



AI-Driven Precision Irrigation in High-Density Apple Orchards: Comparative Analysis of Water Application, Soil Moisture Dynamics, and Fruit Yield

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Authors' contributions

This work was carried out in collaboration among all authors. Author RA designed, analyzed, interpreted and prepared the manuscript. Authors RK and VPS supervised and analyzed the manuscript. All authors read and approved the final manuscript.

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Abstract

Inefficient Irrigation practices in agriculture systems has encouraged the development of sensor-based irrigation systems to increase resource use efficiency and profitability. However, comparisons between automated and manual drip-irrigation systems must consider treatment effects as well as the volume of water applied. This study was conducted at Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir, India. The study included 182 soil-moisture readings recorded over a 100-day period (15 June to 14 August 2021), together with irrigation data, namely the mode of drip-irrigation application (manual or automatic) and the volume of water applied in litres per irrigation event. The records contained 18 automatic irrigation events totaling 79,090 Litres and 36 manual events totaling 126,720 Litres, representing a 37.59% reduction in recorded irrigation water under automatic drip irrigation compared with manual drip irrigation. The system used three identical, indigenously developed soil-moisture sensors installed at a depth of 15 cm in the experimental plot having clay loam soil type. The mean of the three moisture-

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sensor readings was 54.96%, with a standard deviation of 18.45 percentage points. Soil moisture and relative humidity were positively correlated ($p = 0.360$, $p < 0.001$). The Random Forest Machine-Learning Model achieved a mean absolute error of 6.34 percentage points, compared with 10.74 percentage points for the persistence method. Harvested yields were 62.5 versus 36.8 kg for Golden Apple, 46.0 versus 22.7 kg for Decoste Robinjin, and 54.0 versus 28.75 kg for Mitch Gala (automated versus manual; five trees per irrigation mode and variety). These values represent descriptive increases in harvested mass of 69.84%, 102.64% and 87.83%, respectively, relative to manual irrigation. Normalized yield-water response scenarios over the 100-day period illustrate potential improvements in water management. The study suggests that predictive irrigation is feasible and provides data relevant to evaluating irrigation volumes, water-use efficiency and crop yield for resource use efficiency and profitability.

Keywords: Precision irrigation; soil-moisture sensors; machine learning; random forest; water-use efficiency; fruit yield.

1. Introduction

High-density apple plants, like other high-density fruit plants, respond to environmental stresses in various ways. Inconsistent irrigation scheduling during a growing season affects fruit health, quality and yield. Irregular irrigation may increase irrigation costs. Compared with traditional apple varieties, the effects of water stress on high-density apple plants are more prolonged and can affect crop productivity to a greater extent. Recent studies suggest that irrigation of perennial crops, including high-density apples, needs to vary according to the growth stage (Ali *et al.*, 2024; Selahvarzi *et al.*, 2025; Ashraf *et al.*, 2026). Evidence from a potato field study also indicates that crop sensitivity to soil-moisture stress varies with growth stage (Jelos and Gebrekristos, 2025). Conventional irrigation of perennial crops remains largely manual. Manual irrigation of perennial crops must be scheduled at specific times during the growing season. This approach can be effective, but incorporating changes in environmental and crop conditions into the irrigation schedule can be difficult. New systems focus on integrating networks of meteorological and soil-moisture sensors into control systems that support decisions about when and where to irrigate on real-time basis (Togneri *et al.*, 2023). A separate IoT-enabled monitoring study integrated soil-moisture, temperature and humidity measurements for remote visualization, although it did not evaluate irrigation effects in apple orchards (Ganesan *et al.*, 2025). A laboratory evaluation of soil-moisture sensors also demonstrated their integration into an automated drip-irrigation module, highlighting the importance of sensor calibration and threshold-based control (Aashabai *et al.*, 2024). A field evaluation of soil-moisture-sensor-guided irrigation in guava cultivation reported differences in irrigation efficiency across application methods, but its findings cannot be extrapolated directly to apple orchards (Adak, 2025). Recent research on smart irrigation systems has focused on the reliability, calibration, and decision rules of sensors, not the devices themselves (Vallejo-Gómez *et al.*, 2023; Nsoh *et al.*, 2024; Bounajra *et al.*, 2024). A study of apple orchards using dendrometer-guided automated irrigation similarly examined water application and yield outcomes under different sensor-based management strategies (Waldburger *et al.*, 2025). In commercial kiwifruit orchards, a data-driven control system used spatial soil-moisture measurements to inform irrigation decisions, illustrating a related approach in another perennial fruit crop (Baiardi *et al.*, 2026). Sensor data play a key role in machine-learning-based decision-making. Machine-learning tools can forecast short-term soil moisture, but they require historical data. Additional variables may also help predict soil moisture. Ensemble regressors, such as random forests and boosted trees, are suitable for modelling nonlinear relationships and smaller datasets. These methods can support soil-moisture prediction; however, accuracy estimated from a random split of temporally correlated records is often overly optimistic. Chronological testing is important, and comparison with a simple persistence baseline is a minimum requirement. Other studies have shown that noisy and missing sensor data are major obstacles to accurate forecasts (Togneri *et al.*, 2022; Ivanova, 2025; Del-Coco *et al.*, 2024; Abiadi *et al.*, 2024; Ashraf *et al.*, 2025). An IoT-based investigation of soil-moisture prediction has also identified the need for further validation across seasons and field conditions (Maniam *et al.*, 2026). A systematic review of IoT-enabled irrigation systems identified sensor calibration and long-term field validation as continuing limitations for wider implementation (Moustafa *et al.*, 2026). Apple-related studies have shown that the IrriPro system can help address water issues and improve fruit quality (Sun *et al.*, 2022; Wen *et al.*, 2024). Recent research on automated soil-moisture thresholds in Himalayan apple orchards has additionally examined the balance between irrigation inputs, fruit yield, and quality (Nazir *et al.*, 2026). Ali *et al.* (2024) conducted a meta-analysis on apples and stone fruits and found variations between differing climates and deficit regimes. Taken together, this research indicates that applying the least amount of water is not always the most practical goal; irrigation targets may need to accommodate yield and physiological constraints. Nevertheless, the present orchard records have not previously been assessed together for logged irrigation volumes, soil-moisture dynamics, next-record prediction, and separately documented harvest yields. The available harvest groups are not directly linked to the irrigation-volume logs, making a descriptive comparison appropriate without attributing observed differences solely to irrigation mode. The analysis quantifies recorded irrigation volumes and soil-moisture measurements, evaluates weather-moisture associations, and benchmarks next-record moisture prediction on a chronological order. The specific objectives of the study were to: (i) evaluate water savings under AI-driven precision irrigation; (ii) analyze soil-moisture dynamics and their relationships with air temperature and relative humidity in a high-density apple orchard; (iii) evaluate AI-based soil moisture prediction; and (iv) compare fruit-yield outcomes under automatic drip and manual drip irrigation.

2. Materials and Methods

2.1 Study Records and Measurement Structure

This study used indigenously developed soil-moisture sensors integrated with a microcontroller that recorded soil-moisture data in real time. The measured data were displayed on an OLED screen for on-site monitoring and simultaneously transmitted via a remote communication module to a remote base station for storage and further analysis. The working algorithm of the developed system is shown in Fig. 1. The developed prototype for a smart irrigation system was installed in a high-density apple orchard at Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir (SKUAST-K), Shalimar Research Farm, located at 34.08° N, 74.87° E, and 1615 m above mean sea level. The research farm has apple trees on M9 rootstock, a dwarf, shallow-rooted stock

that is described as facilitating soil-moisture measurements by minimizing leaching effects. The selected plot area was 14700 m² with 12 rows and 20 plants per row, for a total of 220 plants. The plot had a total of 440 drippers, each with a discharge of 4 Lph; thus, the total dripper discharge is 1760 LPH. A water flow meter (SPARKS), a pressure gauge, and other accessories were used in the system setup.

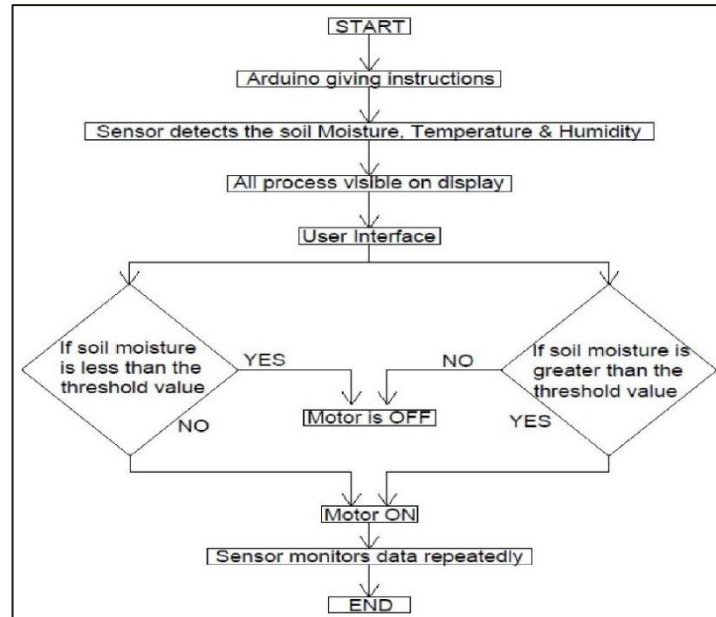


Fig. 1. Algorithm of the Developed System for Automatic Drip Irrigation

2.2 Data Handling

The sensor mean was calculated arithmetically from the three sensors for each observation. The highest absolute difference was 7.0 percentage points. Dynamic plots were generated from the data-acquisition sequence, and next-record forecasting was performed without assuming uniformly spaced samples.

2.3 Irrigation Volume Indicators

An irrigation event was defined as a positive, clearly recorded water volume in the relevant application data column. The descriptive indicators included recorded total volume (L and m³), number of applications, volume per application, and the ratio of cumulative automatic drip to manual drip volumes. The difference relative to manual was computed as $100 \times (\text{manual total} - \text{automatic total}) / \text{manual total}$.

2.4 Statistical Inference

Continuous variables were summarized by complete-case sample size, mean, sample standard deviation, median, and observed range. Spearman's rank correlation was used to assess the relationship between recalculated mean soil moisture and air temperature or relative humidity. Descriptively, conventional two-sided p-values were reported. A Mann-Whitney U test was performed to compare the distributions of event volumes.

2.5 Predictive AI evaluation

We predicted the three-sensor mean at the next logged record using information available in the recorded dataset: the three moisture channels, recomputed moisture mean, air temperature, relative humidity, pump-status flag and current recorded automatic irrigation volume as shown in Fig. 2. This is next-record forecasting, not prediction at a fixed elapsed time. Of the 181 record pairs, 144 (79.6%) were used to develop and train the Ridge, Random Forest and Gradient Boosting models. The remaining 37 pairs were used for chronological testing. Random Forest had 250 trees, a minimum leaf size of 5, 80% feature and 80% sample subsampling, and a random seed of 42. Gradient Boosting had 100 trees, a learning rate of 0.045, and a maximum depth of 2. Predictions were assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and out-of-sample R² (Coefficient of Determination) with persistence (the next value equals the present value) serving as the baseline. The dataset covers only one season and does not represent an independent deployment.

2.6 Normalized Fruit-Yield Response Scenarios

The cumulative irrigation volume for manual drip irrigation was set to a reference irrigation fraction of 1.0. At any fraction f of this reference, normalized fruit yield was assumed to follow $Y(f) = 100 \times [1 - k \times (1 - f)^2]$, with a central stress coefficient $k = 0.8$ and alternative coefficients 0.4 and 1.2. The relative productivity index was $[Y(f) / 100] / f$.

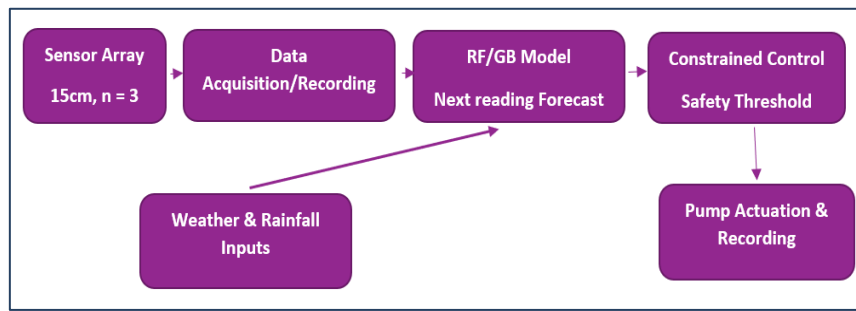


Fig. 2. Proposed measurement–prediction–decision framework

2.7 Supplemental Harvest-Yield Measurements and Calculations

A comparative variety-yield record provides tree-level fruit counts and harvested mass under the labels 'With Automation in drip irrigation using IoT' and 'Without Automation in drip irrigation' for three high-density apple varieties viz; Golden Apple, Decoste Robinjin and Mitch Gala. Five trees were chosen for each variety under each irrigation mode. Recorded mass (kg) and fruit counts were summed by variety and mode; yield per tree was calculated as total mass / 5, and descriptive percentage change was $100 \times (\text{automated total} - \text{manual total}) / \text{manual total}$. The original source occasionally divided by the automated total, and the Decoste Robinjin total is given as 46.2 kg, whereas its five tree rows sum to 46.0 kg; the present analysis consistently uses the tabulated tree entries.

3. Results and Data Analysis

3.1 Measurement Coverage and Descriptive Results

All 182 experimental records contained numerical measurements of temperature and relative humidity. The mean temperature was 30.32 ± 5.30 °C (range 16.7 to 40.9 °C) and relative humidity was $48.20 \pm 15.95\%$ (range 23.7 to 86.8%). The recalculated mean of three soil moisture sensors was $54.96 \pm 18.45\%$ (range 29 to 100%) as shown in Table 1.

Table 1. Descriptive statistics derived from the 182 recorded observations

Parameter	Observations	Mean $\pm$ SD	Minimum	Maximum
Air temperature (°C)	182	30.32 ± 5.30	16.7	40.9
Relative humidity (%)	182	48.20 ± 15.95	23.7	86.8
Sensor 1 (%)	182	55.16 ± 18.34	29.0	100.0
Sensor 2 (%)	182	54.97 ± 18.73	28.0	100.0
Sensor 3 (%)	182	54.74 ± 18.47	28.0	100.0
Three-sensor mean (%)	182	54.96 ± 18.45	29.0	100.0
Rainfall entries (mm)*	62	10.41 ± 10.85	0.8	37.4

The sensor channels were broadly synchronized, but short-lived departures were common, including high readings at or approaching the reported 100% ceiling. The 15-cm sampling depth records shallow-profile soil moisture, a characteristic relevant to high-density apple plants on M9 rootstock. Fig. 3 displays faint raw observations and overlays a five-record moving mean to emphasize the temporal pattern while preserving the measurement variability.

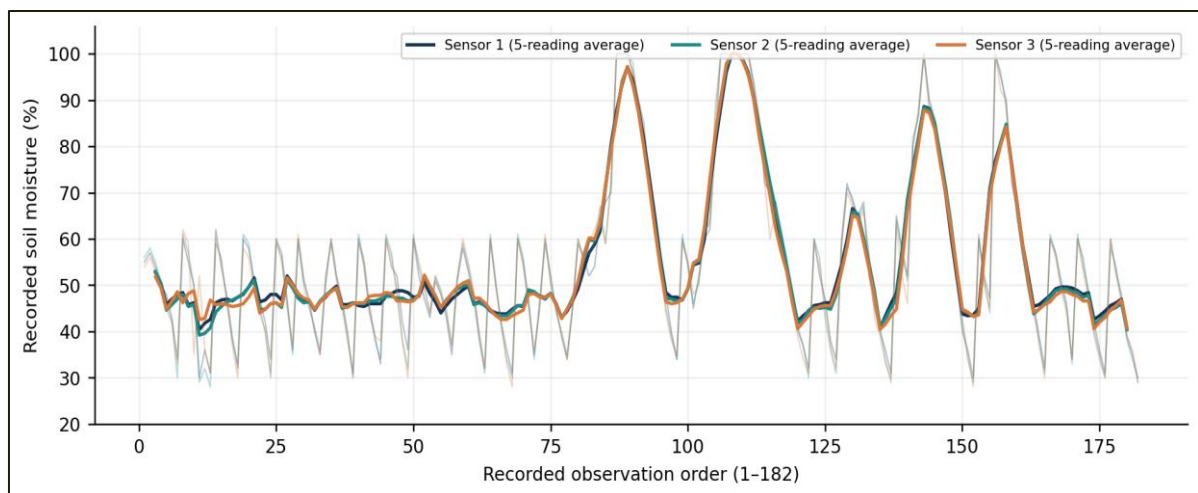


Fig. 3. Soil-moisture dynamics for the three recorded sensors

Table 2. Soil sensor comparison

Sensor channel	N	Mean (%)	SD (%)	Median (%)
Sensor 1	182	55.16	18.34	52.00
Sensor 2	182	54.97	18.73	53.00
Sensor 3	182	54.74	18.47	52.00

The Friedman rank statistic for within-record differences was $\chi^2(2) = 11.18$, $p = 0.0037$. This small difference in the location of channel measurements is not evidence of a variety effect because calibration, within-tree site characteristics and independence across dates are not established. The manuscript therefore avoids inferring varietal responses from these channels.

3.2 Automatic and Manual Irrigation-Volume Comparison

Automatic irrigation records contained 18 applications totaling 79,090 L (79.09 m³); manual logs contained 36 applications totaling 126,720 L (126.72 m³), as shown in Fig. 4. The automatic total represented 62.41% of the manual total, equivalent to a 37.59% lower recorded aggregate volume. However, manual irrigation had twice as many logged applications, and each recorded manual event was exactly 3,520 L, whereas automatic application size averaged 4,394 L (Table 3). Thus, the comparison describes a difference in logged volumes and application scheduling, not a replicated estimate of treatment efficacy.

Table 3. Recorded irrigation water applications

Indicator	Automatic	Manual
Event count	18	36
Total recorded water (L)	79,090	126,720
Total water (m ³)	79.09	126.72
Mean per event (L)	4393.89	3520.00
Per-event SD (L)	83.96	0.00
Range per event (L)	4,240-4,520	3,520-3,520
Difference vs manual total (%)	37.59	Reference

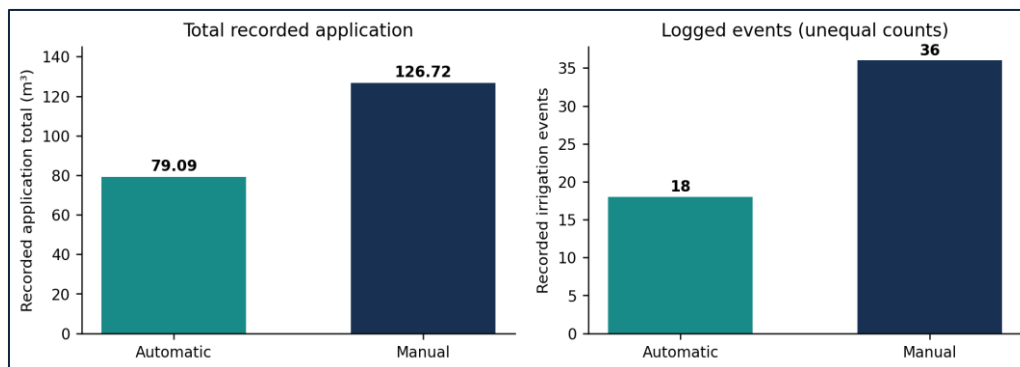


Fig. 4. Different recorded cumulative irrigation volumes and different counts of recorded applications

Fig. 4 shows two side-by-side bar charts comparing automatic and manual irrigation modes. The left chart presents the total recorded application volumes, showing that manual irrigation (126.72 m³) exceeded automatic irrigation (79.09 m³). The right chart, labelled “Logged events (unequal counts),” shows the number of recorded irrigation applications, with 36 manual events compared to only 18 automated events

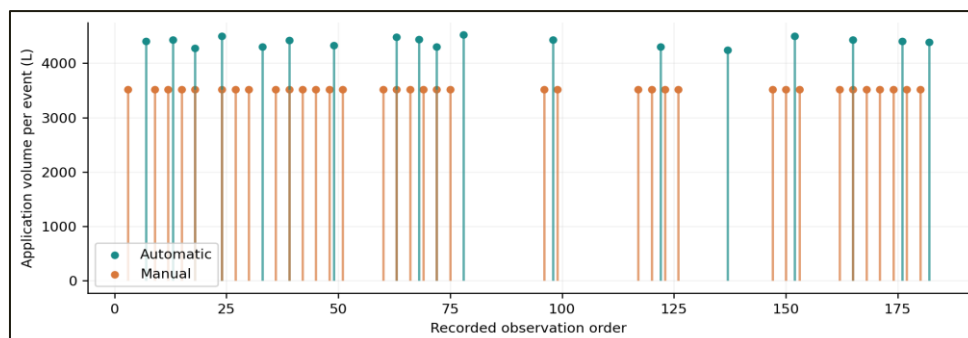


Fig. 5. Irrigation event volumes

Fig. 5 distinguishes the two modes by their fixed application volumes. Manual irrigation events were consistent, occurring at a strict uniform volume of 3,520 L. In contrast, automatic event volumes varied between approximately 3,520 L and 4,400 L. The comparison indicates that the larger total volume for manual irrigation (126.72 m³ vs. 79.09 m³) reflects the higher event frequency (36 vs. 18 events), not by larger individual volumes. The per-event dose distributions differed (Mann–Whitney U = 648, nominal p = 1.47e-12). Because all manual doses were identical and irrigation events are not randomised experimental units, the small p-value indicates a deterministic logging difference rather than statistical proof that automatic irrigation saves water under equivalent crop demand.

3.3 Soil Moisture-Weather Relationships

As shown in Table 4, mean sensor moisture had a modest negative rank association with air temperature ($\rho = -0.259$, nominal p = 0.00041, n = 182) and a positive association with relative humidity ($\rho = 0.360$, p = 6.10e-07, n = 182). Rainfall measurements were positively correlated with recorded moisture ($\rho = 0.541$, p = 5.68e-06, n = 62).

Table 4. Rank associations with recalculated mean soil moisture

Environmental variable	Available n	Spearman ρ	Nominal two-sided p
Temperature (°C)	182	-0.259	0.000408
Relative humidity (%)	182	+0.360	6.1e-07
Rainfall (mm)	62	+0.541	5.68e-06

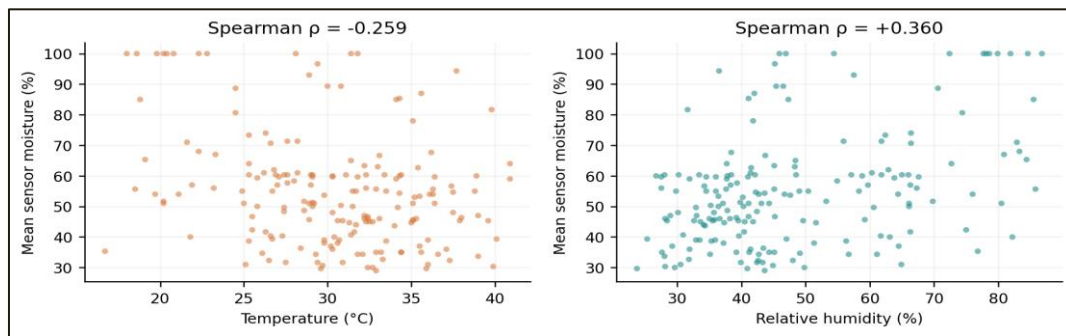


Fig. 6. Observed relationships of mean soil moisture with temperature and relative humidity

Fig. 6 illustrates the relationship between mean soil moisture and environmental drivers. The analysis shows correlations in the expected directions: soil moisture exhibits a negative monotonic association with air temperature (Spearman $\rho = -0.259$), reflecting natural evaporative drawdown, and a stronger positive association with relative humidity ($\rho = +0.360$). The stronger humidity correlation indicates an association between atmospheric moisture and recorded orchard soil moisture. Furthermore, the observable scatter and ceiling effects (100% readings) highlight periods of rapid sensor saturation and complex moisture retention. These observed associations provide a rationale for considering environmental covariates in the predictive Random Forest model.

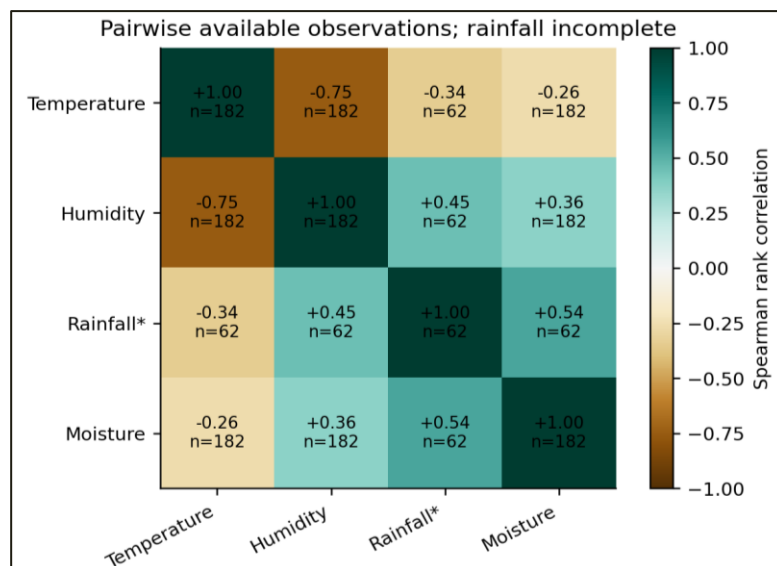


Fig. 7. Pairwise Spearman correlation matrix

Fig. 7 presents a Spearman rank-correlation heatmap of environmental variables and soil moisture. The heatmap depicts associations within the orchard microclimate. A distinct inverse relationship exists between temperature and humidity ($\rho = -0.75$), reflecting standard diurnal atmospheric dynamics. Rainfall exhibits the strongest positive association with soil moisture ($\rho = +0.54$). Relative humidity also shows a positive association ($\rho = +0.36$).

3.4 Predictive Modelling Performance

Table 5. Chronologically held-out next-record soil moisture prediction (n = 37)

Model	MAE (percentage points)	RMSE (percentage points)	Out-of-sample R ²
Persistence	10.74	14.86	0.292
Ridge	6.83	11.79	0.554
Random forest	6.34	11.50	0.576
Gradient boosting	6.45	11.79	0.554

The Random Forest model attained MAE = 6.34 percentage points, RMSE = 11.50 and test R² = 0.576. Persistence yielded MAE = 10.74, RMSE = 14.86 and R² = 0.292; the forest therefore reduced test MAE by 40.9% relative to the simplest baseline in this specific split. Ridge and Gradient Boosting achieved intermediate accuracy as shown in Table 5. These findings demonstrate retrospective prediction of the next *recorded* state, not model-controlled water application or stable hourly forecast skill.

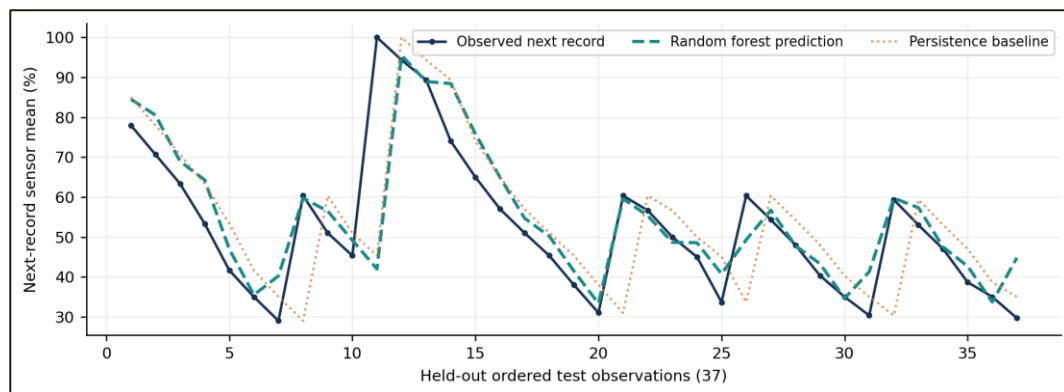


Fig. 8. Next-record moisture: held-out measurements versus Random Forest forecast and persistence comparator, on the last 37 ordered record pairs

Fig. 8 shows a time-series comparison of observed next-record soil moisture against Random Forest predictions and a persistence baseline across the 37 held-out test observations. The Random Forest model (teal dashed line) shows predictive performance on this holdout, tracking the observed fluctuations (solid line) and effectively capturing major peaks and troughs. In this holdout, the machine-learning model outperformed the persistence baseline (dotted orange line), which frequently over-predicts during drying periods. The comparison is limited to next-record prediction within the observed series and does not establish performance under independently deployed irrigation control.

3.5 Normalized Fruit-Yield Response and Decision Scenarios

Table 6. Modeled normalized irrigation–yield sensitivity

Irrigation volume (% ref.)	Volume reduction (%)	Yield index (ref. = 100)	Relative WP index
100.00	0.00	100.00	1.000
90.00	10.00	99.20	1.102
80.00	20.00	96.80	1.210
70.00	30.00	92.80	1.326
62.41	37.59	88.70	1.421

Table 6 shows a simulated water–yield response and water productivity under incremental irrigation reduction. The assumed scenario illustrates an irrigation–yield trade-off: as irrigation volume is progressively reduced from 100% to 62.41%, the relative yield index declines to 88.70. Consequently, the relative water productivity (WP) index increases, rising from a baseline of 1.000 to 1.421. Notably, at the recorded 37.59% volume reduction (matching the automatic-vs-manual field comparison), the simulated yield penalty is restricted to roughly 11%, while water productivity gains exceed 42%. This pattern reflects the assumptions of the scenario and does not establish the observed yield effects of reduced irrigation in high-density apple orchards.

Fig. 9 shows a dual-axis line graph illustrating the modelled comparison between irrigation volume, yield, and water productivity. The solid dark blue line shows the assumed yield index rising steadily from 88.7% to 100% as irrigation volume increases from approximately 62% to 100%. Conversely, the dashed teal line demonstrates a clear inverse relationship for relative crop water

productivity (WP index), which peaks near 1.45 at the lowest irrigation volume and scales down to 1.00 at the full baseline. This graphical intersection illustrates the modelled trade-off: significant water reductions yield disproportionately smaller crop yield penalties, under the assumed response function.

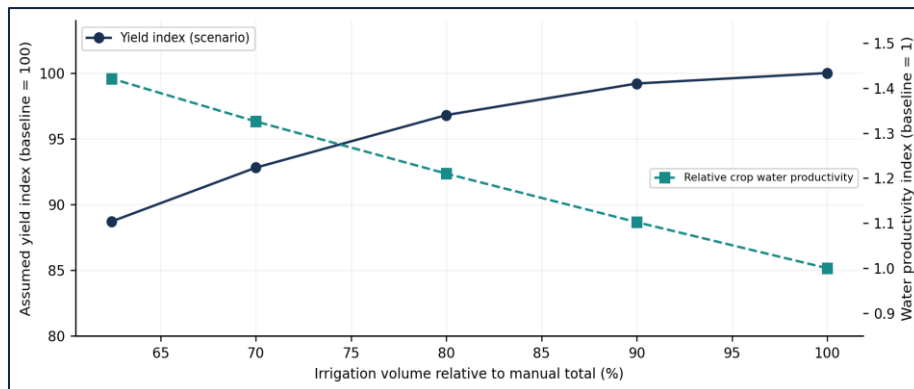


Fig. 9. Modeled irrigation fraction, normalized yield index and relative productivity under the explicitly assumed quadratic response ($k = 0.8$)

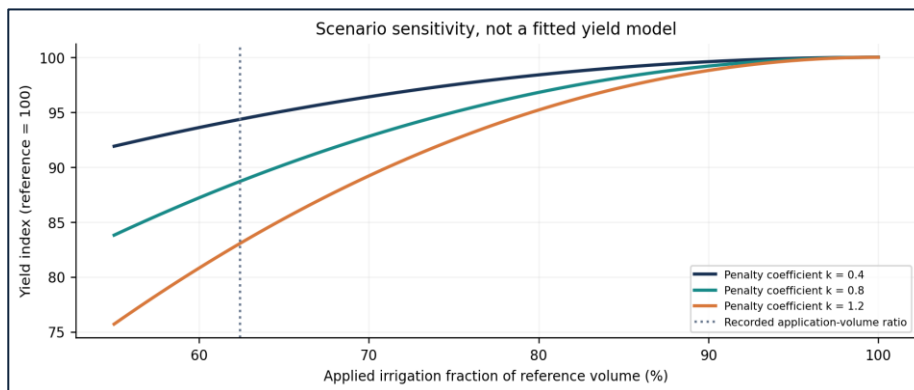


Fig. 10. Sensitivity of the assumed normalized fruit-yield response to three stress coefficients

Fig. 10 shows the sensitivity of the scenario yield index across varying penalty coefficients ($k = 0.4, 0.8, 1.2$) relative to applied irrigation fractions. The curves demonstrate that while reduced irrigation universally lowers the yield index, the magnitude of this penalty is highly dependent on the crop's sensitivity parameter. It illustrates potential yield trade-offs under the stated assumptions when adopting water-saving deficit irrigation strategies.

3.6 Supplemental Comparison of Recorded Harvest Yield

The companion tree-level harvest tables show higher recorded fruit mass and fruit counts in the automated groups for each of the three varieties (Table 7). For Golden Apple, five automated trees produced 62.50 kg from 506 fruits, while five manually irrigated trees produced 36.80 kg from 443 fruits. This corresponds to a mass difference of 25.70 kg, or 69.84% of the manual total; mean harvest mass per tree was 12.50 versus 7.36 kg. The corresponding mass differences were 23.30 kg for Decoste Robinjin and 25.25 kg for Mitch Gala. These percentages describe group totals, not adjusted or independently replicated treatment effects.

Table 7. Observed harvested fruit mass and fruit counts in each variety

Variety	Automated kg	Manual kg	Difference kg	Gain vs manual	Fruits auto / manual
Golden Apple	62.50	36.80	+25.70	+69.84%	506 / 443
Decoste Robinjin	46.00	22.70	+23.30	+102.64%	218 / 160
Mitch Gala	54.00	28.75	+25.25	+87.83%	444 / 309

Across the three high-density apple varieties, as shown in Fig. 11, automated-to-manual fruit counts were 506/443 for Golden Apple, 218/160 for Decoste Robinjin and 444/309 for Mitch Gala. Mean fruit mass, calculated by dividing total mass by fruit count, was approximately 123.5 versus 83.1 g, 211.0 versus 141.9 g and 121.6 versus 93.0 g, respectively. The descriptive tree-level mean $\pm$ sample SD of harvested mass was 12.50 ± 5.77 versus 7.36 ± 3.75 kg/tree for Golden Apple, 9.20 ± 3.04 versus 4.54 ± 2.10 kg/tree for Decoste Robinjin and 10.80 ± 2.36 versus 5.75 ± 1.70 kg/tree for Mitch Gala (automatic versus manual). These summaries show within-group variability without assuming random treatment allocation or paired trees.

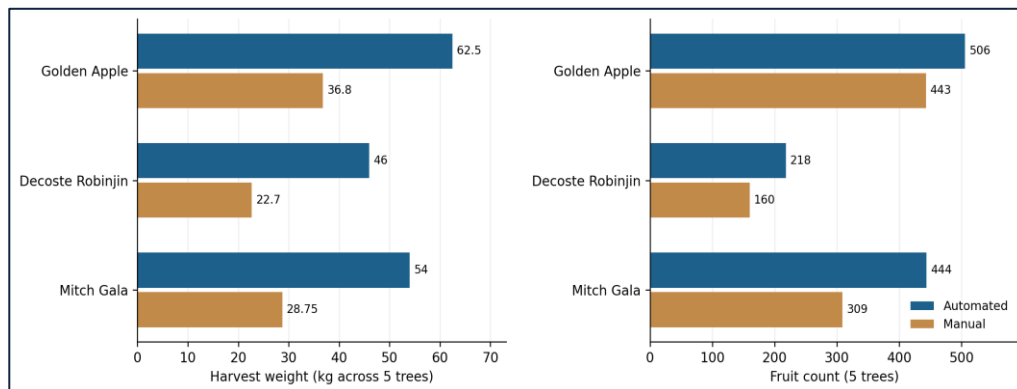


Fig. 11. Harvest mass and fruit count by varieties and recorded irrigation mode

4. Discussion

The irrigation data recorded in the study contain lesser automatic irrigation event than manual applications, but former were larger doses per event. The cumulative recorded irrigation volume was 79.09 m³ in the automatic column and 126.72 m³ in the manual column. These considerations are important in perennial apple orchards, where water timing, stress intensity, tree condition and irrigation configuration can influence fruit outcomes independently of total delivered volume. Orchard research has investigated rainwater integration, intelligent irrigation, emitter placement and sensor-guided schedules (Sun *et al.*, 2022; Ali *et al.*, 2024; Wen *et al.*, 2024; Mir *et al.*, 2025; Balkhi *et al.*, 2023). Such published responses provide context, but effects observed elsewhere cannot be assumed to apply to these records without matched treatment allocation, calibrated measurements and orchard-level replication.

Associations observed with moisture are generally in the expected direction. Hotter conditions are generally associated with higher moisture demand, and rainfall and humidity tend to increase moisture content. However, the nominal p-values are calculated across repeated time series and therefore cannot be interpreted as independent causal effects. A more refined analysis would distinguish between-day and within-day effects and align rainfall with the period for which it is reported, while accounting for irrigation. Time-series block bootstrapping or a hierarchical mixed-effects approach would be more appropriate once a set of independently replicated and dated orchard plots are available. Kelly *et al.* (2021) suggest that the operational scheduling strategy and measurement error combine to determine the outcomes; hence, sensor quality is important only if the decisions made from sensor outputs are also of sufficient quality.

The machine-learning contribution is retrospective next-record forecasting, with Random Forest improving test MAE over persistence on the available chronological split. This indicates predictive performance within the observed series, not AI-controlled field deployment or an independently validated agronomic treatment. Limited seasonal coverage and potentially correlated records constrain generalization (Challa *et al.*, 2024).

A practical architecture should place decision safeguards between forecasts and pump actuation. Sensors require calibration against volumetric water content or soil-water potential; irrigation thresholds must account for growth stage, root-zone depth and maximum event duration. Valves and pumps also need safeguards against pressure loss, stuck actuation and sensor failure. To test yield benefits, future work should randomize replicated, variety-matched orchard blocks among manual, rule-based and AI-assisted scheduling, measuring calibrated irrigation volume and harvested fruit on the same documented blocks, with tree size, fruit quality, production costs and return bloom monitored over multiple seasons (Peeters *et al.*, 2024; Katimbo *et al.*, 2023; Gao *et al.*, 2023).

The supplementary harvest observations provide a variety-specific outcome that the original irrigation log did not contain. In Golden Apple, Decoste Robinjin and Mitch Gala, the automated groups recorded higher harvest weights and fruit numbers than the manual groups. The magnitude of the differences varies across varieties, indicating why variety, tree maturity, block conditions and treatment assignment must be accounted for before interpreting irrigation effects. The five-tree totals are descriptive and cannot establish whether AI forecasting, rather than other differences between the groups, caused the yield contrast. Furthermore, the harvest weights cannot be divided by the 79.09 m³ and 126.72 m³ irrigation totals: there is no evidence linking those totals to the harvested tree groups (Zhang *et al.*, 2023; Wen *et al.*, 2024; Tsoulas *et al.*, 2024). The normalized sensitivity scenarios help distinguish reduced irrigation volume from improved crop-water productivity and sustained fruit yield. A productivity ratio can rise when its assumed water denominator decreases, even while assumed fruit yield declines.

5. Conclusion

The study recorded differences in irrigation-event frequency, aggregate water application, soil-moisture behaviour and harvested fruit mass in a high-density apple orchard. Automatic irrigation accounted for 18 events and 79,090 L, compared with 36 events and 126,720 L under manual irrigation. The resulting 37.59% lower aggregate recorded volume is a descriptive comparison of unequal event logs rather than an independently replicated treatment effect. Across 182 observations, mean soil moisture was 54.96%, with negative and positive rank associations with temperature and relative humidity, respectively. Random Forest predicted the next recorded soil-moisture value with a mean absolute error of 6.34 percentage points, improving on the persistence benchmark of 10.74

percentage points within the chronological holdout. Supplementary five-tree harvest groups recorded higher fruit masses under the automated label for Golden Apple, Decoste Robinjin and Mitch Gala; however, their outcomes cannot be quantitatively attributed to the logged irrigation volumes. The normalized irrigation–yield relationships represent assumed scenarios rather than measured treatment responses. Replicated, variety-matched studies with linked water-application and harvest measurements are required to establish irrigation effects and actual crop-water productivity.

6. Limitations

The analysis used records from a single season and one orchard setting. Repeated sensor observations may be temporally dependent, and soil-moisture measurements were not independently calibrated. Automatic and manual irrigation logs contained unequal numbers of events and did not represent independently replicated, randomized treatments. The supplementary harvest groups were not linked to the logged irrigation volumes, limiting causal interpretation and preventing calculation of observed water productivity. Next-record prediction was evaluated retrospectively on one chronological holdout rather than through independent, model-controlled field deployment. Normalized irrigation-yield responses were assumed rather than fitted to experimental yield observations.

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Declaration of AI Use

This manuscript was prepared through the intellectual contributions of the author(s) to the study design, data analysis, interpretation of results, and scholarly content. Grammarly and ChatGPT were used solely to assist with grammatical refinement and reference formatting during manuscript revision. The author(s) accept full responsibility for the accuracy, integrity, and final content of the manuscript.

Competing Interests

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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