Integration of smart irrigation with AI-based disease detection: A field-based agro-technical evaluation for tomato (*Solanum lycopersicum* L.)

Mvondo Nganti Dorothée*[1,2], Nchange Kouotou Adamou[2], Mefire Nchouwat Youssouf[1,2], Nana Modeste[2], Lombeko Tomo Obe Victorine[1,3], Manga Essouma François[1,3]

[1]Laboratory of Phytopathology, Department of Plant Biology, University of Yaoundé, Yaoundé, Cameroon

[2]Agrix Tech Sarl Cameroon

[3]Agricultural Research Centre, Institute of Agricultural Research for the Development (IRAD), Yaoundé, Cameroon

ARTICLE INFORMATION

ABSTRACT

This study, conducted in the Centre Region of Cameroon, evaluated the agronomic and economic effectiveness of an integrated production system for tomato cultivation (*Solanum lycopersicum* L.). The experimental design, a complete randomized block design, compared five treatments combining different irrigation methods (traditional manual vs. smart sensor-driven SynField) and phytosanitary control strategies (traditional preventive/curative vs. smart via the Agrix Maladies application). The aim was to address the sector's major constraints: empirical water management, high disease pressure (late blight, early blight), and low profitability. The results demonstrated the systematic and synergistic superiority of the fully integrated treatment (IICI: Intelligent Irrigation + Intelligent Control). This treatment optimized plant physiology, leading to the best performance in height, number of leaves, and number of flowers. It produced the highest yield (20.06 t/ha), a record water use efficiency (WUE) of 85.6 kg/m³, and exceptional disease control (25% incidence for late blight and 0% for early blight). Economically, despite a higher total cost due to technology depreciation, the IICI system generated the largest gross margin (6,996,500 FCFA/ha), thanks to optimized input use and maximum production value. This research validates that a systemic approach, combining precision irrigation and targeted crop protection, is the most powerful lever for tomato production that is simultaneously productive, resource-efficient, sustainable, and profitable in Cameroon.

Key words: Smart Irrigation, AI-based disease detection, Precision agriculture, *Solanum lycopersicum* L., Water use efficiency

INTRODUCTION

Tomato (*Solanum lycopersicum* L.) is a cornerstone of food security and the agricultural economy in Cameroon and the wider sub-region. However, the sector's productivity and sustainability are severely constrained by two interconnected challenges: inefficient water management and significant losses due to pests and diseases, which can account for 20-40% of global crop production (FAO, 2022; Strange and Scott, 2005). Firstly, tomato cultivation requires precise irrigation, yet practices in many regions, including Cameroon, often remain empirical and inefficient (Donato Buttaro *et al.*, 2015). In a context of increasing water scarcity and climate variability, this leads to substantial waste of both water and inputs (Talaviya *et al.*, 2020). Secondly, the timely detection of diseases is critical for effective control. While traditional methods are often subjective and slow, emerging technologies like computer vision and artificial intelligence (AI) offer promising avenues for automated, early diagnosis (Bock *et al.*, 2008; Muhammad *et al.*, 2021). Recent advances demonstrate the high accuracy of convolutional neural networks (CNNs) in classifying tomato diseases (Kaur and Bathia, 2021; Rahman *et al.*, 2019), while precision irrigation systems using soil moisture sensors can optimize water use (Abioye *et al.*, 2022; Tüzel *et al.*, 2019).

While the literature extensively documents the development of smart irrigation systems (Abioye *et al.*, 2020) and AI-based disease detection tools (Muhammad *et al.*, 2021) in isolation, a critical gap exists. Few studies have empirically evaluated the integrated agronomic and economic performance of combining these two technologies, particularly under real field conditions in sub-Saharan Africa. Such an integrated approach is hypothesized to create synergies, where optimal water management enhances plant health and a healthy canopy uses water more efficiently, thereby simultaneously boosting resilience, productivity, and resource use efficiency.

To address this gap, this study, conducted under the Nestler project in Cameroon, evaluates a novel system that synergistically combines a sensor-driven intelligent irrigation module with an AI-powered early disease detection model. The primary objective is to assess the effects of this integrated technology on key parameters: (i) tomato growth and yield, (ii) water use efficiency (WUE), (iii) disease incidence and severity, and (iv) economic profitability. The ultimate aim is to validate a practical, scalable solution for enhancing the sustainability and economic resilience of smallholder tomato production in the region.

MATERIALS AND METHODS

Study area description

The studies were conducted in Bibe, located in the Centre Region of Cameroon. Bibe lies within the bimodal rainfall forest zone, classified as agro-ecological Zone V, with geographical coordinates 3°43'19.4"N, 11°25'15.2"E. The main characteristics of agro-ecological Zone V are: an area of 165,770 km²; rainfall between 1500 and 2000 mm with two rainy seasons; ferralitic, acidic, clayey soils with low water and nutrient retention capacity; and typical crops including cocoa, coffee, cassava, plantain, maize, oil palm, pineapple, and vegetables.

Plant material

The Rio Grande tomato is a hardy, high-yielding Roma-type variety that produces numerous medium-sized (60-100 g), elongated, bright red fruits. It has an indeterminate growth habit and exhibits resistance to diseases, particularly viral diseases.

Nutrient sources

For this experiment, we used laying hen manure as organic matter at a rate of 20 tonnes per hectare, equating to 16 kg per 8 m² ridge. This manure serves as a primary organic amendment commonly used in agricultural practices in the Centre Region of Cameroon, especially for vegetable crops. It is poultry manure (a mixture of droppings and litter residues): a more or less decomposed byproduct of intensive poultry farming.

Phytosanitary products

The fungicide Mancomax 80 WP with the active ingredient "Mancozeb" was used to control fungal diseases of tomato. The insecticide Cypercal with the active ingredient "Cypermethrin" was used to control insects. The selection of these phytosanitary products was based on their relative

efficacy in controlling tomato pests and diseases and their availability on the local market.

Description of the precision irrigation system

The evaluated precision irrigation system consisted of a pumping unit, a distribution network, and an intelligent automatic control module. Water was supplied by a motor pump from a nearby stream. This water was conveyed to a storage tank (capacity: 1,000 liters). The primary distribution network comprised PVC pipes, leading to secondary lines of polyethylene pipes that were perforated and spaced 50 cm apart, ensuring a nominal flow rate.

The technological core of the system was the SynField module by Synelixis. This device integrates a capacitive soil moisture sensor buried at a 20 cm depth within the root zone. The sensor measurements are processed by a control unit (microcontroller) connected to a solenoid valve. When soil moisture falls below a predefined threshold, the system automatically triggers irrigation until moisture reaches an upper threshold, thereby creating optimized irrigation cycles.

Sensor calibration and determination of dynamic irrigation thresholds

The automatic irrigation management by SynField was based on dynamic volumetric moisture thresholds, calibrated according to the critical phenological stage of the tomato, rather than on a fixed temporal schedule. This calibration was performed by coupling the capacitive sensor readings with the standard gravimetric method for the specific site soil (ferralitic soil), enabling the establishment of a reliable conversion curve between dielectric tension and actual soil moisture. The irrigation trigger thresholds were defined as follows, as a percentage of Readily Available Water (RAW = Refill Point - Permanent Wilting Point):

Vegetative stage (transplanting to flowering): Irrigation was triggered at 70% of RAW, promoting root development under mild, controlled water stress.

Flowering and fruit set stage: The threshold was raised to 80% of RAW to avoid any stress affecting fruit set, the most sensitive stage.

Fruit enlargement stage: The threshold was maintained at 85% of RAW to ensure optimal fruit filling, guaranteeing fruit size and yield.

Maturation stage: The threshold was lowered to 60% of RAW to induce mild water stress beneficial for sugar concentration and to promote uniform ripening.

Experimental design

The trial was conducted according to a Complete Randomized Block Design with four replications. Five treatments were evaluated on ridges measuring 1.6 m × 5 m, with a planting density of 22 plants per ridge (spacing of 50 cm within the row and 80 cm between rows), equating to 11 plants per row. Each treatment comprised 88 plants, and the entire experiment involved 440 plants over an area of 200 square meters. The treatments factorially combined the irrigation method and the phytosanitary control strategy:

1. An absolute control (T0) received only minimal watering without disease control.

2. Treatment ITCT (T1) combined traditional manual irrigation (application of 10 L of water per ridge morning and evening) with traditional disease control via preventive and curative applications of phytosanitary products.

3. Treatment IICT (T2) coupled intelligent irrigation driven by a SynField device with traditional disease control. Intelligent irrigation was automatically triggered when soil moisture, continuously measured by the SynField sensors, fell below a predefined threshold specific to the tomato's phenological stage. A connected water meter recorded the total volume of water used.

4. Treatment IICI (T3) combined this same intelligent irrigation with intelligent disease control via the Agrix Maladies mobile application, which uses an AI model for symptom identification and targeted treatment recommendations.

5. Finally, treatment ITCI (T4) combined traditional irrigation with intelligent disease control.

This design allowed for the evaluation and comparison of the individual and interactive effects of the two technologies on water use, plant health, and yield.
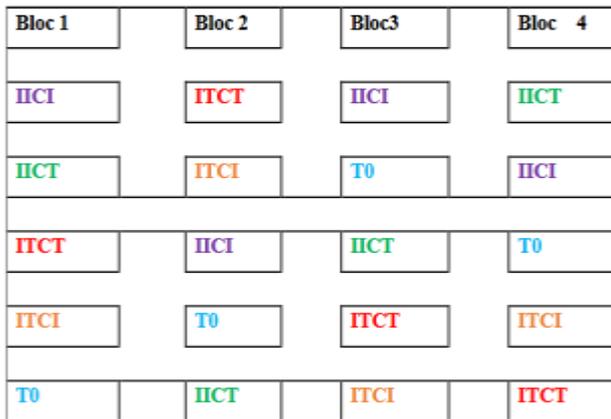
Fig. 1. Experimental setup: Each rectangle is a plot (1.6 m × 5 m)

The five treatments (ITCT, IICT, IICI, ITCI, To) are randomized within each block.

Measured parameters and analyses

Vegetative growth and yield parameters

From the tenth day after transplanting and on a weekly basis, agro-morphological parameters were recorded on five tagged indicator plants within each elementary plot. Measurements included plant height (cm), number of leaves, number of flowers, and number of fruits. At the end of the crop cycle, the yield for each ridge was determined by the total weight of all harvested fruits. The yield per hectare was extrapolated using the following formula, considering the net area occupied by the plants:

Yield (t/ha)= [Total fruit weight per ridge (kg) × 10,000 (m²)] / [Area of the ridge (m²)]

where 10,000 m² corresponds to one hectare.

Evaluation of intelligent irrigation efficiency

The impact of the different irrigation regimes was quantified by calculating the Water Use Efficiency (WUE).

For the intelligent irrigation treatments (IICT, IICI), the total volume of water applied (V water) was recorded directly by the water meter connected to the SynField system. For the traditional irrigation treatments (ITCT, ITCI), this volume was calculated by multiplying the unit volume applied (20 L/day/ridge) by the total number of irrigation days. For the control treatment To, this volume was calculated by multiplying the unit volume applied (10 L/day/ridge) by the total number of irrigation days.

Water Use Efficiency (WUE) was calculated as the ratio between fresh fruit yield (t ha⁻¹) and the total depth of irrigation water applied (Gencoglan *et al.*, 2006). This water depth was obtained for each experimental unit (ridge) by dividing the total volume of water delivered (liters) by its area (m²). It was calculated per hectare using the standard formula below:

WUE (kg/ha/mm) or (t/ha/mm)= Yield (kg/ha or t/ha)/ Total Irrigation Water Applied (mm)

Since our water volume was in liters, we first converted it to a water depth in millimeters (mm) over a one-hectare area using the following steps:

1. Calculate the irrigation water depth applied in mm for one ridge:

Water Depth (mm)= Total Water Volume (L) / Area of the Ridge (m²)

2. Express the yield per hectare.
3. Calculate the WUE for each treatment:
Using the yield (t/ha) and the corresponding water depth (mm) according to the irrigation type.

Evaluation of intelligent disease control efficiency

The effectiveness of phytosanitary protection strategies was assessed by calculating the incidence and severity of the main identified diseases. Incidence, which reflects the proportion of affected plants, was calculated using the formula:

Incidence (%) = (Number of symptomatic plants / Total number of plants observed) × 100

Severity, estimating the extent of symptoms on diseased plants, was determined using standard diagrammatic scales for each disease (Bock *et al.*, 2010). It represents the average percentage of leaf area affected per plant and is expressed as a percentage.

Economic evaluation of treatments

The economic analysis was conducted to determine the comparative profitability of the different tested

production systems and to formulate informed advice for farmers. The methodology follows a standard approach to agricultural production cost analysis, calculating a gross margin per hectare for each treatment.

Cost data collection

For each treatment, all intermediate consumptions (inputs and services) were inventoried and valued at local market prices during the experimental period. The following cost items were considered:

1. Variable inputs: seeds, organic fertilizers, phytosanitary products, and fuel for irrigation pumping.

2. Labor: costs related to trial establishment, monitoring, treatment application, and harvesting were estimated.

3. Services and depreciation: the cost of the license for the intelligent disease control application (Agrix Maladies) was included. For treatments using intelligent irrigation (IICT and IICI), the acquisition cost of the electronic equipment (SynField controller) and the initial investment in the system installation (piping, labor) were each depreciated linearly over a 5-year period, in accordance with sustainable agricultural investment analysis practices.

Calculation methods

1. Total production cost (TC): For each treatment (i), the total cost per hectare was obtained by summing all the items listed above:

$$TC_i = \Sigma \, (\text{Variable Costs } i) + \text{Annual Depreciation } i$$

2. Production value (PV): Potential revenue was calculated by multiplying the fresh fruit yield (in tonnes per hectare) obtained for each treatment by an average tomato selling price, set at 500 FCFA/kg based on market observations.

$$PV_i = \text{Yield } i \text{ (kg/ha)} \times 500 \text{ (FCFA)}$$

3. Gross margin (GM): A key indicator of direct profitability, the gross margin was defined as the difference between the production value and the total cost of inputs and services required to obtain it.

$$GM_i = PV_i - TC_i$$

The treatment with the highest gross margin is considered the most profitable at the scale of a single growing season.

Treatment of investment costs

To fairly compare systems with and without capital investment, the purchase cost of the Synfield (2,000,000 FCFA) and the cost of installing the precision irrigation system (1,500,000 FCFA/ha) were spread over their estimated lifespan. An annual depreciation of 400,000 and 300,000 FCFA/ha/year was thus allocated to treatments IICT and IICI, respectively. This method avoids excessively penalizing these treatments by distributing the investment cost over several farming seasons.

Statistical analysis

All collected data (growth parameters, yield, WUE, incidence, and severity) were subjected to a two-factor analysis of variance (ANOVA) (irrigation mode × control strategy), according to the complete randomized block design. Treatment means were separated by Tukey's multiple comparison test at a 5% significance level ($p < 0.05$). The analyses were performed using the XLSTAT software (version 2019.2).

RESULTS

Plant height

The analysis of plant height at the end of the cycle revealed a highly significant effect of the treatments ($p < 0.001$). The Tukey test distinguished three performance groups A, B, C (Fig. 2). The untreated control (T) showed the weakest growth (Group A). The ITCT and ITCI treatments formed a homogeneous intermediate group (B). Finally, the treatments incorporating intelligent irrigation (IICT and IICI) achieved the maximum heights, forming the superior group (C). These results highlight the major impact of optimized irrigation on the vegetative vigor of tomato plants.
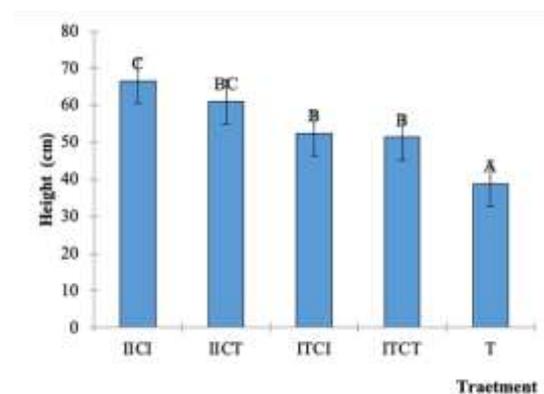

Fig. 2. Average plant height per treatment

Number of leaves

Leaf development, evaluated by the average number of leaves, was significantly influenced by the treatments (Fig. 3). Treatment IICI exhibited the highest number of leaves (28), forming the superior statistical group (B). Treatments IICT and ITCI occupied an intermediate position (groups A B), not being significantly different from either the least performant treatments (T, ITCT) or the best one (IICI). The control (T) showed the weakest development (17 leaves, group A). These results indicate that optimized irrigation is the predominant factor for stimulating leaf growth, with the combination of both intelligent technologies (IICI) leading to the maximum performance.
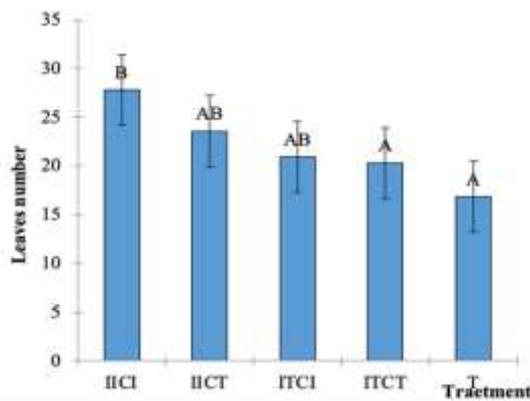
Fig. 3. Average number of leaves per treatment

Number of flowers

The analysis of the number of flowers revealed an influence of the treatments, with a progression of means according to the technological level (Fig. 4). Treatment IICI presented the highest number of flowers (18.25), forming the superior statistical group (B) and being significantly different from the control (T, group A). Treatments ITCI, ITCT, and IICT formed a broad intermediate group (A B) not statistically distinct from the two extremes. These results suggest that while precision irrigation improves vegetative vigor, it is its combination with intelligent disease control (IICI) that creates the most conducive environment for optimal flowering, thereby laying the groundwork for the exceptional yield recorded for this treatment.
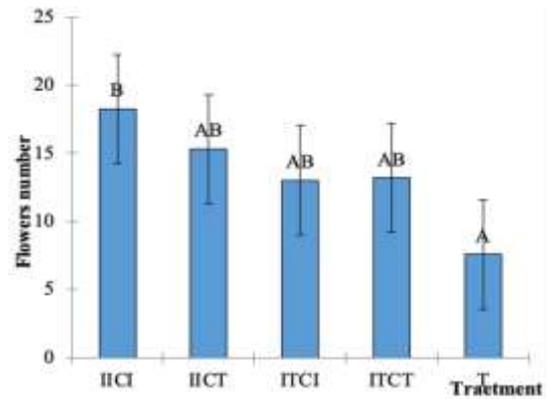
Fig. 4. Average number of flowers per treatment

Yield

Analysis of variance revealed a highly significant treatment effect on fruit yield ($p < 0.001$). Comparison of means using the Tukey test ($\alpha=0.05$) established a significant hierarchy among the treatments (Fig. 5). Treatment IICI showed the highest yield (20.06 t/ha), significantly greater than that of all other treatments. No significant difference was observed between treatments IICT, ITCT, and ITCI, although the first two showed numerically higher yields, at 16.1 t/ha, 15.53 t/ha, and 14.55 t/ha, respectively. The control, as expected, recorded the lowest yield (6.33 t/ha), significantly lower than all other treatments.
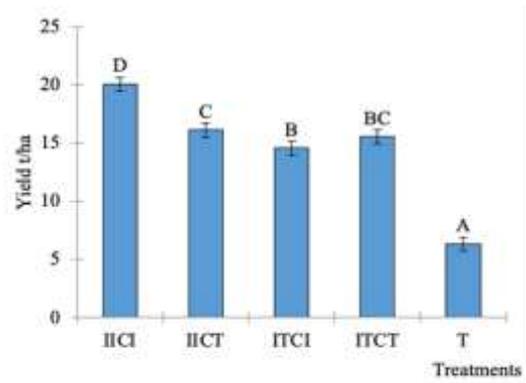
Fig. 5. Average yield in tonnes/ha of the different treatments per treatment

Water use efficiency

Statistical analysis of Water Use Efficiency (WUE) revealed highly significant differences between treatments ($p < 0.001$). The Tukey test established four distinct significance groups (A, B, C, D), demonstrating a clear progression. Treatment IICI achieved the highest

WUE (85.6 kg/m³), which was significantly superior to all others (Fig.6). Treatment IICT (68.7 kg/m³) was significantly differentiated from traditional practices (ITCT: 57.02 kg/m³ and ITCI: 53.40 kg/m³), highlighting the major contribution of precision irrigation. Finally, the control To (46.5 kg/m³) confirmed the lower efficiency of plants under water stress.
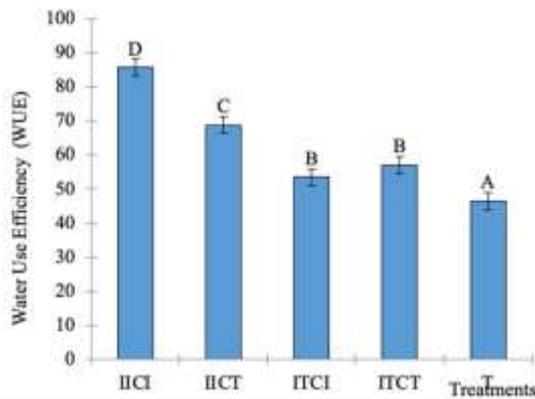

Fig. 6. Water use efficiency by treatment

Incidence and severity of late blight
Statistical analysis of late blight incidence and severity reveals distinct dynamics in treatment efficacy (Fig. 7).
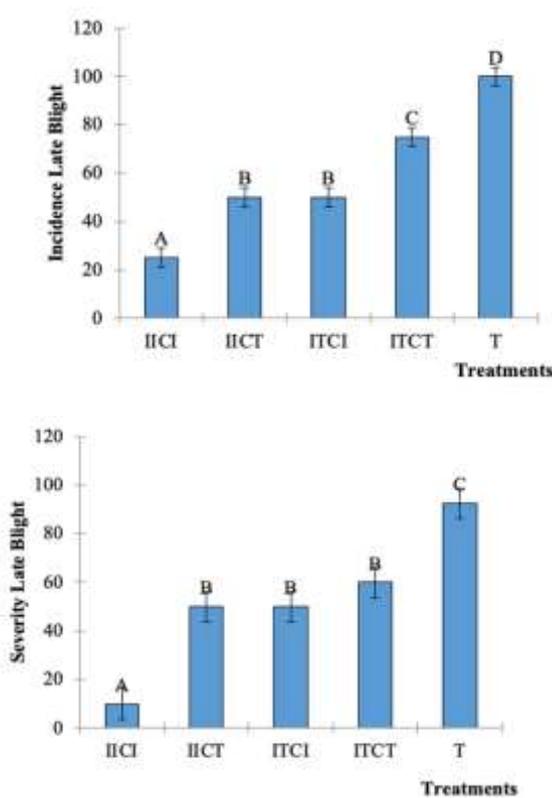

Fig. 7. Incidence and severity of late blight by treatment

For incidence (disease spread rate), the results establish a significant progression across four distinct groups (A to D). The combined treatment IICI showed the lowest incidence (25%), forming an isolated and optimal group. Treatments using a single intelligent technology, IICT and ITCI, displayed similar efficacy (50%) and formed an intermediate group, which was significantly more effective than the traditional practice ITCT (75%). The untreated control, with a 100% incidence, confirmed the disease pressure.

In contrast, the group structure for severity (symptom intensity) differs, comprising only three groups. Only the combined treatment IICI managed to drastically reduce severity (10%), maintaining its isolated group. A key finding is that treatments IICT, ITCI, and ITCT (with severities of 50%, 50%, and 60%) are statistically grouped without a significant difference between them. This indicates that while the intelligent technologies applied individually are effective at reducing disease spread, they did not, in this experiment, significantly limit the severity of symptoms on already infected plants compared to traditional protection. The control To showed the highest severity (92.5%).

Incidence and severity of early blight
The analysis of early blight reveals a particularly clear and effective control pattern for treatments incorporating intelligent irrigation (Fig. 8). The results for incidence and severity are perfectly consistent, structuring the treatments into four distinct statistical groups (A to D).

Treatments IICI and IICT form the top-performing Group A, with estimated incidence and severity of 0%. Their confidence interval includes zero, indicating a statistical absence of the disease. This demonstrates that intelligent irrigation alone (IICT) is as effective as the combined system (IICI) in completely eliminating early blight, suggesting that optimized moisture management is a decisive factor against this pathogen.

Treatment ITCI (intelligent control alone) constitutes Group B, with 20% incidence and 25% severity. Although significantly less effective than Group A treatments, it remains markedly superior to the traditional treatment ITCT (Group C, 40% incidence, 51% severity). Finally, as expected, the untreated control (Group D) presents the highest values, confirming the strong disease pressure.
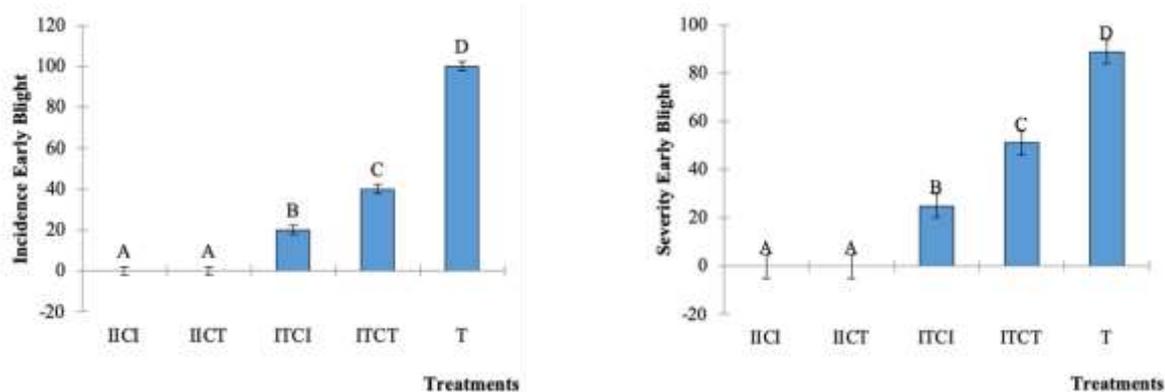
Fig. 8. Incidence and severity of early blight by treatment

Table 1. Analysis of production costs and profitability (gross margin) for the different treatments, expressed in FCFA per hectare

Cost and revenue items (FCFA/ha)	ITCT	ITCI	IICT	IICI	Control (T)
Variable costs					
Fertilizer (FCFA)	1 200 000	1 200 000	1 200 000	1 200 000	1 200 000
Labor (FCFA)	500 000	500 000	500 000	500 000	400 000
Phytosanitary products + Seeds (FCFA)	337 500	200 000	337 500	200 000	30 000
Agrix Maladies app license (4 quarters)	0	20 000	0	20 000	0
Fuel for pumping	483 750	483 750	415 000	415 000	242 500
Subtotal variable costs (A) (FCFA)	2 521 250	2 403 750	2 452 500	2 335 000	1 872 500
Depreciation (5 years) (FCFA)					
SynField device (2,000,000 FCFA)	0	0	400 000	400 000	0
SynField installation (1,500,000 FCFA)	0	0	300 000	300 000	0
Total production cost (B = A + Depreciation)	2 521 250	2 403 750	3 152 500	3 035 000	1 872 500
Yield (tonnes/ha)	15,535	14,555	16,100	20,063	6,333
Selling price (FCFA/kg)	500	500	500	500	500
Production value (C) (FCFA)	7 767 500	7 277 500	8 050 000	10 031 500	3 166 500
Gross margin (C-B) (FCFA)	5 246 250	4 873 750	4 897 500	6 996 500	1 294 000

Economic evaluation of different treatments

The comparative economic analysis of the five modalities reveals significant differences in profitability (Table 1). The gross margin, the primary indicator, varies from 12,94,000 FCFA/ha for the Control treatment (T) to a value nearly 5.3 times higher, reaching 6,996,500 FCFA/ha for the IICI treatment (Intelligent Irrigation with Sensors and Integrated Detection system).

The cost structure shows a clear distinction. Conventional treatments (T, ITCT, ITCI) display a total production cost ranging between 1.9 and 2.5 million FCFA/ha, primarily consisting of variable costs. In contrast, treatments incorporating the integrated SynField technological system (IICT, IICI) see their total cost rise to over 3 million FCFA/ha, due to the annual depreciation of the investment (700,000 FCFA/ha).

However, this increase in costs is more than compensated for by the revenues. The IICI treatment generates the highest production value (10,031,500 FCFA/ha), driven by a record yield of 20.1 tonnes/ha. Thus, although its production cost is 62% higher than that of the Control, its gross margin is 426% higher. The treatment using only precision irrigation without integrated detection (IICT) presents a gross margin (4,897,500 FCFA/ha) slightly lower than that of the improved conventional treatment ITCT (5,246,250 FCFA/ha), despite a higher yield.

DISCUSSION

The analysis of growth and reproductive development parameters reveals a progressive improvement, structured into distinct statistical groups ranging from the Control (empirical practices) to the integrated IICI system. This hierarchy demonstrates that water stress and pest pressure, which are unmanaged in the Control treatment, constitute major constraints to vegetative

vigor and floral initiation. The systematic superiority of the IICI system, particularly for the number of flowers, results not from a simple additive effect but from synergy. Precision irrigation maintains optimal water status, while early detection preserves the functional integrity of the foliage. As observed by Bwambale *et al.* (2023), an intelligent control strategy based on a predictive model, by integrating various environmental and growth parameters, significantly improves growth components (height, diameter, flowering) compared to manual control. Thus, systemic innovation creates the physiological conditions for the plant to express its full genetic potential, establishing a strong causal link with subsequent productivity gains.

The significant yield hierarchy, distributed across four statistical groups (A to D), faithfully reflects the technological intensification gradient. The progressive improvement, from the Control's minimum yield (6.33 t/ha) to the IICI system's record yield (20.06 t/ha), is explained by the successive mitigation of major physiological stresses. This progression confirms that empirical practices, exposing the crop to alternating drought and water excess, directly harm flowering, fruit set, and fruit filling. In contrast, precision systems provide regular water tailored to needs. These results corroborate those of Bwambale *et al.* (2023), who obtained an average yield of 20 t/ha with intelligent irrigation compared to 14 t/ha with manual irrigation, attributing this advantage to the capacity of predictive models to integrate a multitude of parameters for optimized management. The study by Abioye *et al.* (2023) on greenhouse cantaloupe supports this, validating the effectiveness of the predictive approach for yield maximization.

The analysis reveals a consistent progression in WUE, in perfect correlation with the technological level, demonstrating that precision management simultaneously optimizes productivity and resource sustainability. The initial leap from the Control (Group A) to technical irrigation treatments (Group B) illustrates the benefit of simple mechanical optimization of water distribution, reducing losses through evaporation or percolation. Entry into Group C with sensor-driven

intelligent irrigation (IICT) marks an additional advantage: by triggering irrigation only in response to the plant's real needs, both water stress and excess are avoided, reaching an optimal application point. Finally, the record performance of the integrated IICI system (Group D) reveals a synergistic effect. Early disease detection preserves the photosynthetic apparatus and avoids water waste on plants with compromised transpirational efficiency. These results align with several studies: Shahadha *et al.* (2023) showed that precision irrigation could improve WUE by 35%; Bwambale *et al.* (2023) and Lozoya *et al.* (2016) also documented substantial gains in water use efficiency through predictive control strategies that dynamically adapt to crop needs.

The differential efficacy of treatments against late blight (*Phytophthora infestans*) and early blight (*Alternaria solani*) highlights distinct mechanisms of action, providing essential nuance for agronomic advice. For early blight, a weakness pathogen, intelligent irrigation alone (IICT) proved sufficient to eradicate the disease (0% incidence). By maintaining optimal, stress-free water status, this system strengthens plant vigor and constitutive resistance, eliminating the primary predisposing factor. In contrast, against late blight, whose explosive infection cycle depends on free moisture on the foliage, IICT offers only partial control. The decisive advantage of the integrated IICI system then lies in its early detection module, enabling targeted and ultra-rapid phytosanitary intervention at the onset of an outbreak. This combined approach of micro-climatic prophylaxis and rapid diagnosis also applies to preventing other fungal and bacterial pathologies favored by leaf wetness, as highlighted by Anonymous (2021). Thus, the IICI system validates the concept of integrated and versatile protection, paving the way for a sustainable reduction in pesticide use.

The profitability analysis demonstrates that financial viability is conditioned by the degree of technological integration. The integrated IICI system, despite a higher total production cost due to the depreciation of precision equipment, generates the largest gross margin (7.00 million FCFA/ha). This exceptional economic

performance is the result of synergy: on one hand, the system optimizes variable costs by drastically reducing phytosanitary expenses (thanks to early detection) and saving fuel (thanks to optimized irrigation); on the other hand, it maximizes production value via the record yield. Conversely, an isolated innovation like intelligent irrigation alone (IICT) struggles to justify its investment over a single season, as the yield gain does not fully compensate for the depreciation cost. Consequently, faced with the low profitability of empirical practices, the adoption of an integrated technological package emerges as the most powerful lever for reconciling the economic resilience of farms and the sustainable use of resources.

CONCLUSION

This study conclusively demonstrates that the systemic integration of sensor-driven precision irrigation and an AI-based early disease detection tool represents a transformative innovation for Cameroon's tomato sector. The fully integrated IICI treatment proved superior across all metrics: agronomic (plant vigor, record yield of 20.06 t/ha), environmental (optimal water use efficiency of 85.6 kg/m³), and economic (highest gross margin of 6,996,500 FCFA/ha). The results validate that a holistic approach simultaneously tackling abiotic (water) and biotic (disease) stresses is essential to unlock the productivity potential and resilience of farms in the face of climate change and pest pressures.

RECOMMENDATIONS

For farmers and cooperatives: Promote phased adoption

To overcome the initial investment barrier, a stepwise adoption strategy is advised. Farmers should first invest in core precision irrigation (IICT-level), which delivers significant water and yield gains. Subsequently, adding the intelligent disease module to achieve the full IICI system would maximize profitability and crop protection, a critical step in areas with high disease pressure.

For policy makers: Integrate and incentivize

This proven technological package should be formally integrated into national agricultural modernization and climate resilience programs. Policymakers should develop targeted subsidy schemes or low-interest loan facilities specifically for integrated precision packages rather than isolated components, to encourage holistic adoption and maximize systemic impact.

For future research: Expand and adapt

Future work should focus on longitudinal studies to assess long-term economic and agronomic sustainability. Research should also aim to adapt and expand the system's AI models to cover a broader spectrum of region-specific pests and diseases, and to tailor the irrigation algorithms for other high-value vegetable crops.

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