Estimation of Wheat Crop Coefficient Using GIS and Remote Sensing- A case study of Akola District of Maharashtra, India

Abstract

Efficient water use in agriculture is crucial for sustainability, requiring precise irrigation practices to maximize every drop of water. This study addresses the challenge of accurately estimating wheat crop coefficients, which are vital for effective water management. Using Sentinel-2A satellite data, the research examines the relationship between vegetation indices (EVI, NDVI, NDWI, and SAVI) and wheat crop coefficients in Akola District, Maharashtra. Ground truth data was collected to validate the satellite observations. Profiles of all the four vegetation indices of wheat were studied in detail and compared with profiles of crop coefficients of wheat recommended by Mahatma Phule Krishi Vidyapeeth (MPKV) Rahuri. Among the indices, NDWI (Normalized Difference Water Index) demonstrated the strongest correlation with wheat crop coefficients, expressed by the linear equation K_c=3.8078 NDWI+0.5396 with highest value of R^2. This finding underscores the potential of NDWI as a robust tool for estimating crop coefficients, thus enhancing water use efficiency in irrigation practices. It is recommended that NDWI be utilized in local irrigation management to optimize water resources effectively.

Keywords: Water use efficiency, crop coefficients, NDWI, Sentinel-2A, wheat, irrigation management.

INTRODUCTION:

"Determination of actual crop evapotranspiration (ETc) is a fundamental requirement for accurate irrigation scheduling of crops. To determine ETc, the FAO recommends using the crop coefficient approach, in which ETc is calculated by multiplying a crop coefficient (Kc) by reference evapotranspiration" (ETO) (Allen *et al*., 1998). "The method of calculating Kc was detailed" by Doorenbos and Pruitt (1977). "The values of crop coefficients for crops under standard conditions at initial, mid, and end seasons are tabulated. For non-standard conditions, the FAO suggests using corrections and locally developed Kc values for accurate results. However, these developed Kc values apply to large areas and are time-based, lacking spatial dimension. These limitations can be overcome by adopting advanced technologies such as satellite remote sensing. Many studies have shown that satellite-derived vegetation indices (VIs) can be used for this purpose, considering the similarity between the growth pattern of VIs and Kc"(Pimpale*et al*.,2020 and Adawadkar *et al*.,2024). Different researchers have used VIs for estimating crop coefficients (Bashir et al., 2006; Rahiman et al., 2011; Farg *et al*., 2012) and crop water requirements at different scales (Jayanthi *et al*., 2000; Gontia and Tiwari, 2010; Ozcan *et al*., 2014). This study explores the relationship between crop coefficient (Kc) and various remote sensing-derived vegetation indices (VIs) for the rabi session wheat crop in Maharashtra to identify the best-performing relationship for calculating spatial crop coefficients.

MATERIAL AND METHODS:

Study area: The study was conducted in complete area of Akola district, in the state of Maharashtra, India. This district covers an area of 5,428 km² and is situated between latitudes 20.17° N and 21.16° N and longitudes 76.7° E and 77.4° E. Akola represents approximately 1.76% of the total land area of Maharashtra and has an average elevation of 285 meters above mean sea level.

The climate of the Akola district exhibits variation from north to south. The majority of the district experiences a tropical savannah climate, while the northern parts, surrounded by hills and mountains reaching heights of approximately 950 to 1000 meters, have a subtropical climate with chilly winters. Summers are characterized by extremely high temperatures, while winters are dry and range from mild to cold. The district receives rainfall predominantly during the southwest monsoon season, occurring from June to September, with rain occurring about 90% of the time during this period. The average annual rainfall in the district ranges from 750 to 1000 mm (Anonymous.,2024)

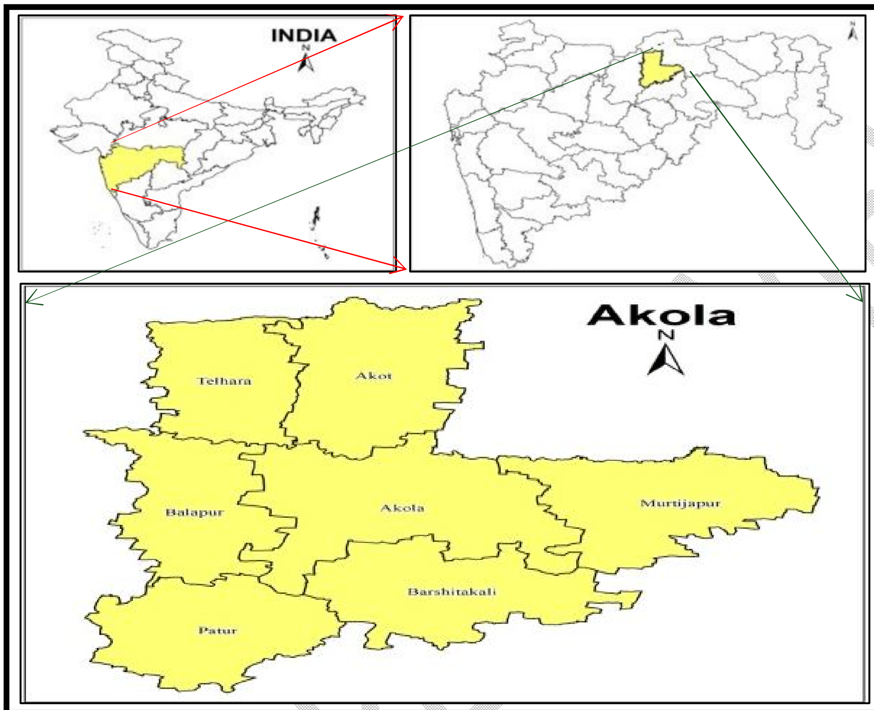


Fig. 1 Location of Study Area

Remotely sensed data

Multi-date, multispectral satellite images of Sentinel Sensor for six consecutive months of rabiseason (November/ December /January/February/March/April) of the year 2023-24were used for this study (Table1).

Table1. Multi-date, Multispectral Sentinel 2A satellite data used for the study.

Sr.No	Satellite	Sensor	Tile No.	DateofPass
1	Sentinel -2A	MSI	L2A_T43QFC_A029546_20231107T052958 L2A_T43QFD_A029546_20231107T052958 L2A_T43QGC_A029546_20231107T052958 L2A_T43QGD_A029546_20231107T052958	07-11-2023
2	Sentinel -2A	MSI	L2A_T43QFC_A038669_20231122T052416 L2A_T43QFD_A038669_20231122T052416 L2A_T43QGC_A038669_20231122T052416 L2A_T43QGD_A038669_20231122T052416	22-11-2023
3	Sentinel -2A	MSI	L2A_T43QFC_A029975_20231212T052600 L2A_T43QFD_A029975_20231212T052600 L2A_T43QGC_A029975_20231212T052600 L2A_T43QGD_A029975_20231212T052600	12-12-2023
4	Sentinel -2A	MSI	L2A_T43QFC_A039098_20240101T052227	01-01-2024

			L2A_T43QFD_A039098_20240101T052227 L2A_T43QGC_A039098_20240101T052227 L2A_T43QGD_A039098_20240101T052227	
5	Sentinel -2A	MSI	L2A_T43QFC_A030404_20240116T052722 L2A_T43QFD_A030404_20240116T052722 L2A_T43QGC_A030404_20240116T052722 L2A_T43QGD_A030404_20240116T052722	16-01-2024
6	Sentinel -2A	MSI	L2A_T43QFC_A039527_20240205T053205 L2A_T43QFD_A039527_20240205T053205 L2A_T43QGC_A039527_20240205T053205 L2A_T43QGD_A039527_20240205T053205	05-02-2024
7	Sentinel -2A	MSI	L2A_T43QFC_A039813_20240220T052730 L2A_T43QFD_A039813_20240220T052730 L2A_T43QGC_A039813_20240220T052730 L2A_T43QGD_A039813_20240220T052730	20-02-2024
8	Sentinel -2A	MSI	L2A_T43QFC_A031119_20240306T052919 L2A_T43QFD_A031119_20240306T052919 L2A_T43QGC_A031119_20240306T052919 L2A_T43QGD_A031119_20240306T052919	06-03-2024
9	Sentinel -2A	MSI	L2A_T43QFC_A031262_20240321T052948 L2A_T43QFD_A031262_20240321T052948 L2A_T43QGC_A031262_20240321T052948 L2A_T43QGD_A031262_20240321T052948	21-03-2024
10	Sentinel -2A	MSI	L2A_T43QFC_A031405_20240410T052443 L2A_T43QFD_A031405_20240410T052443 L2A_T43QGC_A031405_20240410T052443 L2A_T43QGD_A031405_20240410T052443	10-04-2024
11	Sentinel -2A	MSI	Akola 2024-04-25_utm43	25-04-2024

"Subset images covering the study area were obtained and processed in ERDEAS Imagine to generate four most commonly used vegetation indices (VIs) *i.e.* Enhanced Vegetation Index (EVI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Soil Adjusted Vegetation Index (SAVI) (Table 2)on all the dates of satellite pass". [23]

Table 2.Vegetation Indices (VIs) used for study

Sr. No.	Indices	Equation	References
1.	EVI	$G \times \frac{NIR - RED}{NIR + C1.Red - C2.Blue + L}$	Liu and Huete (1995)
2.	NDVI	$\frac{(NIR - R)}{(NIR + R)}$	Rouse *et al.* (1973)
3.	NDWI	$\frac{NIR - SWIR}{NIR + SWIR}$	Gao in 1996
4.	SAVI	$\left[\frac{(NIR - RED)}{(NIR + RED + L)}\right] * (1 + L)$	Huete (1988)

Ground truth data

Ground truth work was carried out in January and March2024coincidingwiththeseasonof*rabi*wheatcrop in the study area. Data were collected from 40 sites of crop spread throughout the study area. A mobile device with locatesoftwarewereusedtoobtainthelocationsand elevations of the sites. The information obtained from each site was recorded in ground truth Proformasheets. Information on sowing date, variety, and probable harvesting date were collected through discussion with the farmer. In absence of farmer indirect method for determiningthecropagewasfollowedbyreferringthecriterion suggested by Feek's scale consultations with experts in theregion.

Image Processing

Rabi wheat polygon vector layer was prepared based on the actual data in ArcGIS.Images of all vegetation indices (VIs) at each passing date were created. Multi-date VIs of pure *rabi* wheat were extracted using Signature Editor in ERDAS Imaginesoftware. These VI values were classified into weeks based on the age of wheat crop at different locations in weeks.

The date of pass January 1, 2024 was taken as reference image date. The ages of crop on the dates of pass and after the reference image were determined taking into account the time difference between the images.

Establishment of VI-K_c relations and their evaluation:

The study investigated how vegetation indices change with the growing age of rabi wheat using scattered graphs, which were then smoothed. To determine the empirical relationship between the weekly crop coefficient (Kc) for wheat, as proposed by Mahatma Phule Krishi Vidyapeeth Rahuri (MPKV 2013), and the corresponding vegetation indices (VI), linear regression analysis was performed for each of the four vegetation indices studied. The goodness of fit was evaluated using the correlation coefficient (R) and the coefficient of determination (R^2), where an R^2 value of 0 indicates no fit and an R^2 value of 1 indicates a perfect fit. Additionally, model accuracy was assessed through several metrics: Mean Absolute Error (MAE), Mean Absolute Relative Error (MARE-1) relative to predicted values, Mean Absolute Relative Error (MARE-2) relative to desired values, and Root Mean Square Error (RMSE). Model performance was further evaluated using percent deviation (PD), Willmott's index (D) of agreement, and the Nash-Sutcliffe model efficiency (E). The model with the best performance was selected based on these statistical analyses.

RESULTS AND DISCUSSION

The multidate values of pure crop vegetation indices (VIs) obtained were arranged according to the age of crop in terms of week at each location. These values were averaged for each week and the weekly average values of the vegetation indices obtained for wheat are presented in Table 3. As the crop developed, these indices increased steadily throughout the stem elongation stage until reaching a maximum value around weeks 7, 8 and 9. This peak coincided with the period of maximum growth in the middle of the crop, more precisely during the booting and head emergence stages. After the peak, the VI values gradually decreased, indicating that the crop had matured and senesced towards the end of the season. Overall, the VI profile provides a comprehensive understanding of the temporal evolution of VI in relation to the growth stages of wheat, highlighting the dynamics of vegetation growth and senescence throughout the crop life cycle. The VI model resembles the crop coefficient model reflecting the ability to model Kc in terms of VI. Similar trends were observed by Pimple *et al.* (2019) for wheat and sorghum, Kosle. (2021) for wheat, Akkara (2022) for chickpea and Adawadkar (2023) for wheat and onion. When plotting VI and Kc together in the weeks past sowing, it was found that the growth trend of all VIs was almost similar to that of crop coefficient. VI and Kc showed similar time trends. (Figures 2a, 2b, 2c and 2d)

Table 3**.** Average weekly values of vegetation indices of wheat

Weeks PastSowing	Vegetation Indices			
	EVI	**NDVI**	**NDWI**	**SAVI**
1	0.2189	0.2272	0.0364	0.1983
2	0.2378	0.2430	0.0394	0.2122
3	0.2534	0.2669	0.1007	0.2256
4	0.2888	0.2809	0.1411	0.2341
5	0.2965	0.3031	0.1686	0.2493
6	0.3417	0.3106	0.1856	0.2642
7	0.4011	0.3407	0.2213	0.2735
8	0.4302	0.3561	0.2465	0.2826
9	0.4168	0.3405	0.2379	0.2693
10	0.3618	0.3193	0.2036	0.2495
11	0.3331	0.2697	0.1978	0.2168
12	0.2875	0.2207	0.1222	0.1805
13	0.2349	0.2051	0.0931	0.1718
14	0.2252	0.1928	0.0737	0.1516
15	0.1898	0.1816	0.0379	0.1459
16	0.1731	0.1769	0.0079	0.1243
17	0.1566	0.1612	0.0608	0.1162

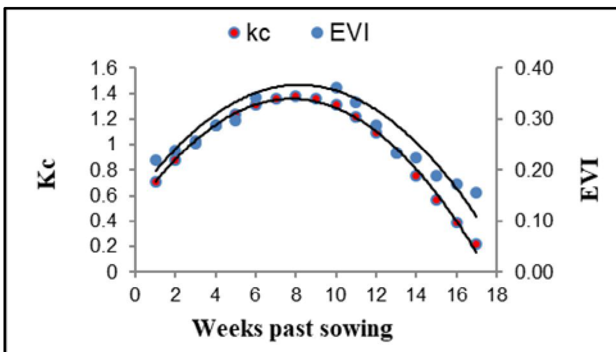


Fig. (a) Kc and EVI

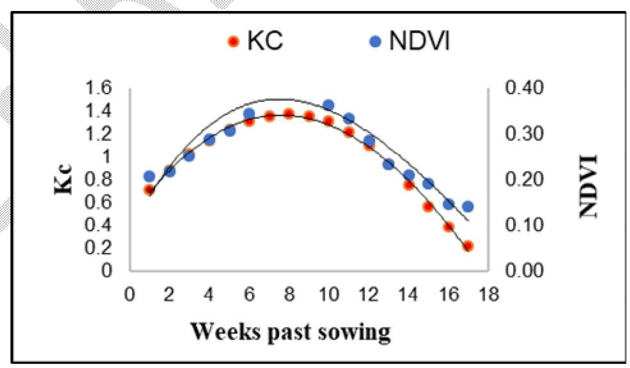


Fig. (b) Kc and NDVI

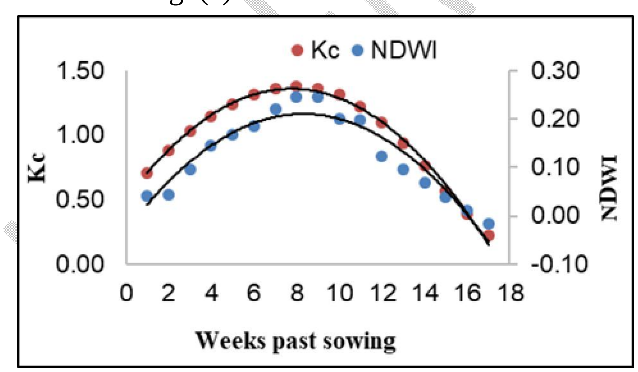


Fig. (c) Kc and NDWI

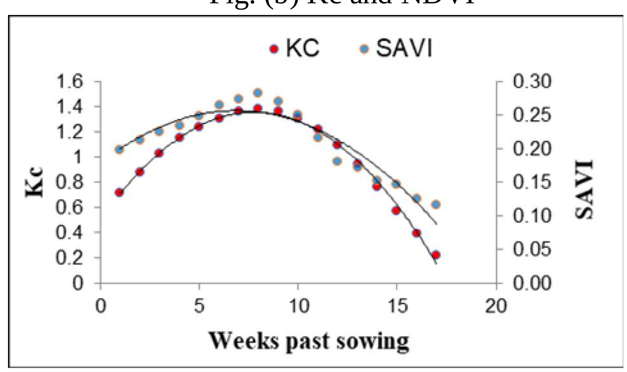
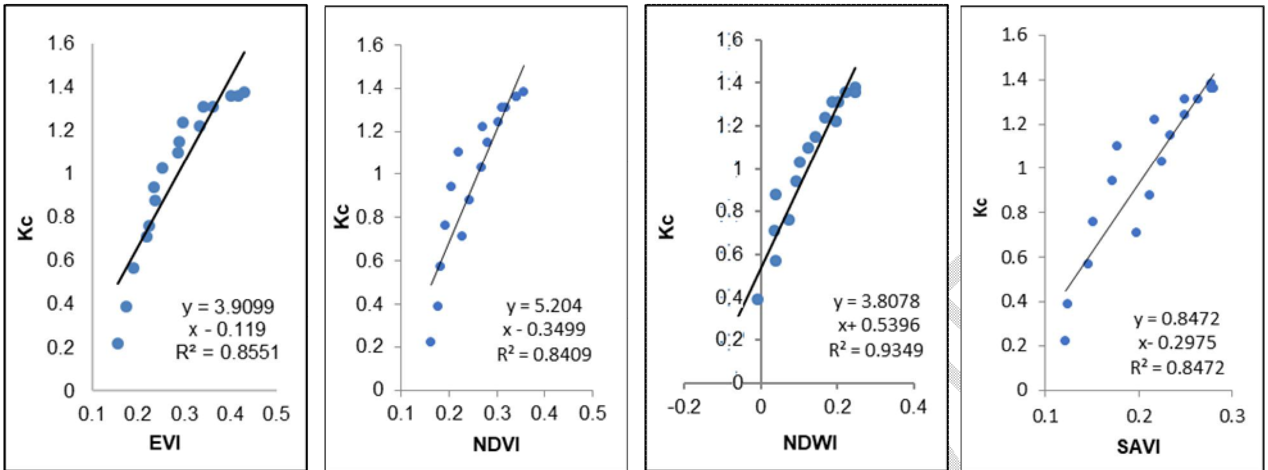


Fig. (d) Kc and SAVI

Fig. 2(a, b, c and d) Comparison of patterns of Crop coefficient (Kc) and Vegetation Indices

Simple linear regression analysis was conducted to examine the relationship between the vegetation indices and crop coefficients. The analysis revealed a strong linear relationship between these vegetation indices and the crop coefficients. Figures 3a, 3b, 3c and 3d illustrate the relationships of EVI, NDVI, NDWI and SAVI respectively, with the recommended weekly crop coefficients of the wheat crop



(a) EVI Vs K_c (b) NDVI Vs K_c (c) NDWI Vs K_c (d) SAVI Vs K_c

Fig. 3 (a, b, c and d) Relationship of crop coefficients with Vegetation Indices for wheat crop

Based on the regression analysis, linear prediction models were derived, providing a useful tool for predicting crop coefficients based on these vegetation indices.
The resulting linear prediction models are as follows:

K_c = 3.9099 EVI - 0.119 $R^2 = 0.8551$ ----------------- 1

K_c = 5.204 NDVI - 0.3499 $R^2 = 0.8409$ ----------------- 2

K_c = 3.8078 NDWI + 0.5396 $R^2 = 0.9349$ ----------------- 3

K_c = 0.8472 SAVI + 0.1521 $R^2 = 0.8472$ ----------------- 4

These prediction models enable the estimation of crop coefficients using the corresponding vegetation indices, facilitating a more accurate understanding of crop water requirements for wheat cultivation.Models developed above were statistically evaluated by most frequently used statistical parameters as given in Materials and methods. The results of statistical analysis are presented in Table 4.

Table4. Results of statistical analysis of VI-Kc prediction models of wheat crop

Model	**Statistical Parameters**									
2023-24	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	MAE	**MARE1**	**MARE2**	**RMSE**	**SE**	**PD**	**D**	**E**	**R**	**R^2**
EVI x Kc	0.1140	0.1469	0.1897	0.1495	0.1304	7.3633	0.9481	0.8156	0.9032	0.8551
NDVI x Kc	0.1046	0.1400	0.1739	0.1394	0.1338	3.2976	0.9545	0.8396	0.9170	0.8409
NDWI x Kc	0.0849	0.1117	0.1393	0.1040	0.0997	0.6747	0.9761	0.9107	0.9556	0.9320
SAVI x Kc	0.1242	0.1559	0.1847	0.1531	0.1333	6.1868	0.9441	0.8065	0.8981	0.8472

The correlation analysis showed that all vegetation indices showed a relatively good correlation with wheat crop coefficients as indicated by relatively high R^2 values. Among the vegetation indices studied, the NDWI-K_c model showed the highest R^2 value of 0.9320 and the highest D, E and R values i.e. 0.9761 0.9107and 0.9556 respectively with lowest values of error indicators MAE, MARE1, MARE2, RMSE, SE and PD i.e. 0.0849, 0.1117, 0.1393, 0.1040, 0.0997 and 0.6747 respectively. NDWI showed superiority over all other VIs under study and is given by equation, K_c = 3.7738 NDWI + 0.5419.

The EVI-K_c models showed good results after the NDWI-K_c model. The EVI-K_c model had a higher R^2 value of 0.8551 and the higher D, E and Rvalues i.e. 0.9481, 0.8156 and 0.9032 respectively. Whereas the lower error values MAE, MARE1, MARE2, RMSE, SE, PD and D values were found as 0.1140, 0.1469, 0.1897, 0.1495, 0.1304 and 7.3633 respectively.

The NDVI-K_c model also showed quite similar results like EVI-Kc. The NDVI-K_c model showed an R^2 value of 0.8409 and good values of D, E and R, 0.9545, 0.8396 and 0.9170 respectively whereas slightly greater values error values of MAE, MARE1, MARE2, RMSE, SE, and PD, which recorded as 0.1046, 0.1400, 0.1739, 0.1394, 0.1338 and 3.2976 respectively

On the other hand, the SAVI-K_c model showed an almost similar trend but with a slightly lower R^2 value of 0.8472 compared to other vegetation indices with moderate values of D, E and R as 0.9441, 0.8065 and 0.8981, respectively. The errors showed comparatively larger values in terms of MAE, MARE1, MARE2, RMSE, SE, and PD and were recorded as 0.1242, 0.1559, 0.1847, 0.1531, 0.1333, and 6.1868 respectively. Although the SAVI-K_c model still produced an acceptable correlation, it showed a relatively weaker relationship compared to the other indices.

A similar study by Gontia and Tiwari (2010) in West Bengal showed that SAVI had a higher significance (R^2) compared to NDVI. Kamble *et al.* (2013) found a strong correlation between NDVI and crop coefficients (K_c) of irrigated plants in Nebraska, USA, which is consistent with the results of the present study. Duchem*et al.* (2006) also reported a similar trend for wheat in central Morocco and Suifan*et al.* (2007) found comparable results for irrigated vegetable crops. Studies by Calera and Gonzalez (2004) in Spain and Lei and Yang (2014) in China produced results that support the superiority of NDVI in predicting wheat crop coefficients. Using AWiFS data, Pimpale (2014) found a high correlation between NDVI and Kc of wheat crop considering different vegetation indices. In similar studies conducted by Kosle (2021) in Pratapgarh district of Uttar Pradesh ,Adawadkar *et al.* (2023) for wheat crop coefficients found NDWI to be the best for VI modeling, confirming the results of this study.Adawadkar *et al.* (2024) found that significant potential of NDWI-Kc models, exhibiting strong relationships with high R^2 values, thereby enhancing the reliability of water demand estimations.Shao et al (2021) indicated that the combination of UAV multispectral remote sensing technology and the RFR algorithm provides a potential solution for the distribution of water use and precision irrigation on a field scale.

It is important to note that the vegetation index is influenced by factors such as greenness and leaf area index. The wheat crop, usually grown under irrigated conditions with dense plant populations, develops rapidly after emergence, covering considerable ground. Thus, the soil background has minimal effect on the vegetation indices.

CONCLUSION:

1. All vegetation indices (VI) followed the same pattern as that of crop coefficient. However, reference information for physical changes can be found in VI. The defined VI growth profiles can be used to detect expected planting dates.

2. The similarity of the VI and K_c curves indicates that K_c can be estimated based on the vegetation index of wheat crop. This conclusion confirms the hypothesis of this investigation.
3. Wheat crop area estimation showed that the estimated crop areas were very close to the actual measurements, with a percentage deviation of 4.36. Thus, by using remote sensing and GIS techniques, timely and accurate estimates of the cultivated area can be obtained.
4. NDWI, the vegetation index of wheat crop, was found to have a best linear relationshipwith the crop coefficient, i.e. $Kc = 3.8078\ NDWI + 0.5396$.Therefore, this developed VI-K_c relationship can be incorporated into the FAO-56 method instead of the tabulated K_c method.
5. Irrigation water can be controlled using remote sensing and GIS techniques to release the precise amount of irrigation water to different areas according to the crop needs. This approach can be used to provide optimal irrigation water for life-saving irrigation and avoid crop failure even in water-scarce situations.
6. Real-time, high-resolution remote sensing data and automated weather stations can create an expert system to ensure accurate irrigation amounts and interval.

7. Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

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