Journal of Agrometeorology

ISSN : 0972-1665 (print), 2583-2980 (online)
Vol. No. 26 (3) : 374-376 (September - 2024)
https://doi.org/10.54386/jam.v26i3.2568
https://journal.agrimetassociation.org/index.php/jam

Short Communication

Relationship between NDVI, LST and simulated wheat yield with district wise reported yield: A case study of Bathinda, Punjab

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Food security is threatened by the sensitivity of crops to changes in temperature, precipitation, and carbon dioxide levels. Research suggests that climate change is a major driver of crop yield variability, accounting for 30-50% of global fluctuations (Rezaei *et al.,* 2018). To mitigate these climate risks and ensure food security, accurate predictions of future climate impacts on agricultural production are essential. Wheat production in India reached an impressive 112.18 million tonnes during the 2022-23 crop year (FAO, 2024). Wheat faces significant challenges due to rising temperatures and elevated CO_2 levels and a potential wheat yield decline up to 25% by 2080 has been projected in India (Kumar *et al.,* 2014). Lobell *et al.,* (2012) focused on the Indo-Gangetic Plain (IGP), highlighting the localized reductions in yield up to 20% in certain areas. Pandey (2023) reported a decline in the yield of different crops including wheat under projected climate change, the extent of which were found to vary with the locations and crops in different districts of Gujarat, India. Therefore, safeguarding wheat production in India becomes critical.

Remote sensing plays a crucial role in estimating biomass and crop yields, monitoring plant health and drought stress, tracking crop development stages, and mapping land cover changes. The vegetative indices, when compared with factors like leaf area index (LAI) or photosynthetically active radiation (fAPAR), provide reliable estimates that closely match actual harvest data. It's important to remember that local calibration is essential for ensuring data accuracy (Myneni *et al.,* 2002). Crop growth models estimate factors like biomass and grain yield, but extensive training data and calibration for specific scenarios is require (Kasampalis *et al.,* 2018). While offering reasonable accuracy, limitations exist. These include long runtimes, data storage constraints, and the inability to fully capture local variations in soil, weather, and crop parameters (Shahhosseini *et al.,* 2019). So, by integrating with remote sensing data, crop models can be enhanced for regional applications. In view of this the current study was planned to yield estimation using crop simulation model and relate with normalized difference vegetation index (NDVI) and land surface temperature (LST) to optimizing resource use, and to develop effective climate-resilient strategies.

The daily weather data for 2000-2022, consisting of maximum temperature (^{0}C), minimum temperature (^{0}C), rainfall (mm) and sunshine duration (hr) were sourced from the nearest Agrometeorological Observatory situated at the PAU Regional Research Station, Bathinda (30.58°N, 74.18°E). Essential soil characteristics parameters, such as sand, silt, clay composition, bulk density, pH level, permanent wilting point, saturation water content, initial water content, field capacity collected from previous study by Pal and Yadav (2018) were used for creating the soil file in DSSAT. The wheat yield data for Bathinda district from 2000-2022 was sourced from the Statistical Abstract of Punjab (Directorate of Statistics, Government of Punjab).

The daily product of MODIS land surface temperature (LST) of 1 km spatial resolution was downloaded from the site https://search.earthdata.nasa.gov/ for the period 2000-2022. The scaling factor used to extract LST was 0.02. For calculation of NDVI, MODIS daily surface reflectance data (1 km product) was downloaded and NDVI was computed from Band 1 (Red) and Band 2 (NIR) using following formula:

$$\text{NDVI} = \frac{(\text{NIR-R})}{(\text{NIR+R})}$$

CERES-wheat model was run using the long-term weather and soil data collected, along with genetic coefficients for the wheat variety HD 3086, previously fine-tuned by Singh *et al.,* (2022). The CERES-wheat model was executed for each growing

Article info - DOI: https://doi.org/10.54386/jam.v26i3.2568
Received: 10 April 2024; Accepted: 01 June 2024 ; Published online : 01 September 2024

season from 2000 to 2022 for wheat sown on 10th November, using the collected soil and weather data. The model outputs, including simulated wheat yields, were then compared to the actual yield data obtained from the statistical abstracts. Several statistical methods such as root mean square error (RMSE), the index of agreement (d), and the coefficient of determination (R^2) were employed to check model performance.

Simulated v/s reported wheat yield

The wheat yield was simulated for HD 3086 variety of wheat for the period of 2000 to 2022 and was related with the reported yield of Bathinda district. between simulated and observed wheat yields variety spanning the. The outcomes of the simulation were examined using scatter plots, where the simulated yields were plotted against the actual recorded yields. The results highlight a reasonable degree of correspondence between the simulated and observed yields with R^2 value 0.75 (Fig. 1). The Root Mean Square Error (RMSE) values (313.5 kg ha^{-1}) quantify the average magnitude of the differences between observed and simulated yields. The relatively low RMSE values is further validating the model's capability to mimic real-world outcomes. The d-Stat values (0.88) signify the efficiency of the simulation model in terms of yield prediction. Higher d-Stat values denote a better match between simulated and observed yields. Studies by Pal *et al.,* (2015) reported good agreement between model outputs and observed data for phenological events, biomass accumulation, and grain yields. Similarly, Kumar *et al.,* (2024) observed close agreement between simulations and field data for phenology, grain yield, and biomass yield.

NDVI v/s reported yield

Fig. 2 illustrates the relationship between NDVI and reported yield of wheat on Bathinda district. Analysis revealed a good correlation (R^2 = 0.693) between recorded wheat yield and NDVI values in the Bathinda region of Punjab for the period 2000-2022. The slope in regression equation revealed a positive relationship between yield and NDVI (Fig. 2). This relationship reflects the seasonal variations in crop growth, wherein increases in NDVI values correspond with enhanced vegetation vigor during the wheat growing season, typically leading to higher wheat yields. Conversely, declines in NDVI may indicate stress or adverse conditions that could impact yield outcomes. However, it's important to recognize that various environmental factors, such as water availability, temperature fluctuations, soil quality, and agricultural practices, pest outbreaks, can interact with NDVI to influence crop productivity. Despite these complexities, the observed correlation highlights the practical utility of NDVI as a valuable tool for agricultural management and decision-making. Previous studies support the positive correlation between NDVI and crop yield. Panek and Gozdowski (2020) reported strong correlations (0.50-0.80) between cereal yield and NDVI in Central Europe using MODIS satellite data. Similarly, Kumar *et al.,* (2022) also showed significant relation (R^2=0.87) between NDVI and observed yield.

LST v/s reported yield

The correlation analysis conducted between recorded wheat yield and LST (Land Surface Temperature) values for the Bathinda region of Punjab over a span of 23 years, from 2000 to 2022. With a coefficient of determination (R^2) of 0.606, it indicates a good relationship between wheat yield and LST values (Fig. 3). This suggests that variations in LST, which reflect surface temperature conditions, have a notable influence on crop yield fluctuations in the region. The slope in regression equation revealed a negative relationship between yield and LST. Specifically, higher LST values may signify increased temperature stress on crops, potentially leading to reduced yields, while lower LST values may indicate more favorable temperature conditions conducive to higher yields. A negative correlation suggests that monitoring LST could be a helpful tool in Bathinda to identify areas potentially at risk due to heat stress. However, it's essential to consider the factors like rainfall, soil moisture, and agricultural practices can also significantly impact wheat yield.

Thus, the results revealed that the validated CERES-wheat model exhibited good agreement with observed yield data. The NDVI was positively correlated with the reported wheat yield

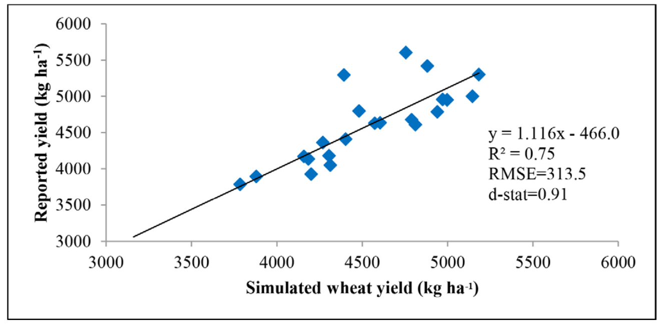

Fig. 1: Simulated and reported yield of wheat in Bathinda district

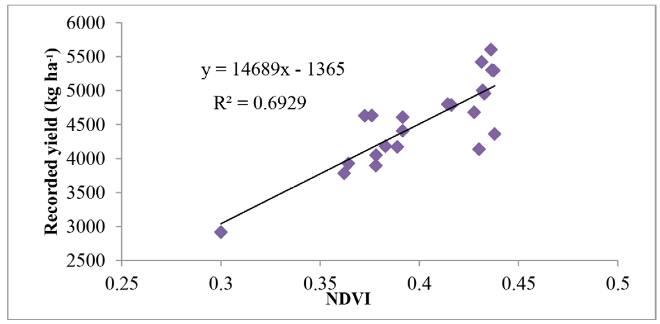

Fig. 2: Relationship between recorded wheat yields with NDVI

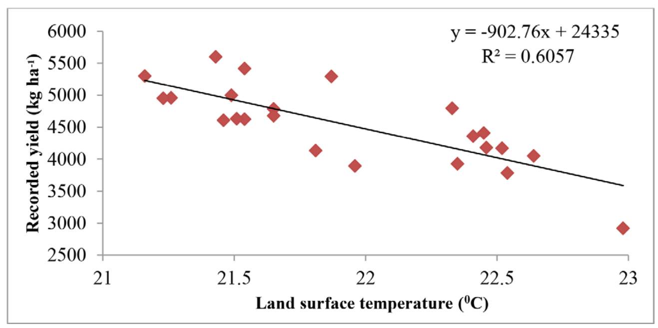

Fig. 3: Relationship between recorded wheat yields with LST

highlighting the potential of NDVI as a tool for monitoring crop health and productivity. Similarly, LST was negatively correlated with the yield which suggests that monitoring LST could be beneficial in identifying areas potentially at risk from heat stress. Overall, this study demonstrates the effectiveness of the CERES-wheat model for simulating wheat yields in the Bathinda region. The relations developed between yield and NDVI, as well as yield and LST suggest the potential for using these tools for agricultural management and decision-making.

ACKNOWLEDGEMENT

The research supported by the Punjab Agricultural University, Ludhiana, Punjab is duly acknowledged. The contents and views expressed in this research article are the views of the authors and do not necessarily reflect the views of the organization they belong to.

Funding: No funding was taken from any organization. It was supported by Punjab Agricultural University, Ludhiana.

Conflict of Interests: The authors declare that there is no conflict of interest related to this article.

Data availability: The data are available in public domain.

Author's contribution: **A. S. Gawai**: Data collection and manuscript writing, **R. K. Pal**: Guided and supervised, **S. Bora:** Data analysis and conceptualization and **Annie:** Reviewing and editing.

Disclaimer: The contents, opinions, and views expressed in the research article published in the Journal of Agrometeorology are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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