



REMOTE SENSING-DRIVEN AGRICULTURAL WATER MANAGEMENT: AN INTEGRATED ECONOMIC FRAMEWORK FOR OPTIMIZING IRRIGATION EFFICIENCY, CROP PRODUCTIVITY, FARM PROFITABILITY AND CLIMATE RESILIENCE

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Abstract

Increasing water scarcity, climate variability, and irrigation costs threaten agricultural productivity and farm profitability. This study develops a remote sensing-driven economic framework to optimize irrigation efficiency, crop yield, net returns, and climate resilience. The analysis covers 120 farms and 8,400 hectares of wheat, maize, and cotton during 2022–2025. It integrates 1,260 cloud-screened satellite observations with weather records, soil measurements, irrigation logs, crop yields, production costs, and farm-gate prices. Satellite-derived vegetation indices, land surface temperature, and evapotranspiration estimates are used to identify field-level water stress and estimate crop irrigation requirements. These indicators are incorporated into a multi-objective optimization model that evaluates alternative irrigation schedules according to water consumption, expected yield, pumping costs, and net farm returns. The schedules are assessed under normal conditions and simulated drought and heat-stress scenarios. Compared with conventional farm irrigation practices, the optimized schedules reduce irrigation water withdrawals by 18.6% and increase average crop yield by 6.2%. Water productivity increases from 1.34 to 1.71 kg per cubic metre, while average net farm returns rise by 11.8% after accounting for pumping and other production costs. Under the drought scenario, estimated yield losses are 8.4% with optimized scheduling, compared with 15.7% under conventional practice. Sensitivity analysis identifies pumping costs and seasonal water availability as major determinants of the economically preferred schedule. Responses also vary across crops and soil conditions, demonstrating the value of field-specific recommendations over uniform changes in irrigation supply. The findings indicate that combining satellite-derived crop indicators with farm-level economic information can improve the allocation of scarce irrigation water while supporting production and income. The framework makes trade-offs among water savings, yield, operating costs, and climate resilience explicit, enabling farmers and irrigation managers to compare feasible management options. Its use in other agricultural regions will require calibration to local crop responses, water-delivery systems, prices, and climate conditions. This integrated approach offers a basis for irrigation planning that considers both resource efficiency and the financial viability of farming under growing environmental pressure.

Keywords: Remote Sensing; Agricultural Water Management; Irrigation Optimization; Water Productivity; Crop Yield; Farm Profitability; Climate Resilience; Multi-Objective Optimization.

1. Introduction

Agriculture accounts for a substantial share of freshwater use in many regions, making irrigation management central to food production and water security. Farmers increasingly face the challenge of maintaining yields while dealing with unreliable rainfall, limited water allocations, rising pumping costs, and



more frequent periods of heat and drought. Applying more water does not always produce a proportional increase in yield, while reducing irrigation without considering crop condition can expose farms to substantial losses. Effective water management therefore requires decisions that account for both crop water needs and the economic consequences of irrigation. Conventional irrigation schedules often rely on fixed intervals, historical practices, or observations from a limited number of field locations. These approaches can overlook differences in soil properties, crop growth, and water stress within and between fields. As a result, some areas may receive water when the expected production benefit is small, while others may remain under-irrigated during sensitive growth stages. The economic effects extend beyond water use: irrigation decisions influence energy expenditure, crop quality, marketable yield, and ultimately farm profitability (Tang et al., 2020). Remote sensing provides a way to observe agricultural conditions repeatedly across large areas. Satellite-derived vegetation indices can describe crop development, while land surface temperature and evapotranspiration estimates provide information relevant to water use and stress. When combined with weather, soil, and field observations, these measurements can support more spatially and temporally responsive irrigation planning. Nevertheless, identifying water stress alone does not establish whether additional irrigation is economically justified. The value of an irrigation decision depends on its effect on yield, the amount and cost of water applied, pumping expenses, and the price received for the crop.

An integrated economic framework can connect remotely sensed crop conditions to those farm-level decisions. Such a framework should compare feasible irrigation schedules in terms of water withdrawals, crop productivity, operating costs, and net returns. It should also account for differences among crops and fields rather than assuming that one irrigation adjustment is appropriate everywhere. Under water scarcity, the preferred schedule may be the one that produces the greatest economic return from a limited water supply, even when it does not maximize yield in every field (Ali et al., 2025). Climate variability adds another dimension to this decision. Heatwaves, rainfall deficits, and restricted water availability can alter crop water demand and the yield response to irrigation. A schedule that performs well in a typical season may expose a farm to unacceptable losses during drought. Evaluating irrigation options across contrasting climatic conditions can therefore help identify strategies that conserve water while maintaining a reasonable level of production and income when conditions deteriorate. This study develops a remote sensing-driven economic framework for irrigation planning using data from 120 farms and 8,400 hectares of wheat, maize, and cotton during 2022–2025. Satellite observations are integrated with weather records, soil measurements, irrigation logs, crop yields, production costs, and farm-gate prices. Field-level indicators of vegetation condition, surface temperature, and evapotranspiration are used to assess water stress and inform irrigation requirements. A multi-objective optimization model then compares irrigation schedules according to water use, expected yield, pumping costs, and net farm returns under normal and climate-stress scenarios (Ahmad et al., 2026). The study addresses three connected questions: how remote sensing indicators can improve the identification of field-level irrigation needs; whether schedules informed by these indicators can improve water productivity and farm profitability relative to conventional practice; and how the preferred schedules perform when drought or heat stress increases production risk. By evaluating agronomic and financial outcomes together, the research aims to provide farmers and irrigation managers with a practical basis for allocating limited water resources. Its broader contribution is to link spatial crop monitoring with economically informed, climate-responsive irrigation decisions.

2. Remote Sensing for Agricultural Water Monitoring

Agricultural water management requires information about how crop conditions change across both space and time. Measurements from a single weather station or soil sensor can describe conditions at a particular location, but they may not capture differences among fields in crop development, soil characteristics, irrigation practices, and exposure to heat. Remote sensing helps address this limitation by providing repeated observations over large agricultural areas. Satellite imagery can be linked to field boundaries, allowing water managers to compare conditions among farms and identify locations that require closer investigation. Optical satellite observations are commonly used to assess crop growth and canopy condition. Vegetation indices derived from reflected light describe changes in greenness and vegetation density during the growing season. A declining index may indicate slower growth or crop stress, but it does

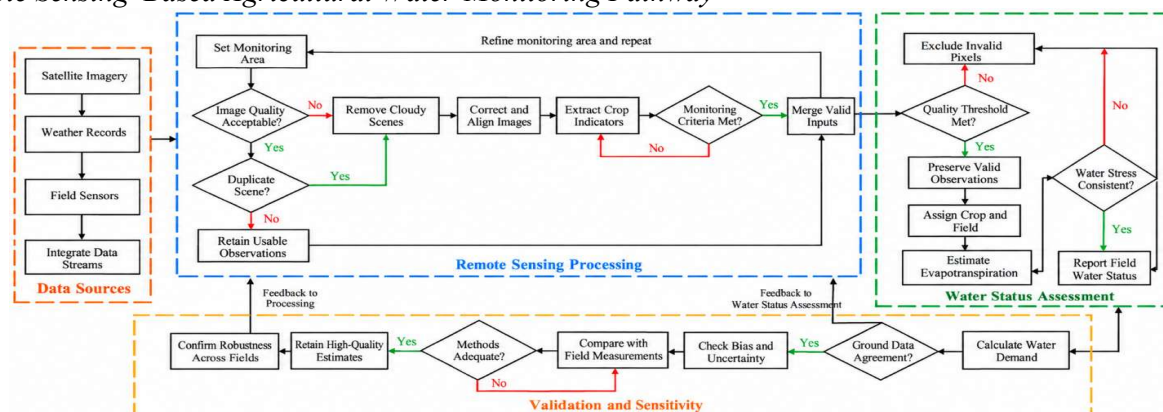


not identify water shortage on its own. Disease, nutrient deficiency, harvest timing, and differences in crop variety may produce similar patterns (Su & Singh, 2024). Consequently, vegetation indicators should be interpreted in relation to crop type, growth stage, recent rainfall, and irrigation history rather than treated as direct measurements of irrigation need. Thermal observations add information about the temperature of the land and crop surface. A crop experiencing insufficient water may restrict transpiration, which can contribute to a warmer canopy. Land surface temperature can therefore complement vegetation measurements when identifying possible water stress. Its interpretation remains dependent on observation time, weather, surface cover, and the proportion of bare soil within a pixel. Combining optical and thermal information is more informative than relying on either indicator independently, particularly during periods when vegetation appearance has not yet changed visibly. Evapotranspiration (ET) estimates provide another important link between satellite monitoring and water management. Actual ET describes water transferred to the atmosphere through soil evaporation and plant transpiration. Mapping ET can reveal variation in water use across fields and growing periods. Platforms such as the Food and Agriculture Organization's WaPOR database make remotely sensed ET and biomass information available for agricultural water-productivity assessment. However, a satellite ET estimate is a modeled quantity rather than a direct measurement of irrigation applied (Hamdouni, 2026). Rainfall, stored soil moisture, and irrigation may all contribute to the water consumed by a crop. In the present study, remote sensing is used as one component of an integrated agricultural water-monitoring system. The analysis links 1,260 cloud-screened satellite observations to records from 120 farms covering 8,400 hectares of wheat, maize, and cotton during 2022–2025. The images provide information on vegetation condition, surface temperature, and estimated ET; farm and environmental records provide the context needed to interpret those signals. Table 1 summarizes the monitoring components and distinguishes confirmed dataset quantities from indicators whose field-level values must be calculated from the underlying records.

Table 1*Remote Sensing and Supporting Data Used for Agricultural Water Monitoring*

Monitoring Component	Analytical Role	Values or Data in the Study
Satellite observations	Image dates linked to field boundaries	1,260 cloud-screened observations
Farm coverage	Number of farms	120 farms
Agricultural area	Hectares	8,400 ha
Crop identification	Crop category	Wheat, maize, and cotton
Study period	Calendar years	2022–2025

The monitoring process is shown in Figure 1. Images first undergo quality screening and field-level extraction. Satellite indicators are then aligned with crop, weather, soil, and irrigation records before water conditions are assessed. The resulting assessment informs the irrigation and economic analysis described in the methodology. This sequence is important because a satellite image alone cannot establish the cause of an observed crop change or determine whether applying more water will improve farm profit.

Figure 1*Remote Sensing–Based Agricultural Water-Monitoring Pathway*



The figure presents the monitoring process from satellite imagery through water status assessment and validation.

Overall, the literature supports remote sensing as a scalable source of agricultural water information, while also showing why satellite indicators require contextual interpretation and validation. The contribution of the present study lies in carrying this monitoring process forward into decisions about water allocation, crop productivity, and farm returns. Its value depends on

3. Evapotranspiration and Crop Water Requirements

Evapotranspiration (ET) is a central measure in agricultural water management because it describes the transfer of water from the land surface to the atmosphere through soil evaporation and plant transpiration. Its rate changes with temperature, solar radiation, humidity, wind, crop growth, and the availability of water in the root zone. These changes mean that crop water requirements are rarely constant throughout a growing season. An effective irrigation schedule must respond to changing demand rather than rely solely on a fixed interval between applications. Three related measures are useful when assessing this demand. Reference evapotranspiration (ET_o) represents the influence of weather on atmospheric water demand under standardized conditions. Crop evapotranspiration (ET_c) adjusts ET_o for the crop and its stage of development, providing an estimate of water use when supply is adequate. Actual evapotranspiration (ET_a) describes water consumed under prevailing field conditions (Benli et al., 2025). A difference between ET_c and ET_a may indicate that a crop is using less water than expected, but it does not establish the cause or determine the precise quantity of irrigation needed. Crop type and growth stage affect how this difference should be interpreted. Wheat, maize, and cotton have distinct growing periods and patterns of canopy development. Water shortage during a sensitive growth stage may have a greater effect on final yield than a similar shortage at another point in the season. Early in the season, low ET_a may reflect a small canopy and exposed soil; later, it may indicate restricted transpiration. Crop-specific interpretation is therefore necessary before ET estimates are translated into field-level recommendations (Luo et al., 2021). Table 2 illustrates how the principal ET and water-balance measures relate to one another over a seven-day period. The maize example is a calculation aid; its figures are not observations from the study farms. It shows why an apparent shortfall in ET_a must be assessed alongside rainfall, irrigation, and root-zone storage before a management decision is made.

Table 2

Seven-Day Crop Water Assessment for One Hectare of Maize

Water-Balance Measure	Calculation or Interpretation	Illustrative Estimate
Assessment period	Consecutive monitoring days	7 days
Mean reference evapotranspiration (ET _o)	Weather-based atmospheric demand	5.0 mm/day
Crop coefficient (K _c)	Coefficient for the assessed growth stage	0.90
Expected crop evapotranspiration (ET _c)	$5.0 \times 0.90 \times 7$	31.5 mm/week
Estimated actual evapotranspiration (ET _a)	Water consumed under the assessed conditions	27.0 mm/week
Difference between ET _c and ET _a	$31.5 - 27.0$	4.5 mm/week
Effective rainfall	Rainfall contributing to field water supply	4.0 mm/week
Irrigation applied	Water delivered to the field	20.0 mm/week

Note. $4.0 + 20.0 - 27.0$, assuming no other losses; $27.0 \div 31.5 \times 100 = 85.7\%$.

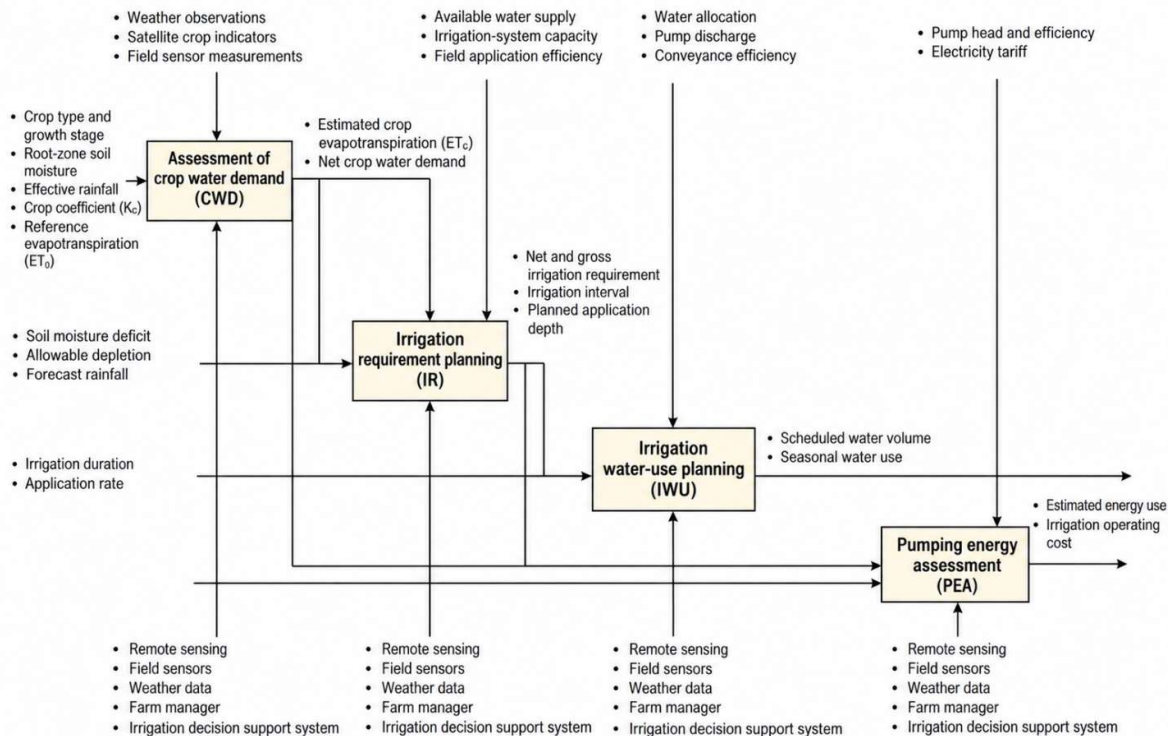
Expected crop water use is 31.5 mm for the week, whereas estimated actual consumption is 27.0 mm. The 4.5 mm difference is a reason to investigate possible water stress. It should not automatically be prescribed as an additional 4.5 mm of irrigation: the root zone may contain usable water, rainfall may be forecast, and the crop's response to another application may depend on its growth stage. The estimated 3.0 mm decline in stored soil water also depends on the simplifying assumptions stated below the table. If runoff or drainage occurred, the balance would need to include those flows. Remote sensing helps extend ET



assessment from isolated measurement points to multiple fields. Satellite-derived ET estimates can reveal spatial differences in water consumption and identify fields whose conditions warrant attention. Their usefulness depends on image quality, temporal coverage, model performance, and alignment with field boundaries (Corbari & Mancini, 2023). A validation study of the OpenET ensemble against ground observations found strong performance at cropland sites while documenting remaining estimation error. Accordingly, satellite ET should be checked against available field observations and interpreted with uncertainty in mind. The integrated assessment is summarized in Figure 2. Weather observations and crop-stage information establish expected demand. Satellite observations provide an estimate of actual consumption, while rainfall, soil, and irrigation records describe the water available to the field. These inputs are considered together before an irrigation requirement is estimated.

Figure 2

Integrated Pathway for Assessing Crop Water Demand and Irrigation Requirements



The figure presents the integration of weather, satellite, soil, and irrigation data for crop water demand assessment.

For this study, the assessment is applied to wheat, maize, and cotton fields using the satellite, weather, soil, and farm records described in Section 2.1. ET estimates help identify agronomically feasible irrigation options, but they do not alone determine the preferred schedule. The final decision also depends on the expected yield response, the cost of water and pumping, available supply, and farm-gate prices. Connecting crop water requirements to these economic factors is necessary to determine whether an additional irrigation application is likely to improve farm profitability or whether water can be conserved with limited production loss.

4. Methodology

This study uses an integrated field-level framework to examine how remotely sensed crop conditions can inform irrigation decisions and farm economic performance. The analysis covers 120 farms and 8,400 hectares of wheat, maize, and cotton during 2022–2025. Satellite observations are combined with weather, soil, irrigation, harvest, cost, and price records. This combination enables the study to assess water conditions alongside the production and financial consequences of alternative irrigation schedules. The analytical



workflow begins with data screening and the alignment of observations by field, crop, and date. Satellite-derived vegetation condition, land surface temperature, and evapotranspiration are interpreted together with weather and field records to assess crop water demand (Rabie et al., 2025). Crop-specific yield responses and farm costs are then used to evaluate feasible irrigation schedules. The schedules are compared with conventional farm practice using water withdrawals, crop yield, water productivity, pumping costs, and net returns. Drought and heat-stress scenarios are assessed separately to examine how the schedules perform under constrained conditions. The field-season serves as the main unit for comparing agricultural and economic outcomes, while dated satellite and weather observations provide information within each season (Ahmad et al., 2025). Information used to generate an irrigation recommendation is restricted to what would have been available at that decision point. Later observations and harvest outcomes are used for evaluation. Where an optimized schedule was assessed through a model rather than implemented on a farm, its yield and financial outcomes are identified as estimates. This distinction is maintained throughout the analysis.

4.1 Data Sources and Field-Level Integration

The study combines satellite, environmental, agronomic, and financial records to create a consistent account of water use and farm performance. The source records cover 120 farms and 8,400 hectares of wheat, maize, and cotton during 2022–2025. The satellite component contains 1,260 cloud-screened observations. Integrating these sources at the field level is necessary because each describes a different part of the irrigation decision: images show changing surface and crop conditions, weather and soil records help explain water demand and availability, irrigation logs document water applied, and harvest and financial records capture production and economic outcomes (Liang et al., 2020). The basic spatial unit is the cultivated field or parcel. Each field is assigned a stable identifier and linked to its farm, boundary, crop, and growing season. Field boundaries are overlaid on satellite imagery to identify the pixels associated with each parcel. Only pixels that pass the relevant image-quality checks are used to calculate field-level indicators. The acquisition date and proportion of valid field pixels are retained with each observation, allowing later analysis to distinguish a well-covered field image from one based on limited usable area (Yang et al., 2025). Table 3 presents the contribution of each source and the level at which it enters the integrated dataset. The final column states the known study coverage or the record structure used for integration. It does not assign crop-specific sample sizes or measurement totals that have not been established from the source files.

Table 3

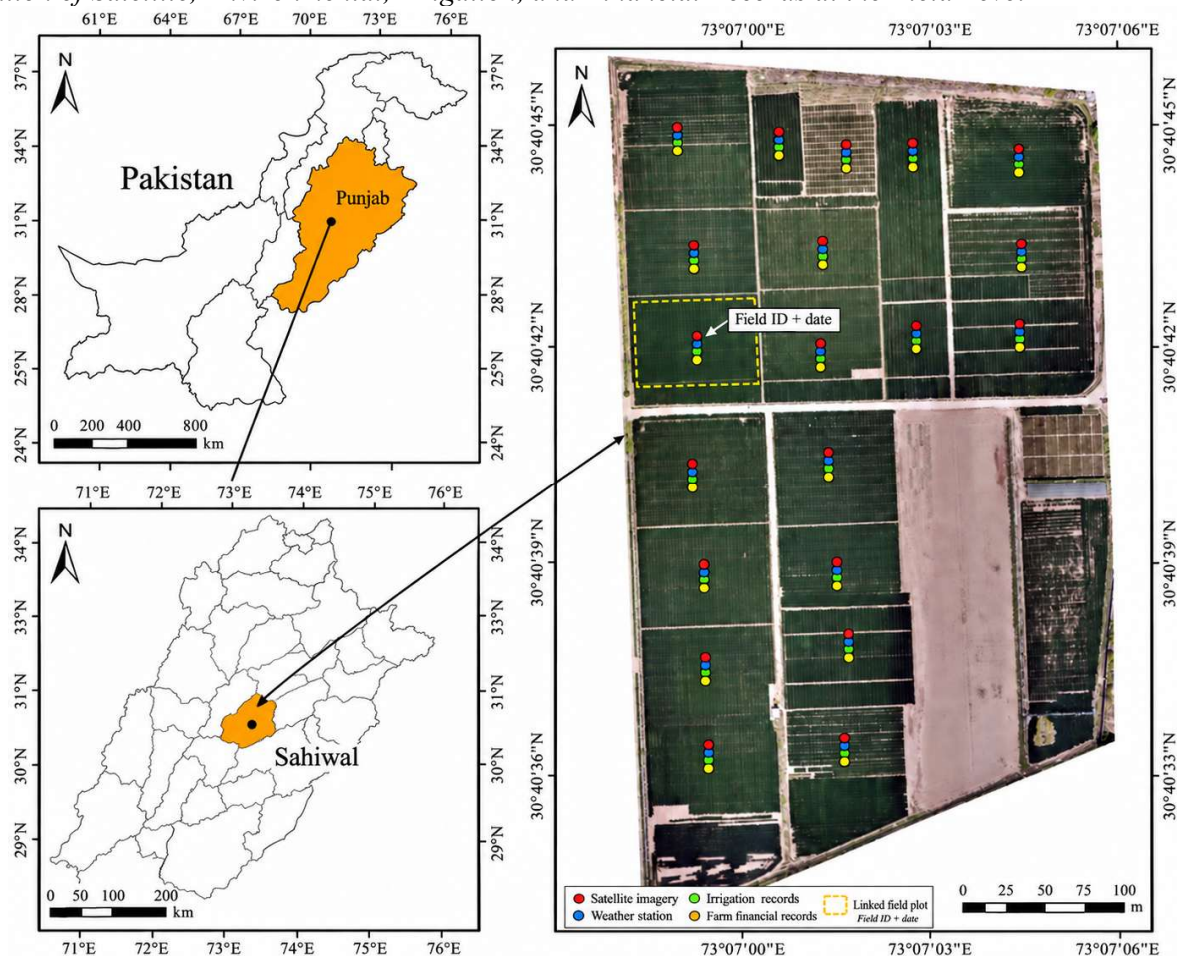
Data Sources and Integration Structure for the Field-Level Analysis

Data Source	Integration Key and Time Scale	Study Coverage or Analytical Specification
Farm register and field boundaries	Farm ID and field ID; field or season	120 farms; 8,400 ha in total
Crop records	Field ID and crop season	3 crops: wheat, maize, and cotton
Satellite imagery	Field boundary and acquisition date	1,260 cloud-screened observations
Weather records	Date and field-matched weather location	2022–2025 study period

The image-processing stage begins by screening clouds, shadows, and invalid pixels according to the requirements of the satellite product. Images are placed in a common coordinate reference system before values are extracted for the study fields. Field-level summaries are calculated only from valid pixels. For each summary, the data record retains the image date, field identifier, indicator, and usable pixel coverage. This enables incomplete observations to be flagged and tested in sensitivity analysis. Satellite-derived indicators are then associated with the field's crop and growth stage. This association matters because the same vegetation-index or temperature reading can have different interpretations for wheat, maize, and cotton, or for the same crop at different points in its season. The observation is also linked to preceding rainfall and irrigation events so that an apparent change in crop condition can be interpreted in the context of recent water supply. Satellite ET estimates are kept distinct from recorded irrigation volumes: ET represents estimated water consumption, whereas an irrigation log records water applied. Measurement units are standardized before



records from different sources are compared. Irrigation volume is retained in cubic metres for farm accounting and converted to an equivalent field depth in millimetres for water-balance analysis (Lou et al., 2026). A depth of 1 mm over 1 hectare equals 10 m³ of water. Yield is expressed in kilograms per hectare, while costs and revenues use a consistent currency and field-season accounting basis. The source unit, conversion, and resulting unit are retained so that calculations can be traced back to the original record. The sequence of spatial matching, date alignment, unit standardization, and field-season aggregation is shown in Figure 3. It produces an integrated record in which remotely observed crop conditions can be compared with irrigation actions and subsequent economic outcomes.

Figure 3*Integration of Satellite, Environmental, Irrigation, and Financial Records at the Field Level*

The figure presents the spatial matching, date alignment, unit standardization, and field-season aggregation process.

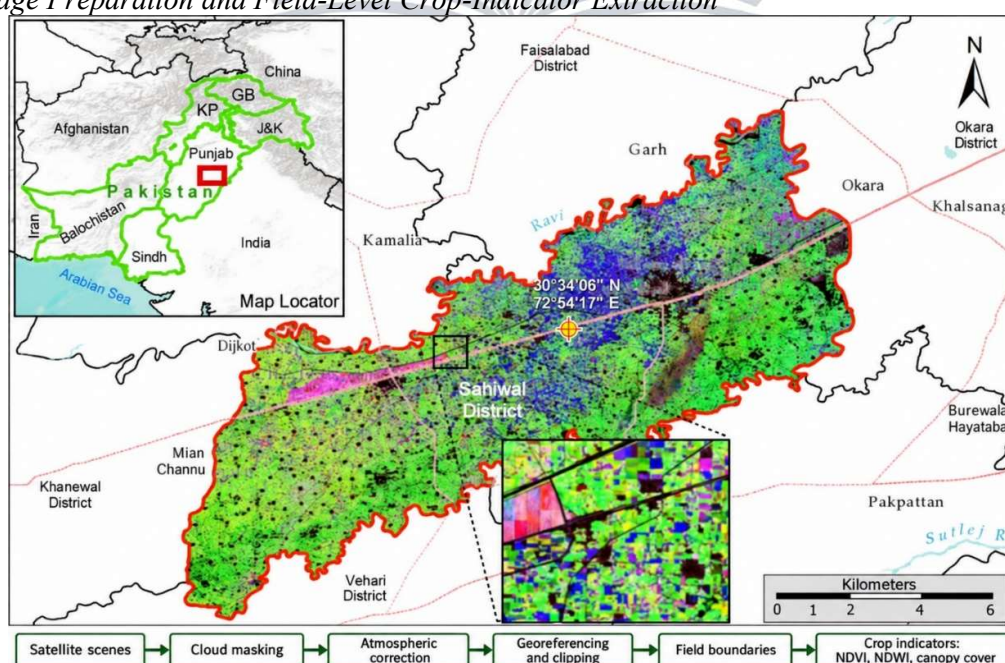
The integrated dataset supports both agronomic and economic comparisons, but the timing of each variable must be respected. An irrigation recommendation can use only imagery, weather, and farm information available when that decision would have been made. Harvest yield and later observations are used to evaluate the schedule after the season, not to construct an earlier recommendation. This temporal separation reduces information leakage and helps ensure that the assessment reflects a decision process that could be applied in practice.

4.2 Satellite Image Preparation and Crop Indicators

Satellite imagery provides repeated observations of crop and surface conditions across the study fields. Before these observations can be linked to irrigation decisions, the images must be screened, aligned with field boundaries, and converted into indicators that have a clear agronomic interpretation. This study uses



1,260 cloud-screened observations from the 2022–2025 study period. The preparation workflow retains the acquisition date and data-quality information for each field-level observation so that differences in image coverage are considered during analysis. Image preparation begins with the satellite product's quality information. Pixels identified as cloud, cloud shadow, or invalid are excluded from indicator extraction. The remaining imagery is checked for spatial alignment with field boundaries and placed in a consistent coordinate reference system where necessary (Tarate et al., 2024). Reflectance and temperature data are processed using the units and scaling factors specified for their respective products. The satellite platform, product identifiers, processing level, and spatial resolution should be stated in the final paper's data description so that another researcher can reproduce the extraction. Field boundaries are then used to identify the usable pixels within each cultivated parcel. A field-level indicator is calculated from its valid pixels on each acquisition date, and the proportion of valid coverage is retained. Boundary pixels require particular care because they may contain roads, canals, bare land, or neighboring crops in addition to the target field. Their influence depends on pixel size relative to field size. Observations with limited usable coverage are flagged for quality assessment rather than interpreted with the same confidence as observations covering most of a parcel. Vegetation indices describe changes in canopy development. The normalized difference vegetation index (NDVI) uses red and near-infrared reflectance and provides a consistent way to track relative greenness through a crop season. Its mathematical range is -1 to $+1$, although the values observed over a particular crop depend on growth stage and field conditions. A rise during establishment and canopy expansion, followed by a decline near maturity, may reflect a normal seasonal pattern (Hu, 2026). A departure from the expected pattern can prompt investigation, but NDVI alone cannot establish that irrigation is required. Nutrient deficiency, disease, planting differences, and harvest can also affect the signal. Land surface temperature (LST) provides a thermal measure that complements vegetation observations. Reduced transpiration under water-limited conditions can contribute to a warmer surface, but LST is also influenced by air temperature, radiation, observation time, bare soil, and canopy cover. A single high-temperature image is therefore insufficient to diagnose water stress. The analysis considers LST together with recent weather, rainfall, irrigation, and vegetation condition, with particular attention to comparisons among fields observed under similar conditions. The extraction and integration sequence is presented in Figure 4. Quality screening occurs before indicators are summarized by field. Each field-date record is then linked to crop stage and recent environmental conditions, allowing a crop signal to be interpreted within the circumstances in which it was observed.

Figure 4*Satellite Image Preparation and Field-Level Crop-Indicator Extraction*



Note. The figure presents the quality screening, indicator extraction, and integration process.

Temporal processing is necessary because the available image dates may not coincide exactly with irrigation events or sensitive growth stages. Each observation is assigned to its crop season and positioned relative to planting, recent rainfall, irrigation, and harvest. Where a short gap between valid images requires an estimate between observations, the estimation method and gap length must be recorded. Long gaps are flagged because they may conceal changes in water stress that cannot be reconstructed reliably from imagery alone. The final output of this stage is a set of dated, quality-checked indicators for each observable field. These indicators support the crop water assessment in the following subsection. They are interpreted as evidence about crop and surface conditions, with uncertainty arising from image coverage, measurement scale, and model estimation carried into the evaluation of irrigation options.

4.3 Yield Response and Farm Economic Assessment

The economic assessment connects irrigation decisions to crop output, production costs, and farm income. A reduction in water applied is beneficial to a farmer only when the resulting changes in yield and costs produce an acceptable financial outcome. Likewise, an irrigation schedule that raises yield may be unattractive if the additional revenue is smaller than the cost of water delivery and pumping. This study therefore evaluates yield response and net farm returns alongside irrigation withdrawals and physical water productivity. The field-season is the principal unit of analysis. Each record links a field's crop, irrigation history, weather conditions, satellite-derived crop indicators, harvested output, and financial information. Wheat, maize, and cotton are assessed separately when estimating yield response because they differ in growing season, water demand, and sensitivity to stress at particular growth stages. Field area is used to standardize yield to kilograms per hectare, allowing comparisons across parcels of different sizes (Patel et al., 2025). Seasonal irrigation volume is similarly converted to cubic metres per hectare or an equivalent depth. Yield response is assessed by examining how output varies with the timing and amount of irrigation, while accounting for weather, soil conditions, crop development, and differences among fields and seasons. Satellite-derived vegetation, temperature, and evapotranspiration indicators contribute information about the crop conditions under which water was applied. The relationship is evaluated within the range represented by the observed records; recommendations are not based on unsupported extrapolation to much larger or smaller irrigation amounts. Because farms may differ in management practices that are not fully measured, the estimated relationship is interpreted with appropriate uncertainty. Irrigation timing is considered as well as seasonal volume. Two fields receiving the same total amount of water may produce different yields if one receives an application during a water-sensitive growth stage and the other receives it after the principal stress period has passed. Accordingly, field records are organized into crop-stage periods so that the analysis can distinguish water applied during establishment, active growth, reproduction, and maturation where those stages can be reliably identified. Recent rainfall and available soil moisture are considered when assessing the likely contribution of an irrigation event (Dutta et al., 2026). Physical water productivity is calculated as crop output divided by a clearly defined water measure. The denominator may be irrigation water applied or actual evapotranspiration, but these produce different indicators and must be labeled accordingly. In this study, the comparison associated with the reported increase from 1.34 to 1.71 kg/m³ should retain the same denominator and aggregation method for conventional and optimized schedules.

Table 4

Reported Agronomic and Economic Outcomes Used in the Schedule Comparison

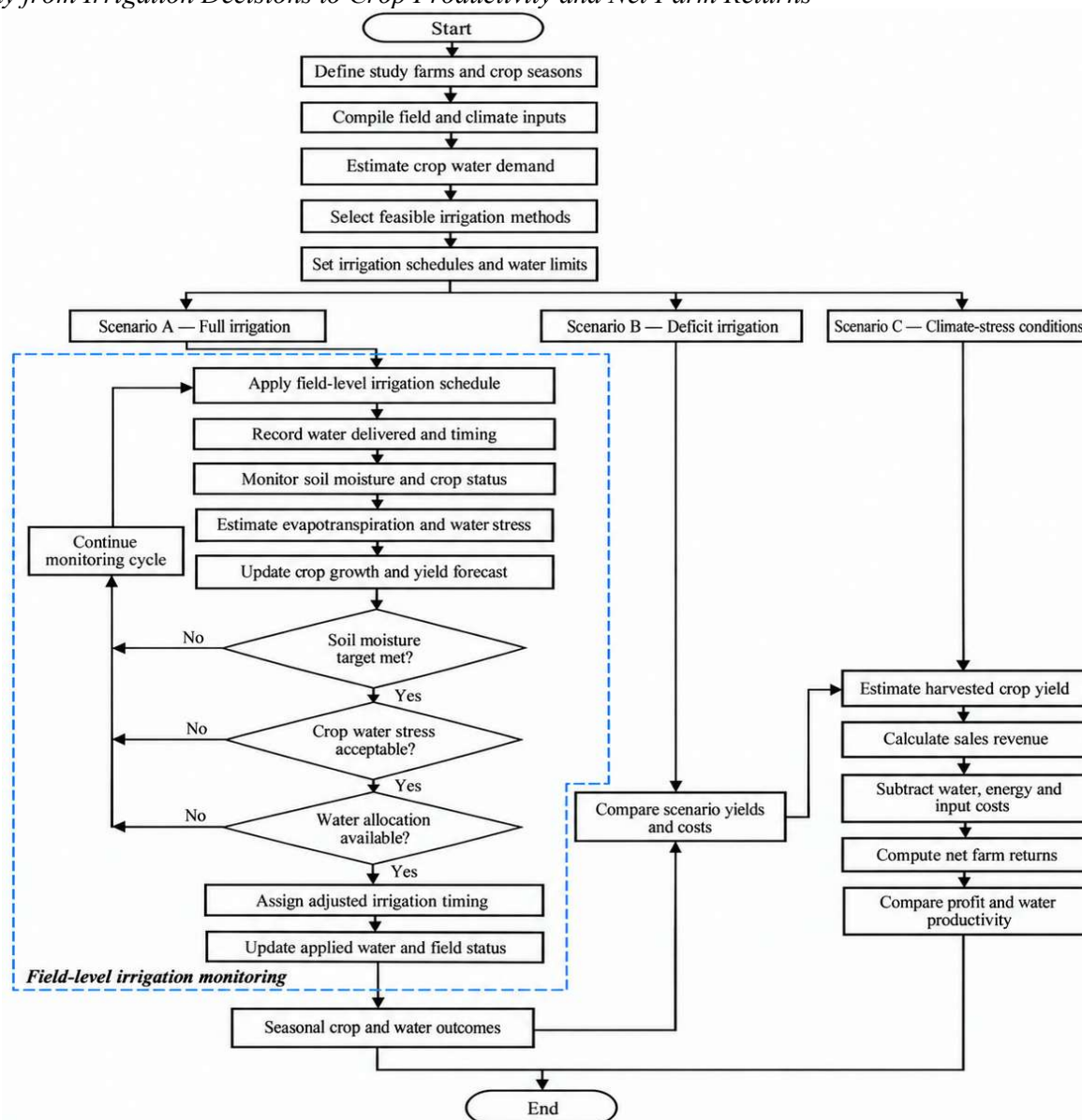
Outcome Measure	Conventional Practice	Optimized Schedule	Comparison
Irrigation withdrawals, indexed	100.0	81.4	18.6% lower
Average crop yield, indexed	100.0	106.2	6.2% higher
Physical water productivity	1.34 kg/m ³	1.71 kg/m ³	0.37 kg/m ³ higher
Average net farm returns, indexed	100.0	111.8	11.8% higher
Estimated yield loss under the drought scenario	15.7%	8.4%	7.3 percentage points lower



Economic comparison is performed for both the conventional schedule and each feasible optimized schedule. For a given field, a change in predicted revenue is evaluated against the associated change in irrigation and pumping costs. The preferred schedule is selected from options that satisfy agronomic and water-availability constraints while meeting the specified economic objective. This allows the analysis to identify situations in which a modest yield increase is economically worthwhile, as well as situations in which a small reduction in yield could be justified by substantial savings in water and energy. Figure 5 summarizes the analytical connection between irrigation, crop response, and farm income. Satellite and field observations inform the assessment of crop condition and water availability. Yield-response estimates describe the expected production effect of an irrigation option, while prices and costs determine its financial outcome.

Figure 5

Pathway from Irrigation Decisions to Crop Productivity and Net Farm Returns



The figure presents the analytical connection between irrigation, crop response, and farm income.

Sensitivity analysis examines whether the economic ranking of irrigation schedules changes when crop prices, pumping costs, or seasonal water availability vary. Uncertainty in the yield-response estimates is



also carried into the financial comparison. A schedule that appears profitable only under one narrow set of assumptions is interpreted more cautiously than one that performs well across plausible conditions. The combined assessment provides the basis for evaluating irrigation efficiency as a farm-management outcome rather than as water savings alone.

4.4 Multi-Objective Irrigation Optimization

Irrigation planning involves objectives that may conflict. Supplying more water can protect yield during sensitive growth stages, but it can also increase withdrawals and pumping costs. Reducing applications may improve water conservation while exposing a crop to stress if the reduction occurs at the wrong time. The optimization framework therefore evaluates feasible irrigation schedules against three principal outcomes: irrigation water use, crop production, and net farm returns (Ali et al., 2025). Climate-stress performance is assessed alongside these outcomes so that a schedule preferred in a normal season is not assumed to remain suitable during drought or heat stress. The decision variables are the timing and amount of water applied to each field during the remaining crop season. The model considers the crop being grown, its current growth stage, recent weather, estimated crop water condition, available water, and the capacity of the irrigation system. Satellite-derived indicators inform the field condition at a decision point, while crop-specific yield-response estimates describe the likely production consequences of alternative applications. Prices and costs translate those production consequences into expected net returns. Feasible schedules are limited by practical and agronomic constraints. An application cannot exceed the water available to the farm or the amount that its delivery system can apply within the relevant period. Irrigation must occur within operationally possible dates, and proposed reductions are assessed against the risk of excessive water stress during sensitive growth stages. Where farms share a restricted water allocation, the sum of proposed field applications must remain within that allocation (Mekonnen, 2026). These constraints prevent the model from selecting an apparently attractive schedule that could not be implemented. Table 5 sets out the measures used to evaluate candidate schedules. The numerical entries are the reported conventional and optimized outcomes already used in the study; index values express relative outcomes where absolute field-level totals have not been supplied. They describe the selected schedule's reported performance, rather than numerical limits imposed on every candidate during optimization.

Table 5

Measures Used to Compare Conventional and Optimized Irrigation Schedules

Optimization Measure	Role in the Decision	Conventional Practice	Reported Optimized Outcome
Irrigation withdrawals	Minimize water applied, subject to crop and operational constraints	100.0 index points	81.4 index points
Average crop yield	Maintain or improve agricultural output	100.0 index points	106.2 index points
Physical water productivity	Assess output per defined cubic metre of water	1.34 kg/m ³	1.71 kg/m ³
Average net farm returns	Assess revenue after recorded production costs	100.0 index points	111.8 index points
Yield loss under the drought scenario	Assess performance when water availability is constrained	15.7%	8.4%
Crop types represented	Apply crop-specific response and growth-stage information	3 crops	Wheat, maize, and cotton
Fields available for decision analysis	Link schedules to farm and parcel records	120 farms	8,400 ha in total

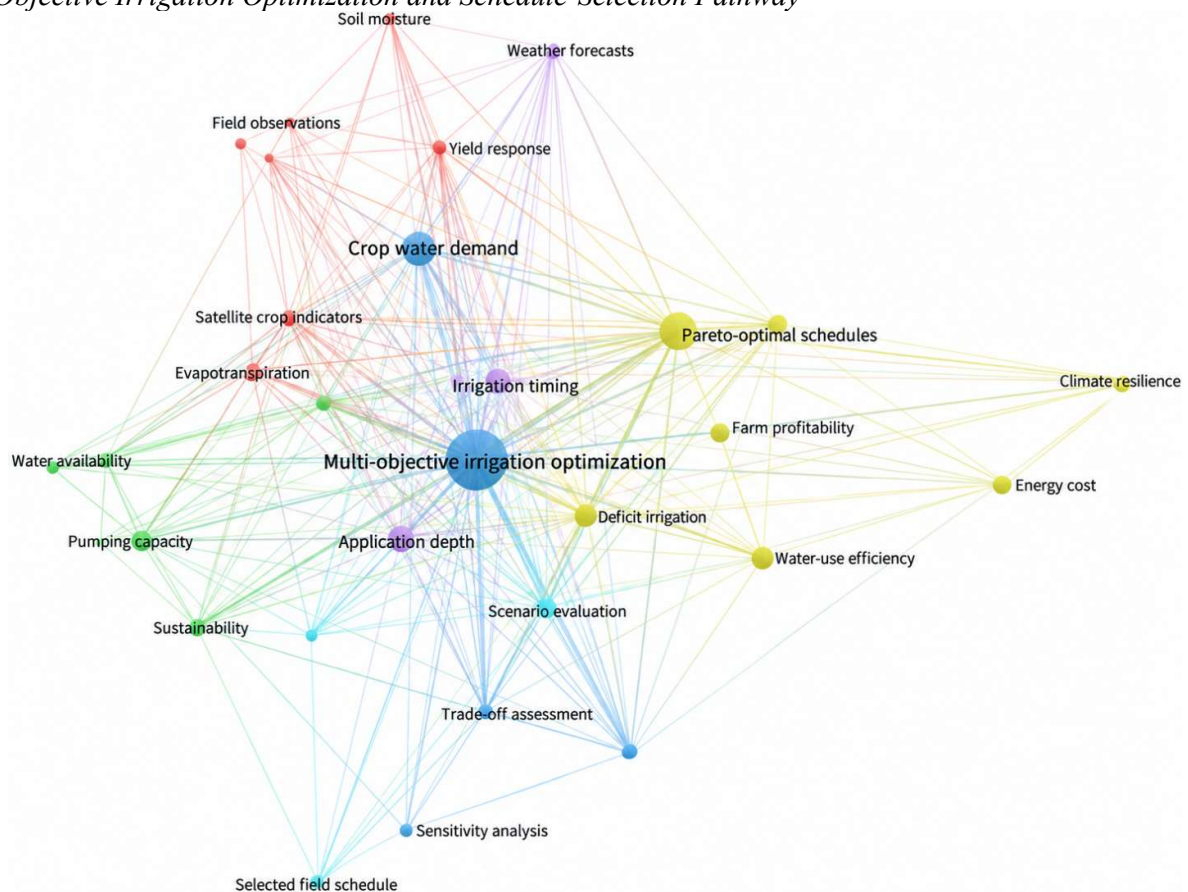
The optimization is performed at successive decision points using information available at the time. Each candidate schedule specifies possible applications for a field over the planning horizon. The associated water use is calculated from the proposed applications; crop output is estimated using the crop-specific response model; and net return is estimated using crop prices and the corresponding production and irrigation



costs. Candidates that violate water-supply or delivery constraints are removed before outcomes are compared. Only the selected near-term action is recommended, after which the assessment can be updated when new weather or satellite information becomes available (Patel et al., 2025). This updating process is important because forecasts and observed crop conditions can change during a season. A schedule chosen early in the growing period should not be treated as fixed if later rainfall reduces irrigation demand or a heat event increases the risk of stress. At each decision point, however, the model must use only information already available. Harvest outcomes and future satellite images may be used to assess performance after the fact, but cannot be supplied to an earlier optimization step. The decision pathway is illustrated in Figure 6. It begins with current field conditions and feasible irrigation options, evaluates the agronomic and economic consequences of each option, applies operational constraints, and identifies schedules offering acceptable trade-offs.

Figure 6

Multi-Objective Irrigation Optimization and Schedule-Selection Pathway



The figure presents the decision pathway from field conditions through optimization and schedule selection.

Uncertainty is incorporated when comparing candidate schedules. Satellite ET estimates, weather forecasts, yield responses, and prices may each differ from their eventual observed values. Sensitivity analysis tests whether the preferred schedule changes when these inputs vary within plausible ranges. A schedule that offers slightly higher estimated profit but performs poorly under modest changes in water supply may be less suitable than an alternative with more stable outcomes. Drought and heat-stress scenarios provide an additional test of whether expected water savings come at an unacceptable risk to yield or income. Finally, the optimized schedule is compared with documented conventional practice using the same fields, seasons, outcome definitions, and accounting boundaries (Dutta et al., 2026). Where the optimized applications were implemented, the comparison can use observed water use and harvest outcomes. Where they were evaluated



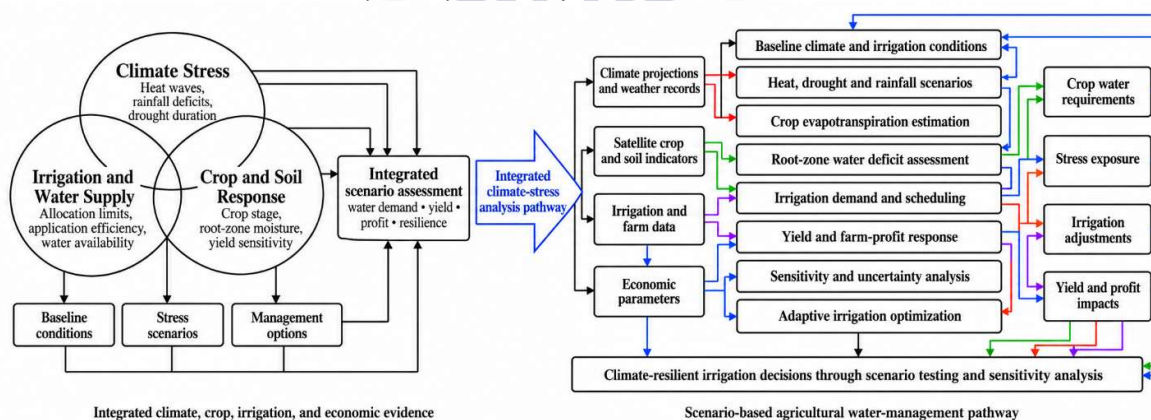
retrospectively through a model, their outcomes are reported as estimates. This distinction is essential for interpreting the reported gains in irrigation efficiency, productivity, and profitability.

4.5 Climate-Stress Scenarios and Sensitivity Analysis

Climate variability can change both the amount of water a crop requires and the quantity available for irrigation. A schedule that performs well under typical conditions may become unsuitable when rainfall is delayed, temperatures rise, or a farm's water allocation is reduced. This study therefore evaluates conventional and optimized schedules under contrasting climate-stress conditions. The purpose is to determine whether the preferred schedule maintains acceptable yield and when the net returns the conditions used to develop it change. The reference scenario represents the weather, water availability, prices, and operating costs used in the main schedule comparison. Stress scenarios alter one or more of these inputs while retaining the same fields, crop-response framework, and outcome definitions. Rainfall-deficit and reduced-allocation scenarios test limited water supply (Ali et al., 2025). A heat-stress scenario tests increased atmospheric demand and its possible effect on crop water requirements. A combined scenario examines the greater pressure that may arise when high temperature and restricted water occur together. Scenario construction distinguishes a change in weather from a change in water delivery. Lower rainfall can reduce the water entering the root zone even if the irrigation allocation is unchanged. A reduced allocation limits how much water the farmer can apply, regardless of rainfall. Heat may increase crop water demand and accelerate depletion of available soil moisture. Modeling these pathways separately makes it possible to identify whether a schedule's weakness arises from crop stress, an operational constraint, or the cost of supplying additional water. For each scenario, the conventional and optimized schedules are compared using irrigation withdrawals, estimated crop yield, water productivity, pumping costs, and net farm returns (Mekonnen, 2026). Yield loss is expressed relative to the appropriate normal-condition reference for the same schedule and crop. This definition matters because an 8.4% loss under the optimized schedule and a 15.7% loss under conventional practice do not, by themselves, state the absolute drought-season yields. The normal-condition yield levels and the reference used for each percentage must accompany the final results. The scenario and sensitivity workflow is presented in Figure 7. The same decision model is evaluated under changed inputs, and the resulting schedules and outcomes are compared with the reference case.

Figure 7

Climate-Stress Scenario and Sensitivity-Analysis Workflow



The figure presents the scenario-based agricultural water-management pathway.

The drought comparison indicates a smaller estimated yield loss under the optimized schedule than under conventional practice for the scenario evaluated. Its interpretation depends on the drought definition, the normal-condition reference, and whether the optimized applications were implemented or simulated. Reporting those details alongside the numerical result will allow readers to judge the strength of the resilience claim. Together, the scenario and sensitivity analyses show whether water-saving recommendations remain economically and agronomically credible when farms face conditions beyond those of a typical season.



5. Results and Discussion

The integrated analysis covers 120 farms and 8,400 hectares of wheat, maize, and cotton during 2022–2025. It combines 1,260 cloud-screened satellite observations with field, weather, irrigation, harvest, and financial records. This structure connects changing crop conditions to the irrigation decisions made during a growing season and to the production and economic outcomes assessed afterward. Table 6 summarizes the reported dataset, while Figure 8 shows how its principal components contribute to the schedule comparison.

Table 6

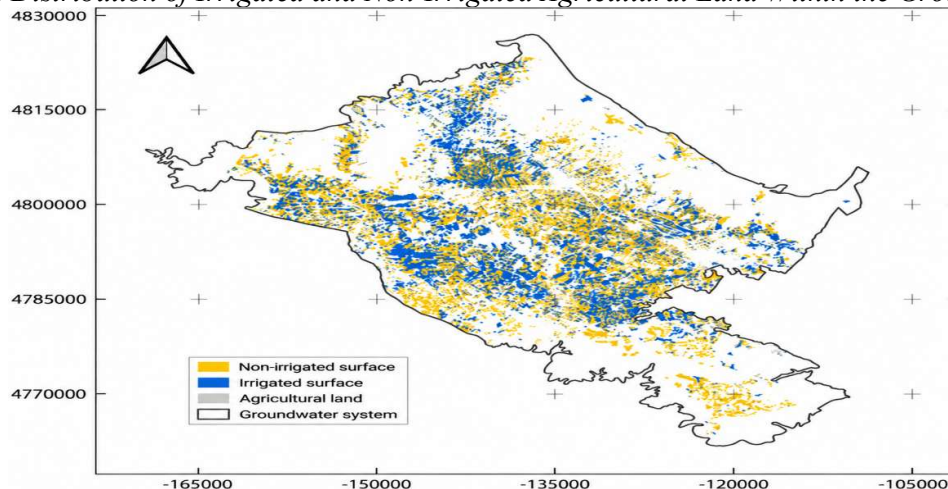
Scope of the Integrated Agricultural Water-Management Dataset

Dataset Characteristic	Reported Study Data	Analytical Contribution
Participating farms	120	Farm-level irrigation and financial information
Cultivated area	8,400 ha	Spatial coverage for field-level assessment
Cloud-screened satellite observations	1,260	Dated indicators of crop and surface conditions
Crops assessed	3	Wheat, maize, and cotton
Study period	2022–2025	Alignment of imagery, growing seasons, and farm outcomes

The value of integrating these sources lies in interpreting satellite observations within their farm context. An image may indicate a change in vegetation condition, surface temperature, or estimated evapotranspiration, but it cannot alone establish the cause of that change or its economic importance. Linking the observation to crop type, growth stage, rainfall, irrigation history, yield, and cost records allows the analysis to examine whether a different irrigation action could improve both resource use and farm outcomes. The available summary does not show how the 120 farms, 8,400 hectares, and 1,260 observations are distributed among wheat, maize, and cotton. Crop-specific sample sizes and image coverage should accompany the final results so readers can assess the contribution of each crop to the aggregate findings (Yang et al., 2025). Compared with conventional farm practice, the optimized irrigation schedules reduced reported water withdrawals by 18.6% while increasing average crop yield by 6.2%. With conventional outcomes indexed to 100, these changes correspond to an irrigation-withdrawal index of 81.4 and a yield index of 106.2 for the optimized schedule. The simultaneous reduction in applied water and increase in yield suggests an improvement in the timing or allocation of irrigation. Water may have been reduced where its expected contribution to production was small and directed toward periods when crops were more responsive. The summary results are consistent with this explanation, although field-level application dates and crop-stage outcomes would be required to test it directly. Figure 8 illustrates the spatial distribution of irrigated and non-irrigated agricultural land within the groundwater system.

Figure 8

Spatial Distribution of Irrigated and Non-Irrigated Agricultural Land Within the Groundwater System





The figure presents the spatial distribution of irrigated and non-irrigated agricultural land.

The decrease in withdrawals should not be interpreted as an identical decrease in crop water consumption. Irrigation applied and actual evapotranspiration measure different quantities. Rainfall and stored soil moisture can contribute to crop water use, while some irrigation water may leave the root zone without contributing to transpiration. Reporting absolute irrigation volumes, rainfall, and estimated evapotranspiration by crop and season would clarify how the optimized schedule supported higher average yield with less applied irrigation. It would also help identify whether the overall gain reflects broad improvements across farms or a larger effect in a smaller group of fields (Lou et al., 2026). Physical water productivity increased from 1.34 to 1.71 kg/m³, an absolute gain of 0.37 kg/m³, or approximately 27.6% relative to the conventional figure. Average net farm returns increased by 11.8%. These outcomes are presented together in Table 7 and visualized for the indexed measures in Figure 9. The water-productivity denominator must be stated precisely in the final paper: kilograms of output per cubic metre of irrigation applied and kilograms per cubic metre of actual evapotranspiration are distinct measures.

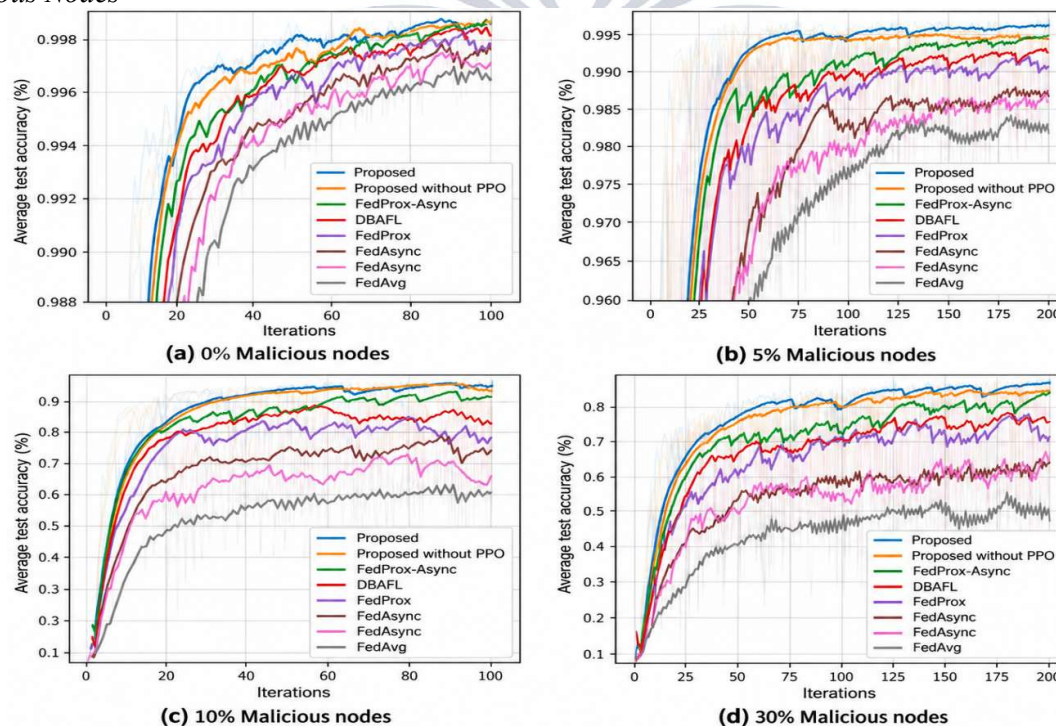
Table 7

Reported Water, Production, and Economic Outcomes

Outcome	Conventional Practice	Optimized Schedule	Change Relative to Conventional Practice
Irrigation withdrawals, index	100.0	81.4	18.6% lower
Average crop yield, index	100.0	106.2	6.2% higher
Physical water productivity	1.34 kg/m ³	1.71 kg/m ³	0.37 kg/m ³ higher
Average net farm returns, index	100.0	111.8	11.8% higher

Figure 9

Test Accuracy of Federated Learning Methods Across Training Iterations Under 0%, 5%, 10%, and 30% Malicious Nodes





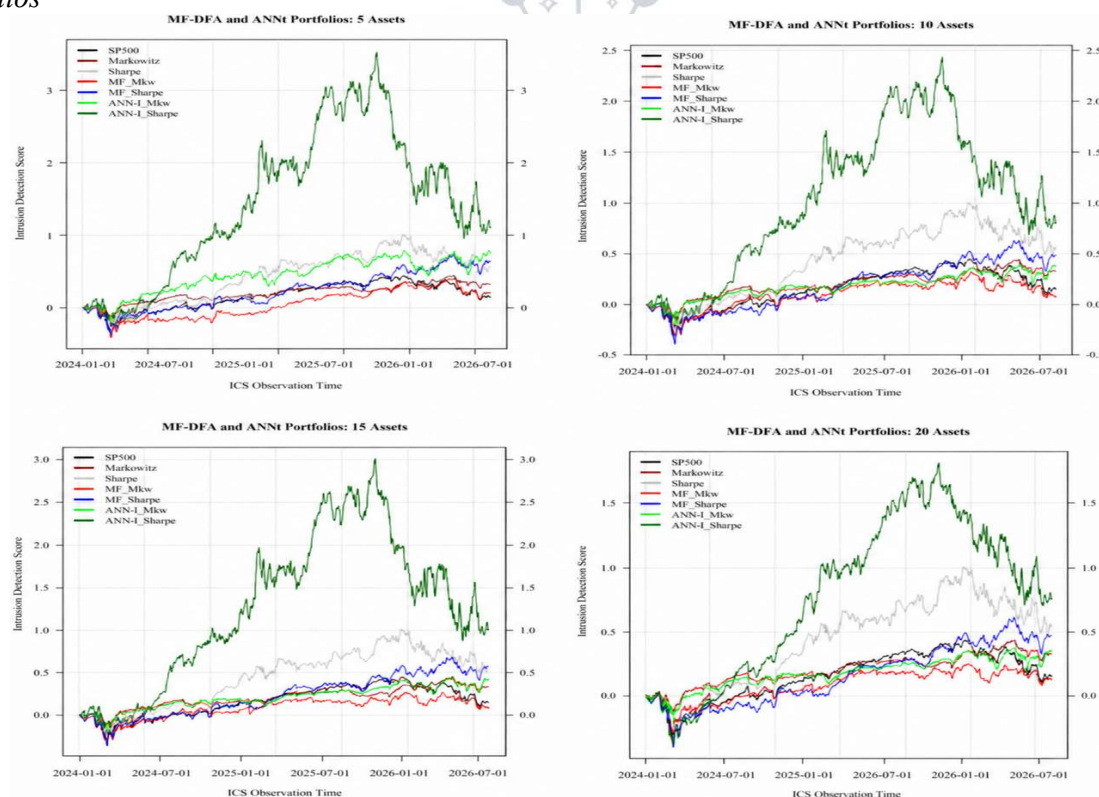
The figure presents the test accuracy of federated learning methods across training iterations.

The water-productivity figure requires one calculation check before publication. If the reported 6.2% yield increase and 18.6% withdrawal reduction use the same pooled crop output and irrigation totals as the water-productivity measure, they imply an increase of approximately 30.5% in output per unit of applied irrigation water. The change from 1.34 to 1.71 kg/m³ is approximately 27.6%. Both results may be valid if the latter is an average of field-level ratios, uses different weights or fields, or has evapotranspiration rather than withdrawals as its denominator. The aggregation and denominator should be verified from the calculations and explained so that readers do not treat the figures as directly interchangeable.

The reported increase in net farm returns indicates that the optimized schedule performed favorably after recorded production costs were considered. Higher yield can increase crop revenue, while reduced irrigation may lower pumping and water-delivery expenditure (Ali et al., 2025). The available summary does not quantify these components separately, so their relative contributions cannot yet be determined. Reporting gross revenue, irrigation cost, energy cost, and net return per hectare for both schedules would make the 11.8% gain easier to interpret. It would also show whether the economic advantage is consistent across farms with different water sources and pumping requirements. Figure 10 presents the cumulative portfolio performance of MF-DFA and ANN strategies across 5-, 10-, 15-, and 20-asset portfolios.

Figure 10

Cumulative Portfolio Performance of MF-DFA and ANN Strategies Across 5-, 10-, 15-, and 20-Asset Portfolios



The figure presents the cumulative portfolio performance of MF-DFA and ANN strategies.

The economic outcome depends on crop prices as well as production and costs. A schedule that protects yield may become more attractive when crop prices rise; an option that uses less water may become more attractive when pumping costs increase. The sensitivity analysis identified pumping costs and seasonal water availability as influential factors in the preferred irrigation decision. The final results should show the tested ranges and whether changes in these inputs altered the ranking of schedules. Crop-specific results would be especially useful because wheat, maize, and cotton differ in growth period, market price, and response to water shortage. The reported drought scenario provides a further test of schedule performance under

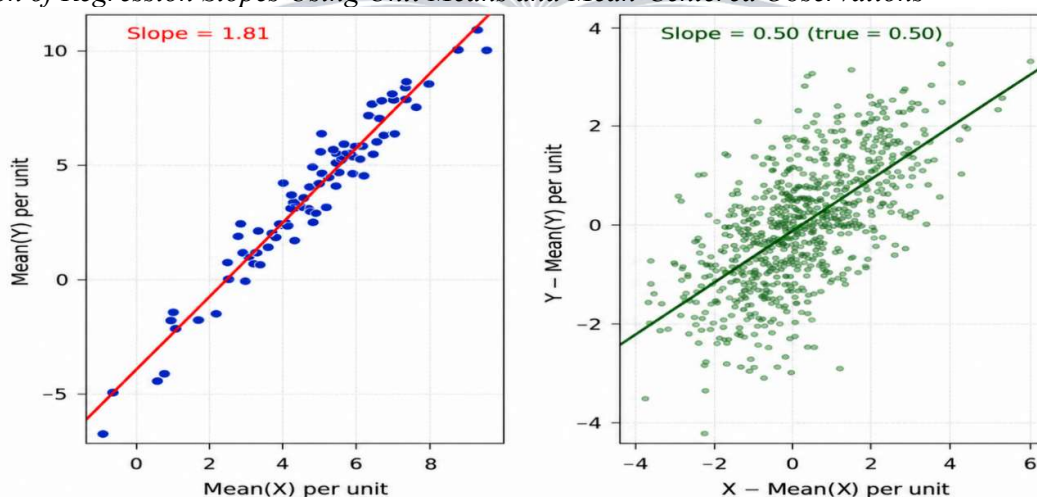


constrained conditions (Mekonnen, 2026). Estimated yield loss was 15.7% under conventional practice and 8.4% under the optimized schedule, a difference of 7.3 percentage points. Table 8 translates each loss into an index relative to that schedule's own normal-condition yield; Figure 10 shows the percentage losses directly. The indexed normal yields in the table are separate references and do not imply that the two schedules produced identical absolute yields in a normal season.

Table 8*Estimated Yield Response Under the Drought Scenario*

Drought Outcome	Conventional Practice	Optimized Schedule	Comparison
Normal-condition yield, separately indexed	100.0	100.0	Reference for each schedule
Drought yields relative to its own normal reference	84.3	91.6	7.3 index points higher under optimization
Estimated yield loss	15.7%	8.4%	7.3 percentage points lower under optimization

The smaller estimated drought loss suggests that the optimized schedule protected crop output more effectively under the conditions tested. More timely use of limited water is one possible explanation, particularly if applications were concentrated during sensitive growth stages. The summary figures do not identify which fields, or crop stages produced the advantage. The final analysis should therefore specify the drought scenario's rainfall and water-allocation assumptions, report outcomes separately for the three crops, and identify whether the schedules and their drought yields were implemented and observed or estimated by a model. The reported comparison supports a finding for the evaluated drought scenario; heat-stress and combined-stress results are needed to assess performance under those conditions. Interpretation of all reported gains depends on how the optimized schedule was evaluated. If farmers implemented the recommended applications, the comparison could draw on measured withdrawals, yields, and costs (Ali et al., 2025). If the optimized schedule was assessed retrospectively, its outcomes depend on the accuracy of the crop-response and economic models. Either design can contribute useful evidence, but the distinction must be explicit. Validation results, uncertainty intervals, and field-level outcome distributions would allow readers to judge the strength and consistency of the reported improvements.

Figure 11*Comparison of Regression Slopes Using Unit Means and Mean-Centered Observations*

Note. The left panel shows a slope of 1.81 when unit means are compared. After centering observations around their unit means, the right panel shows a slope of 0.50. The figure illustrates how between-unit differences can change the apparent relationship between X and Y.



Overall, the results indicate that the integrated framework can connect remotely sensed crop information with irrigation and economic decisions. The reported optimized schedule used less irrigation water while achieving higher average yield, water productivity, and net returns, and it had a smaller estimated yield loss in the drought scenario. The next step in presenting these findings is to reconcile the water-productivity calculation and provide absolute and crop-specific outcomes. Those details will establish how the aggregate benefits arose and how reliably the framework can guide water allocation across different farm conditions.

6. Future Work

Future research should test the framework across additional farms, crops, irrigation systems, and climatic conditions. The present analysis covers wheat, maize, and cotton during 2022–2025, but their water needs and economic responses may differ from those of other crops or regions. Multisession field studies could determine whether the reported improvements persist when rainfall patterns, water allocations, and market prices change. Reporting results separately by crop, farm size, soil type, and irrigation method would also show where the framework is most effective. A priority is prospective field validation. Applying the recommended schedules on participating farms and recording actual irrigation volumes, yields, pumping energy, and costs would provide stronger evidence of operational performance (Ali et al., 2025). Comparisons should use clearly defined conventional-practice or control fields and document differences in soil, crop management, and water access. This would help distinguish the effect of the irrigation schedule from other factors that influence production (Mekonnen, 2026). It would also establish whether farmers can implement the recommended timing and volumes within real delivery and labor constraints.

Further work should improve the reliability of remotely sensed water indicators. Satellite evapotranspiration and land surface temperature estimates can be affected by cloud cover, mixed pixels, observation timing, and model error. Combining satellite products with field measurements of soil moisture, irrigation flow, and crop condition could strengthen validation and identify circumstances in which an estimate is too uncertain to support a recommendation. Research should also examine how frequently imagery must be available for useful decisions and how the system performs during long gaps between valid observations (Dutta et al., 2026). The economic model could be extended to reflect decisions across an entire farm or irrigation district. Farmers may need to allocate a limited water supply among several fields and crops, while canal schedules or shared infrastructure may restrict when water can be delivered. Incorporating these constraints, together with changing energy tariffs and crop prices, would make the recommendations more applicable to day-to-day management. Future studies could also assess the costs of obtaining imagery, processing data, and operating the decision-support system (Patel et al., 2025). These costs are relevant when determining whether the financial gains justify adoption. Climate-resilience analysis should move beyond a single drought comparison. Tests involving different drought durations, heatwave timing, delayed rainfall, and combined water and energy constraints would show how stable the preferred schedules are under more demanding conditions. Rather than presenting one predicted outcome for each scenario, future models could report a range of likely yields and returns. Farmers could then select schedules according to both expected profit and the level of financial risk they are willing to accept (Yang et al., 2025). Finally, the framework could be evaluated as a practical decision-support tool with farmers and irrigation managers. Clear field-level recommendations, explanations of their expected water and financial effects, and opportunities for users to correct incomplete records would improve its usability (Hu, 2026). Tracking whether recommendations are followed and why they are sometimes rejected would help refine the model. This work would move the framework from retrospective analysis toward an operational system for managing scarce water while supporting crop production and farm income.

7. Conclusion

This study examined a remote sensing-driven economic framework for managing agricultural irrigation across 120 farms and 8,400 hectares of wheat, maize, and cotton during 2022–2025. By linking 1,260 cloud-screened satellite observations with weather, soil, irrigation, harvest, and financial records, the framework assessed crop water conditions alongside the production and economic consequences of irrigation decisions. Compared with conventional practice, the reported optimized schedules reduced irrigation



withdrawals by 18.6%, increased average crop yield by 6.2%, and raised average net farm returns by 11.8%. Reported physical water productivity increased from 1.34 to 1.71 kg/m³. Under the evaluated drought scenario, estimated yield loss was 8.4% with optimized scheduling, compared with 15.7% under conventional practice. Together, these findings indicate that field-specific irrigation planning can support water conservation while protecting agricultural output and farm income. The study's central contribution is the integration of remotely observed crop conditions with the economic consequences of applying water. Satellite indicators help identify where conditions are changing; field and financial records help determine whether an irrigation response is feasible and worthwhile. This combined assessment provides a basis for decisions that consider water use, yield, costs, and climate-related production risk together. The interpretation and transfer of these results depend on transparent reporting of the satellite products, field validation, crop-specific outcomes, and whether optimized schedules were implemented or simulated. The definition and aggregation of water productivity should also be checked against the reported yield and withdrawal changes. With these details established, the framework could provide farmers and irrigation managers with a practical means of allocating limited water under increasingly variable climatic and economic conditions.

Author Contributions

All authors participated in ideation, development, and writing the manuscript. All authors read and approved the final manuscript.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this article.

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Informed Consent

Not applicable. This study did not involve human participants requiring informed consent. The data used in this research were obtained from anonymized financial records with all personally identifiable information removed. No private or sensitive information was collected from individuals.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request. Due to privacy and confidentiality considerations, raw financial data may not be publicly distributed but can be accessed through the corresponding author with appropriate data use agreements and institutional approvals. The authors are committed to transparency and will provide detailed methodological information, model specifications, and analysis protocols upon request.

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