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ORIGINAL ARTICLE

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Satellite-Based Spatiotemporal Variability and Mapping the Irrigation Water Requirements of Wheat Crop in Ludhiana District, Punjab

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ABSTRACT

This study evaluated the spatial and temporal patterns of evapotranspiration (ET) and irrigation water requirement (IWR) for wheat in the Ludhiana district, Punjab, using satellite data and statistical modeling. MODIS-derived ET and WorldClim rainfall data were processed in QGIS using the Inverse Distance Weighting (IDW) method for spatial interpolation. Sentinel-2A multispectral imagery was used to generate wheat crop masks. Pearson correlation analysis revealed strong positive relationships between ET, temperature, and wind speed, and a significant negative correlation with relative humidity, while rainfall showed no significant association. A two-way ANOVA indicated significant effects of both month and block (spatial) on ET, with the highest values observed in February. The interaction between block and month emphasized the role of localized climatic and soil conditions. IWR was calculated using rainfall and ET data, with peak irrigation demand during February and March, coinciding with critical growth stages of wheat. The developed ET and IWR maps serve as valuable tools for location-specific irrigation scheduling. Findings support groundwater conservation efforts by promoting efficient water use and provide a framework to work with the real-time weather data and auxiliary spatial layers to enhance precision irrigation.

1 | INTRODUCTION

Water is the most essential yet limited natural resource. Although three-fourths of the Earth's surface is covered by water, only about 0.04% is freshwater in lakes, rivers, and soil moisture (Stephens *et al*., 2020). With the rising global population, food demand is increasing, making it challenging to achieve the Sustainable Development Goals by 2030 (Moyer & Hedden, 2020). Meeting these demands and enhancing land productivity is required despite limited resources. In India, wheat is the second most important staple crop after rice, with demand projected to reach 105 million tons by 2025 for a population of 1.25 billion (Pramod *et al*., 2018). The Indo-Gangetic Plains account for nearly 10 million hectares under the rice–wheat cropping system, including 3.18 million hectares in Punjab (Anonymous, 2024). Approximately 70% of anthropogenic water use is for irrigation, which is expected to increase by 8% by 2070 due to climatic variations that alter precipitation and evapotranspiration (ET) (Johnson *et al*., 2019; Woznicki *et al*., 2015). Inefficient irrigation and groundwater depletion, especially in Punjab, exacerbate water scarcity (Sidhu *et al*., 2021). The hydrological imbalance caused by climate change has made water the most limiting factor in crop production. Wheat accounts for 28% of the water demand in Punjab's rice-wheat system, requiring 510 mm of water, of which only 110 mm comes from precipitation, leaving the rest as a deficit met by irrigation. This water deficit underscores the need to reduce ET and improve water-use efficiency (WUE) (Jalota *et al*., 2014).

Efficient water management requires precise estimation of crop water requirements and well-planned irrigation schedules, supported by strategies to enhance WUE and productivity (Yousaf *et al*., 2021). One of the most important aspects of irrigation planning is determining crop evapotranspiration. Irrigating fields according to crop water needs could improve water use efficiency. There are various methods to estimate evapotranspiration. ET can be determined through direct methods (e.g., lysimeters, experimental field plots, Bowen ratio, eddy covariance, water balance, soil moisture depletion) or indirect methods (e.g., Hargreaves, Blaney–Criddle, Radiation method, Penman-Monteith, Modified Penman). Among these, the FAO-56 Penman-Monteith method is the most widely recommended, but it remains time-consuming and labour-intensive. Recent advancements in machine learning remote sensing (RS) and geographic information system (GIS) offer powerful tools for ET estimation and irrigation management (Mandal *et al*., 2021; Tomar, 2022; Trivedi *et al*., 2022). Satellite and aerial remote sensing provide spatially distributed ET estimates, enabling monitoring of land surface conditions and water availability at varying temporal and spatial scales. These ET estimates, when mapped using GIS, can guide policymakers, extension agencies, and farmers in identifying site-specific crop water needs and scheduling irrigation accordingly. Therefore, the present study was undertaken to estimate the irrigation water requirements of wheat in the intensive rice–wheat system in the semi-arid region of Punjab, with a focus on leveraging geospatial technologies to support sustainable water management.

2 | MATERIALS AND METHODS

2.1 | Study Area

Ludhiana district is centrally located in the Punjab plain region, in the northwest part of India (Fig. 1). It lies between 30.80°N and 31.30°N latitude and 75.40°E and 76.40°E longitude, at an elevation of 247 meters above mean sea level. The topography of the district represents an alluvial plain. The soil type in the significant part of the district is light- to medium-textured (loam to silty clay loam), except in a few areas with medium- to heavy-textured soils, with pH values ranging from 7.8 to 8.5.

The climate of Ludhiana district can be classified as sub-tropical, hot, and semi-arid. Hot and dry summers are observed from April to June, a hot and humid period from July to September, and cold winters from November to January. The mean maximum and minimum temperatures are 29.8 ± 0.6°C and 17.3 ± 0.5°C (Jalota *et al*., 2020). The average annual rainfall of the district is 544 mm. However, during the rabi season, the average rainfall is around 170 mm (India Meteorological Department [IMD], 2025). The crop's water requirement is primarily met through tubewell irrigation.

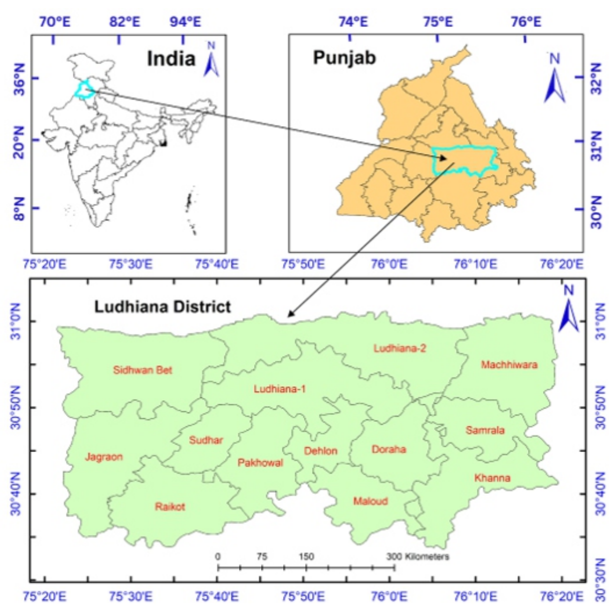

FIGURE 1 Map of the study area.

HIGHLIGHTS

- First block-level, satellite-based (MODIS ET and Sentinel-2A crop mask) spatio-temporal mapping of evapotranspiration and irrigation water requirement for wheat in Ludhiana district, Punjab.
- February and March emerged as the peak irrigation-demand months, coinciding with the flowering to grain-filling stages of wheat.
- Temperature, wind speed and relative humidity, rather than rainfall, were identified as the dominant climatic drivers of evapotranspiration, with a significant block × month interaction underscoring the need for localized irrigation scheduling.

2.2 | Satellite Data Acquisition

Satellite data from Sentinel 2A and Moderate-resolution Imaging Spectroradiometer-MOD16A2/A3 (MODIS) MOD16A2/A3 were used in this study. Blue, green, red, and near-infrared bands from Sentinel 2A (10 × 10 m) were used to represent crop acreage. The data obtained were processed in ERDAS Imagine using various tools, such as layer stacking, mosaicking, and subsetting (Nelson *et al.*, 2018), to produce a false-color composite (FCC) image of the study area. The satellite imagery was obtained in January, and atmospheric and geometric corrections were made. Unsupervised classification was performed to extract pixel-wise wheat-cropped area as per the study's requirements. The wheat crop mask of Ludhiana district is shown in (Fig. 2).

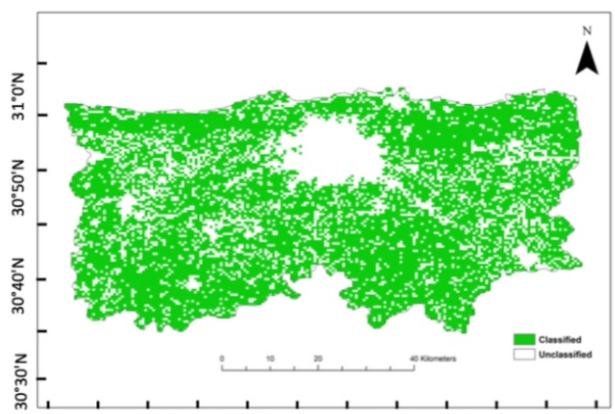

FIGURE 2 Wheat crop mask of Ludhiana District.

The wheat crop mask was further used to clip and extract reference ET of wheat in the study area. ET data for three wheat-growing seasons, i.e., 2019-20, 2020-21, and 2021-22 (November-April), were derived from 8-day composite MODIS images with a spatial resolution of 500 m. The Penman-Monteith equation is the basis for obtaining the ET product from MODIS images (Mu *et al.*, 2007; Jang *et al.*, 2010), which includes reference evapotranspiration (ref ET) and potential evapotranspiration (PET). This depicts evaporation from soil, evaporation of rainwater intercepted by the canopy before it reaches the ground, and transpiration through stomata in the plant. We confirmed the validity of the seasonal ET values derived from MODIS by comparing them with the seasonal ET (365-449 mm) obtained under wheat field experimentation at research farm of the Punjab Agricultural University, Ludhiana (Singh *et al*., 2019); as well as with the irrigation water requirement computed by Satpute *et al*. (2021) for different crops including wheat by using the FAO-Penman-Monteith equation (Allen *et al.*, 1998) for the present study area. The images were downloaded from Google Earth Engine and pre-processed. Pre-processing involves defining the coordinate system, projecting the data to the Universal Transverse Mercator projection system, and extracting the required pixels by overlaying the wheat crop mask. ArcGIS was used to carry out these procedures. The processed raster image was converted to points using the “Raster to Point” tool in ArcGIS software. The “Extract multi-values to points” tool in ArcGIS was used to obtain monthly pixel-wise ET values, along with X and Y coordinates, from the image. The sum of monthly ref ET was used to obtain the district's seasonal ref ET. Using the “Zonal Statistics” provision, blockwise ET was obtained for an intensive study.

2.3 | Meteorological Data

Meteorological data, i.e., maximum temperature (T_{max}), minimum temperature (T_{min}), and rainfall (mm) during the study period (November 2019 to April 2022), were obtained from the Department of Climate Change and Agricultural Meteorology, Punjab Agricultural University, Ludhiana. Additional data, such as sunshine hours and wind speed, for the entire district were downloaded from the NASA Power Access Data Viewer (https://power.larc.nasa.gov/data-access-viewer/) to capture spatial variability. This website provided the data with a spatial resolution of ½ × ½ degree. To obtain the spatial variation of rainfall over the district, satellite data from the 'Worldclim' database with 2.5-minute resolution was used. Monthly rainfall data in TIFF format were obtained for the three seasons and mapped using QGIS. The TIFF file was opened in QGIS and clipped to the study area. Later, using the 'xyz gdal' tool, the data was converted into CSV format. This CSV was reopened in QGIS as vector points. Using these vector points, the data was interpolated using the 'IDW Interpolation' tool. This interpolated dataset represented the overall spatial variation of rainfall across the district. This rainfall data was later used to obtain the spatio-temporal variation in the crop's irrigation water requirement.

2.4 | Statistical Analysis

2.4.1 | Correlation Analysis

To evaluate the relationships between reference ET (ET_o) and key climatic parameters, Pearson correlation analysis was conducted. Monthly data from November to April on ET_o, maximum temperature (Tmax), minimum temperature (Tmin), mean temperature (Tmean), rainfall (RF), relative humidity (RH), sunshine hours, and wind speed were used in the analysis (https://power.larc.nasa.gov/data-access-viewer/). Prior to computing correlations, all variables were cleaned, standardized, and checked for completeness to ensure consistency in formatting and scale. Pearson's correlation coefficient (r) was chosen as it is appropriate for assessing the strength and direction of linear relationships between continuous, normally distributed variables. The correlation coefficients and corresponding p-values were computed in R (version 4.5.1) using the 'cor()' and 'cor.test()' functions. A correlation heatmap was generated using the 'ggcorrplot package to visually represent significant associations.

2.4.2 | Two-way ANOVA

To further investigate the variability in reference ET (ET_o) across spatial and temporal dimensions, a two-way analysis of variance (ANOVA) was performed using block and month as fixed factors. This analysis aimed to assess the individual effects of agricultural blocks (spatial factor) and months (temporal factor) on ET, as well as their interaction effect. The dataset consisted of block-wise ET values recorded monthly from November to April across 13 administrative blocks in Ludhiana district. Month-wise and block-wise values were treated as categorical factors, and ET was treated as the continuous response variable. The two-way ANOVA was then conducted using the 'aov()' function in R, followed by 'TukeyHSD()' for post-hoc pairwise comparisons. The model output included main effects for both block and month, as well as a block × month interaction term. An interaction plot was also constructed to visualize how ET varied simultaneously across months and blocks. This allowed identification of temporal trends, spatial variability, and block-specific ET dynamics during critical stages of the wheat crop. The analysis provided insight into whether ET differences were more strongly influenced by seasonal changes, spatial microclimates, or a combination of both.

2.5 | Preparation of Monthly Evapotranspiration Maps and Irrigation Water Requirement Maps

MODIS-derived evapotranspiration (ET) images were processed to generate spatio-temporal ET maps of the Ludhiana district. The monthly MODIS-derived ET data were imported into QGIS, and these raster layers were first converted into point data using the "Raster pixels to points" tool. The resulting point layers served as the input for spatial interpolation. The Inverse Distance Weighting (IDW) method was employed to interpolate monthly ET across the district. The interpolated surfaces were clipped using the Ludhiana district shapefile to match the study area boundary. Each monthly ET map was then exported as a JPEG using the “Export map” tool in QGIS.

To derive irrigation water requirement (IWR), both spatial rainfall and ET data were integrated. Monthly rainfall data at 2.5-minute resolution were obtained from the WorldClim database, while ET data were sourced from MODIS. Since the spatial resolutions of the two datasets differed, the rainfall data were resampled using the 'r.resample' tool to match the ET resolution.

Effective rainfall was estimated from total monthly rainfall using an empirical equation provided by the FAO (Food and Agriculture Organization) (Eq. 1).

$$P_e = 0.0011\, x^2 + 0.4422x \qquad (1)$$

Where P_e is the effective rainfall in mm and x is the total rainfall in mm.

Pixel-wise IWR was then computed using the 'Raster Calculator' by subtracting effective rainfall from ET for each corresponding pixel (Allen *et al*., 1998) (Eq. 2).

$$IWR = ET - P_e \qquad (2)$$

Where ET is monthly evapotranspiration (mm), Pe is effective rainfall (mm), and negative values are set to zero, i.e., no irrigation is required.

The resulting IWR raster layer was similarly converted to points, interpolated using IDW, clipped to the district boundary, and exported as JPEG maps. IDW method was chosen for its simplicity, computational efficiency, and proven ability to produce reliable estimates, particularly in areas with moderately dense spatial observations. Although more advanced geostatistical methods, such as kriging and spline interpolation, can offer improved accuracy, IDW requires fewer assumptions about the data distribution and has been widely applied to the spatial interpolation of ET and climatic variables (Hodam *et al.*, 2017). To evaluate the robustness of the IDW interpolation, a leave-one-out cross-validation was performed on a sample of monthly ET point layers. The predicted values showed reasonable agreement with observed values, indicating that IDW was appropriate for interpolating ET, rainfall, and IWR in this study.

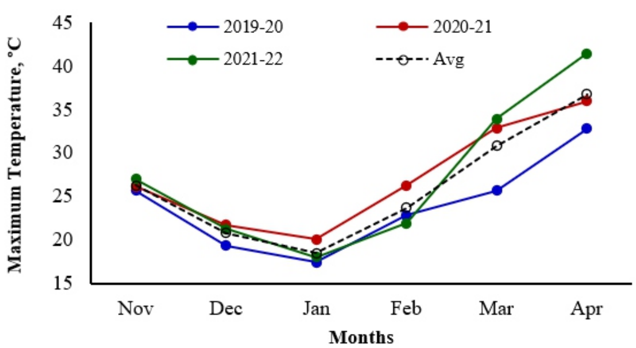

FIGURE 3 Maximum temperatures at different wheat growing seasons.

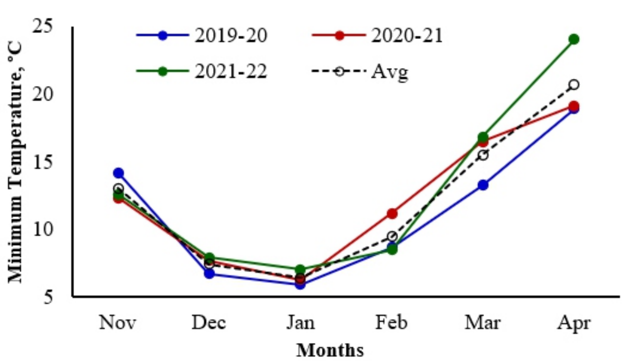

FIGURE 4 Graph showing minimum temperatures at different wheat growing seasons.

3 | RESULTS AND DISCUSSION

In the study area, various parameters, including climate, evapotranspiration, and irrigation water requirements, were estimated and analyzed. The results of the study have been discussed below.

3.1 | Climate of the Study Area

The meteorological data obtained from *the Power Access Data Viewer were analyzed for temporal variation during the wheat seasons from* 2019-20 to 2021-22. Figs. 3 and 4 represent the maximum and minimum temperatures, respectively, over different wheat growing seasons.

3.2 | Rainfall Distribution

Rainfall data from 'Worldclim' was used to create maps in QGIS to represent spatio-temporal variation of rainfall in the study area. The highest rainfall in Ludhiana district (ranging from around 40-70 mm) was observed in January 2022 (Fig. 5). It has been observed that the Machhiwara, Ludhiana-2, and Samrala blocks usually received higher rainfall, whereas Raikot and Jagraon consistently *received lower rainfall throughout the 2021- 22 season*.

3.3 | Evapotranspiration of Wheat crop in Ludhiana district

The evapotranspiration (Fig. 6) increased from November (germination stage) through December (crown root initiation stage) to January and February (tillering, jointing, and flowering stages), peaking. A decrease in ET was observed in March (grain formation stage) and April (ripening stage).

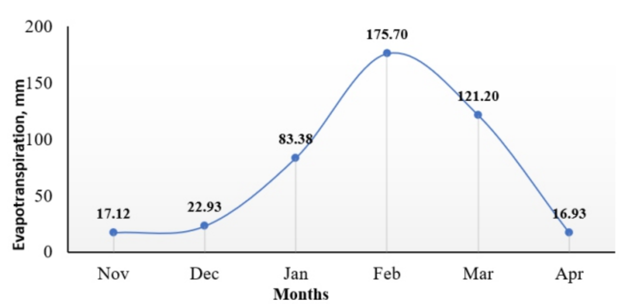

FIGURE 6 Average Monthly Evapotranspiration of wheat crop in Ludhiana district.

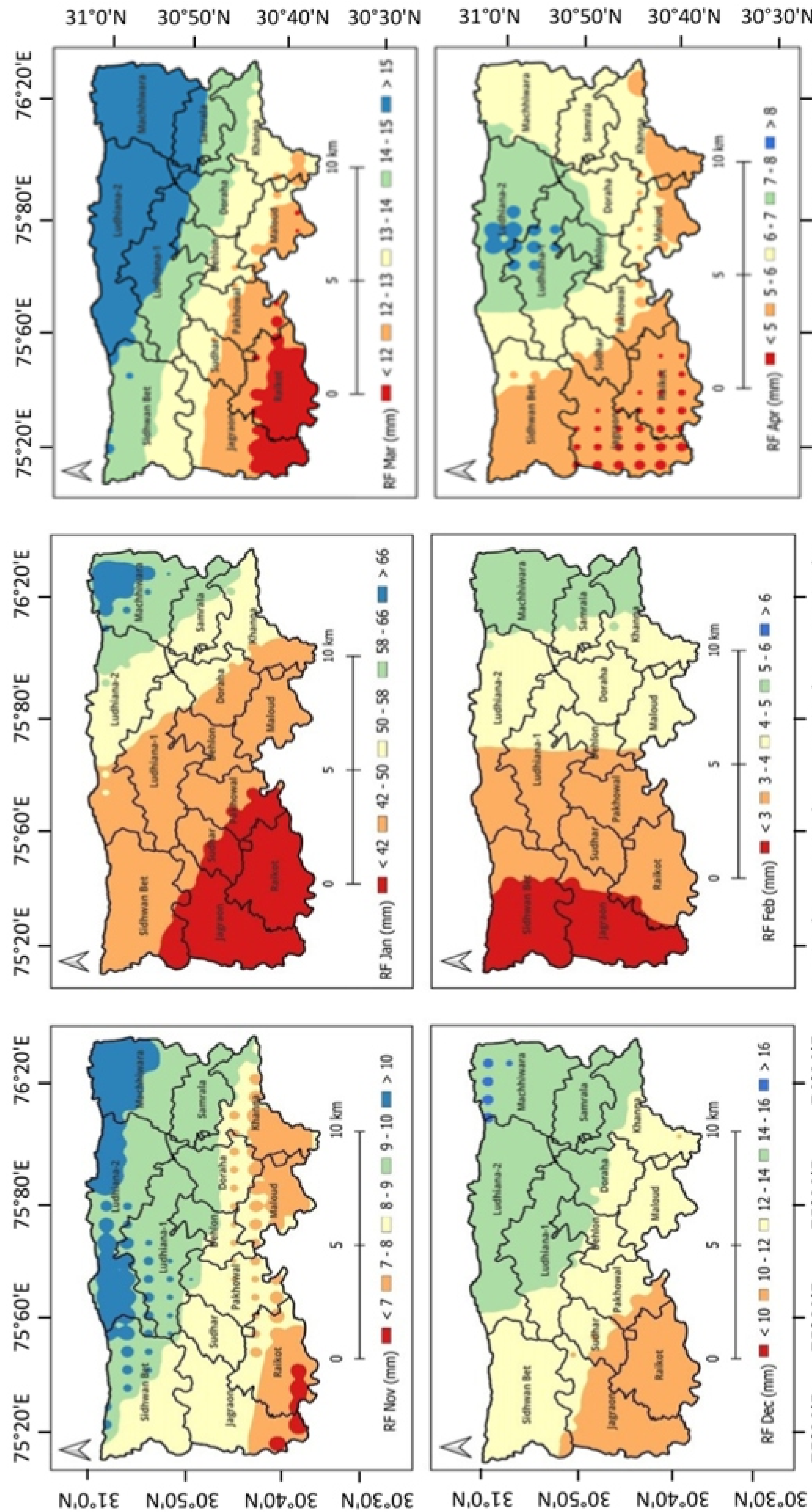

FIGURE 5 Spatio-temporal variation of rainfall in mm during the crop season 2021-22.

The average monthly ET trend during different wheat seasons is presented in (Fig. 7). During the crown root initiation stage (December), the highest evapotranspiration (32.83 mm) was seen in 2020-21. ET during the tillering, jointing, and flowering stages (January, February) was nearly the same across all three seasons. During grain formation (March), the highest ET was observed in 2020 (152.82 mm), and during ripening (April), the highest ET was recorded in 2020 (36.49 mm), and the lowest ET was recorded in 2022 (17 mm).

3.4 | Block-wise Evaluation of Evapotranspiration

Seasonal evapotranspiration for each block was estimated and compared (Fig. 8). In the blocks Jagraon, Khanna, Ludhiana-1, Machhiwara, Pakhowal, Samrala, and Sudhar, evapotranspiration decreased over the three years. In Dehlon and Sidhwan Bet, evapotranspiration was higher in 2019-20 than in other seasons, whereas during 2020-22, ET values were nearly equivalent. In Doraha, Ludhiana-2, Maloud, and Raikot, evapotranspiration decreased from 2019-20 to 2020-21 and then increased in 2021-22. Higher evapotranspiration was observed in Raikot and Maloud, due to higher vapor pressure deficit from higher solar radiation, wind speed, lower relative humidity, and rainfall. Ludhiana-1 showed lower ET values due to urbanization and lower crop coverage than other blocks.

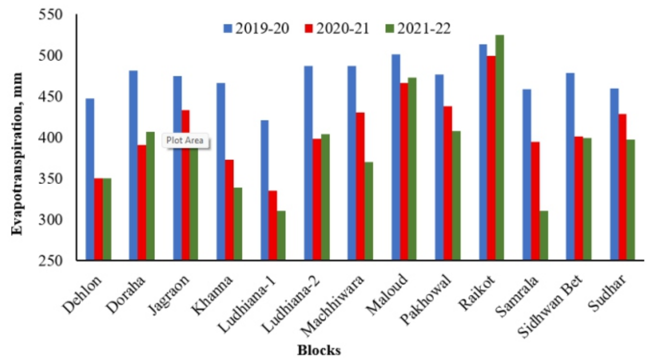

FIGURE 8 Evapotranspiration of wheat crop during grow-ing seasons 2019-20, 2020-21, and 2021-22 in various blocks of Ludhiana district.

3.5 | Statistical Analysis

3.5.1 | Correlation Analysis

Pearson correlation analysis was conducted primarily as a diagnostic and site-specific validation to quantify the climatic controls on evapotranspiration (ET) during the wheat-growing season (November–April) and to support interpretation of the spatial IWR estimates. As expected from ET physics, ET was strongly and positively correlated with temperature and wind speed. ET showed strong positive correlations with Tmax ($r = 0.90$, $p = 0.014$) and Tmean ($r = 0.88$, $p = 0.020$), indicating that seasonal warming is the dominant driver of atmospheric water demand in the study area. Wind speed also exhibited a strong positive correlation with ET ($r = 0.88$, $p = 0.021$), consistent with enhanced turbulent transfer under windier conditions.

Relative humidity (RH) was strongly and negatively correlated with ET ($r = -0.84$, $p = 0.035$), reflecting reduced vapor pressure deficit under more humid conditions. In contrast, rainfall displayed a weak and non-significant correlation with ET ($r = -0.11$, $p = 0.835$). This weak coupling is not unexpected in an irrigated rice–wheat system, where ET is primarily governed by atmospheric demand and irrigation supply rather than by precipitation alone during the Rabi season. Sunshine hours showed a moderate positive correlation with ET ($r = 0.76$) with marginal significance ($p = 0.08$). Fig. 9 summarizes these relationships; non-significant associations were masked for clarity.

3.5.2 | Two-way ANOVA

A two-way ANOVA was conducted to examine the effects of block, month, and their interaction on mean ET. The results (Table 1) revealed that both block ($p < 0.05$) and month ($p < 0.001$) had significant effects on ET, with month contributing the largest proportion of variance (Sum Sq = 296,182). The interaction between block and month was also notable (Sum Sq = 11,015), suggesting that the pattern of ET across months varied by block.

The interaction plot (Fig. 10) illustrates seasonal variation in ET across the 13 blocks from November to April. All blocks exhibited a similar temporal trend, with ET peaking during February, coinciding with the flowering to grain-filling stage of wheat and then declining sharply by April, when the crop reaches maturity.

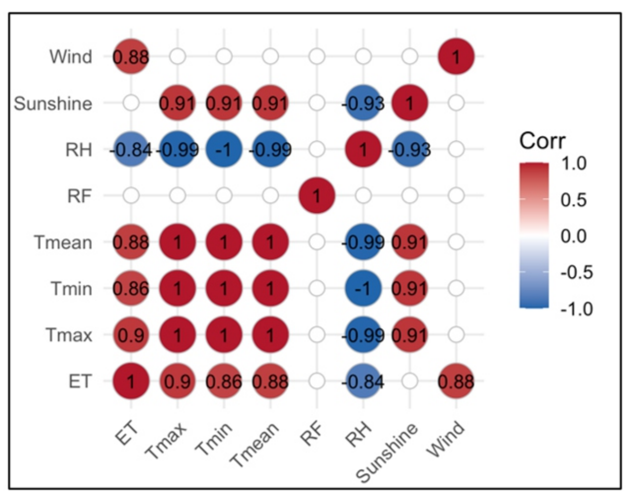

FIGURE 9 Correlation matrix between evapotranspi-ration and climatic variables.

TABLE 1 Two-way ANOVA summary showing the effect of block, month, and their interaction on evapotranspiration (ET).

Source	DF	Sum Sq	Mean Sq
Block	12	6,071	506
Month	5	296,182	59,236
Block: Month	60	11,015	184

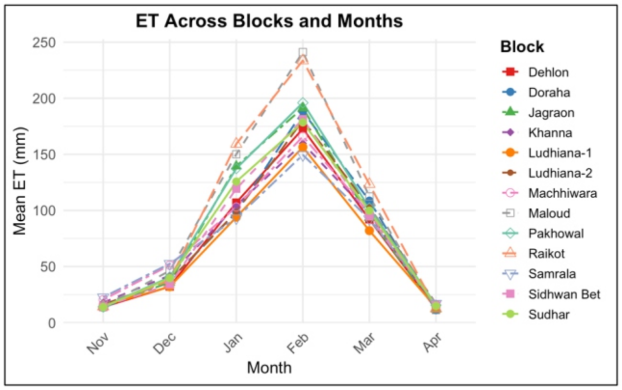

FIGURE 10 Seasonal interaction of mean evapotranspiration (ET) across blocks from November to April in Ludhiana district.

3.6 | Evapotranspiration and Irrigation Water requirement maps of Wheat crop in Ludhiana district

The monthly evapotranspiration obtained from MODIS data was mapped in QGIS to represent the spatio-temporal variation of ET (Fig. 11). An increase in ET can be observed by comparing the color ranges across months. As discussed in previous sections, ET reached its highest value in February, ranging across the district from 15 to 440 mm, while the range further narrowed in March, varying from 9 to 226.5 mm. The ET decreased across the district as crop growth progressed from February to March and into April. Fig. 12 represents the spatio-temporal variation of irrigation water requirements in Ludhiana district. IWR was higher in February and March, as wheat was at its peak growth stage.

This study assessed climate variables, evapotranspiration, and irrigation requirements over multiple wheat seasons in Ludhiana district. The findings highlight temporal and spatial variability influenced by climatic and agronomic factors. The results of the correlation analysis underscore the critical role of climatic factors, particularly temperature, wind speed, and relative humidity in influencing evapotranspiration during the wheat-growing season. The strong positive correlations between ET and temperature variables (Tmax, Tmin, and Tmean) reflect that higher temperatures increase atmospheric evaporative demand. As temperatures rise, both evaporation from the soil surface and transpiration through plant stomata intensify, resulting in elevated ET values. These findings are consistent with earlier studies that emphasize temperature as a primary driver of evapotranspiration in semi-arid agricultural systems (Trivedi *et al*., 2018). Wind speed also exhibited a strong positive correlation with ET, confirming its importance in enhancing evaporative loss through increased turbulence and vapor pressure deficit. Strong winds can remove saturated air from the crop surface, thereby maintaining a gradient that favours continued water vapor loss (Yadav *et al.,* 2021). The significant correlation observed between wind speed and ET further support the inclusion of this parameter in predictive models and irrigation scheduling tools. On the other hand, relative humidity showed a strong and statistically significant negative correlation with ET. Higher humidity levels reduce the vapor pressure gradient between the plant surface and the surrounding air, thereby suppressing water loss (Chahal *et al.,* 2007). This inverse relationship highlights the dampening effect of humid conditions on evapotranspiration, especially during periods of low wind activity. Interestingly, rainfall showed no significant correlation with ET in this analysis. This may be attributed to the relatively low monthly rainfall totals during the rabi season or a temporal mismatch between rainfall events and peak ET periods. Rainfall, while essential for replenishing soil moisture, may not directly influence ET at the monthly scale if it is not synchronized with crop water uptake (Buttar, 2017). Although sunshine hours had a moderately strong positive correlation with ET, the relationship did not reach conventional levels of statistical significance ($p = 0.080$). Nonetheless, sunshine is a key factor influencing net radiation and energy availability for ET processes (Rodriguez & Sadras, 2007). The lack of significance could be due to the small number of monthly observations ($n = 6$) and the inclusion of only winter months, which may limit the statistical power to detect associations.

The strong month-wise effect observed in the two-way ANOVA confirms the seasonal pattern of evapotranspiration driven by crop growth stages and climatic conditions. February consistently showed the highest ET values, aligning with earlier observations and supporting literature, such as Trivedi *et al*., (2018), which report higher crop water use during active vegetative and reproductive stages. The significant block effect, although comparatively smaller in magnitude, indicates spatial variability in ET across the Ludhiana district. Blocks such as Raikot and Maloud demonstrated higher ET, possibly due to increased solar radiation, higher wind speeds, or lighter soil textures (e.g., sandy soils), which promote greater evaporative loss (Wang *et al.*, 2016). In contrast, blocks like Ludhiana-1 and Samrala exhibited relatively lower ET, likely due to urban influence (reduced vegetative cover) or heavier soil types that restrict water movement. The significant block × month interaction further emphasizes that the effect of seasonality on ET differs among blocks, likely due to localized variations in soil properties, microclimate, and crop management. This interaction highlights the importance of location-specific irrigation scheduling rather than a one-size-fits-all approach.

Spatio-temporal differences in ET were dependent on the variability of climatic parameters. For instance, higher maximum temperatures in April 2022 than in 2019-20 and 2020-21 likely resulted from a heat wave that deviated from normal seasonal patterns. Such thermal extremes can affect evapotranspiration and crop performance (Panda *et al*., 2017). Rainfall patterns also showed clear spatial heterogeneity, with blocks like Machhiwara and Samrala receiving more rainfall. This could influence irrigation planning and groundwater recharge potential. The increase in ET from November to February aligns with wheat crop development, particularly during tillering and flowering stages. These stages are characterized by high vegetative growth and canopy cover, which increase transpiration losses. Lower ET in April reflects the crop's transition to ripening, where reduced canopy cover and physiological activity limit water loss. These findings are consistent with those of Trivedi *et al*., (2018). Similarly, soil textural differences control soil water-holding capacity and groundwater availability, and ultimately influence ET dynamics (Kumar *et al.,* 2020; Casa *et al.,* 2009; Li *et al*., 2008). For instance, sandy and loamy sand soils in blocks such as Sidhwan Bet and Ludhiana-1 retain less water, thereby limiting ET. IWR maps showed peak water demand in February and March, aligning with crop growth stages such as flowering and grain filling. These months should be prioritized for irrigation scheduling across the district.

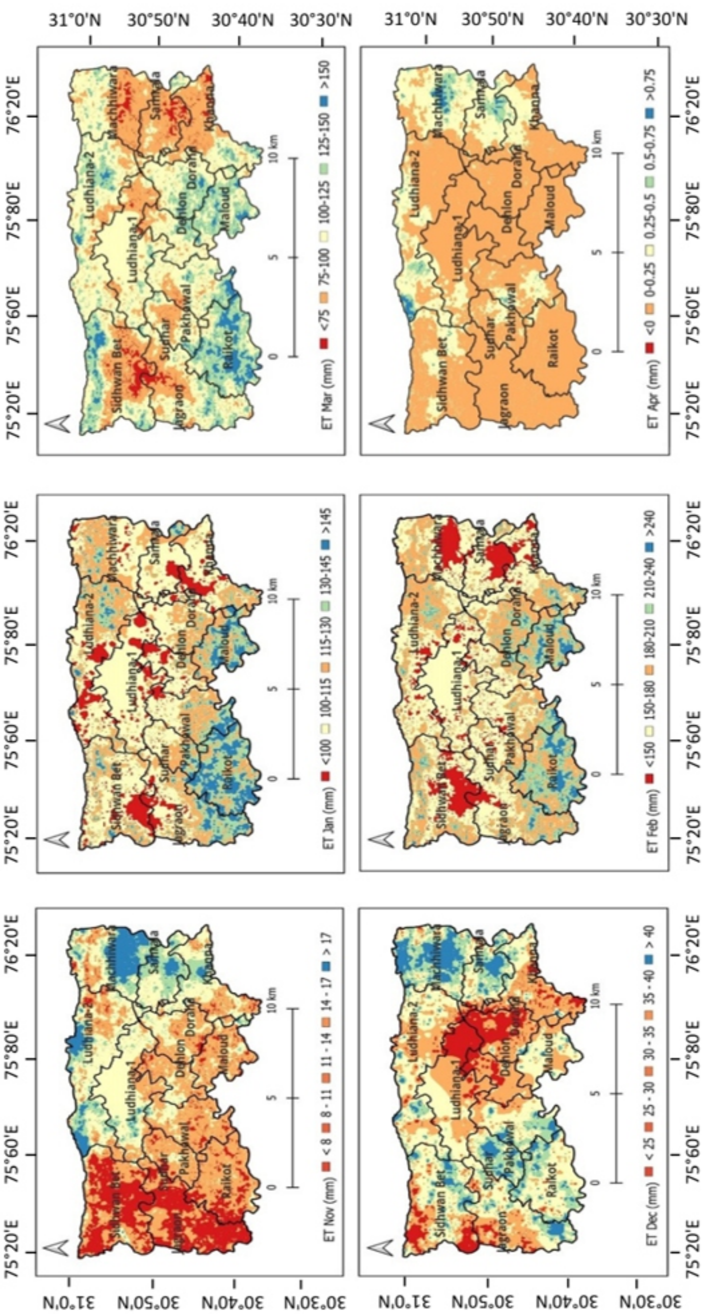

FIGURE 11 Spatio-temporal variation of evapotranspiration (mm) during the crop season 2021-22.

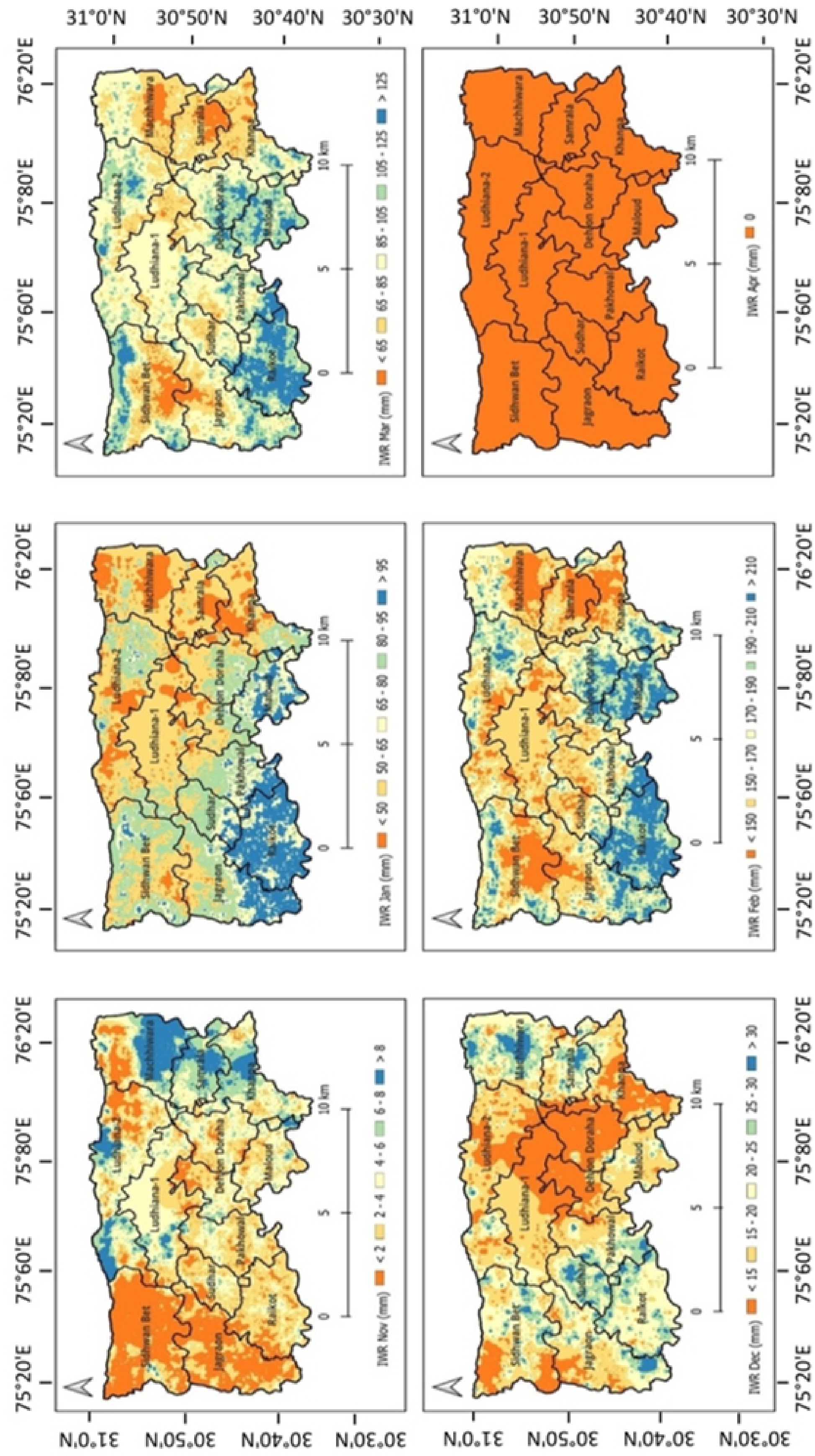

FIGURE 12 Spatio-temporal variation of irrigation water requirement (mm) during the crop season 2021-22.

4 | CONCLUSIONS

This study demonstrated an integrated geospatial approach for estimating evapotranspiration (ET) and irrigation water requirement (IWR) for wheat by combining satellite-based observations with ground-based meteorological data. MODIS-derived ET products successfully captured both temporal and spatial variability across three consecutive wheat-growing seasons, while Sentinel-2 imagery enabled accurate delineation of wheat-cropped areas. The integration of spatial rainfall data from WorldClim facilitated pixel-wise estimation of IWR, enabling assessment of irrigation demand variability at both the seasonal and block scales. The statistical analyses provided insight into the climatic controls governing ET dynamics, and the significant block × month interaction highlighted the spatial variability in the crop water demand due to localized factors, including soil texture, microclimatic conditions, and urbanization. The spatio-temporal ET and IWR maps generated in this study provide actionable insights for irrigation management. The identification of February and March as the most irrigation-intensive months underscores the need for timely and targeted irrigation during these periods. Overall, the results emphasize the importance of localized, data-driven irrigation scheduling that accounts for climatic variability, crop phenology, and spatial heterogeneity. Such spatially explicit information can support block-level irrigation advisories and groundwater conservation efforts in Punjab's wheat-based systems, while future integration of high-resolution soil data and real-time weather inputs could further enhance precision irrigation planning.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or financial relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

All data are reported in the paper.

AUTHOR'S CONTRIBUTION

NV and BBV: Conceptualization, methodology, data curation, formal and geospatial analysis, investigation, manuscript writing, supervision, manuscript review and editing; HK: Geospatial methods and analysis, manuscript review and editing; MA: Remote sensing data methods and analysis, manuscript review and editing.

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