutrient concentrations. Correlations vary with canopy stage, cultivar, soil background, and illumination, so indices must be validated for species, growth stage, and environment.

Several studies demonstrate that multispectral approaches can monitor biophysical variables and predict yield variability. Multispectral indices and tailored transforms have shown superior spatial sensitivity in the onion compared to generic NDVI in some field studies [24]. UAV and ground–based sensors have both been used; inter–platform comparisons reveal scale and resolution effects that are important for narrow–row crops like onions. Most onion remote sensing work remains field–based rather than greenhouse. Field studies benefit from strong contrast and uniform illumination at scale; greenhouse conditions need artificial light, reflective structures, container substrates, and different canopy microclimates that change spectral responses and can invalidate calibration developed in open fields. Consequently, the direct transfer of field–derived vegetation indices thresholds to greenhouses is risky without greenhouse–specific calibration and validation [25].

Recent papers evaluate affordable multispectral modules and handheld devices and compare them with research–grade hyperspectral systems. Low–cost multi–spectral sensors show promise for routine monitoring and on–plant measurements and have limitations in spectral resolution and signal–to–noise. It is critical when discriminating between subtle nutrient differences. Hyperspectral sensors provide richer spectral signatures useful for diagnosing specific nutrient deficiencies that are costlier and demand more complex processing [26]. For greenhouse operations, sensor selection must balance spectral sensitivity, integration ability, cost, and maintenance. Several studies call for cross–validation of a low–cost sensor laboratory for tissue N analyses before operational use.

2.3 *Multispectral sensing platforms and principles*

The traditional RGB cameras offer high spatial resolutions, even at significant altitudes, and are generally more cost–effective compared to other sensor types; however, their capacity for spectral data is limited. Multispectral cameras offer high spatial resolution and comprehensive reflectance data across a few bands, with broader bandwidths typically much pricier than RGB cameras [27]. Multispectral cameras, once primarily used for Remote Sensing (RS) tasks through satellites and crewed aircraft, are increasingly being utilized in photogrammetry. Additionally, the widespread adoption of Unmanned Aerial Vehicles (UAVs) has created a demand for smaller sensors, leading to the availability of a diverse selection of relatively affordable and lightweight cameras. As a result, compact multispectral cameras attached to UAVs present an efficient and cost–effective method for capturing airborne radiometric data. Given the rising interest in such sensors for photogrammetric applications, calibrating the cameras is a crucial step to ensure accurate geometric and reliable information [28]. Five bands are simultaneously captured by this camera from separate lens cones: two in the invisible region, and Red Edge and Near Infrared, three in the visible region, such as Red, Green, and Blue. With five comparable lens cones and sensors, the MicaSense Red Edge–M multi–lens multispectral camera (Figure 1) has certain unique design features. Software that can be used to extract and analyze patterns that are not readily visible to humans already exists, allowing us to fully utilize the potential that remotely sensed data offers. This provides early information that is not readily visible to the naked eye by providing a window into the growth cycle.

Figure 1: Multispectral camera.

A multispectral camera is one of the most widely adopted technologies in precision agriculture due to its capacity to detect subtle changes in crop physiology that are not visible to the human eye. Multispectral sensors capture reflectance at discrete spectral bands, typically in the visible (VIS: 400–700 nm), red edge (RE: 700–740 nm), and near–infrared (NIR: 740–1,100 nm) regions [29].

The near infrared region is highly sensitive to leaf pigments, canopy structure, and water content, making it suitable for diagnosing nutrient deficiencies, water stress, and disease pressure [30]. Vegetation indices derived from spectral band ratios are commonly used to interpret crop conditions. The Normalized Difference Vegetation Index (NDVI) is commonly used to monitor green biomass, canopy vigor, and nitrogen. However, NDVI often saturates in dense canopies such as onions at advanced growth stages. To address this limitation, green NDVI replaces the red band with the green band, and the Soil–Adjusted Vegetation Index (SAVI), which minimizes soil background effects, has been increasingly applied in vegetable crops [30], [31].

More advanced indices, such as the Photochemical Reflectance Index (PRI), exploit narrow spectral features to assess photosynthetic light–use efficiency and stress responses [32]. Studies in onions have shown that PRI, when combined with NDVI or GNDVI, enhances the detection of early nitrogen and sulfur deficiencies, allowing corrective fertigation before irreversible yield losses occur [33].

In a controlled environment, multispectral sensing faces challenges due to light scattering, reflection, and absorption by greenhouse covers, which can distort spectral signatures. Recent advances, however, demonstrate that UAV–mounted multispectral sensors, when calibrated with reference panels, can generate reliable indices under greenhouse conditions [34]. Machine learning approaches are improving the interpretation of these indices by linking spectral features to chlorophyll, nutrient uptake, and bulb development with higher accuracy than traditional regression [35]. The images were taken using a MicaSense RedEdge–M multi–lens multispectral camera with the specifications given in Table 2. This camera captures five bands from independent lens cones, three in the visible part of the spectrum (red, green, and blue) and two in the part (RedEdge and Near Infrared).

Table 2: Multispectral camera specifications.

Parameter	Units	Dimensions
Focal Length	Mm	5.4
Sensor Size	Mm	4.8 x 3.6
Resolution	Pixels	1280 x 960
Pixel Size	µm	3.75
FOV	H° x V°	47.9 x 36.9
Weight	G	163
Dimensions	cm	9.4 x 6.3 x 4.6

*MicaSense, 2017

2.4 *Vegetation indices*

Conventional methods for detecting plant diseases tend to be slow and expensive; there is a need for a faster and more affordable alternative provider for early warning farmers to avert pest and disease outbreaks and facilitate timely intervention [36]. Monitoring nutrient deficiencies in onion crops using multispectral imaging has gained traction as precision agriculture technologies advance. Vegetation indices, computed from spectral reflectance ratios of visible and near–infrared wavelengths, provide quantitative indicators of crop health, chlorophyll concentration, and stress response. NDVI remains the most widely used due to its simplicity and effectiveness in capturing plant [37]. However, its tendency to saturate at high canopy density and sensitivity to soil background can limit performance in sparsely planted onion fields.

To address the limitations of NDVI, methods have been employed to enhance sensitivity to chlorophyll and nitrogen variations during early onion growth [38]. Similarly, the Normalized Difference Red–Edge Index (NDRE), using the red–edge wavelength instead of the red band, improves detection of nitrogen and magnesium deficiencies before visual symptoms appear [39]. These red–edge–based indices leverage multispectral sensors to capture subtle physiological responses to nutrient stress.

Soil background effects are a problem in onions, whose narrow leaves and sparse canopy often expose bare soil. The Soil Adjusted Vegetation Index (SAVI) incorporates a correction factor (L= 0.5) to minimize soil interference, making it suitable for early–season monitoring [40]. Meanwhile, the Visible Atmospherically Resistant Index (VARI), based only on visible bands, offers a cost–effective alternative for UAV–based monitoring when NIR bands are unavailable [41]. Although VARI's sensitivity to deep chlorophyll loss is lower, it remains valuable for the rapid visual detection of stress patterns in smallholder systems.

Multispectral–based vegetation index calculation provides a non–destructive and scalable method to diagnose onion nutrient deficiencies. Selection of the most appropriate VI depends on the sensor configuration, crop growth stage, and canopy density. Red–edge indices are most effective for early detection of N and Mg deficiencies, while NDVI and SAVI remain practical for monitoring overall growth and vigor in operational settings. Integrating these into automated fertigation systems could enhance nutrient management and optimize fertilizer use efficiency in onion cultivation.

2.4.1 Vegetation index calculation

Vegetation indices, which are mathematical combinations of reflectance values from different spectral bands, are widely used in precision agriculture to assess crop health, nutrient status, and early stress symptoms that often appear late. Vegetation indices offer a non–destructive and timely method for monitoring plant conditions. Table 3 summarizes the primary vegetation indices used for diagnosing nutrient–related stress in onion fields, highlighting the formulas, diagnostic purposes, and supporting literature.

Table 3: Vegetation indices for monitoring nutrient deficiency in onion.

Vegetation Index	Formula	Purpose	Ref.
Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - Red}{NIR + Red}$	General crop vigor, canopy density, nitrogen, and chlorophyll status	[39], [40]
Green Normalized Difference Vegetation Index (GNDVI)	$\frac{NIR - Green}{NIR + Green}$	Nitrogen content and chlorophyll concentration; early stress detection	[40],[44]
Normalized Difference Red Edge Index (NDRE)	$\frac{NIR - Red\ edge}{NIR + Red\ edge}$	Early detection of nitrogen, sulfur, and magnesium deficiencies	[41]
Soil Adjusted Vegetation Index (SAVI)	$\frac{((NIR - Red)(1 + L)}{(NIR + Red + L)}$ L = 0.5	Reduces soil background effects; effective in sparse onion canopies	[42]
Photochemical Reflectance Index (PRI)	$\frac{(Green - Yellow)}{(Green + Yellow)}$	Photosynthetic efficiency and stress response to nutrient imbalance	[41]

3 Water Use Efficiency for Onion Production

Onion is a shallow–rooted, high–value vegetable with substantial irrigation demand. Improving water use efficiency (WUE) in onion production is essential where water is scarce. Recent field studies and analyses report consistent WUE gains from drip systems, deficit irrigation strategies, and combined fertilizer–irrigation management [45]. Drip irrigation and subsurface drip irrigation significantly enhance WUE in onion production, 45% water saving, and 30% higher WUE under drip compared to furrow irrigation. Irrigating at 85% of crop evapotranspiration to maintain yield and increase WUE by 18% compared to full irrigation in arid regions. Conversely, water deficits by > 70% ET caused significant yield reductions. Scheduling irrigation based on soil moisture sensors to ensure efficient water allocation and prevent stress–induced bulb shrinkage. Integration of remote sensing and crop simulation models further improves precision irrigation [46].

Nutrient management strongly influences plant water productivity. Balanced fertilization supports photosynthetic efficiency and root activity, allowing plants to maintain yield under limited water supply [47]. Fertigation system through drip irrigation enhances both nutrient use efficiency and water use efficiency by synchronizing nutrient availability with plant demand. Studies highlight that fertigation can increase WUE by up to 20% compared to conventional fertilizer broadcasting.

The comparison of irrigation systems shown (Table 4) clear progression in water use efficiency (WUE) as irrigation methods shift from conventional surface applications to precision–based technologies. Surface furrow irrigation, characterized by a broad and uneven wetting pattern, exhibited the lowest WUE (30–45%), largely due to substantial conveyance losses, surface runoff, and deep percolation beyond the effective root zone. These inefficiencies are consistent with previous findings showing that furrow irrigation often results in non–uniform soil moisture distribution and suboptimal water uptake by onion crops, particularly under variable field conditions [48].

Table 4: Irrigation system.

Irrigation System	Wetting Pattern	Water Use Efficiency (%)	Ref.
Surface, Furrow	Broad, uneven	30–45	[48]
Sprinkler	Circular, Uniform	50–70	[49]
Drip, Trickle	Localized near the root zone	80–85	[50]
Automated Drip + Fertigation	Targeted sensor–based	90–98	[51]

3.1 *Automated drip fertigation system*

An automated drip fertigation system integrates scheduling with nutrient delivery with sensors and programmable controllers. This approach reduces human error while ensuring uniform root–zone moisture and nutrient availability. Recent controlled–environment studies have demonstrated potential reductions of up to 30% in water use and 15% in fertilizer inputs, without adversely affecting crop yield [52].

The system comprises nutrient tanks, venturi injectors or dosing units, solenoid valves, and sensors that monitor soil pH, electrical conductivity [53]. A programmable controller governs the timing and quantity of water and nutrient application. At the same time, the Arduino or Raspberry Pi processes real–time sensor data to adjust fertigation frequency and nutrient concentration dynamically. Advancements in spectral feedback systems now enable the integration of vegetation indices into fertigation control loops, allowing irrigation and nutrient delivery to respond automatically to crop stress thresholds [54].

Across the literature, a consistent emphasis is placed on the precision calibration of nutrient injection systems, which is critical for synchronizing fertilizer application with the crop's changing nutrient requirements. Studies highlight that fertigation efficiency largely depends on stage–specific calibration, where nutrient concentration and injection timing are tailored to distinct phenological stages. Rather than converging on a universal approach, current research reflects an ongoing debate regarding the optimal calibration frequency and the appropriate level of automation required for nutrient management in controlled–environment agriculture.

A growing body of works demonstrates that linking multispectral imagery data to fertigation controllers provides real–time diagnostic feedback for nutrient management. Vegetation indices such as NDVI and NDRE have been widely used as early indicators of nitrogen and chlorophyll status. Still, their sensitivity to environmental noise remains a limiting factor, such as greenhouse illumination and canopy occlusion [55]. The consensus suggests that integrating these indices with sensor–based EC and pH monitoring enhances precision but demands robust calibration studies that remain limited compared with tomato and lettuce, underscoring a critical research gap in developing species–specific spectral thresholds.

Furthermore, comparative analyses highlight that while automated systems have successfully demonstrated improved water and nutrient use efficiency of 15–30% in several horticultural crops, challenges persist regarding data harmonization, hardware costs, and farmer training for sensor maintenance. Thus, the current trajectory of research converges on a hybrid framework that blends automated control with human oversight, ensuring reliability while maintaining operational flexibility. Overall, evidence across the literature positions automated, feedback–driven fertigation as a promising but still–evolving strategy toward sustainable, resource–efficient greenhouse production, and the automation intensity must suit local power reliability and farmer skills. Low–cost analog timers or GSM–based alerts remain viable in limited areas, whereas IoT–linked controllers offer scalability for larger fields.

3.1.1 *Automation system block diagram*

The automated drip fertigation system follows a structured flow, starting with regular soil moisture checks at predetermined intervals. The system checks nutrient levels. If the moisture level is below the set parameters, the system activates the fertigation process using a doser to mix nutrients into the irrigation water. After confirming the water flow through the drip lines. Real–time monitoring of flow rates, moisture, and nutrient levels continues throughout this process, with adjustments made to prevent over–irrigation or over–fertilization. Simultaneously, a data logger and real–time clock (RTC) record all readings and system operations for analysis and future optimization. Once irrigation and fertigation are complete, the solenoid valve closes, and the system pauses until sensor data prompts reactivation, ensuring efficient and precise nutrient and water management for the crops. Figure 2 illustrates an automation system block diagram designed to control irrigation and fertigation in an onion field using real–time sensor feedback and programmable logic. It shows how different components interact to deliver the correct mixture of water and fertilizer based on field conditions. The two preparation units: Fertilizer preparation and water preparation. These components store and prepare the inputs needed for drip irrigation. Both units supply materials to the dripping system. One provides fertilizer, and the other provides water. The combination of these inputs forms the mixture that is eventually delivered to the onion field. Central to the system is the Programmable Controller, which receives data from different sensors and gives commands to actuators. From the field, soil moisture is captured by a moisture sensor, and NPK data are collected through an NPK sensor. Information from the water preparation unit is also fed into the controller. After processing these inputs, the controller sends ON/OFF signals to the actuators, regulating the flow from the fertilizer preparation tank and water tank, where the prepared fertilizer–water mixture is delivered through the dripping system.

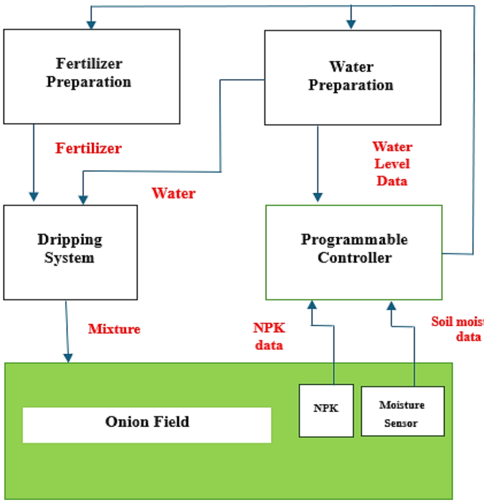

Figure 2: Automation system block diagram.

3.2 *Drip irrigation system design procedure*

The outline below is the design procedure from determining the crop water requirement to selecting a number and appropriate emitters, and layout arrangements for achieving an efficient drip irrigation system based on PAES 224:2017–Design of a Pressurized Irrigation System Part B [55], shown in Equations (1)–(9).

3.2.1 Crop water requirements

The water requirement is considered localized evapotranspiration based on the formula below. This was computed on a monthly or decadal basis.

$$ETcrop - loc = ETa \times kr \tag{1}$$

Where:
ETcrop-loc–localized evapotranspiration, mm/day
ETa–actual evapotranspiration, mm
kr–ground cover reduction factor

3.2.2 Leaching requirements

$$\mathrm{LR_t} = \frac{\mathrm{EC_w}}{2\mathrm{x}[\mathrm{maxEC_e}]} \tag{2}$$

Where:
LR–leaching requirement (mm/day)
LRt–leaching requirement ratio under drip irrigation
IRn–net irrigation requirement (mm/day)
Ea–application efficiency (%)

3.2.3 Irrigation requirements

$$IR_g = \frac{ETcrop-loc}{Ea} - \mathrm{R} + \mathrm{LR} \tag{3}$$

Where:
IRg–gross irrigation requirement (mm/day)
ETcrop-loc–localized evapotranspiration (mm/day)
Ea–application efficiency (%)
R–rainfall (mm/day)
LR–leaching requirement (mm/day)

3.2.4 Percentage wetted area

$$P_w = \frac{100 \text{ x Np x Se x W}}{\text{Sp x Sr}} \tag{4}$$

Where:
Pw–percentage wetted area (%)
W–wetted width or width of the wetted strip along the lateral with emitters (m)
Sr–distance between plant rows or row spacing (m)

3.2.5 Number of emitters per plant and emitter spacing

$$N_p = \frac{Area\ per\ plant\ x\ P_w}{A_w} \tag{5a}$$

Where:
Np–number of emitters per plant
Pw–percentage wetter area/100 (%/100)
Aw–area wetted by one emitter

$$S_e = \frac{S_p}{N_p} \tag{5b}$$

Where:
Se–Emitter spacing (m)
Sp–Distance between the plants within a row (m)
Np–Number of emitters per plant

$$A_w = \frac{\pi \ x \ D^2}{4} \tag{5c}$$

Where:
Aw–area wetted by one emitter (m²)
D–diameter of the wetted area (m)

3.3 *Design emission uniformity*

In drip irrigation, emission uniformity is a key metric to indicate the expected variation in flow rates from emitters along lateral lines [56]. Several factors influence the uniformity of an irrigation system, such as the emitter manufacturing quality, land slope, hydraulic design, and emitter response to changes in pressure, temperature, and potential clogging [57]. Among these, inconsistencies in emitter production have a major effect on the performance of drip irrigation systems, due to variations in pressure head within the pipe network [58]. Moreover, design deficiencies involving inadequate pressure can reduce the uniformity of water distribution, resulting in inconsistent flow rates [59]. As a result, the Philippine Agricultural Engineering Standard (PAES)–224 (2017) specifies the design criteria for emission uniformity in drip irrigation systems, considering the manufacturer's coefficient of variation of the emitters, their discharge rates, and the average discharge rate within a sub–unit [35].

$$E_u = 100 \text{ x } \frac{1-2.27 \, cv}{(\sqrt{Np})} \text{ x } \frac{qm}{qa} \tag{6}$$

Where:
Eu–design emission uniformity (%)
Np–numbers of emitters per plant
Cv–manufacturer's coefficient of variation
qm–minimum discharge for minimum pressure in the subunit (L/h)
qa–average or design emitter discharge for the subunit (L/h)

3.4 *Irrigation scheduling for enhanced water productivity*

Efficient irrigation scheduling is widely recognized as a cornerstone for improving agricultural water productivity and maintaining crop yield under constrained water availability. Contemporary reviews of precision irrigation technologies report that integrating data–driven scheduling with improved conveyance and distribution systems substantially increases water–use efficiency while mitigating the environmental footprint of irrigated agriculture. Precision irrigation approaches are being promoted as pivotal for climate–resilient water management in unnecessary applications, and match water delivery more closely to crop demand [60].

Irrigation scheduling approaches in the literature are grouped into three categories: soil moisture and water balance, plant stress indicators, and phenology and evapotranspiration. Soil–based methods offer direct site–specific control and have been shown to improve irrigation timing and reduce over–irrigation when sensors are properly calibrated and maintained. ET–based methods scale well for regional planning and are often combined with remote sensing inputs to estimate crop water demand; plant–based methods can detect stress earlier but are more labor–intensive. Comparative reviews of hybrid frameworks that combine methods to achieve the best balance of accuracy and operational feasibility [39]. Remote sensing, networked soil sensors, and Internet of Things–assisted controllers are rapidly reshaping scheduling practice. Recent syntheses show that satellite and UAV–derived indices combined with soil moisture and micrometeorological data enable scalable, near–real–time estimation of crop water status and irrigation need. Advances in low–cost soil moisture sensors, wireless telemetry, and machine–learning models for short–term soil moisture forecasting further support automated scheduling and can reduce labor and human error. The data quality and connectivity provided are managed. Nonetheless, barriers remain for many smallholders, including upfront costs, sensor maintenance, and the need for localized calibration [40].

Deficit irrigation emerges repeatedly in analyses and reviews as an effective strategy to raise crop water productivity by applying less water than full crop evapotranspiration while accepting controlled yield reductions. Global syntheses find that drip irrigation often increases water–use efficiency but may reduce yields to varying degrees depending on crop, the growth stage at imposition, and local conditions; therefore, optimal drip irrigation levels are crop–specific. The literature thus recommends staged and regulated deficit approaches and coupling drip irrigation with improved nutrient management to mitigate yield loss while capturing water saving [41].

3.4.1 Determination of water productivity

Water productivity refers to the effectiveness of water utilization in agricultural systems for producing output, usually represented as crop yield or economic return per unit of water consumed.

- Physical Water Productivity

This is the ratio of crop yield to the amount of water used in crop production. It can be calculated as:

$$WP_p = \frac{Crop\ yield\ (kg)}{Total\ Water\ used\ \ (m^3\ or\ mm)} \tag{7}$$

- Irrigation Water Productivity

Used in irrigation systems, excluding rainfall. It is calculated as:

$$\mathrm{IWP} = \frac{Crop\ yield\ (kg)}{Total\ Water\ Used\ (m^3 or\ mm)} \tag{8}$$

- Water Use Efficiency

This refers to the efficiency of a crop in utilizing water. It is calculated

This refers to the productivity of the water as:

$$\mathrm{WUE} = \frac{Crop\ yield\ (kg)}{Water\ used\ (m^3 or\ mm)} \tag{9}$$

4 Onion Production in the Philippines

The Department of Agriculture announced the country's onion output, expecting a rise of 105.28% in the second quarter of 2024. This increase is projected from the 84,903.99 metric tons noted in the second quarter of 2023 to 174,288.98 MT this year [61]. Onion *(Allium cepa)* is a staple vegetable in Philippine cuisine and an important cash crop. Production is concentrated in a few regions, and high seasonality, periodic supply shocks, and postharvest losses characterize the sector. Annual production and area planted have shown irregularity due to climatic events, pest outbreaks, and import decisions. National estimates and sector roadmaps indicate rapid year–to–year fluctuation in output and area, emphasizing the crop's vulnerability to shocks.

A range of local and introduced cultivars is grown, including short–day and intermediate types adapted to local planting windows. Agronomic practices reported across studies in raised bed planting, spacing, and seedling transplanting schedules, fertilization regimes tailored to soil tests, and reliance on irrigation for off–season production. Variety evaluation studies aim to improve yield and adaptability, but adoption depends on seed availability and farmer economics [41], [42].

4.1 *Onion pests and diseases*

The fall armyworm *(Spodoptera frugiperda)* is a highly destructive invasive pest that poses a major threat to onion production. Since its detection in the Philippines in 2016, farmers have struggled to control infestations that have caused severe yield losses, damaging over 800 hectares of onion fields. In response, many growers have become heavily dependent on chemical pesticides, leading to financial strain and escalating production costs. This excessive pesticide use has also contributed to the pests' resistance, trapping farmers in an unsustainable cycle of increasing chemical application and declining effectiveness [62]. Moreover, climate change is altering the pest's geographic range, further intensifying its impact on the environment and agricultural systems [63].

Thrips *(Thrips tabaci)* and related vectors, purple blotch *(Alternaria porri),* Stemphylium blight *(Stemphylium vesicarium)*, anthracnose twister *(Colletotrichum gloeosporioides)*, and bulb rots are recurrent constraints. These pests and diseases reduce bulb quality and yield, and outbreaks have been associated with substantial production losses in local reports. Integrated pest management, resistant varieties, and proper cultural practices are widely recommended [43].

4.2 *Nutrient management in precision fertigation*

Effective nutrient management is a fundamental component of precision fertigation systems for onion production. Nutrient deficiencies, including nitrogen (N), phosphorus (P), potassium (K), sulfur, manganese (Mn), zinc (Zn), and iron (Fe), manifest through distinct physiological and visual symptoms such as chlorosis, yellowing, tip burn, and overall stunted growth. Each deficiency affects specific metabolic pathways critical for bulb formation and photosynthetic efficiency. Corrective nutrient applications are tailored to the specific deficiency identified. Urea serves as a rapid nitrogen source, while diammonium phosphate supplies both nitrogen and phosphorus. Potassium sulphate (K_2SO_4) is commonly used to correct potassium and sulfur deficiencies, ensuring optimal ionic balance and osmotic regulation within plant tissues. Under precision fertigation, these nutrient solutions are delivered at controlled intervals and concentrations, improving uptake efficiency and reducing nutrient losses compared to conventional broadcast fertilization [64].

Maintaining a balanced nutrient supply is essential for achieving uniform bulb development, size, and storability [44]. Imbalances in nitrogen and sulfur reduce chlorophyll synthesis and photosynthetic activity, leading to lower biomass accumulation and altered spectral reflectance in the near–infrared (NIR) region [45]. Integrating nutrient monitoring through soil and tissue analyses or sensor feedback adjustments that sustain plant vigor, optimize yield, and enhance postharvest quality. Practical recommendations emphasize the balance and early application of nitrogen and sulfur fertilizers to maintain chlorophyll formation and enzymatic activity throughout the growth cycle [46]. These approaches collectively enhance bulb uniformity, productivity, and postharvest quality in precision onion cultivation [47].

4.2.1 Precision Nitrogen, Phosphorus, and Potassium Management in Automated Fertigation Systems

Nitrogen (N), phosphorus (P), and potassium (K) serve distinct yet interdependent functions in onion *(Allium cepa)* physiology, influencing chlorophyll synthesis, bulb development, and the plant's capacity to tolerate abiotic stress. Conventional fertilizer practices that rely on uniform, blanket applications often lead to nutrient imbalances, reduced nutrient use efficiency (NUE), and increased environmental losses through leaching and volatilization. In contrast, precision fertigation, which delivers NPK in controlled, crop–specific doses, has emerged as a transformative approach for optimizing NUE and improving bulb quality under greenhouse and controlled environment systems. Recent studies indicate that data-driven nutrient scheduling can increase bulb yield and uniformity while minimizing nitrate accumulation in the soil profile [65].

Through precision fertigation, nutrient application can be dynamically adjusted according to the phenological stage of onion growth, supplying higher nitrogen concentrations during vegetative development and increased potassium during bulb expansion. Normalized Difference Vegetation Index (NDVI) and Green NDVI (GNDVI) have proven effective in monitoring canopy nitrogen status, facilitating automated nutrient regulation via fertigation software integrated with valve control systems. In onion cultivation, NPK management significantly influences bulb size, total soluble solids (TSS), and dry matter accumulation. Experimental findings have demonstrated that the nitrogen source and concentration can alter the mineral composition and antioxidant activity of short–day onion varieties, emphasizing the need for precisely tuned N supply [66]. Likewise, machine learning–based nutrient modelling has enabled real–time adjustments of the N: K ratio, improving yield stability and reducing input costs [67]. Integration of these approaches into IoT–enabled fertigation systems allows growers to automate nutrient delivery based on real–time canopy reflectance data derived from multispectral imaging, bridging the gap between plant sensing and adaptive nutrient control [68].

Each macronutrient contributes uniquely to onion growth and quality: nitrogen promotes vigorous leaf and protein synthesis; phosphorus supports robust root and flower development; and potassium regulates osmotic balance and strengthens plant defences against pathogens. However, while NPK fertilization effectively boosts yield, excessive application poses serious environmental and soil degradation risks, including nutrient runoff and salinity [69]. Under greenhouse conditions, phosphorus management requires particular attention due to its low soil mobility; thus, precision drip fertigation ensures localized phosphorus availability near the root zone, fostering early bulb establishment and stronger vegetative growth. Potassium plays a critical role in maintaining osmotic balance and disease resistance, and modern automated monitoring systems can now adjust potassium application rates in response to Normalized Difference Red Edge (NDRE) signals, which correlate with photosynthetic efficiency [70].

This integration of spectral monitoring with automated nutrient dosing represents a dynamic, feedback–driven strategy for sustainable onion production. Future research should prioritize region–specific calibration of fertigation algorithms and the validation of spectral indices against ground–truth nutrient assays to ensure economic viability and environmental sustainability across diverse growing systems.

5 Soil Moisture

Soil moisture is a pivotal factor in agricultural systems because it governs the availability and movement of nutrients in the soil–plant continuum. When water is either deficient or in excess, plant survival and productivity are jeopardised. In regions with low rainfall, maintaining soil moisture above a threshold often results in greater economic returns from nutrient applications, as sufficient moisture facilitates nutrient uptake and root activity. Indeed, soil moisture directly affects nutrient solubility, ion exchange, microbial mineralisation, and root access to nutrients.

5.1 *Measurement of soil moisture*

Soil moisture measurement is fundamental to precision irrigation and nutrient management, as it directly influences plant–water relations and overall crop productivity. Broadly, soil water content can be quantified through direct and indirect methods. Gravimetric analysis involves oven–drying soil samples to determine water loss, which remains the most accurate but is labour–intensive and destructive, making it unsuitable for continuous monitoring. Indirect methods enable real–time, non–destructive measurement by exploiting the dielectric or thermal properties of soil. These include tensiometers, neutron probes, time–domain reflectometry (TDR), and capacitance sensors, which offer reliable estimations of volumetric water content with varying spatial resolutions and cost implications.

Recent advancements in remote sensing technologies have extended soil moisture monitoring from point–scale to field and regional–scale analysis, integrating data into decision support systems for irrigation scheduling. However, high–resolution, continuous monitoring over large areas remains constrained by equipment cost, calibration requirements, and spatial variability in soil texture and structure [71]. Traditional field techniques, such as gravimetric sampling, neutron scattering, and tactile testing, continue to serve as practical benchmarks for sensor calibration and ground–truthing in precision irrigation research. A critical challenge lies in balancing measurement accuracy, spatial representativeness, and affordability to support sustainable, data–driven water management across diverse farming systems.

5.2 *Soil analysis report*

Soil analysis serves as a diagnostic tool for understanding soil fertility, structure, and nutrient dynamics that underpin sustainable crop production. A well–conducted soil analysis report provides detailed information on macronutrients and micronutrients, along with essential soil health parameters such as pH, cation exchange capacity, electrical conductivity, and organic matter content [72], [73]. These data–driven frameworks improve spatial accuracy in nutrient management in heterogeneous field conditions common in tropical and semi–arid agroecosystems. However, ensuring that smallholder farmers can access and interpret soil analysis data remains a persistent barrier to adoption in developing regions [74].

Recent studies highlight the environmental co–benefits of soil testing, noting reductions of 15–30% in fertilizer use and parallel improvements in soil organic carbon when recommendations are based on periodic soil analysis. Life cycle assessments further suggest that soil testing contributes to reduced greenhouse gas emissions by aligning fertilizer inputs with actual crop requirements. Despite these advantages, the timeliness and frequency of soil testing remain critical; many growers still rely on single pre–season soil analyses, neglecting mid–season nutrient dynamics that could inform fertigation adjustments.

To address these challenges, emerging research promotes IoT–integrated soil monitoring systems that capture parameters such as EC, moisture, and temperature, feeding real–time data into predictive nutrient management algorithms. When combined with traditional soil reports, these systems create hybrid monitoring frameworks capable of both long–term fertility assessment and short–term management optimization. Future studies should focus on standardizing analytical protocols and harmonizing laboratory sensor calibration datasets across agroecological zones to enhance the comparability and interpretability of soil analysis reports worldwide.

5.3 *Economic feasibility and smallholder adoption*

The capital costs of remote sensing and automation are nontrivial and may exceed the investment capacity of individual smallholders in many regions. However, the alternative models can improve feasibility: sensor service providers, cooperative ownership, low–cost sensor bundles, and incremental adoption. Recent reviews underline that economic justification depends on crop value, scale, and water and nutrient prices; high-value protected onion production and cooperative models are likely to recover investments through yield and input savings at commercial scale [75].

The high upfront cost is real and meaningful for Philippine smallholders, but several economic and delivery methods, such as service providers, cooperatives subsidies, and shared infrastructure, are clear evidence of input–savings and yield and profit improvements, which means the investment can be justifiable if the system is adapted and supported.

Multispectral sensors, UAV platforms, and automation hardware carry substantial capital and operating costs for hardware purchase, maintenance, data connectivity, and training, and complexity is a major adoption barrier. Government and independent assessments emphasize this point: high up–front costs and technical complexity limit access for smaller farms and require policy intervention to avoid excluding resource–poor growers [76].

Nevertheless, existing literature highlights the agronomic and environmental benefits of precision agriculture technologies, which can offset their initial investment costs over time. Numerous reviews and field-based case studies report measurable reductions in fertilizers, water, and energy. When effectively implemented, precision systems such as sensor–based fertigation, variable–rate application, and automated irrigation have demonstrated both economic and ecological gains, with the fertilizer savings of 10–30% and increased yield of 5–20% across diverse cropping systems. Life–cycle assessment (LCA) studies further reveal that precision agriculture can enhance farm profitability while significantly lowering greenhouse gas emissions, nutrient leaching, and the overall environmental footprint of crop production [77]. However, these positive outcomes are contingent upon proper calibration, farmer training, and long-term management support, emphasizing that technological efficiency must be paired with practical capacity–building for sustainable adoption. These benefit streams from the economic argument for investment [78].

For smallholders in the Philippines who operate small plots, have limited cash liquidity, and face variable market access, it is rarely viable. Adoption studies and analyses show farm size, access to capital, and farmer education strongly influence uptake of PA [79]. In practice, the technology becomes justifiable when developed via alternative delivery mechanisms: service provider models, cooperative ownership of equipment, shared sensor networks, rental UAVs, and targeted subsidies. Such models reduce the per–farm capital burden while capturing the agronomic benefits at scale [80].

Policy levers and practical steps that make adoption justifiable for smallholders include:

- subsidized pilot or demo farms and training programs to lower knowledge barriers and demonstrate Return on Investment (ROI)
- grants for farmer cooperatives to purchase shared equipment
- public–private partnerships that finance sensor networks and local UAV service providers
- development of simple, user–friendly decision–support apps that translate spectral maps

Philippine government analyses also recommend combining digital infrastructure investments with extension services to make digital agriculture inclusive, with a practical cost–benefit framing to estimate the total cost of ownership for a basic multispectral and IoT fertigation setup, annual savings from fertilizer and water, and payback period under different scenarios. Sensitivity analyses in recent reviews show payback periods shrink when equipment is shared and when fertilizer savings exceed 15%, a plausible figure reported in precision agriculture case studies [77].

6 Growth Phases of Onion

Onion (Allium cepa) exhibits a distinct sequence of physiological growth phases from establishment, vegetative, bulb initiation, bulb enlargement, and maturity, which are characterized by specific morphological and biochemical processes that dictate yield, bulb quality, and nutrient requirements (Table 5). Understanding these growth stages is fundamental for optimizing irrigation, nutrient management, and pest control practices within precision agriculture systems.

Table 5: Growth phases of onion.

Growth Phase	Numerical Growth Stage	Approximate days after planting	Description
Germination	1	7–30 days	Radicle and flag led to the emergence
Leaf Growth	2	30–70 days	1 to 4 true leaves
Bulb Initiation	3	70–90 days	5 to 7 true leaves
Bulb Growth	4	90–150 days	The bulb diameter is twice that of the neck
Maturation	5	More than 150 days	Bulb enlargement near completion

6.1 *Germination*

This initial phase begins at seed germination and lasts until the seedling is fully established, typically within 2 to 3 weeks after sowing or transplanting. Root initiation and leaf primordia development dominate during this stage. Successful establishment requires well–drained, aerated soils with optimal temperature at 20 to 25^o and moisture conditions to promote uniform germination. Prolonged saturation or crusted soils limit oxygen diffusion, reducing root vigor and stand uniformity.

6.2 *Leaf growth*

During the vegetative phase, which spans roughly 30 to 45 days after transplanting, the plant undergoes rapid leaf expansion and root proliferation. Nitrogen demand peaks during this stage, as it fuels chlorophyll formation, photosynthetic efficiency, and biomass accumulation. Deficiencies in nitrogen, stunted growth, and reduced leaf area index ultimately constrain assimilate availability for bulb formation. Precision fertigation studies show that stage–specific nitrogen and potassium supply enhances leaf vigor and reduces leaching losses in greenhouse onion systems.

6.3 *Bulb initiation*

Bulb initiation begins once environmental cues, such as photoperiod and temperature, trigger the transformation of the basal stem into a storage organ. The phase typically commences when plants have developed 7 to 10 functional leaves. Short–day cultivars initiate bulb under 10 to 12 hours of daylight, while long–day types require 14 to 16 hours. Adequate phosphorus and potassium supply during this phase promotes efficient carbohydrate translocation and root–to–bulb energy partitioning.

6.4 *Bulb growth*

This is the most yield–determining stage, characterized by rapid cell expansion and carbohydrate accumulation in bulb tissues. Optimum soil moisture and potassium levels are vital, as both deficits and excesses can restrict bulb growth to fungal diseases. Precision irrigation, guided by soil moisture sensors and remote sensing indices, ensures that water and nutrients are delivered in synchrony with crop demands. Studies under semi–arid conditions report that maintaining soil water potential at 70 to 80% field capacity maximizes bulb size and water use efficiency.

6.5 *Maturation*

In the maturation phase, leaves senesce, photosynthetic activity declines, and assimilates are remobilized to the bulb. Outer bulb scales desiccate and form protective layers that influence storability. Irrigation is gradually reduced to promote curing, while excess nitrogen or late watering can delay maturity and impair storage quality. This phase culminates 90–110 days after transplanting, depending on cultivar and environmental conditions.

7 Simulation and Analytical Layout

To ensure reproducibility and transparency, a standardized computational environment is established using Python 3.10, supported by analytical and geospatial libraries in NumPy (1.25.2), Pandas (2.2.2), Scikit–learn (1.3.0), XGBoost (2.1.5), Rasterio (1.3.8), and GeoPandas (0.13.2). The environment is containerized using Docker, ensuring consistency across operating systems and allowing precise version control. All dependencies were documented in the environment configuration and requirements files to facilitate replication by other researchers [81].

The analytical framework comprised three major modules: (1) data preprocessing, (2) model training and validation, and (3) fertigation control simulation [82]. In the preprocessing module, UAV–acquired multispectral images were radiometrically calibrated and geometrically corrected using ground control points, followed by orthomosaic generation via Pix4D Mapper or GIS tools. Multispectral bands were then aligned with ground–truth data of soil and leaf nutrient analyses (N, P, K) and chlorophyll indices derived from SPAD and Leaf Color Chart (LCC) meters. This integration enabled pixel–level correlation between vegetation indices and actual nutrient concentration across the onion canopy, forming a foundation for predictive model development [83].

In the model training and validation module, learning algorithms are used to estimate nutrient deficiencies based on vegetation indices. Predictive performance was assessed through the Root Mean Square Error (RMSE) and the coefficient of determination (R^2), ensuring reliability and generalization of the models. A feature importance analysis was also conducted to identify the most sensitive spectral indices influencing nutrient prediction accuracy, providing insights into wavelength responsiveness under greenhouse conditions [84].

The fertigation control simulation module integrated trained models into an IoT–based fertigation management framework, simulating variable–rate nutrient and water application according to predicted crop requirements. This digital twin system dynamically adjusted irrigation and fertilizer delivery based on real–time feedback from spectral and soil moisture data, effectively replicating adaptive fertigation processes in a controlled environment [85]. Through iterative simulations, the framework evaluated multiple irrigation and nutrient scenarios, identifying strategies that maximize water and nutrient use efficiency while minimizing environmental losses.

All analytical scripts, configuration files, and model parameters were version–controlled to ensure transparency and replicability. This modular analytical design provides a transferable blueprint for other high–value crops cultivated in controlled–environment agriculture, promoting sustainable, data–driven production optimization.

7.1 *Data Management, Calibration, and Integration Challenges*

Modern greenhouse fertigation systems increasingly rely on multispectral imaging and IoT–enabled data streams; however, effective management of these data flows remains a critical challenge to ensuring consistent, interpretable, and actionable outcomes. The vast, heterogeneous datasets generated by soil sensors, UAV–mounted cameras, and climate control systems are often poorly integrated, resulting in temporal misalignment and inconsistent spatial resolution across measurements. Recent reviews emphasize that existing data fusion frameworks in controlled–environment agriculture still lack standardized protocols for synchronizing multi–source inputs in rapidly changing microclimatic conditions [86]. This fragmentation hampers the calibration of spectral indices for nutrient estimation in onions, where generic vegetation indices such as NDVI and NDRE may yield misleading interpretations of nutrient stress unless corrected for crop–specific reflectance dynamics and phenological variability.

A secondary technical constraint arises from sensor occlusion within greenhouse structures, where shading from support frames, condensation, and leaf overlaps can distort spectral signals and undermine data reliability [87]. Even minor variations in humidity or shading can induce spectral deviations exceeding 10%, potentially leading to significant nutrient misdiagnosis. These challenges highlight the urgent need for robust, phenology–based calibration models that are not only onion–specific but also adaptive to the fluctuating microenvironmental conditions prevalent in the Philippine greenhouse systems.

Addressing these constraints requires an integrated analytical architecture capable of unifying data acquisition, processing, and decision–making within a single system. Recent studies in smart agriculture propose multi–source data fusion and edge–to–cloud computing as scalable approaches to harmonize soil, spectral, and climatic data streams for precision fertigation management [88]. The automated drip fertigation proposed in this review is driven by multispectral imaging and IoT–linked controllers, which represent a strategic advancement. By leveraging real–time vegetation indices calibration for onion phenology, the system minimizes fertilizer wastage, enhances nutrient use efficiency, and delivers timely, data–informed insights to greenhouse operators.

In the Philippine setting, where onion production is largely dominated by smallholder farmers constrained by high input costs and limited technical capacity, such integration offers a viable pathway toward sustainable intensification. Beyond addressing the "know–how" gap, this system translates complex spectral data into user–friendly fertigation decisions, contributing to national goals for climate–resilient, smart greenhouse production. At the policy level, it aligns with the Department of Agriculture's Precision Agriculture Roadmap, promoting data–driven, resource–efficient, and environmentally sustainable food systems.

7.1.1 Know–How gap in precision agriculture

Despite significant advances in multispectral sensing and automated fertigation, the human element remains a decisive factor in the successful implementation of precision agriculture systems. The development of these technologies requires not only robust hardware and software but also parallel investments in digital literacy, farmer training, and technical capability building. Studies indicate that even where precision agriculture infrastructure is available, adoption is frequently constrained by limited understanding of system operations, misinterpretation of algorithmic outputs, and insufficient technical support from extension services [89].

In the Philippines, where smallholder farmers dominate onion production, reliance on experiential and intuitive knowledge often hinders the transition toward data–driven decision–making based on vegetation indices or model calibration outputs. Moreover, trust in algorithms and automated decision tools, farmers remain cautious about relying on AI–assisted fertigation recommendations without clear local validation and demonstrable yield benefits. This underscores the importance of a participatory co–design framework and inclusive training models that demystify automation and enhance user confidence [90].

Evidence from developing economies further highlights the role of technical support ecosystems, emphasizing that the availability of trained local technicians capable of maintaining sensors, UAVs, and IoT infrastructures directly influences sustained technology use [91]. Addressing the persistent know–how gap requires institutional interventions, including digital literacy programs, accessible training hubs, and demonstration farms that bridge traditional agronomy with precision data workflows. Integrating PA–oriented curricula into agricultural extension and cooperative systems would build farmer trust, promote hands–on competence, and enable the confident use of IoT–based fertigation and multispectral analysis tools. In doing so, these technologies can evolve from perceived high–cost novelties into practical, scalable solutions for sustainable onion production.

8 Integrated Multispectral Fertigation Monitoring Framework for Onion Production Under Greenhouse

The integration of multispectral remote sensing with automated drip fertigation represents a comprehensive precision agriculture framework that directly links crop physiological monitoring to real–time management interventions. For onion *(Allium cepa),* a crop with distinct nutrient demands and narrow tolerance to both moisture deficit and excess, such integration offers significant potential to enhance yield performance and optimize resource–use efficiency [92].

Recent studies reveal a growing trend toward combining multispectral imaging automation and precision fertigation in high–value horticultural systems; however, there remains a notable research gap concerning the full system integration of these technologies for onion cultivation under greenhouse conditions. For instance, multispectral sensing has demonstrated high accuracy in quantifying magnesium–induced stress in onion using specific vegetation indices, thereby providing a foundation for nutrient status diagnostics within *Allium* species. Moreover, advances in proximal and remote sensing techniques for soil and nutrient monitoring indicate that fertigation efficiency improves markedly when spectral feedback mechanisms are coupled with automated nutrient control systems. Collectively, these findings underscore that dynamic, feedback–driven nutrient management can serve as the cornerstone for next–generation smart greenhouse fertigation systems.

Nevertheless, unlike widely studied crops such as tomato and potato, where multispectral imagery has been effectively integrated into IoT–linked fertigation controllers, onions present unique physiological and spectral challenges. The crop's narrow, erect leaf architecture modifies canopy reflectance patterns and complicates the application of standard vegetation indices, the development of onion spectral calibration models [93]. Furthermore, the feasibility of multispectral–sensor fusion frameworks for nutrient optimization in controlled environments, but also the persistent barriers of cost, data management, and farmer technical know–how, hinder real–world adoption [94].

The integration model proposed in this review is not a replication of existing work, but a synthesis drawn from successful cross–crop implementations and component–level validation in onion. Tomato–based systems have proven that combining NDVI or

NDRE indices with closed–loop fertigation can dynamically adjust nutrient dosing according to canopy vigor and phenological stage [95].

8.1 *Conceptual framework*

In an Israeli–type greenhouse, the workflow begins with multispectral image acquisition using a UAV–mounted. The vegetation indices NDVI, GNDVI, and PRI are commonly computed and correlated with chlorophyll concentration, nitrogen status, and canopy vigor in onion crops. These indices serve as proxies for plant physiological status and are further analyzed using machine learning or regression models to translate the spectral signal into actionable fertigation recommendations. Within this framework, the automated fertigation controller executes the prescribed adjustments by modulating fertilizer injectors, electrical conductivity setpoints, and irrigation pulses, effectively creating a closed–loop decision support system. Through feedback loops, the system iteratively refines its decision that each fertigation event influences crop condition, and subsequent multispectral monitoring validates treatment efficacy, prompting further adjustments when deviations are detected.

In the context of onion production within a 1,000 m^2 sawtooth greenhouse integration, both technological innovation and agronomic advancement, when combined with soil–plant sensor data fusion and adaptive nutrient injection control. A growing body of literature indicates that sensor–based fertigation guided by multispectral data enhances nutrient–use efficiency, mitigates environmental nutrient losses, and promotes sustainable intensification of controlled–environment agriculture.

However, despite the technical promise of integrating remote sensing with automated fertigation, several critical gaps and conflicts persist in the literature. There is limited consensus regarding the economic feasibility of systems for smallholder operations in constrained settings. Likewise, robust calibration models specific to onion phenology remain underdeveloped, and existing data fusion algorithms for combining soil sensors and spectral datasets still require optimization to ensure reliability across variable microclimates. Moreover, the persistent knowledge and training gap among farmers represents a social barrier to large–scale adoption.

8.2 *Camera setup*

The MicaSense Rededge–M camera mounted on a UAV and set up as a stationary ground–based system.

Five Spectral Bands

- Blue (400 to 500 nm): Sensitive to chlorophyll absorption, used to detect plant stress and monitor water quality.
- Green (500 to 600 nm): Sensitive to green vegetation, used to assess plant vigor
- Red (600 to 700 nm): Important for chlorophyll absorption, used in vegetation indices like NDVI and GNDVI
- Red Edge (700 to 740 nm): Highly sensitive to changes in chlorophyll content, used for early stress detection and nutrient status monitoring
- Near–Infrared (740–900 nm): Strongly reflected by healthy vegetation used in NDVI and other vegetation indices.

8.3 *Ground truthing data and calibration for multispectral–based nutrient monitoring*

Accurate ground truth data for validating multispectral nutrient monitoring systems. However, existing literature indicates uneven calibration practices, inconsistent sampling protocols, and significant methodological gaps for uncontrolled environmental conditions. Biophysical assessment conducted on onion reported moderate correlations (r = 0.72) between leaf area index (LAI) and remotely estimated LAI derived from Sentinel–2 imagery, reaffirming the relevance of canopy–level metrics as validation benchmarks [26]. Nevertheless, the same study emphasized the difficulty of temporal synchronization between satellite overpasses and field sampling, an issue that becomes even more critical in greenhouse systems, where spectral fluctuations occur due to artificial illumination and variable roof geometry.

While several studies recommend destructive tissue sampling at key phenological stages to establish calibration accuracy, others advocate for non–destructive proxies such as SPAD or chlorophyll meter readings for estimating leaf nitrogen content. This divergence underscores a trade–off between spatial representativeness and measurement precision in dense onion canopies characterized by high within–row variability [94]. Although investigations in related crops such as tomato and lettuce have achieved strong correlations of $R^2 > 0.9$ between vegetation indices and tissue nitrogen concentration when supported by extensive calibration datasets [95], comparable datasets for onion remain scarce.

Recent advances point toward hybrid calibration frameworks that integrate spectral indices, soil electrical conductivity, and thermal imaging data as a pathway to more accurate and real–time nutrient mapping [92], [94]. However, these innovations also expose a practical divide: while sensor fusion enhances model robustness, the high costs of dense sampling and the technical expertise required for data processing constrain adoption among smallholder growers, who form the backbone of onion production.

To bridge this gap, future efforts should prioritize the development of standardized, low–cost, and crop–specific calibration protocols that maintain scientific rigor while ensuring accessibility and scalability for farmer–oriented precision fertigation systems. Frameworks would enable equitable participation in digital agriculture and support the broader goals of sustainable intensification under controlled–environment production.

8.3.1 Multispectral image processing

Multispectral image processing has emerged as an analytical tool in greenhouse precision fertigation systems, providing real–time insights into nutrient dynamics, crop vigor, and spatial variability. The fusion of spectral data with automated fertigation control enhances nutrient–use efficiency (NUE) by synchronizing fertilizer delivery with the crop's physiological demand. The importance of accurate radiometric calibration, geometric correction, and vegetation index selection for reliable nutrient diagnostics in high–value crops under controlled environments [90], [96].

Software platforms like Pix4D facilitate orthomosaic generation, spectral calibration, and vegetation index mapping, bridging UAV–based data acquisition with IoT–enabled fertigation systems. In the arid–region zone, onion production, multispectral imaging effectively detected growth–stage variations and nutrient–induced spectral shifts, confirming its utility as an early diagnostic and decision–support tool [96]. Beyond visualization, Pix4D's integration potential extends into automated fertigation control, converting spectral indices into actionable management adjustments.

When coupled with machine learning, hyperspectral and multispectral imaging significantly improve the accuracy of nutrient deficiency detection, though hyperspectral imaging offers superior spectral resolution, multispectral systems represent a cost–effective, operationally feasible alternative for frequent greenhouse monitoring.

Despite advancements, research gaps remain; the existing spectral–nutrient correlation models are crop–specific and rarely optimized for onion phenology and canopy architecture. Moreover, the narrow, erect leaves of onions alter light interception and spectral reflectance, reducing the reliability of standard vegetation indices. Future studies should prioritize the development of onion spectral calibration models. validated using SPAD readings, Leaf Color Charts (LCC), and nutrient assays, to close the gap between spectral indices and actual plant nutrition parameters.

8.3.2 Analytical setup

The analytical framework for integrating multispectral imagery with automated fertigation control is designed to correlate remote sensing outputs with biophysical and biochemical indicators of onion growth. The process begins with multispectral image acquisition from UAV–mounted sensors operating within a 1,000 m^2 sawtooth greenhouse. The captured imagery undergoes radiometric correction, orthomoisaic stitching, and vegetation index computation, producing spatial maps that reflect the physiological condition of the onion canopy. Extracted indices are statistically correlated with ground–truth measurements of plant height, leaf area index (LAI), and biomass with soil and leaf nutrient concentrations. These datasets are then used to validate the sensitivity of spectral indices to nutrient status, forming the basis for predictive regression models capable of estimating nutrient sufficiency thresholds. Machine learning approaches in Random Forest and Partial Least Squares Regression to quantify nutrient stress from spectral signatures [97]. Model outputs feed directly into IoT–based fertigation controllers, adjusting irrigation and fertilizer dosing in real time to enhance nutrient–use efficiency and reduce leaching losses [98].

This analytical pipeline transforms conventional greenhouse management into an adaptive feedback system. While individual workflow components have been validated in isolation, comprehensive onion–specific integration remains limited. Addressing this gap through multi-season trials and sensor–fusion calibration in Philippine greenhouse initiatives could enable full–scale implementation. This represents a convergence of agronomy, data analytics, and automation, positioning production at the frontier of smart greenhouse agriculture.

9 Feasibility of Integrating Multispectral Remote Sensing with Automated Drip Fertigation in Onion Production

The convergence of remote sensing and automated fertigation marks a significant step toward sustainable intensification in onion cultivation. Multispectral sensors enable early detection of nutrient deficiencies and water stress through analysis of vegetation indices such as NDVI, GNDVI, and red–edge reflectance [67]. By integrating these indices with sensor–based drip irrigation, nutrient and water delivery can be continuously adjusted in response to real–time plant feedback.

Evidence supports the technical feasibility of this integration, as multiple studies have validated spectral indices for detecting nitrogen, sulfur, and water stress in onions. The combination of automated fertigation systems and spectral feedback loops represents a baseline framework for precision onion production, offering a foundation for developing standardized calibration models, cost–benefit analyses, and sustainability metrics to controlled environments such as Israeli greenhouses. Future experimental trials should refine nutrient–stress calibration, optimize fertigation algorithms, and assess scalability for both greenhouse and open field systems.

10 Future Perspective and Research Direction

The integration of multispectral remote sensing and automated fertigation for onion *(Allium cepa)* production remains in its nascent stage compared with major cereal and horticultural crops. However, advances in sensor miniaturization, machine learning, and protected cultivation technologies suggest strong potential for scaling these systems. Current vegetation indices developed for broadleaf species underestimate canopy vigor in onion due to their narrow–leaved morphology, emphasizing the need for onion–specific spectral models capable of accurately capturing canopy reflectance in both greenhouse and field conditions.

To fully realize this potential, future research should align precision fertigation technologies with climate–smart agriculture goals. Multispectral Remote Sensing guided fertigation can enhance nutrient use efficiency, reduce nitrogen leaching, and improve water productivity, contributing to low carbon with renewable energy sources to reduce the carbon footprint of protected onion cultivation.

11 Conclusion

This review has synthesized the emerging body of knowledge on the integration of multispectral remote sensing, precision fertigation, and automated greenhouse control systems for sustainable onion production. The evidence demonstrates a clear trend toward digitalized nutrient management using IoT-enabled systems, real-time vegetation indices, and machine learning models to optimize NPK delivery and minimize input losses. Across multiple studies, multispectral imagery has proven effective for early detection of nutrient deficiencies, offering a non-destructive, spatially explicit tool that links plant physiological status with fertigation control decisions. The integration of Pix4D image analytics with fertigation scheduling represents a decisive step toward closed-loop management systems capable of real-time feedback.

However, the literature reveals persistent gaps and challenges that limit full-scale adoption in the developing agricultural context in the Philippines. There remains a lack of crop-and region-specific calibration models for onion phenology under protected cultivation. Studies heavily rely on indices validated in open-field conditions for crops such as tomato and lettuce, leaving the onion-based greenhouse model underexplored. Moreover, while IoT-driven fertigation systems show strong potential for optimizing water and fertilizer use, their high initial capital costs, maintenance complexity, and limited farmer training create socio-economic barriers to widespread implementation. Data management and integration issues in fusing soil sensor data with spectral imagery continue to constrain real-time decision accuracy and scalability.

From a policy standpoint, the review highlights the need for localized digital agriculture frameworks. The Philippine greenhouse policy can benefit from targeted subsidies that lower the barrier for sensors and automation technologies. Government-supported demonstration farms could accelerate technology diffusion by providing hands-on training for farmers, technicians, and Agri-extension officers. The establishment of open-access calibration datasets for onion phenotyping and spectral signatures would further democratize technology adoption.

Looking forward, the most promising trajectory lies in developing adaptive fertigation algorithms that combine spectral diagnostics, IoT sensor feedback, and predictive AI models trained on local environmental and crop data. Cross-disciplinary collaborations between agronomists, engineers, and data scientists are essential to create robust, farmer-centered systems. If implemented strategically, innovations could transform onion cultivation, aligning with the Philippines' broader goals of sustainable intensification and digital agriculture.

Acknowledgments

The authors would like to acknowledge the Department of Agricultural and Biosystems Engineering, College of Engineering, Central Luzon State University, and the Engineering Research and Development for Technology Scholarship program of the Department of Science and Technology-Science Education Institute.

Author Contributions

G.M.D.O.: conceptualization, investigation, reviewing and editing; writing an original draft, research design C.M.M.C.: investigation, methodology, writing an original draft; J.P.C.S.: conceptualization, data curation, writing, reviewing and editing; J.R.G.F.: conceptualization, investigation, reviewing and editing.

Conflicts of Interest

The authors declare no conflict of interest.

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