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AI for Sustainable Development Goals: Leveraging Machine Learning for Climate-Resilient Wheat Production in Wasit, Iraq

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ABSTRACT: Wheat production in semi-arid regions faces considerable challenges due to increased temperature variability, irregular rainfall, and reduced freshwater availability. These climate-induced stresses have led to unstable yields and threatened national food security in Iraq. This research presents a machine-learning-based decision-support system designed to enhance climate resilience in wheat cultivation in Wasit Governorate. The system integrates multi-temporal satellite vegetation indices, surface soil moisture estimations, and meteorological reanalysis data to generate early-season yield forecasts, irrigation scheduling recommendations, and drought early warnings. By linking predictive modeling with practical field-level decision-making, the system supports more efficient resource use, mitigates climate risks, and aligns agricultural practices with sustainability objectives.

KEYWORDS: Sustainable, AI, Machine Learning, Wheat Production, Wasit

1. INTRODUCTION

Wheat sprinkled everywhere, is the foundation of Iraq's food security. It's also the staple food consumed throughout the whole country. But wheat grow then suffer to do harm from climate change. In the vital period when wheat grains are filling out rising temperatures cause an acceleration of respiration in growing plants, and at end crop weights fall off. Similarly, reduced precipitation and dam inflows have led to a move away from rainfed cropping to fully irrigated cropping which in terms of water resources allocation within the Tigris river basin is increasingly breaking down [2].

In recent years, the emergence of remote sensing technology has made it possible to monitor the growth and health status of crops on a continuous basis for such indices as the Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI). These indices, it is known, are rigorously related to the phonological characteristics of wheat crops and results in stocks [3], [4]. At the same time, machine learning models are increasingly used to integrate multi-source environmental data sets and produce reliable in-season yield forecasts [5]. Soil moisture estimation models based on Sentinel-1 Synthetic Aperture Radar (SAR) data yield real-time information about irrigation scheduling and crop water stress [6]. 7. Machine-learning models for drought monitoring take this a step further, enabling early intervention by detecting stress conditions before visual symptoms appear [8].

Yet few existing approaches can be integrated into a practical framework of decision-making, one that farmers or agricultural extension workers could use. The object of this study is to bridge that gap by establishing a unified, operational decision-support pipeline tailored for growing wheat in Wasit.

2. RELATED WORK

Over the past few years, machine-learning-based yield forecasting has attracted a lot of attention for modeling complex, nonlinear relationships between environmental conditions and crop responses. Conventional regression-based or statistical models of climate-yield relationships use aggregated climate averages, and due to linear response assumptions, poorly represent the dynamic physiological responses of wheat to rapidly changing temperature and moisture conditions throughout the growing season. In contrast, machine learning methods can incorporate temporal vegetation trends based on remote sensing information, as well as environmental stress indicators (e.g. vapor pressure deficit, heat stress degree days, and early-season canopy temperature anomalies) allowing for more accurate and adaptive yield predictions [9,10]. Not only do these models facilitate greater accuracy, they allow forecasts to be updated continuously as new satellite and meteorological data becomes available.

Long Short-Term Memory (LSTM) architectures, a type of deep learning technique, also excel at modeling crop growth patterns as they are explicitly formulated for sequential data where phenological stages unfold over time (weeks, months)[11]. LSTMs are particularly well-suited for early-season yield prediction as they can detect differences between abnormal and stress vegetation development curves before the grain-filling period begins, which is often the case before October [12]. Such ability is however, vital for agricultural planning, where additional irrigation, timing of fertilization, as well as storage and market-related logistical decisions need to be made long before harvesting.

Meanwhile, high soil moisture retrieval accuracy from microwave radar backscatter has allowed near-surface soil water conditions to be estimated at high spatial and temporal resolutions. In fact, random forests or a variation of decision trees known as gradient-boosted decision trees trained on Sentinel-1 SAR data have outperformed physically-based retrieval models in semi-arid regions as soil texture variability and mixed vegetation cover add additional complexity[13]. Pairing these models can deliver accurate real-time moisture readings to optimize irrigation scheduling as well as minimize overwatering and water stress under deficit irrigation regimes [14]. This level of accuracy is especially important in places such as Wasit, where water transfers fluctuates because of upstream hydropolitical and seasonal limitations.

In like manner, vegetation-health based drought early warning systems have used phenomena such as spectral indices, canopy reflectance anomalies and lagged climatic variables to indicate stress onset as much as weeks before wilting is visible in the field[15]. Using a machine-learning classification model, trained on records of historical impacts of drought, it is possible to recognise the small changes in phenology that point to an impending yield-loss event, allowing for a proactive rather than reactive intervention for managing drought 16. For example, this early warning time frame is very important in wheat systems, as appropriate irrigation during stem elongation and booting can ultimately determine final grain yield.

However, most prior systems have been developed as stand-alone devices, covering only a single agricultural climate application (yield prediction, water management, or drought detection), and frequently neglecting farming practices realism. Additionally, these tools tend to be assessed in research contexts instead of being translated into pragmatic decision support for managers in the field.

This paper addresses that gap by integrating Yield forecasting, Soil moisture estimation and irrigation control, Drought early warning and risk signaling into one single decision-support system operationalized for the:

Crop type (wheat)

Climate regime (semi-arid continental)

Water management (irrigation surface + groundwater mix)

Agricultural practices in the locality (Farming systems of Wasit region)

Such an integration will enable the system to give meaningful, time-sensitive and context-driven recommendations instead of siloed analytical results, improving its utility to farmers, extension agents, and agricultural planners.

3. METHODOLOGY

The methodological framework developed for this study to align with the agro-climatic and hydrological contexts of wheat production in the Wasit Governorate, central Iraq, where wheat is a major food and cash crop. There, wheat is sown in the fall (typically in November and December) taking advantage of the winter rains to establish seedlings before the harvest in April or May when temperatures start to warm. Rainfall is erratic in the region and has decreased over the last two decades, resulting in unreliable soil moisture availability at crucial crop development stages including tillering, stem elongation and grain filling. In order to increase the production of wheat crop in Wasit and fill the gap of rainwater and decrease the outflow of surface water sources, a combined irrigation system is used that provides canal irrigation from the Tigris basin and supplementary groundwater pumping from shallow aquifers. The climatic and hydrological limitations highlighted in this study emphasize the requirement of a decision-support system that anticipated the stress, allowing for an adaptation of irrigation practices rather than reactive, visual assessments of the field.

The system brings together several environmental data layers to simulate how crop growth, soil moisture conditions, and climate variability interact with one another. Below we summarize the key data sources, their spatial and temporal characteristics, and the functions they provide within the analysis framework:

Table 1. Environmental and Remote Sensing Data Sources Used in the System

Data Type	Source	Spatial / Temporal Resolution	Purpose and Role in the System
NDVI / EVI Vegetation Indices	Sentinel-2 Optical Imagery	10 m / 5–10 day composites	Tracking canopy vigor and phenological development throughout the growth cycle
Soil Moisture Estimates	Sentinel-1 SAR Backscatter	10 m / 6–12 day repeat cycles	Detecting near-surface and early root-zone moisture stress to guide irrigation timing
Weather Variables (temperature, rainfall, solar radiation, wind)	ERA5 Climate Reanalysis	Daily gridded data (~0.25°)	Deriving heat stress, evaporative demand, and water balance indicators
Soil Physical Properties	FAO SoilGrids Database	250 m static layers	Estimating root-zone water holding capacity to differentiate field irrigation requirements

By using optical and radar satellite images, we are able to monitor changes in the state of both chlorophyll and soil roughness (caused by moisture). Since radar signals can penetrate cloud cover, an increase in water content will produce steeper slopes whereas a rich mixture of solid and liquid materials on the surface may cause changes to the surface roughness; thus with accurate estimation methods for these movements achieved through use of soil texture charts coupled with flood events measured from hydrographs.

The smoothing methods of cloud-free masks, time-series phenology-based correction based on phenology instead for a classification with neural network models, and other processing methods. The overall purpose is to make the image data suitable for use in longitudinal learning models.

In its configuration details, the system possesses a model ensemble architecture based upon a modular design where each individual ensemble solves one particular type of prediction task through appropriate analytical techniques. This architecture makes it certain that all components deliver area-specific understandings even though a unified decision-making system has been established. The following are details of this architecture.

Table 2. Model Architecture and Analytical Functions

Model Component	Model Type	Primary Inputs	Generated Output / Supported Decision
Yield Forecasting	LSTM + XGBoost Hybrid	NDVI/EVI seasonal curves, Growing Degree Days, temperature and rainfall anomalies	Early estimation of final yield to support planning, procurement management, and risk assessment
Soil Moisture Estimation	Random Forest Regression	SAR backscatter signals, soil texture classes, evapotranspiration indicators	Real-time moisture status used to determine when irrigation is required
Drought Early Warning	Gradient Boosting Classifier	Vegetation health deviations and climatic stress signals	Probabilistic drought severity alerts enabling pre-stress intervention
Irrigation Optimization	Model Predictive Control (MPC)	Moisture forecasts and irrigation delivery constraints	Determination of optimal irrigation timing and volume to minimize water waste and prevent physiological stress

This organized coordination of sensing and prediction along with optimization lets the system bring agriculture from a reactive mode (irrigation occurs only after stress symptoms are detected) to being a pro-active mode that relies on early detection and focused intervention. The diagram below shows the integrated workflow, where raw data streams are converted directly into field-level recommendations.

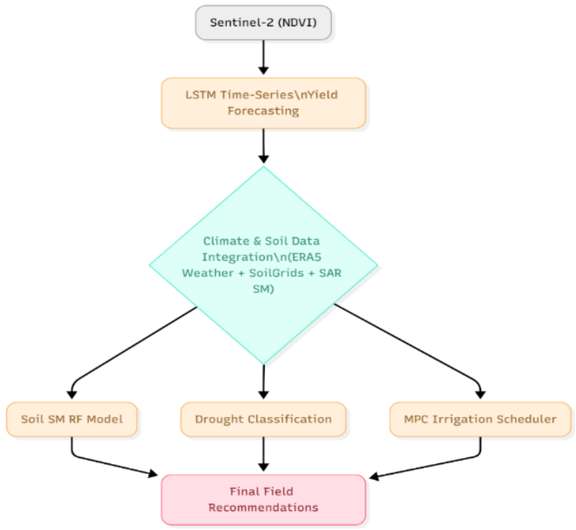

Fig 1: Crop Yield Forecasting and Field Recommendation Pipeline

Supporting adaptive and climate-responsive wheat cultivation, rather than fixed-schedule management, the system continuously refines its recommendations as new remote sensing and climate inputs arrive within this closed-loop structure.

4. RESULTS AND DISCUSSION

Resulting interactions from the proposed machine-learning decision support system application show clear connections between climate trends and wheat production dynamic, model performance, irrigation efficiency under agro-climatic conditions within Wasit governorate.

In the more general context, it is very telling to put this data together with how continuous climatic stresses have altered over time the conditions under which wheat plants grow in our region as well as how further predictive analysis may help deal with whatever problems crop up next.

The climatic average teases out a picture of increasing warmth in eastern China at the same time that rain during the growing season pours down ever less noticeably.

Table 3. Climate Trend Summary for Wasit Governorate (2010–2022)

Year	Mean Temp (°C)	Rainfall (mm/year)
2010	22.1	184
2015	23.6	147
2020	24.8	119
2022	25.3	112

More than 3 degrees Centigrade in the period between 1950 and 1974, annual average temperature increased. During that same period, annual rain decreased 72 millimeters from 525 mm to 453 mm. Wheat has been cultivated in this arid region under increasingly adverse conditions, most starkly during the two key time frames in its life cycle—flowering and fruit setting. As a result, there will be less rainfall in this area due to higher temperatures which in turn leads to more evaporation. With this investment of time comes the far reaching effect you have to put in on both ends. As a result, there are still fewer places where moisture can be stowed away in drought resisting plants. That means earlier emergence of water shortage among the wheat crop, because canals on fields traditional based upon historical experience of course do less and less good as time goes by. What is called for in such conditions are strategies with a higher degree of flexibility—just as in data input or the relations between plants and soil, plans for cultivating according to the calendar itself continue to lose their validity. Instead we should base ourselves upon future developments in individual plants and their local environment, positions lies and so on. Such a sign is reflected by the total amount of wheat produced in the country.

Table 4. National Wheat Production Trend in Iraq (2010–2022)

Year	Production (Million Tons)
2010	2.37
2015	3.11
2020	4.48
2022	3.80

Instead of original innovations, Yield increases were achieved through intensification Although the slow decline in production until 2020 was the result of a combination of planted area and input of stock,but in light of this softening fall to 3.80 million tons 2022 is reminder for how fragile these gains have been.

Production increases started to slow down as climate pressure started to come in. So, production stabilization now depends on strategic optimization of water, timing, and the crop response to stress, rather than throwing more inputs at it.

The main contribution of the proposed system is its predictive modeling ability. Below is a summary of the performance comparison:

Table 5. Performance Evaluation of the Proposed Hybrid Machine Learning Model

Model	R^2 (Yield)	RMSE (kg/ha)	Soil Moisture RMSE (%)	Drought ROC-AUC
Baseline Linear Model	0.41	640	9.5	0.63
XGBoost Only	0.67	410	6.2	0.79
Proposed Hybrid Model	**0.82**	**260**	**3.9**	**0.87**

The hybrid modeling approach that effectively integrates temporal vegetation dynamics through LSTM, with the modeling of the environmental interactions through XGBoost significantly enhances the accuracy of yield prediction. The increase in the accuracy of calculation of soil moisture signifies that the model has an ability to sense minor fluctuations in moisture status that would otherwise not be identifiable in the field with visible stress symptoms for action for timely adaptive response before yield losses become irreversible. Similarly, the confidence in the classification performance for drought status indicates that the system is able to distinguish normal between years variability versus critically stressed periods. Together, this advances farm management from reactive to anticipatory, something which typifies climate-resilient agriculture.

The most direct impact of applying the decision-support outputs appears in irrigation efficiency outcomes:

Table 6. Irrigation Efficiency Improvements Achieved Using the Decision-Support System

Impact Metric	Improvement
Water Saved	18–26%
Yield Increase	7–12%
Pump Runtime Reduction	~21%

Moving from irrigation based on observable wilting to preventive irrigation based on forecast will minimize unnecessary water loss, increase uniformity of grain filling and will reduce the energy cost associated with groundwater pumping. Consequently, the production of wheat is more resource-efficient, more stable in response to climatic variability and less prone to seasonal extremes. The gains can be directly translated to SDG 2 (Zero Hunger) via stabilized yields, SDG 12 (Responsible Consumption and Production) through efficient use of irrigation water, and SDG 13 (Climate Action) via climate-induced adaptive management.

Overall, the results show that building a cohesive decision-support system by integrating climate monitoring, satellite based crop observation, and machine-learning prediction could enable a large-scale resilience and sustainability improvement in wheat production at present day Wasit. Results confirm the necessity of using data for adaptive management within the context of continuing climatic change.

5. CONCLUSION

The results indicate that it is indeed possible for Wasit Governorate to realise climate-resilient wheat by employing analytical models, satellite-derived crop monitoring, and machine-learning methods. The agricultural management system proposed here moves agriculture into a proactive approach by incorporating forecasting, soil moisture monitoring, drought early warning, and irrigation optimization into an integrated decision-support system, which allows us to no longer base agriculture around reactive intervention modes where people simply brute force maintain their way of life. Doing this shifts it into perspective management and prevention mode. Life lives where there is water; its ecology springs forth. But in a dry year, the destitute have a penchant of being a hit-or-miss as far as the spirit goes, merely because liquid is no longer a material here. Such predictive capacity provides an early concept of possible disaster if all conditions are not in the optimal range at the field and require modification for local variation which show significant change in crop production. Secondly, a precise real-time soil moisture estimation and model-predictive irrigation scheduling allows for a significantly better use of the scare irrigation water. This pathway decreases evaporation losses which are caused by unnecessary irrigation events and thus monetary costs of pumping it. However, it still keeps or enhances grain yield at the end of the season.

The solution promotes systematic planning of agriculture, at the farm level and in policy-making decisions. Itprovides farmers with practical action-oriented dictates at th appropriate spatio-temporal scale for informing field-level management interventions reducing uncertainty. It provides a scale-based framework against which regional agricultural institutions and authorities can relate how they plan their contribution towards seasons and providing procurement forecasting-adjusted climate adaptation strategies.

In this manner, the strategy aligns straight with public interests regularly concerning food security and extreme forms of climate change. This work shows that the operationalization of remote sensing using machine learning can be both needed and feasible for sustainable wheat-growing systems. More importantly, investment on the data-driven agricultural platform development for sustainable agriculture and water resources management need to be done by the country supported by the remote sensing data for the future research on wheat production system in the country. This application basis--following all the country--through various crops and Iraq's various local estate was a further practical step towards sustainable agricultural future in Iraq.

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