

SPATIO-TEMPORAL IRRIGATION DEMAND FORECASTING USING SATELLITE DATA AND MACHINE LEARNING

PREVISION SPATIO-TEMPORELLE DE LA DEMANDE EN EAU D'IRRIGATION À L'AIDE DE DONNÉES SATELLITAIRES ET D'APPRENTISSAGE AUTOMATIQUE

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ABSTRACT

Accurate and timely forecasting of crop evapotranspiration (ETa) is essential for demand-responsive irrigation management in water-stressed canal irrigation systems. Existing studies on crop water demand rely on biophysical models that use climate, soil, and irrigation data, often assuming fixed water schedules and focusing on broad trends rather than on stage-specific irrigation. While machine learning has been applied, it primarily focuses on yield estimation. Therefore, this study develops a spatio-temporal ETa estimation and irrigation demand forecasting framework that integrates Landsat 8-derived biophysical variables with machine learning and deep learning approaches at the Water Management Research Farm in Okara, Punjab, Pakistan, which is equipped with an eddy covariance flux tower for observed ETa measurements. Landsat Analysis Ready Data (ARD) at 30 m spatial resolution from 2015 to 2025 were processed to extract the historic information of the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Land Surface Temperature (LST), and Net Radiation (Rn) for the machine learning models training. These variables, along with temporal descriptors, served as input features for model training, using an 80:20 patch-based split. The Convolutional Neural Network (CNN) model used in this study achieved the predictive accuracy ($R^2 = 0.90$, RMSE = 0.21 mm/day, MAE = 0.34 mm/day), outperforming Random Forest - RF ($R^2 = 0.87$) and XGBoost ($R^2 = 0.84$), across Kharif and Rabi cropping seasons. Field-scale validation showed CNN's accuracy in ETa estimates within 0.02-0.09 mm/day of eddy covariance flux tower measurements. Weekly cumulative ETa forecasts demonstrated strong agreement with observations ($R^2 = 0.94$, NSE = 0.87), showing the framework's suitability for operational irrigation scheduling. These findings demonstrate that integrating remote sensing with machine learning offers a scalable, cost-effective approach for irrigation demand management in data-scarce, water-stressed agricultural systems across South Asia.

Keywords: Evapotranspiration; machine learning; CNN; Remote Sensing; Eddy Covariance; Irrigation Demand; Punjab; Pakistan.

RESUME

Une prévision précise et opportune de l'évapotranspiration des cultures (ETa) est essentielle pour une gestion de l'irrigation adaptée à la demande dans les systèmes d'irrigation par canaux soumis à un stress hydrique. Les études existantes sur la demande en eau des cultures s'appuient sur des modèles biophysiques qui utilisent des données climatiques, pédologiques et d'irrigation, en supposant souvent des programmations fixes d'eau et en se concentrant sur les tendances générales plutôt que sur l'irrigation spécifique à chaque étape. Bien que l'apprentissage automatique ait été appliqué dans ce domaine, il se concentre principalement sur l'estimation du rendement. Par conséquent, cette étude développe un cadre d'estimation ETa spatio-temporelle et de prévision de la demande en irrigation qui intègre les variables biophysiques issues de Landsat 8 avec des approches d'apprentissage automatique et d'apprentissage profond au Ferme de recherche sur la gestion de l'eau à Okara, Pendjab, au Pakistan, qui est équipé d'une tour de flux de Covariance de tourbillon (Eddy Covariance) pour les mesures ETa observées. Les données prêtes pour l'analyse Landsat (ARD) ayant une

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résolution spatiale de 30 m couvrant la période de 2015 à 2025, ont été traitées afin d'extraire les informations historiques de l'indice de végétation par différence normalisée (NDVI), de l'indice de végétation ajusté au sol (SAVI), de la température de surface terrestre (LST) et du rayonnement net (Rn) pour l'entraînement des modèles d'apprentissage automatique. Ces variables, ainsi que les descripteurs temporels, ont servi de caractéristiques d'entrée pour l'entraînement du modèle, en utilisant une division 80:20 basée sur une parcelle. Le modèle de réseau de neurones à convolution (CNN) utilisé dans cette étude a atteint la précision prédictive ($R^2 = 0,90$, RMSE = 0,21 mm/jour, MAE = 0,34 mm/jour), surpassant les modèles tels que la forêt aléatoire - RF ($R^2 = 0,87$) et XGBoost ($R^2 = 0,84$), à travers les saisons de culture Kharif et Rabi. La validation à l'échelle de la parcelle a montré que la précision de CNN dans les estimations d'ETa se situe entre 0,02 et 0,09 mm/jour pour les mesures de tour de flux de Covariance de tourbillon (Eddy Covariance). Les prévisions hebdomadaires cumulées d'ETa ont montré une forte concordance avec les observations ($R^2 = 0,94$, NSE = 0,87), montrant l'adéquation du cadre pour la planification opérationnelle de l'irrigation. Ces résultats démontrent que l'intégration de la télédétection à l'apprentissage automatique offre une approche évolutive et rentable pour la gestion de la demande en irrigation dans les systèmes agricoles d'Asie du Sud soumis à un stress hydrique ayant des données rares.

Mots-clés : Évapotranspiration; Apprentissage automatique; CNN; Télédétection; Covariance de tourbillon (Eddy Covariance); Demande en irrigation; Pendjab; Pakistan.

1. INTRODUCTION

Pakistan's Indus Basin Irrigation System (IBIS), one of the largest contiguous irrigation networks in the world, commanding over 17 million hectares (ha), operates almost entirely under a supply-driven rotational system known as warabandi (Gleick, 2018; R. Li et al., 2018). Under this system, water is allocated to farm outlets in fixed proportions irrespective of crop type, growth stage, or actual evaporative demand (Haseeb et al., 2023). The resulting mismatch between supply and crop water requirement causes chronic over-irrigation, leading to waterlogging and soil salinization across an estimated 6.19 million hectares and acute under-irrigation during peak growth stages. Agriculture accounts for over 90% of Pakistan's freshwater withdrawals, yet field-level water use efficiency remains as low as 20-35% (Allen et al., 1998; Behura et al., 2025).

Actual evapotranspiration (ET_a), the combined flux of soil evaporation and plant transpiration, constitutes 50-90% of the total water balance in semi-arid irrigated systems such as central Punjab (Allen et al., 2007, and Zhao et al., 2023). Unlike reference ET computed from meteorological data using fixed crop coefficients, ET_a integrates the actual state of the crop land, surface temperature, crop type, canopy density, soil moisture, and radiative energy, making it the most operationally actionable measure of actual crop water consumption. Satellite-based surface energy balance algorithms, such as SEBAL (W. G. M. Bastiaanssen et al., 1998) and METRIC (Allen et al., 2007) generate spatially explicit ET_a at 30 m resolution from Landsat data. Machine learning (ML) and deep learning approaches have emerged as powerful complements, learning complex non-linear relationships between satellite-observed biophysical parameters and ground-measured ET_a without prescribing fixed physical assumptions (Chen et al., 2021; Cui & Li, 2011). Applications of ML to Landsat-derived biophysical predictors have demonstrated R^2 consistently exceeding 0.80 across semi-arid irrigated landscapes (Jiang et al., 2024). Despite this progress, critical gaps constrain operational uptake in South Asia, where existing models are predominantly validated at regional scales using coarse-resolution imagery, and field-scale validation against continuous eddy covariance (EC) flux tower observations remains limited. Direct instrument-based quantification of actual latent heat flux remains limited. This study addresses these gaps by developing a 30-m resolution, machine-learning-driven ET_a forecasting framework, validated against independent EC flux tower observations, and translating it into a weekly farm-scale irrigation demand management tool within the Lower Bari Doab Canal (LBDC) command. The specific objectives are: (i) develop a spatio-temporal ET_a estimation framework using Landsat 8 biophysical variables with CNN, RF, and XGBoost, (ii) evaluate and compare model performance using spatially non-overlapping patch-based validation, (iii) validate predictions against EC flux tower measurements across contrasting Kharif and Rabi conditions, and (iv) demonstrate applicability for demand-responsive irrigation planning.

2. MATERIALS AND METHODS

2.1 Study Area

This study was conducted at the Water Management Research Farm (WMRF), located at 30°52'N, 73°36'E in Renala Khurd, district Okara, Punjab, Pakistan (Figure 1). The farm is covered with diverse crops, wheat, rice, maize, potato, guava, and mixed orchards, representative of the central Punjab irrigated plains (Ali et al., 2022) and is equipped with a continuously operating EC flux tower providing independent ET_a ground truth. The WMRF is situated within the LBDC command area, a major irrigation system serving approximately 275,000 farmsteads across a semi-arid landscape with a mean annual temperature of 34°C and a mean monthly precipitation of approximately 22.35 mm (Naeem & Ghazal, 2021).

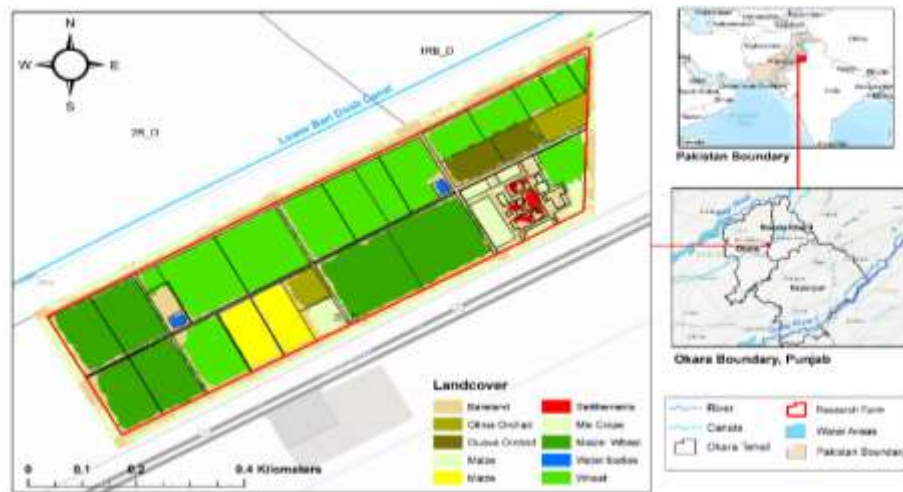


Figure 1. Study area map showing the WMRF location within the LBDC command area in Renala Khurd, Okara, Punjab, Pakistan.

2.2 Data Sources and Preprocessing

The primary dataset comprised Landsat 8 Analysis Ready Data (ARD) surface reflectance products at 30 m resolution spanning 2015-2025, acquired from the USGS Earth Explorer portal. Cloud masking is applied to the Landsat QA band; all bands were processed in Google Earth Engine (GEE). LULC classification used Random Forest applied to multi-temporal PlanetScope composites at 3 m resolution. Ground-based ET_a from the EC flux tower provided independent validation data. Table 1 summarizes all input variables.

Table 1. Input variables used in the ET_a estimation framework.

Parameter	Acronym	Resolution	Data Source
Normalized Difference Vegetation Index	NDVI	30 m	Landsat 8 OLI (B4, B5)
Soil-Adjusted Vegetation Index	SAVI	30 m	Landsat 8 OLI (B4, B5)
Land Surface Temperature	LST	30 m	Landsat 8 TIRS (B10, B11)
Net Radiation	Rn	30 m	Landsat 8 OLI+TIRS (SEBAL)
Actual Evapotranspiration	ET_a	30 m	Landsat 8 OLI+TIRS (SEBAL)
Air Temperature	Ta	0.1°×0.1°	ERA5-Land (ECMWF)
Day of Year	DOY	Daily	Landsat metadata
Land Use Land Cover	LULC	3 m	PlanetScope (RF classifier)

2.3 Biophysical Variable Retrieval

LST was retrieved from Landsat 8 TIRS Band 10 using digital numbers that were converted to TOA spectral radiance (Eq. 1), converted to brightness temperature BT using band-specific calibration constants K_1 and K_2 (Eq. 2), vegetation proportion P_v derived from NDVI (Eq. 3), emissivity estimated (Eq. 4), and LST computed correcting BT for emissivity (Eq. 5):

$$L_\lambda = M_L Q_{cal} + A_L \quad (1)$$

where M_L is the multiplicative radiance rescaling factor, Q_{cal} is the calibrated pixel value (DN), and A_L is the additive radiance term. TOA radiance was converted to brightness temperature (BT) using Eq. (1):

$$BT = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} - 273.16 \quad (2)$$

From eq. (2), where K_1 and K_2 are band-specific thermal calibration constants. Vegetation proportion (P_v) was derived from NDVI:

$$P_v = \frac{\sqrt{NDVI - NDVI_{min}}}{\sqrt{NDVI_{max} - NDVI_{min}}} \quad ; \quad \varepsilon = 0.004 \times P_v + 0.986 \quad (3)$$

where $NDVI_{min}$ and $NDVI_{max}$ represent the minimum and maximum NDVI values in the image. Land surface emissivity (ε) was then estimated. The LST was computed by correcting BT for surface emissivity:

$$LST = \frac{BT}{1 + \left(\frac{\lambda \times BT}{c^2}\right) \ln(\varepsilon)} \quad (4)$$

2.4 Net Radiation (R_n) Estimation

Net radiation at the land surface represents the total available energy driving evapotranspiration:

$$R_n = (SW_{in} - SW_{out}) + (LW_{in} - LW_{out}) \quad (5)$$

Incoming shortwave radiation was estimated from solar geometry and atmospheric transmissivity:

$$SW_{in} = \cos(\theta_{rad}) G_{sc} \tau_{sw} \quad ; \quad SW_{out} = \alpha SW_{in} \quad ; \quad R_{ns} = SW_{in} - SW_{out} \quad (6)$$

where θ is the solar zenith angle, G_{sc} is the solar constant (1367 Wm^{-2}), τ_{sw} is atmospheric shortwave transmissivity, and α is broadband surface albedo. Longwave radiation components were estimated using LST and emissivities:

$$LW_{out} = \varepsilon_s \sigma LST^4 \quad ; \quad LW_{in} = \varepsilon_a \sigma T_{air}^4 \quad (7)$$

where σ is the Stefan–Boltzmann constant ($5.67 \times 10^{-8} \text{ Wm}^{-2} \text{ K}^{-4}$) and T_{air} is ERA5-Land near-surface air temperature. Total net radiation:

$$R_n = R_{ns} + R_{nl} \quad (8)$$

ET_a was computed via SEBAL (W. Bastiaanssen et al., 2010) with soil heat flux G parameterised as a function of R_n , LST, albedo, and NDVI (Eq. 8). Sensible heat flux H was derived iteratively using Monin-Obukhov similarity theory, and the Instantaneous ET_a was upscaled to daily ET_a using the evaporative fraction approach.

2.5 Patch-Level Data Partitioning

All feature layers and the ET_a target variable were subdivided into 320×320 patches to enable memory-efficient batch processing while preserving geospatial alignment (Figure 2). Datasets were partitioned at the patch level using a chronological 80:20 train-test split, ensuring temporal non-overlap prevents spatial autocorrelation from inflating performance metrics.

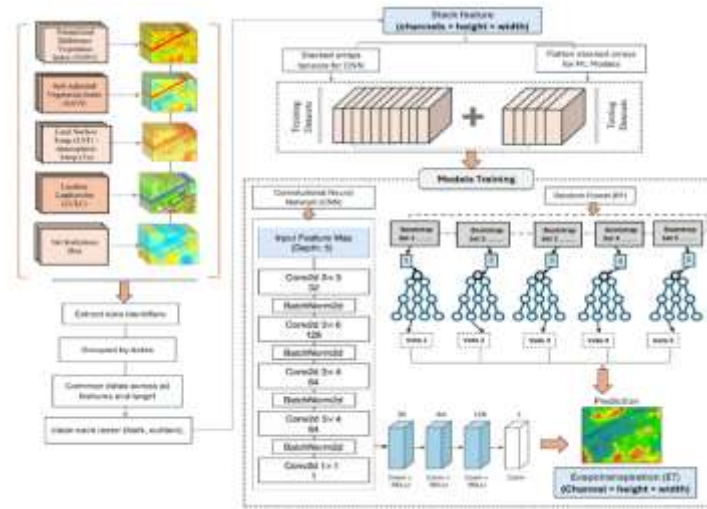


Figure 2. Methodological workflow for the ET_a estimation and irrigation demand forecasting framework.

2.5 Machine Learning Models

For the model training, CNN with Conv2D layers (3×3 kernels) with batch normalisation and ReLU activation, optimised using Adam (learning rate 1×10^{-3} , cosine annealing, batch size 32). Moreover, the Random Forest (RF) with 500 estimators, bootstrap sampling, and five-fold cross-validation hyperparameter tuning, as well as XGBoost with gradient boosting, additive tree updates, and randomized hyperparameter search.

2.6 Model Evaluation

Performance was assessed against EC flux tower ET_a using R^2 , RMSE, MAE, and Kling–Gupta Efficiency (KGE):

$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (9)$$

where r is the Pearson correlation, α is the ratio of simulated to observed standard deviations, and β is the ratio of means.

3. RESULTS AND DISCUSSION

3.1 Spatio-temporal Dynamics of Biophysical Variables (2015–2025)

The Landsat 8-derived biophysical variables showed pronounced seasonal and inter-annual variability consistent with the bimodal Kharif-Rabi cropping calendar (Figure 3). NDVI ranged from ~ 0.05 during fallow periods to 0.45–0.70 during Kharif peak growth (rice and maize), with moderate values of 0.35–0.55 during Rabi (wheat). LST ranged from ~ 290 K to 320 K, with higher values in September–October and lower values during February–March winter conditions. SAVI showed patterns consistent with NDVI but with reduced inter-annual variability during low-canopy periods, demonstrating its robustness in

minimising soil background influence. Net Radiation was consistently higher during Kharif, reflecting increased incoming solar radiation under dense crop canopies.

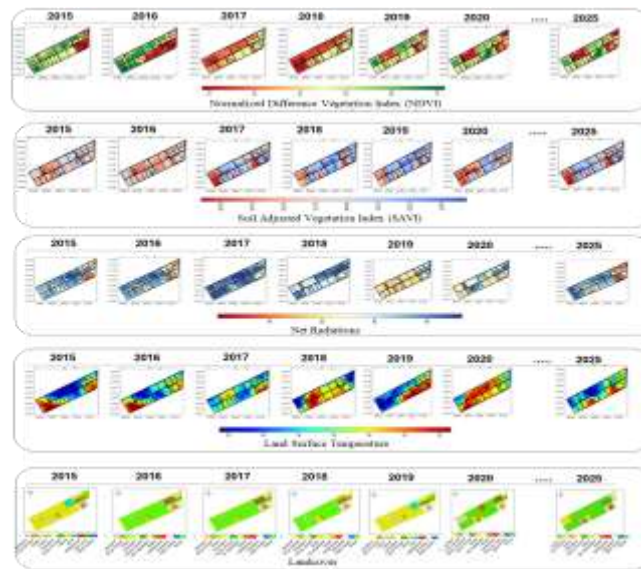


Figure 3. Spatio-temporal distribution of the bio-physical parameters of NDVI, LST, SAVI, Net Radiations, and LULC across WMRF.

The strong positive correlation between LST and R_n ($r = 0.95$) and positive ET_a -NDVI association during growing seasons ($R^2 = 0.75$) are physically consistent with surface energy balance dynamics governing semi-arid irrigated systems (Johnson et al., 2019).

3.2 Seasonal Patterns and Interrelationships

Monthly climatological analysis revealed strong seasonal co-variation. ET_a exhibited a pronounced unimodal cycle, ranging from 1.2-2.0 mm/day in December-February to a peak of 7.5 mm/day in June-August, coinciding with rice transplanting and peak solar radiation (Figure 4). ET_a - R_n correlation ($r = 0.83$) confirms the dominant role of radiation in driving crop water use, while ET_a -NDVI ($r = 0.81$) highlights the role of canopy density. NDVI and SAVI showed high multicollinearity ($r = 0.97$), which was addressed using variance inflation factor (VIF) analysis. Figure 4 shows that NDVI exerts the strongest monotonic positive effect on CNN-predicted ET_a (1.5 to 3.8 mm/day across NDVI 0.1–0.8), while LST revealed negative dependence consistent with stomatal closure under elevated surface temperatures.

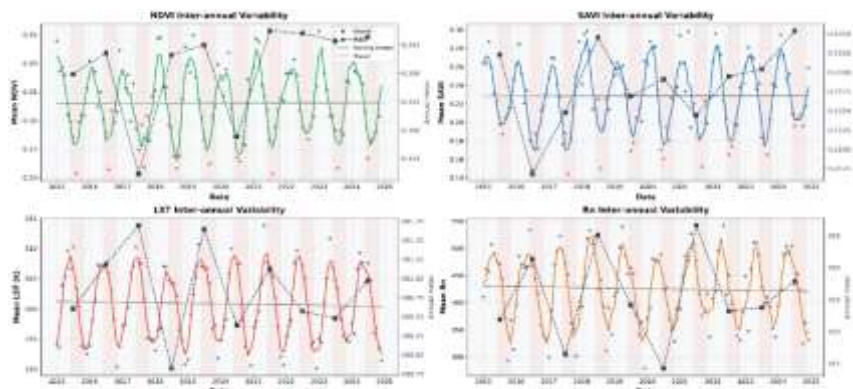


Figure 4. Inter-annual variability of NDVI, SAVI, LST, and R_n across WMRF (2015-2024) and Pearson correlation heatmap among biophysical variables and ET_a .

3.3 LULC and Cropping Pattern Dynamics

The LULC classification (Figure 5) reveals a predominance of wheat–rice and wheat–maize rotations, with potato, guava, and mixed orchards occupying smaller proportions. Overall classification accuracy was ~91% based on stratified ground-truth sampling. Temporal stability of dominant cropping systems over the decade confirms the reliability of the bimodal Kharif-Rabi phenological cycle as a structuring feature in the ET_a modelling framework.

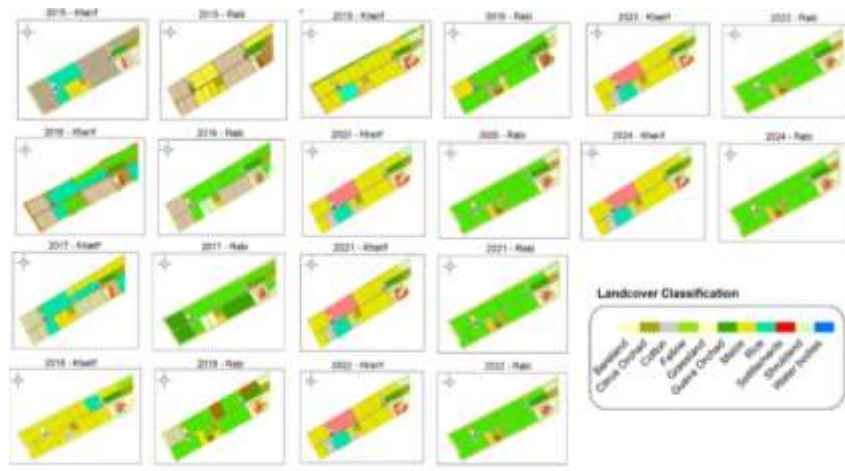


Figure 5. Spatio-temporal LULC distributions across the WMRF for selected Kharif and Rabi seasons (2015-2025).

3.4 Model Performance Evaluation

Table 2 presents performance metrics on the spatially independent 20% test dataset. CNN achieved the highest accuracy ($R^2 = 0.90$, RMSE = 0.21 mm/day, MAE = 0.34 mm/day), representing a 3–10% improvement in R^2 over tree-based models. RF ($R^2 = 0.87$) and XGBoost ($R^2 = 0.84$), suggesting that bootstrap aggregation provides robustness advantages under the heterogeneous patch-based training conditions. The superior performance of CNN is attributed to its hierarchical convolutional feature extraction, which captures both local pixel-level ET_a dynamics and contextual spatial patterns across adjacent agricultural fields, a capability unavailable to pixel-wise tree-based models (Janiesch et al., 2021; Z. Li et al., 2022). Figure 11 presents spatial ET_a maps comparing all models against SEBAL-derived ET_a .

Table 2. Performance metrics (R^2 , RMSE, MAE) of CNN, RF, and XGBoost on the spatially non-overlapping 20% test dataset.

Model	R^2	RMSE	MAE
CNN	0.90	0.21	0.34
RF	0.87	0.38	0.59
XGBoost	0.84	0.41	0.62

3.5 Field-Scale Validation Against Eddy Covariance Flux Tower

Table 3 presents field-scale comparisons against EC flux tower observations across multiple dates and crop types. CNN showed consistently superior agreement: for winter wheat (January 2022), CNN estimated 2.01 mm/day against 1.99 mm/day observed ($\Delta ET = 0.02$ mm/day), while RF (1.76), and XGBoost (1.72) all underestimated under low-transpiration winter conditions. During peak Kharif rice demand (May 2024), CNN estimated 4.46 mm/day, compared with 4.54 mm/day ($\Delta ET = 0.08$ mm/day), while tree-based models severely underestimated (2.97-3.13 mm/day). For August 2024, CNN produced 6.50 mm/day against 5.60 mm/day, which observed a slight overestimation consistent with sensitivity under extreme evaporative demand (Johnson et al., 2019; Wei et al., 2022).

Table 3. Field-scale ET_a estimates (mm/day) from all models versus eddy covariance flux tower measurements for wheat and rice.

Date	Crop	PySEBAL	CNN	RF	XGBoost	Flux Tower
2022-01-08	Wheat	2.75	2.01	1.76	1.72	1.99
2023-02-10	Wheat	3.89	3.46	3.13	3.08	3.54
2024-05-16	Rice	4.55	4.46	3.13	3.05	4.54
2024-08-17	Rice	5.73	6.50	6.08	5.89	5.60
2024-10-06	Rice	1.49	1.30	1.77	1.68	1.27

Weekly cumulative ET_a forecasts demonstrated the highest seasonal agreement ($R^2 = 0.934$, $NSE = 0.865$, $KGE = 0.909$, $PBIAS = -2.59\%$), with a total seasonal difference of only 15.7 mm (605 mm observed vs. 589 mm forecast). The model captures the overall seasonal trend well, including peak ET periods in June-July and declining patterns towards September-October. Minor deviations are observed, with periods of slight over- and underestimation, indicating good agreement within situ measurements, as shown in Figure 6.

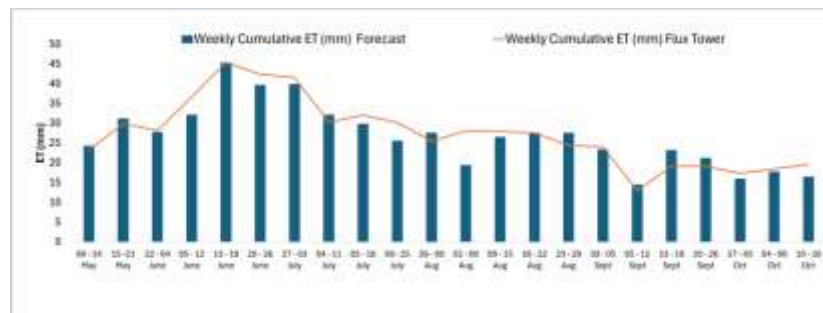


Figure 6. Weekly cumulative ET_a CNN forecast versus eddy covariance flux tower observations (Kharif, 2025), with over-forecast (blue) and under-forecast (red) shaded zones.

This figure presents spatial patterns of ET_a across the study area, comparing PySEBAL-derived estimates with predictions from CNN, Random Forest (RF), and XGBoost models. All models reasonably capture the spatial variability of ET_a , with CNN showing smoother transitions, while RF and XGBoost exhibit localized variations. The results demonstrate the capability of machine learning models to replicate physically derived ET_a patterns at the field scale.

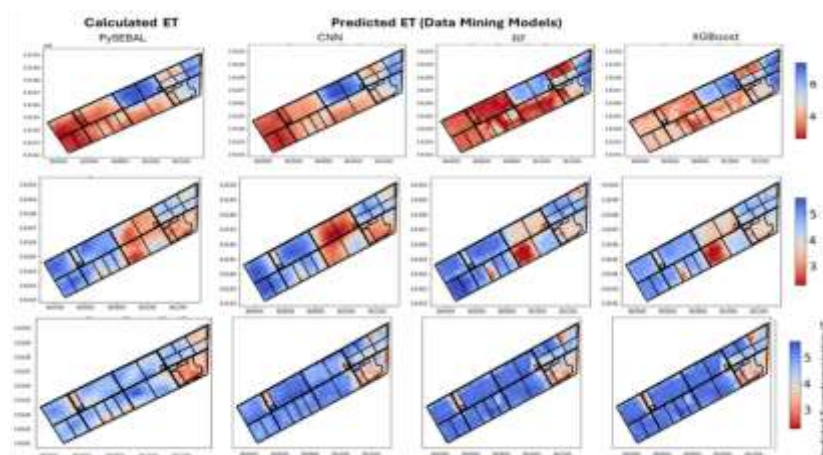


Figure 7. Spatial ET_a estimation and prediction using PySEBAL and machine learning models (CNN, RF, and XGBoost).

3.6. STRATEGIC WATER MANAGEMENT FRAMEWORK

The findings from the CNN-based ET_a forecasting framework enable irrigation planning by applying schedule-based warabandi allocation to proactive, demand-informed management. By generating weekly cumulative ET_a forecasts at 30 m spatial resolution, the framework supports four operational applications: (i) crop-specific irrigation advisories differentiated by crop type and growth stage (Behura et al., 2025) (peak rice ET_a of 5.5-7.5 mm/day in August versus wheat ET_a of 1.5-3.5 mm/day during Rabi); (ii) adaptive warabandi scheduling weighting each outlet's allocation by its projected ET_a relative to the command-wide mean; (iii) conjunctive groundwater management by spatially identifying fields requiring supplemental groundwater during peak demand periods when canal supply is insufficient; and (iv) conservation of surplus water during low-demand periods for strategic aquifer recharge. The pipeline requires only updated satellite inputs and locally calibrated validation measurements, enabling district-level irrigation authorities to generate weekly farm-level water demand across the command area (Jimenez-Bello et al., 2015). Limitations include dependence on cloud-free Landsat acquisitions (which are constrained during the monsoon-dominated Kharif season), a 16-day revisit cycle, and validation currently limited to a single research farm with EC instrumentation.

CONCLUSION

This study developed and validated a spatio-temporal ET_a estimation and irrigation demand forecasting framework that integrates Landsat 8 biophysical variables (NDVI, SAVI, LST, R_n) with CNN, RF, and XGBoost, and was validated against EC flux tower observations at WMRF Renala Khurd, Punjab, Pakistan. CNN achieved superior predictive performance ($R^2 = 0.90$, RMSE = 0.21 mm/day, MAE = 0.34 mm/day) and demonstrated excellent seasonal forecast agreement ($R^2 = 0.934$, PBIAS = -2.59%). The strategic water management framework translates weekly ET_a forecasts into crop-specific irrigation advisories, adaptive warabandi scheduling, conjunctive groundwater management, and surplus water conservation, thereby directly addressing supply-demand mismatches that perpetuate over- and under-irrigation in large canal irrigation systems. The framework developed at WMRF Renala Khurd provides a replicable methodological template for irrigation demand forecasting across South Asia's water-stressed agricultural systems. Future work should explore higher-resolution commercial satellite imagery, multi-week forecast horizons using coupled weather forecast models, and transferability evaluation across other canal commands within the Indus Basin Irrigation System.

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