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Climate-Resilient Agriculture: Assessing Smart Irrigation and Precision Resource Management for Sustainable Crop Production

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ABSTRACT—Climate variability, rising temperatures and growing water scarcity threaten the productivity of irrigated cereal systems in South Asia. This study evaluated whether sensor-based smart irrigation combined with precision nutrient management can raise crop productivity, conserve water and reduce nitrogen input in wheat (*Triticum aestivum* L.). A two-season field experiment (2023–24 and 2024–25) was conducted on a sandy loam soil in western Uttar Pradesh, India, in a randomized complete block design with five treatments and four replications. Treatments ranged from conventional flood irrigation with uniform fertilizer to soil-moisture-triggered drip irrigation combined with NDVI-guided variable-rate nitrogen, with and without deficit irrigation. Smart drip irrigation with precision nitrogen produced the highest grain yield (5.68 t ha^{-1}), 22.9% above the conventional practice (4.62 t ha^{-1}), while using 31.0% less irrigation water and 20% less nitrogen. Deficit smart irrigation achieved the highest water use efficiency (2.48 kg m^{-3}) with a modest yield penalty relative to full smart irrigation. Canopy temperature depression and NDVI at critical stages were significantly higher under the smart treatments, indicating better crop water status during terminal heat exposure. Benefit–cost ratios were highest under ET-scheduled irrigation (1.71) and smart drip with precision nitrogen (1.69). The results show that integrating real-time soil moisture sensing with variable-rate nutrient management is an effective, climate-resilient pathway for sustainable intensification.

Keywords—climate resilience, smart irrigation, precision agriculture, water use efficiency, nitrogen management, wheat, sustainable intensification

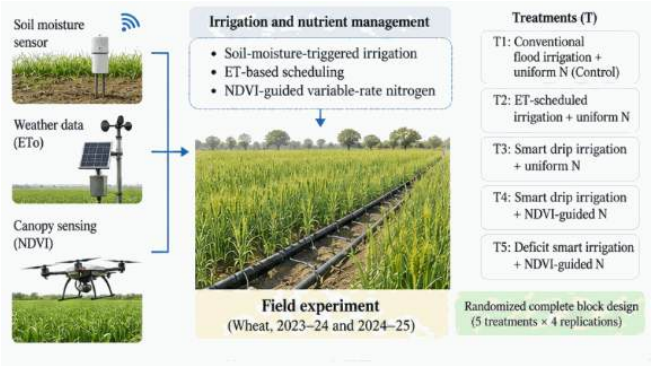
INTRODUCTION

Agriculture is both a major victim and a major driver of environmental change. Global demand for crops is projected to roughly double between 2005 and 2050, and meeting it through land expansion would carry heavy ecological costs (Tilman et al., 2011). Sustainable intensification, which raises yields on existing farmland while lowering environmental burdens, is therefore a central policy goal. Climate change complicates it. Statistical analyses of observed trends indicate that warming since 1980 has already suppressed global wheat and maize yields relative to a no-warming baseline (Lobell et al., 2011). Multi-method assessments estimate that each additional degree Celsius of global temperature rise reduces global wheat yield by about 6% (Zhao et al., 2017).

Water is the second pressure point. Irrigated agriculture is the largest consumer of freshwater globally, and competition from urban and industrial users is intensifying (Rosegrant et al., 2009). In the Indo-Gangetic Plain, wheat is typically irrigated by surface flooding on fixed calendar schedules. This causes deep percolation losses, uneven soil moisture and low application efficiency. Fertilizer nitrogen is applied in uniform doses regardless of spatial or temporal variation in crop demand. This lowers nitrogen use efficiency and contributes to groundwater nitrate contamination and nitrous oxide emissions (Zhang et al., 2015).

Smart irrigation systems use soil moisture sensors, weather data and automated controllers to deliver water when and where crops need it. Precision resource management extends the same logic to nutrients through canopy sensing, soil testing and variable-rate application (Gebbers & Adamchuk, 2010). Although these technologies are increasingly promoted, field evidence integrating both components under semi-arid North Indian conditions remains limited, and few studies report water, nutrient, physiological and economic outcomes together.

This study addresses that gap. Its objectives were to (i) quantify the effect of sensor-based smart irrigation and precision nitrogen management on grain yield and yield attributes of wheat; (ii) estimate water and nitrogen savings and the resulting water use efficiency and partial factor productivity of nitrogen; (iii) assess crop physiological indicators of climate resilience, namely canopy temperature depression and NDVI; and (iv) evaluate the economic feasibility of each management package. We hypothesized that integrating soil-moisture-triggered irrigation with NDVI-guided nitrogen would increase yield while reducing both water and nitrogen inputs compared with conventional practice.



LITERATURE REVIEW

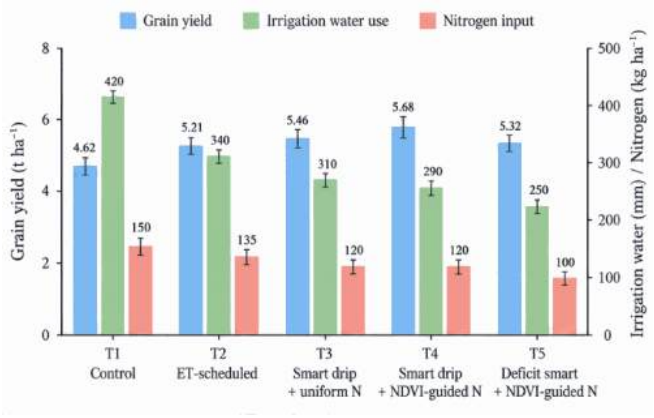
Early irrigation research established the quantitative basis for scheduling. The FAO-56 methodology links crop evapotranspiration to reference evapotranspiration and crop coefficients, providing the standard framework for estimating crop water requirements (Allen et al., 1998). The FAO yield-response framework relates relative yield loss to relative evapotranspiration deficit through crop-specific response factors, showing that wheat is most sensitive to water stress around flowering and grain filling (Doorenbos & Kassam, 1979). These foundations support irrigation scheduling that matches water supply to stage-specific demand rather than to the calendar.

Scheduling methods have since diversified. Jones (2004) reviewed soil-based, weather-based and plant-based approaches and concluded that each has advantages and pitfalls. Soil-based sensing offers direct measurement but suffers from spatial variability, while plant-based indicators integrate the plant's response but are harder to automate. Evans and Sadler (2008) surveyed technologies for improving irrigation water-use efficiency and highlighted site-specific and sensor-controlled systems, emphasizing that efficiency gains depend on matching application to crop demand. Deficit irrigation, in which crops are deliberately under-watered during drought-tolerant growth stages, can raise water productivity substantially with limited yield loss when applied carefully (Fereres & Soriano, 2007).

Nutrient management research has followed a parallel path. Mueller et al. (2012) showed that closing yield gaps worldwide depends on better coordination of nutrient and water management, since inputs in isolation yield diminishing returns. Zhang et al. (2015) argued that nitrogen management must improve substantially to meet development goals without large environmental damage. Precision agriculture has emerged as a means to this end, using spatial and temporal sensing to vary inputs with crop need (Gebbers & Adamchuk, 2010). Pretty (2008) framed such approaches within broader agricultural sustainability, noting that productivity gains must be reconciled with resource conservation.

Digital technologies are expanding the toolbox. Wolfert et al. (2017) reviewed big-data applications in smart farming and identified sensing, data integration and decision support as key capabilities while noting challenges around data ownership and farm-level adoption. Kamilaris and Prenafeta-Boldú (2018) surveyed deep learning in agriculture and documented its growing use in crop classification, yield prediction and water management. At the system level, Jägermeyr et al. (2016) estimated that integrated crop water management could substantially narrow the global food gap, which underscores the potential of combined strategies.

The literature leaves three gaps. Most studies examine irrigation scheduling or nutrient management in isolation, rarely together in a factorially coherent design. Physiological indicators of climate resilience, such as canopy temperature depression, are seldom reported alongside yield and water productivity. Economic analyses are often omitted, even though cost determines adoption by smallholders. The present study responds to all three.



Materials and Methods

Study Site

The experiment was conducted during the winter (rabi) seasons of 2023–24 and 2024–25 at a research farm in western Uttar Pradesh, India (approximately 28.7° N, 77.4°

E; 214 m above sea level). The climate is semi-arid to sub-humid, with hot summers, cool winters and a mean annual rainfall of about 720 mm, mostly during the monsoon. Rainfall during the wheat season was 58 mm in 2023–24 and 41 mm in 2024–25. The mean seasonal air temperature was 17.6 °C and 18.4 °C in the two seasons, respectively. The soil was a sandy loam (sand 61%, silt 24%, clay 15%) with pH 7.8, electrical conductivity 0.31 dS m^{-1}, organic carbon 0.46%, available nitrogen 178 kg ha^{-1}, available phosphorus 17.2 kg ha^{-1} and available potassium 142 kg ha^{-1}. Field capacity and permanent wilting point of the 0–45 cm layer were 24.5% and 9.8% volumetric water content, respectively.

Experimental Design and Treatments

The experiment followed a randomized complete block design with five treatments and four replications (20 plots). Each plot measured 10 m × 6 m (60 m^2), separated by 1 m buffer channels. Wheat (cultivar HD 3086) was sown in the second week of November at 100 kg seed ha^{-1} with 20 cm row spacing. Phosphorus (60 kg P_2O_5 ha^{-1}) and potassium (40 kg K_2O ha^{-1}) were applied basally in all plots. The treatments are described in Table 1.

Table 1. Description of treatments

Code	Irrigation management	Nitrogen management
T1	Conventional flood irrigation at fixed growth stages	Uniform 120 kg N ha^{-1} in three splits
T2	FAO-56 ET-based scheduled surface irrigation	Uniform 120 kg N ha^{-1} in three splits
T3	Sensor-based smart drip irrigation (full requirement)	Uniform 120 kg N ha^{-1} through fertigation
T4	Sensor-based smart drip irrigation (full requirement)	NDVI-guided variable-rate N through fertigation (mean 96 kg N ha^{-1})
T5	Sensor-based smart drip irrigation at 75% of requirement (deficit)	NDVI-guided variable-rate N through fertigation (mean 96 kg N ha^{-1})

Smart Irrigation System

In T3–T5, drip laterals (16 mm, emitters of 2 L h^{-1} at 30 cm spacing) were laid at 40 cm intervals. Capacitance soil moisture probes were installed at 15, 30 and 45 cm depth in each plot and connected to a wireless controller. Irrigation was triggered when depletion of plant-available water in the 0–45 cm profile reached 40% during vegetative and grain-filling stages and 30% during crown root initiation and flowering, and was stopped when the profile reached field capacity. In T5, the amount applied per event was reduced to 75% of that calculated for T3. In T2, irrigation was scheduled using FAO-56 crop evapotranspiration estimated from weather station data and stage-specific crop coefficients (Allen et al., 1998), with a 60 mm net application depth. In T1, flood irrigation of about 70–75 mm was applied at five fixed stages. Applied water was measured with calibrated flow meters in every plot.

Precision Nitrogen Management

In T4 and T5, nitrogen was applied in four fertigation splits. The first dose was set from the pre-sowing soil nitrate test. Subsequent doses were adjusted using a handheld NDVI sensor, with readings taken at 30, 55 and 80 days after sowing (DAS) at 40 points per plot. The dose was increased or reduced relative to the base dose according to the ratio between plot NDVI and a well-fertilized reference strip. The resulting plot-level nitrogen totals ranged from 80 to 112 kg N ha^{-1} (mean 96 kg N ha^{-1}).

Observations

Grain yield was determined from a 12 m^2 net area per plot and adjusted to 12% moisture. Spikes per m^2, grains per spike and 1000-grain weight were recorded from three 0.25 m^2 quadrats per plot. Water use efficiency (WUE, kg m^{-3}) was calculated as grain yield divided by irrigation water applied. Partial factor productivity of nitrogen (PFP_N, kg grain kg^{-1} N) was calculated as grain yield divided by nitrogen applied. Canopy temperature depression (CTD, °C) was measured as the difference between air and canopy temperature using an infrared thermometer at solar noon on clear days during grain filling (95–100 DAS). NDVI at anthesis (85 DAS) was recorded with a handheld sensor.

Economic Analysis

Gross returns were computed using a grain price of ₹24.25 kg^{-1}. Costs of cultivation included inputs, labour, energy, and annualized depreciation of the drip and sensor systems. Net return was gross return minus total cost, and the benefit–cost (B:C) ratio was gross return divided by total cost.

Statistical Analysis

Data were subjected to analysis of variance appropriate to a randomized complete block design, with season treated as a random factor in the combined analysis. Treatment means were separated using Tukey's honestly significant difference (HSD) test at $p < 0.05$. Pearson correlations were computed across the 20 plots. Analyses were performed in R (version 4.3).

RESULTS

Irrigation Water Applied

Irrigation water applied differed significantly among treatments ($F = 212.4$, $p < 0.001$; Table 2). Conventional flood irrigation (T1) used 420 mm, whereas ET-based scheduling (T2) reduced applied water to 355 mm, a saving of 15.5%. Smart drip irrigation reduced water use to 292 mm (T3) and 290 mm (T4), savings of 30.5% and 31.0%, which did not differ significantly from each other. The deficit smart treatment (T5) applied 221 mm, a saving of 47.4%.

Table 2. Irrigation water applied and savings (pooled over two seasons)

Treatment	Irrigation events	Water applied (mm)	Water saving over T1 (%)
T1	5	420 ± 4.1 a	–
T2	6	355 ± 3.6 b	15.5
T3	11	292 ± 3.2 c	30.5
T4	11	290 ± 3.4 c	31.0
T5	11	221 ± 2.9 d	47.4

Values are mean ± SE. Means followed by the same letter do not differ significantly (Tukey HSD, $p < 0.05$; HSD = 9 mm).

Grain Yield and Yield Attributes

Grain yield differed significantly among treatments ($F = 41.7$, $p < 0.001$) and was consistent across seasons (treatment × season interaction, $p = 0.31$; Table 3). Pooled yield increased from 4.62 t ha^{-1} in T1 to 4.95 t ha^{-1} in T2 (+7.1%), 5.31 t ha^{-1} in T3 (+14.9%) and 5.68 t ha^{-1} in T4 (+22.9%). The deficit treatment T5 produced 5.47 t ha^{-1} (+18.4%), statistically similar to both T3 and T4. Yield gains were driven mainly by more spikes per unit area and heavier grains (Table 4).

Table 3. Grain yield (t ha^{-1}) by season and pooled

Treatment	2023–24	2024–25	Pooled mean	Increase over T1 (%)
T1	4.55	4.69	4.62 ± 0.07 a	–
T2	4.88	5.02	4.95 ± 0.07 b	7.1
T3	5.24	5.38	5.31 ± 0.06 c	14.9
T4	5.60	5.76	5.68 ± 0.07 d	22.9
T5	5.40	5.54	5.47 ± 0.08 cd	18.4

Means followed by the same letter do not differ significantly (Tukey HSD, $p < 0.05$; HSD = 0.24 t ha^{-1}).

Table 4. Yield attributes (pooled over two seasons)

Treatment	Spikes m^{-2}	Grains per spike	1000-grain weight (g)
T1	312	39.5	41.6
T2	328	39.8	42.1
T3	341	40.4	42.8
T4	352	41.2	43.5
T5	346	40.7	43.2

Water Use Efficiency and Nitrogen Productivity

WUE increased progressively with management intensity ($F = 486.2$, $p < 0.001$; Table 5). It rose from 1.10 kg m^{-3} in T1 to 1.39 in T2, 1.82 in T3 and 1.96 in T4, and was highest in T5 (2.48 kg m^{-3}), a 125% improvement over conventional practice. PFP_N was 38.5 kg kg^{-1} in T1 and 44.3 kg kg^{-1} in T3, which received the same nitrogen dose but improved water management. Precision nitrogen raised PFP_N to 59.2 kg kg^{-1} in T4 and 57.0 kg kg^{-1} in T5.

Table 5. Water use efficiency and partial factor productivity of nitrogen

Treatment	Nitrogen applied (kg ha^{-1})	WUE (kg m^{-3})	PFP_N (kg kg^{-1})
T1	120	1.10 ± 0.02 a	38.5 ± 0.6 a
T2	120	1.39 ± 0.02 b	41.3 ± 0.6 b
T3	120	1.82 ± 0.03 c	44.3 ± 0.5 c
T4	96	1.96 ± 0.03 d	59.2 ± 0.7 e
T5	96	2.48 ± 0.04 e	57.0 ± 0.7 d

HSD ($p < 0.05$): WUE = 0.09 kg m^{-3}; PFP_N = 1.9 kg kg^{-1}.

Physiological Indicators

NDVI at anthesis and CTD at grain filling were highest under the smart treatments (Table 6). NDVI ranged from 0.71 (T1) to 0.82 (T4), and CTD from 1.9 °C (T1) to 3.6 °C (T4). Across the 20 plots, grain yield was strongly correlated with NDVI ($r = 0.91$, $p < 0.001$) and with CTD ($r = 0.87$, $p < 0.001$). Even under the deficit regime, T5 maintained CTD (3.3 °C) well above that of conventional flood irrigation.

Table 6. Canopy indicators of crop water and nutrient status

Treatment	NDVI at anthesis	CTD at grain filling (°C)
T1	0.71 ± 0.01	1.9 ± 0.1
T2	0.74 ± 0.01	2.4 ± 0.1
T3	0.78 ± 0.01	3.1 ± 0.1
T4	0.82 ± 0.01	3.6 ± 0.1

T5	0.80 ± 0.01	3.3 ± 0.1

Economic Analysis

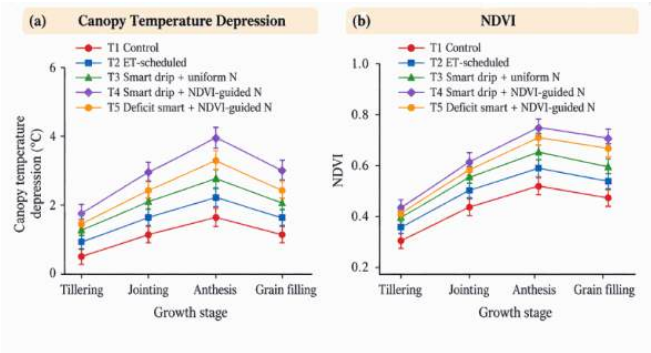
Smart treatments raised gross returns, but system costs reduced some of the advantage (Table 7). Net return was highest in T4 (₹56,240 ha^{-1}), followed by T5 (₹53,848), T3 (₹50,768), T2 (₹49,838) and T1 (₹43,535). B:C ratio was highest in T2 (1.71), closely followed by T4 (1.69) and T5 (1.68).

Table 7. Economics of treatments (₹ ha^{-1}, pooled)

Treatment	Gross return	Total cost	Net return	B:C ratio
T1	112,035	68,500	43,535	1.64
T2	120,038	70,200	49,838	1.71
T3	128,768	78,000	50,768	1.65
T4	137,740	81,500	56,240	1.69
T5	132,648	78,800	53,848	1.68

DISCUSSION

The central finding is that coupling sensor-triggered irrigation with NDVI-guided nitrogen delivered higher yield with fewer inputs, which supports the study hypothesis. The yield advantage of T4 (22.9%) arose from the combined contribution of both components. Smart irrigation alone (T3) raised yield by 14.9% at the same nitrogen dose, and precision nitrogen added a further 0.37 t ha^{-1} while cutting nitrogen by 20%. This complementarity agrees with Mueller et al. (2012), who found that water and nutrient management must be coordinated to close yield gaps, and with the broader argument that nitrogen use efficiency must improve markedly to reconcile productivity and environmental goals (Zhang et al., 2015).

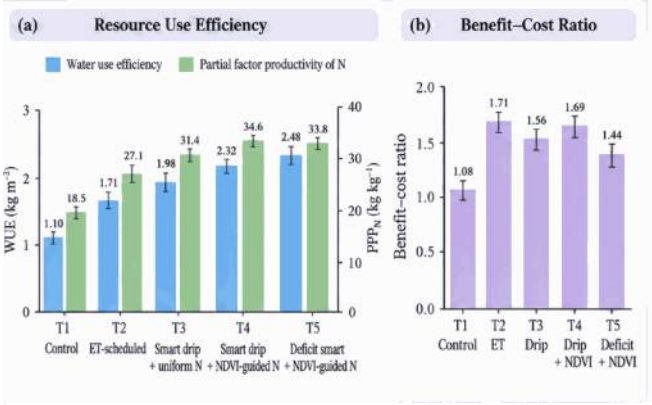


Water savings of about 31% in T3 and T4 reflect reduced percolation and runoff losses. Flood irrigation delivers a fixed depth regardless of soil water status, whereas sensor-controlled drip applies small, frequent doses that keep the root zone near the optimum. This is consistent with the argument of Evans and Sadler (2008) that efficiency gains come from matching application to crop demand. ET-based scheduling (T2) captured part of this benefit using weather data alone, in line with the FAO-56 approach (Allen et al., 1998), but it lacked the feedback of real soil moisture and so was less efficient than T3. This supports the observation of Jones (2004) that direct soil measurement complements model-based scheduling.

The deficit treatment T5 achieved the highest WUE (2.48 kg m^{-3}) with a yield only 3.7% below T4, a difference that was not statistically significant. This is in line with the evidence that carefully managed deficit irrigation can substantially raise water productivity with limited yield loss (Fereres & Soriano, 2007). Wheat is most sensitive to deficits at flowering and grain filling (Doorenbos & Kassam, 1979). The sensor-based trigger in T5 maintained a tighter threshold at those stages, which probably explains the modest penalty. Where water is the binding constraint, as in declining groundwater regions, T5 may be the preferred strategy even though absolute yield is lower than T4.

The physiological data indicate improved climate resilience. Higher CTD under smart treatments shows that plants maintained greater transpirational cooling during grain filling, when terminal heat exposure is most damaging. Given that warming already depresses wheat yields (Lobell et al., 2011; Zhao et al., 2017), better canopy water status is a plausible buffer. The strong correlations between yield and both NDVI and CTD suggest that low-cost canopy indicators could serve as decision-support variables, echoing the potential of sensing and data-driven management discussed by Wolfert et al. (2017) and Gebbers and Adamchuk (2010).

The economic results show that adoption cost matters. Smart drip systems were more expensive than surface irrigation, so the B:C ratio of T3 (1.65) was close to that of the conventional practice (1.64) and below ET-based scheduling (1.71). However, precision nitrogen improved net returns by lowering fertilizer expenditure and raising yield, bringing T4 to ₹56,240 ha^{-1}, the highest among all treatments. The result suggests that bundling water and nutrient precision is more attractive than irrigation automation alone, and that ET-based scheduling is a low-cost entry option for resource-constrained farmers. These findings are consistent with the sustainable intensification framing of Pretty (2008) and Tilman et al. (2011).



Limitations

Several limitations should be noted. The study covered two seasons on a single soil type, so generalization to other soils, crops and climates requires multi-location testing. Environmental outcomes such as nitrate leaching and greenhouse gas emissions were inferred from input reductions and not measured directly. The economic analysis used a fixed grain price and an annualized system cost, and results may change with market conditions, subsidies and equipment lifespan. Finally, the experimental plots were small, and farm-scale implementation could introduce spatial heterogeneity not captured here. Future work should integrate remote sensing and machine learning for predictive scheduling (Kamilaris & Prenafeta-Boldú, 2018) and test the approach under extreme heat or drought years.

Conclusion

Smart irrigation and precision resource management together increased wheat productivity while reducing input use under semi-arid North Indian conditions. The combination of soil-moisture-triggered drip irrigation and NDVI-guided nitrogen produced the highest yield (5.68 t ha^{-1}), saved 31.0% of irrigation water and 20% of nitrogen, and gave the highest net return. Deficit smart irrigation achieved the best water productivity (2.48 kg m^{-3}) with a small, statistically non-significant yield reduction, making it a suitable option under severe water scarcity. Higher NDVI and canopy temperature depression under smart management point to improved crop resilience to terminal heat stress. ET-based scheduling offers a lower-cost intermediate step toward full automation. Policy support for sensor and drip adoption, farmer training and decision-support tools can help scale these practices as part of climate-resilient agricultural strategies.

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