D-6498
[1-10]

RESEARCH ARTICLE Agricultural Science Digest

Spatio-temporal Assessment of Vegetation and NDVI Time Series Forecasting Model using Remote Sensing and Machine Learning for Karnataka, India

Bharathi N. Hassan[1], Dilendra Hiran[1], Amiya Kumar Tripathy[2]

10.18805/ag.D-6498

ABSTRACT

Background: The proposed research presents a precise and efficient forecasting system for normalized difference vegetation index (NDVI) of districts in Karnataka State in India, utilizing machine learning and remote sensing data. NDVI values are employed to assess vegetation and signify varying levels of vegetative health from poor to high. This study aims to create a forecasting model for predicting NDVI values through time series trend analysis. The findings endorse governmental and agricultural initiatives aimed at enhancing resource management, crop surveillance, yield forecasting and strategic planning by providing an effective model for vegetation and climate change monitoring.

Methods: The raster NDVI data from NASA's earth observing system (EOS) is derived from the MODIS (Moderate resolution imaging spectroradiometer) dataset, covering the years 2000 to 2022. Raster NDVI values are mapped to all 31 districts in Karnataka using QGIS and corresponding numeric NDVI values are derived. Preprocessing techniques, including noise reduction and missing value imputation, are employed to enhance data quality. The simple moving average (SMA) and weighted moving average (WMA) machine learning methods are employed to compare the results of the study on temporal vegetation changes. To determine forecasting model yielding more accurate forecasts, the forecasting errors and performance are assessed using metrics: mean absolute deviation (MAD), mean absolute error (MAE), mean squared error (MSE) and root mean square error (RMSE).

Result: The WMA model demonstrates superior accuracy with a lower MAE of 0.03752 compared to the SMA model MAE of 0.03797, followed by lower MSE and RMSE. Consequently, NDVI values are forecasted utilizing the WMA model, which demonstrated prediction exceeding accuracy 95.5% for all 31 districts (*i.e.* 100%) and 99% to 100% accuracy for 15 districts out of 31 (*i.e.* 48.39%). The mean absolute percentage error (MAPE) of WMA shows below 10%, signifies that the annual NDVI patterns prediction is highly precise.

Key words: GIS, Machine learning, Moving average model, NDVI, Remote sensing, Time series forecasting.

INTRODUCTION

Karnataka, an Indian state, predominantly depends on agriculture. Vulnerability assessment of the land exhibits considerable agro-climatic variability. Vegetation is an important components of ecosystems, it plays a crucial role in supporting biodiversity and sustaining agricultural productivity. Vegetation directly effects livelihoods, environmental Sustainability and food security . Monitoring changes in vegetation particularly at the district level, is important for understanding regional variability and effective agricultural planning. The research study revealed techniques like remote sensing, vegetation index, Geographical information system, Spatio-temporal and Machine learning *etc.*, used to assess ecosystem.

Remote sensing technologies revolutionized monitoring of vegetation of large Earth's surface observation from a distance and collection. Satellite-based observations by Sentinel (Chen *et al.*, 2023), Landsat (NIE *et al.*, 2024) *etc.*, provide consistent multi-temporal datasets that are highly suitable for analyzing vegetation dynamics across diverse global, local agro-climatic zones (Bombe, 2023). These technologies are widely used in agriculture, climate studies (Ahlawat *et al.*, 2015) and land resource management due to their efficiency and accuracy.

[1]Faculty of Engineering and Computer Science, Pacific Academy of Higher Education and Research University, Udaipur-313 024, Rajasthan, India.
[2]Department of Computer Engineering, Don Bosco Institute of Technology, Mumbai-400 070, Maharashtra, India.

Corresponding Author: Bharathi N. Hassan, Faculty of Engineering and Computer Science, Pacific Academy of Higher Education and Research University, Udaipur-313 024, Rajasthan, India. Email: bharathi@pacific-university.ac.in
ORCIDs: https://orcid.org/0009-0007-4937-0730, https://orcid.org/0000-0002-9588-0500, https://orcid.org/0000-0002-0688-4092

How to cite this article: Hassan, B.N., Hiran, D. and Tripathy, A.K. (2026). Spatio-temporal Assessment of Vegetation and NDVI Time Series Forecasting Model using Remote Sensing and Machine Learning for Karnataka, India. *Agricultural Science Digest.* 1-10. doi: 10.18805/ag.D-6498.

Submitted: 14-02-2026 **Accepted:** 22-04-2026 **Online:** 20-05-2026

The health of vegetation and greenness, the relative density is indicated by Vegetation index indicator. Normalized Difference Vegetation Index (NDVI) (Kaushalya *et al*., 2014) is one of the extensively used among several vegetation indices. NDVI value is derived from the red and near-infrared bands as NDVI = (NIR - R)/(NIR), values range from -1.0 to +1.0. It allows differentiation between non-vegetated areas, sparse vegetation and dense vegetation. Areas of barren rock, sand, or snow typically display very low NDVI values (0.1 or less). Sparse vegetation, such as shrubs, grasslands or senescing crops, may yield moderate NDVI values (0.2 to 0.5). High NDVI values (0.6 to 0.9) indicate dense vegetation, found in temperate and tropical forests or crops at their peak growth stage. Enhanced applicability of NDVI helps in vegetation assessment at regional and local scales, climate (Raza *et al*., 2023), crop health monitoring (Judith *et al*., 2025), crop yield prediction (Dehghanisanij *et al*., 2022), drought assessment (Janarth *et al*., 2025) and land cover classification (Nandy *et al*, 2025) *etc.*

Spatio-temporal analysis (Dey *et al*., 2025) of NDVI integrates spatial and temporal variation of vegetation, providing insights into seasonal and long-term environmental changes, Time-series NDVI analysis is essential for identifying climatic variation effect on vegetation trends and crop cycle. District-wise analysis has gained importance in recent years as it enables localized assessment of vegetation patterns, which is critical for Karnataka. The state includes coastal, hilly and semi-arid regions, diverse agro-climatic zones leading to significant variation in vegetation cover and agricultural practices across districts.

Remote sensing integrated with geographic information systems (GIS) (Jeyasingh *et al*., 2023; Buraka *et al*., 2022) enhances analysis capability of spatial patterns of vegetation and land use changes. GIS enables vegetation mapping, visualization and quantification at multiple spatial scales, supporting decision-making at various spatial levels. Further incorporation of machine learning techniques significantly improves the analysis of remote sensing data. Machine learning algorithms enable automated clustering, classification and prediction of vegetation dynamics by efficiently handling large and complex datasets (Sarwar *et al*., 2023) to forecast and facilitate decision-making. Recent studies (Thimmegowda *et al*., 2025) demonstrate combining NDVI time-series data with machine learning improves NDVI forecasting, offering timely and spatially explicit predictions of vegetation essential for effective crop, soil (Nalina *et al*., 2016) and water management in agriculture (Kumar *et al*., 2025). Moreover, NDVI-based studies have proven effective in detecting land use and land cover changes, including agricultural expansion, deforestation and urbanization. These changes have significant implications for environmental sustainability and require continuous monitoring for informed policy interventions.

Survey shows assessment of climate variation of few districts of interest were done and not all districts. Therefore, this research focuses on analyzing the district-wise spatio-temporal variation of vegetation in Karnataka for all the districts, using NDVI collected derived from remote sensing data and GIS.

The study also explores the application of machine learning techniques to improve prediction of NDVI efficiently. Spatio-temporal analysis of NDVI for Karnataka, district-wise, enables NDVI forecasting for early evaluations of vegetation variability, cropping season prospects and the impact of climatic factors on agricultural systems (Yadav *et al*., 2024). Such analysis essentially identify vulnerable regions at district level (Kaushalya *et al*., 2014), optimizing resource allocation and enhancing agricultural resilience.

Data collection and ML models

NDVI data collection

The raster NDVI data is collected from NASA' s earth observing system (EOS) MODIS dataset for the Kharif months of Karnataka state, July to November for the years 2000-2022. The details of the data collected is described in Table 1.

Software used

Quantum Geographic Information System (QGIS) (Lemenkova, 2020) is an open-source tool designed for creating, editing, visualizing, analyzing and publishing geospatial data. It serves as a powerful tool for a wide range of tasks, from simple spatial map creation to complex spatial analysis and data management. Excel is utilized to store the quantified, derived NDVI numeric data of the districts of Karnataka state from QGIS in a comma-separated format for enhanced data handling. Open-source python is employed for data preprocessing, machine learning model development, performance analysis, time series analysis and NDVI forecasting. List of the software used in research is provided in Table 2.

Table 1: Details of data collection.

Earth observing system	Instrument	Time period	Season	Months	Vegetation index	Geographic area
NASA's terra satellites	MODIS	2000-2023	*Kharif* season	July-November	NDVI	Districts of Karnataka state, India

Time series forecasting models

Time series forecasting techniques, such as moving averages (Li *et al*., 2021), simple and weighted moving average models are employed for NDVI forecasting. The moving average is a widely used method for forecasting time series data, effective for analysing a variable over several consecutive periods, especially when no other data is available to predict the next period's value. This technique often utilizes historical data to project future values rather than relying on simple estimates. Moving averages help mitigate short-term fluctuations and emphasize longer-term trends or cycles. Essentially, moving averages forecast the next period's value by averaging the values of n prior periods. SMA model forecasts new value by averaging the values from the last n periods. For the SMA model, as per the Eq.1 provided, the preceding n values of D are utilized to calculate the forecasted value F for the upcoming period t+1, where D represents the actual value and F denotes the forecasted value.

$$F_{t+1} = \frac{D_t + D_{t-1} + \ldots + D_{t-n+1}}{n} \qquad \ldots\text{Eq.1}$$

Recent values are more influential as predictors of the value for the coming period, so the WMA model gives more weight to recent values. The weights used can be arbitrary as long as the sum of weights equals to1 as shown in Eq.2.

$$F_{t+1} = \frac{w_1 D_t + w_2 D_{t-1} + \ldots + w_n D_{t-n+1}}{n} \qquad \ldots\text{Eq.2}$$

MATERIALS AND METHODS

The framework of the NDVI timeseries forecasting system is illustrated in Fig 1. It outlines the processes involved, from data collection to forecasting of quantified NDVI value as an output for each district of Karnataka state, the experiment was conducted during November 2024-December 2025, are explained in detail further.

Data collection

The NDVI data is collected from MODIS covering the period from 2000 to 2022, specifically for the *Kharif* season months of Karnataka, July to November, as illustrated in Fig 2. The collected NDVI data was in raster format.

Data preprocessing

The raster NDVI data, collected from MODIS needs to be converted into structured numeric value for concerning districts to develop a forecasting model for time series analysis. The preprocessing of the raster NDVI data was carried out using QGIS and QuickOSM tool to calculate the average numeric NDVI value according to the administrative boundaries of the districts. The steps involved in the preprocessing are as follows- Step 1: Data Loading into QGIS- using Raster-> Extraction->Clip Raster by mask layer, Step 2: Boundary selection for districts - select the original raster file as input file and boundary administrative

Table 2: Softwares.

1	Excel
2	QGIS, K-GIS
3	Python

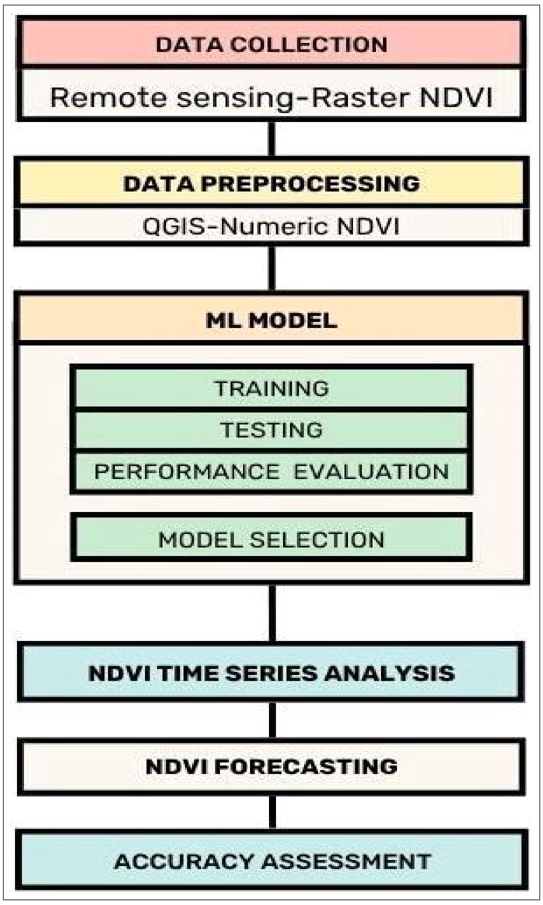


Fig 1: NDVI time series forecasting system framework.

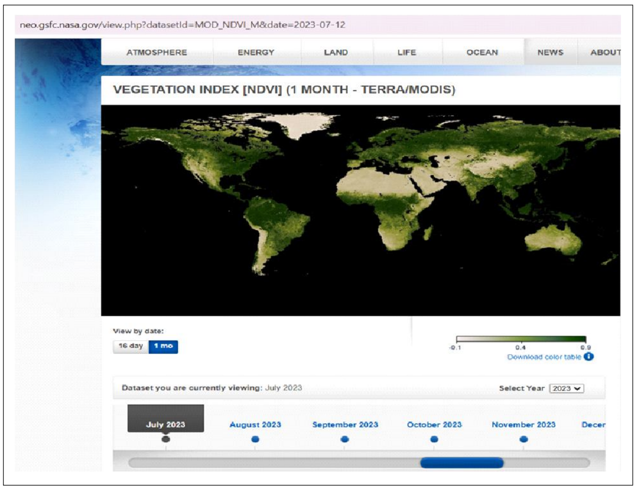


Fig 2: Raster NDVI data collection from MODIS.

layer for the mask layer to get a clipped(mask) raster file as shown in Fig 3.1 and Fig 3.2. Step 3: Zonal Statistics- To assess vegetation health using zonal statistics get a zonal statistics layer in the layer panel for the boundary administrative layer as for input layer and the raster layer is the clipped (mask) raster layer. The output column was named as 'DN_values' in the attribute table of the zonal statistics layer to get the DN_values for each district. Step 4: Numeric NDVI - to get the numeric NDVI value of a month from the DN values, the field calculator tool of the attribute table is used, new value month derived having numeric NDVI with Precision=5. Using the expression DN_valuesmean > 200 THEN 200 ELSE "DN_valuesmean"/200. Step 5: Exporting the numeric NDVI of all districts one month mean data to CSV file July 2022. csv as shown in Fig 4., along with official names of districts in English and in Kannada, state language, where admin level 5 stands for districts. Step 6: calculating yearly average NDVI - For each district for the months July to November from 2000 to 2022, find the numeric NDVI value following Step1 to Step 5. Then for each district calculate yearly average NDVI for all 22 years as shown in Fig 5.

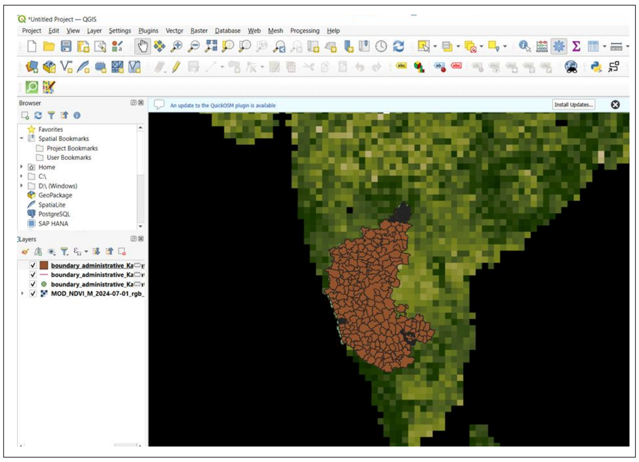


Fig 3.1: Administrative boundaries of Karnataka state, India on QGIS.

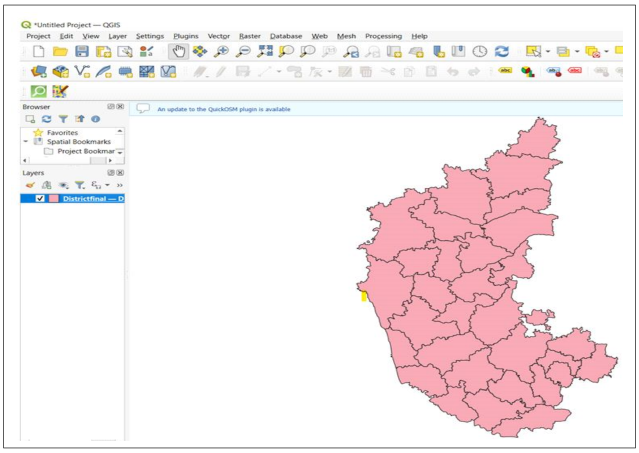


Fig 3.2: Districts administrative boundaries of Karnataka state, India on QGIS.

Zonal Statistics — Features Total: 31, Filtered: 31, Selected: 0

	official_name	name:kn	admin_level	DN_valuesmean	July
1	Chamarajanaga...	ಚಾಮರಾಜನಗ...	5	171.5	0.8575
2	Mysuru District	ಮೈಸೂರು ಜಿಲ್ಲೆ	5	195.571428571...	0.97786
3	Kodagu District	ಕೊಡಗು	5	218.8	1.00000
4	Dakshina Kanna...	ದಕ್ಷಿಣ ಕನ್ನಡ	5	227.571428571...	1.00000
5	Udupi District	ಉಡುಪಿ ಜಿಲ್ಲೆ	5	207.2	1.00000
6	Bengaluru Rural...	ಬೆಂಗಳೂರು ಗ್ರಾ...	5	149	0.745
7	Bengaluru Urba...	ಬೆಂಗಳೂರು ನಗರ	5	152.666666666...	0.76333
8	Kolar District	ಕೋಲಾರ ಜಿಲ್ಲೆ	5	149.6	0.748
9	Mandya District	ಮಂಡ್ಯ ಜಿಲ್ಲೆ	5	161.571428571...	0.80786
10	Chikkamagalur...	ಚಿಕ್ಕಮಗಳೂರು ...	5	199.75	0.99875
11	Hassan District	ಹಾಸನ ಜಿಲ್ಲೆ	5	184	0.92
12	Chitradurga Dis...	ಚಿತ್ರದುರ್ಗ ಜಿಲ್ಲೆ	5	139.416666666...	0.69708
13	Tumakuru Distri...	ತುಮಕೂರು ಜಿಲ್ಲೆ	5	154.727272727...	0.77364
14	Belagavi District	ಬೆಳಗಾವಿ ಜಿಲ್ಲೆ	5	169.277777777...	0.84639
15	Shimoga District	ಶಿವಮೊಗ್ಗ ಜಿಲ್ಲೆ	5	197.3	0.9865
16	Uttara Kannada...	ಉತ್ತರ ಕನ್ನಡ	5	203.75	1.00000
17	Bagalkote District	ಬಾಗಲಕೋಟೆ ...	5	135.555555555...	0.67778
18	Vijayapura Distr...	ಬಿಜಾಪುರ ಜಿಲ್ಲೆ	5	107.933333333...	0.53967
19	Dharwad District	ಧಾರವಾಡ ಜಿಲ್ಲೆ	5	161.857142857...	0.80929
20	Gadag District	ಗದಗ ಜಿಲ್ಲೆ	5	126.5	0.6325
21	Haveri District	ಹಾವೇರಿ ಜಿಲ್ಲೆ	5	164.75	0.82375
22	Ballari District	ಬಳ್ಳಾರಿ ಜಿಲ್ಲೆ	5	112.5	0.5625
23	Koppal District	ಕೊಪ್ಪಳ ಜಿಲ್ಲೆ	5	135.125	0.67563
24	Raichur District	ರಾಯಚೂರು ಜಿ...	5	114.4	0.572
25	Kalaburagi Distr...	ಕಲಬುರಗಿ ಜಿಲ್ಲೆ	5	117.461538461...	0.58731

Show All Features

Fig 4: District wise zonal statistics July 2022.

	A	B	C
1	**district**	**ndvi**	**year**
2	Bagalkote District	0.653332	2000-01
3	Bagalkote District	0.588556	2001-02
4	Bagalkote District	0.576776	2002-03
5	Bagalkote District	0.51222	2003-04
6	Bagalkote District	0.630556	2004-05
7	Bagalkote District	0.67789	2005-06
8	Bagalkote District	0.66111	2006-07
9	Bagalkote District	0.715778	2007-08
10	Bagalkote District	0.62589	2008-09
11	Bagalkote District	0.738554	2009-10
12	Bagalkote District	0.729442	2010-11
13	Bagalkote District	0.666446	2011-12
14	Bagalkote District	0.721112	2012-13
15	Bagalkote District	0.753444	2013-14
16	Bagalkote District	0.764112	2014-15
17	Bagalkote District	0.689668	2015-16
18	Bagalkote District	0.724444	2016-17
19	Bagalkote District	0.726332	2017-18
20	Bagalkote District	0.736	2018-19
21	Bagalkote District	0.817224	2019-20
22	Bagalkote District	0.835222	2020-21
23	Bagalkote District	0.842556	2021-22
24	Bagalkote District	0.874444	2022-23
25	Ballari District	0.684834	2000-01
26	Ballari District	0.6435	2001-02
27	Ballari District	0.602666	2002-03

Fig 5: NDVI for years 2000-2022 (sample).

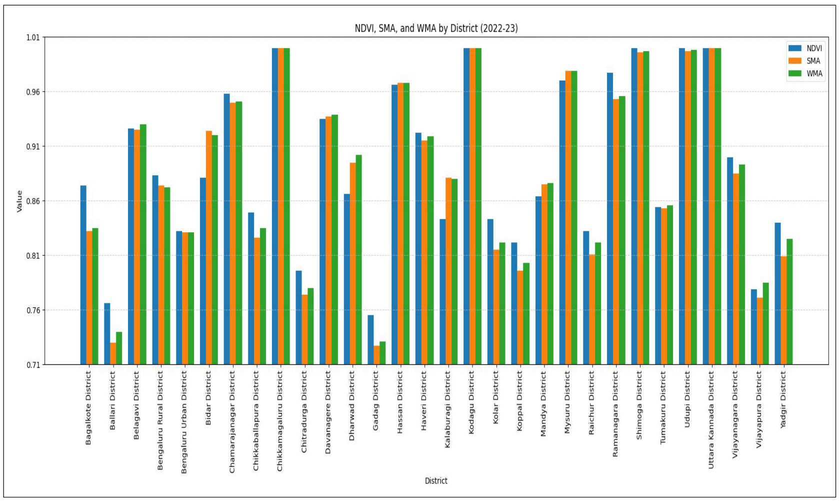
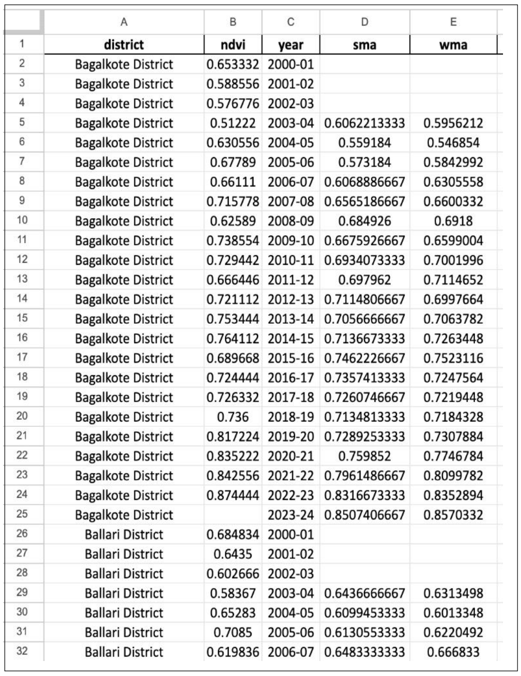
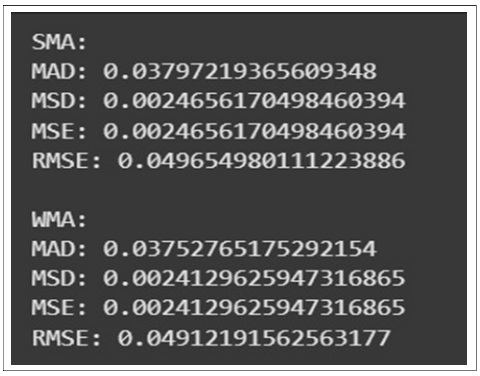


Fig 6: NDVI prediction for 2022 by SMA and WMA models (sample).



	A	B	C	D	E
1	district	ndvi	year	sma	wma
2	Bagalkote District	0.653332	2000-01		
3	Bagalkote District	0.588556	2001-02		
4	Bagalkote District	0.576776	2002-03		
5	Bagalkote District	0.51222	2003-04	0.6062213333	0.5956212
6	Bagalkote District	0.630556	2004-05	0.559184	0.546854
7	Bagalkote District	0.67789	2005-06	0.573184	0.5842992
8	Bagalkote District	0.66111	2006-07	0.6068886667	0.6305558
9	Bagalkote District	0.715778	2007-08	0.6565186667	0.6600332
10	Bagalkote District	0.62589	2008-09	0.684926	0.6918
11	Bagalkote District	0.738554	2009-10	0.6675926667	0.6599004
12	Bagalkote District	0.729442	2010-11	0.6934073333	0.7001996
13	Bagalkote District	0.666446	2011-12	0.697962	0.7114652
14	Bagalkote District	0.721112	2012-13	0.7114806667	0.6997664
15	Bagalkote District	0.753444	2013-14	0.7056666667	0.7063782
16	Bagalkote District	0.764112	2014-15	0.7136673333	0.7263448
17	Bagalkote District	0.689668	2015-16	0.7462226667	0.7523116
18	Bagalkote District	0.724444	2016-17	0.7357413333	0.7247564
19	Bagalkote District	0.726332	2017-18	0.7260746667	0.7219448
20	Bagalkote District	0.736	2018-19	0.7134813333	0.7184328
21	Bagalkote District	0.817224	2019-20	0.7289253333	0.7307884
22	Bagalkote District	0.835222	2020-21	0.759852	0.7746784
23	Bagalkote District	0.842556	2021-22	0.7961486667	0.8099782
24	Bagalkote District	0.874444	2022-23	0.8316673333	0.8352894
25	Bagalkote District		2023-24	0.8507406667	0.8570332
26	Ballari District	0.684834	2000-01		
27	Ballari District	0.6435	2001-02		
28	Ballari District	0.602666	2002-03		
29	Ballari District	0.58367	2003-04	0.6436666667	0.6313498
30	Ballari District	0.65283	2004-05	0.6099453333	0.6013348
31	Ballari District	0.7085	2005-06	0.6130553333	0.6220492
32	Ballari District	0.619836	2006-07	0.6483333333	0.666833

Fig 7: NDVI Prediction by SMA, WMA and performance parameters.



```
SMA:
MAD: 0.03797219365609348
MSD: 0.0024656170498460394
MSE: 0.0024656170498460394
RMSE: 0.049654980111223886

WMA:
MAD: 0.03752765175292154
MSD: 0.0024129625947316865
MSE: 0.0024129625947316865
RMSE: 0.04912191562563177
```

Fig 8: Performance evaluation of SMA, WMA model.

ML model building

Moving average models for time series forecasting are utilized to predict the value of the next period by averaging the values of n previous periods, with n set to 3 years for this model. Two forecasting models: 3-year SMA and 3-year WMA for time series analysis have been built. The weights 3, 2 and 1 are choosen for the 3 recent years Dt , Dt-1, Dt-2 reflecting an importance ratio of 50%: 33%: 17% and meeting the constraint the sum of the weights ratio equals 100%. The formula used to calculate the forecast NDVI value F is given in Eq.3 for the 3-year WMA model.

$$F_{t+1} = 3\,D_t + 2\,D_{t-1} + D_{t-2} \qquad \text{...Eq.3}$$

The SMA, WMA models are constructed for trend analysis using python programming language. Based on NDVI dataset spanning from 2000 to 2022, for each district in the Karnataka, aiming to predict the NDVI value for the year 2023, as illustrated in Fig 6.

Model performance evaluation and selection

The SMA and WMA models are assessed using different performance measures, such as MAE (MAD), MSE(MSD) and RMSE as shown in Fig 7. The forecasted NDVI value for the year 2022 from SMA andWMA models are compared with the actual NDVI of 2022 as visualized in Fig 8. The results from Fig 6, Fig 7 and Fig 8 indicates that the WMA model demonstrates greater accuracy with fewer errors compared to the SMA model. Therefore, the WMA model is chosen to forecast the NDVI values for districts in Karnataka state, along with the corresponding range of values for the year 2023.

NDVI time series forecasting

Chosen 3-year WMA forecasting model is employed to predict the NDVI for year 2023, for all districts in Karnataka state, utilizing historical data from year 2000 to 2022 and forecasted NDVI is mapped to respective districts as per administrative boundaries in QGIS is shown in Fig 9.

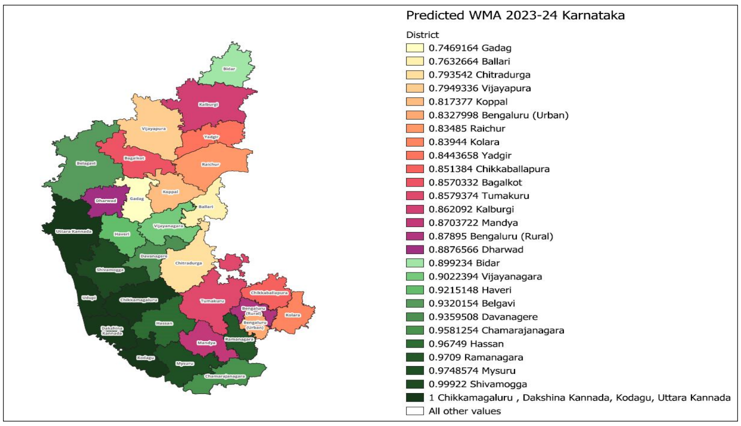


Fig 9: NDVI 2023-24 prediction by 3-year WMA ML model for Karnataka districts.

1	district	MAE	MSE	RMSE	MAPE
2	Bagalkote District	0.0516221	0.003418589453	0.05846870491	7.383415637
3	Ballari District	0.0486218	0.003251581953	0.05702264422	7.02078095
4	Belagavi District	0.04325693333	0.002588539658	0.05087769313	5.174939329
5	Bengaluru Rural District	0.04598333333	0.003437218056	0.05862779252	5.682141118
6	Bengaluru Urban District	0.0402114	0.002844819556	0.05333684989	5.258738813
7	Bidar District	0.03866406667	0.002502799307	0.05002798524	4.417991125
8	Chamarajanagar District	0.0357354	0.001843174796	0.04293221164	4.00038366
9	Chikkaballapura District	0.0534368	0.004167794638	0.06455845907	7.032273772
10	Chikkamagaluru District	0.01019513333	0.0002182915996	0.01477469457	1.037729103
11	Chitradurga District	0.05099636667	0.003587525254	0.05989595357	7.279380205
12	Davanagere District	0.03060356667	0.001300106067	0.03605698361	3.432185868
13	Dharwad District	0.05289203333	0.003661195873	0.06050781663	6.527578816
14	Gadag District	0.05321796667	0.004220347189	0.06496419928	8.374634875
15	Hassan District	0.02904166667	0.001470900389	0.03835231921	3.183235536
16	Haveri District	0.03679406667	0.001894833113	0.04352968083	4.349207134
17	Kalaburagi District	0.05149836667	0.004045057584	0.06360076716	6.407641443
18	Kodagu District	0.0009714	0.0000062907864	0.002508144015	0.09761643709
19	Kolar District	0.0404822	0.002248340068	0.04741666446	5.382838994
20	Koppal District	0.05444243333	0.00358362349	0.05986337353	7.687064811
21	Mandya District	0.04195716667	0.002633048553	0.05131323955	5.257538116
22	Mysuru District	0.02562173333	0.0009551325799	0.0309052193	2.733700343
23	Raichur District	0.05505333333	0.003969625778	0.06300496629	7.590379764
24	Ramanagara District	0.0391592	0.002336992167	0.04834244685	4.431071943
25	Shimoga District	0.0083378	0.0001081476678	0.01039940709	0.8432407157
26	Tumakuru District	0.04305376667	0.002569461542	0.0506898564	5.553216079
27	Udupi District	0.0056	0.00004902933333	0.007002094925	0.5657496101
28	Uttara Kannada District	0	0	0	0
29	Vijayanagara District	0.04291446667	0.002568044323	0.05067587516	5.232904441
30	Vijayapura District	0.06676946667	0.006092258969	0.07805292415	10.02637248
31	Yadgir District	0.04224550877	0.002392064104	0.04890873239	5.493358984

Fig 10: Performance evaluation of 3-year WMA model for districts of Karnataka.

The performance measures MAE, MSE, RMSE and MAPE of each District w.r.t forecasting of NDVI is summarized as given in Fig 10. The NDVI values of the time series forecasting are visualized through line charts, as illustrated in Fig 11, along with the associated range of forecast values having 57% accuracy. For instance, according to the 3-year WMA model, if the forecasted NDVI is 552±87.88 (ranging from 464 to 640), with 57% accuracy based on MAD of 87.88.

RESULTS AND DISCUSSION

The result of NDVI values predicted by time series ML models SMA and WMA for the districts of Karnataka for the year 2022 is shown in Fig 6. The performance evaluation of SMA and WMA models in predicting NDVI values were assessed using different performance measures, such as MAE (MAD), MSE(MSD) and RMSE are given in Fig 7. The forecasted NDVI values for the year 2022 from SMA and WMA models were compared with the actual NDVI of 2022 is presented in Fig 8. l District wise time series analysis of NDVI by WMA model is visualized in Fig 11. The District wise performance of WMA model in forecasting NDVI is summarised in Fig 10. The WMA model predicted NDVI values of the districts for year 2023 are shown in Fig 9.

The performance findings of SMA and WMA models found in Fig 7 indicates The WMA model demonstrates superior accuracy with a lower MAE of 0.03752 compared to the SMA model MAE of 0.03797, followed by lower MSE and RMSE, SMA model's low performance with higher values of MAE, MSE and RMSE show higher error in comparison with WMA model. WMA model demonstrated better performance and accuracy by low values for all the three performance measures compared to the SMA model. The comparison of forecasted NDVI values for the year 2022 from SMA and WMA models with the actual NDVI of 2022, revealed WMA model was successful in predicting accurate NDVI for 27 districts (*i.e* 87.1%), while the SMA model performed better in merely 4 districts (*i.e* 12.9%). Prominent districts where the SMA approach proved beneficial include Bengaluru rural, davanagere and Dharwad as presented in Fig 8. Because of compared better performance WMA model was selected to forecast the NDVI values. The Summarised district wise performance of 3-year WMA model for forecasting NDVI in Fig 10. illustrated all districts of Karnataka have low MAPE value, *i.e* less than 10%, indicating highly precise prediction of NDVI values by 3-year WMA model. NDVI time series analysis of the districts by 3-year WMA model is given in Fig 11 associated with range of forecast values having 57% accuracy for MAD of 87.88. The time series analysis plots interprets vegetation of 25 districts has increased during 2000-2023, which includes around 12 districts showing decreasing vegetation between 2019 to 2023 and

5 districts vegetation has not varied much. District Dakshina kannada's raster NDVI data is not available. The WMA predicted NDVI values for the year 2023 is shown in Fig 9. proves model accuracy exceeding 95.5% for all 31 districts, including accuracy of 99% -100% for 15 districts. The NDVI forecast for 2023, also indicates that all districts exhibit

Fig 11: Continue..

Fig 11: Continue..

Fig 11: NDVI 2023 time series forecasting for districts of Karnataka.

NDVI values surpassing 0.75, with 9 districts registering values between 0.95 and 1.0, signifying robust vegetation for the year 2023.

CONCLUSION

The performance findings of SMA and WMA models indicated SMA model's low performance with higher values of MAE, MSE and RMSE. WMA model demonstrated better performance and accuracy with low values for all three performance measures compared to the SMA model. The comparison of forecasted NDVI values for the year 2022 from SMA and WMA models with the actual NDVI of 2022, revealed WMA model was successful in predicting accurate NDVI for 27 districts (*i.e* 87.1%), while the SMA model performed better in merely 4 districts (*i.e* 12.9%). Prominent districts where the SMA approach proved beneficial include Bengaluru Rural, Davanagere and Dharwad. Because of compared better performance WMA model was selected to forecast the NDVI values. The summarized district wise performance of 3-year WMA model for forecasting NDVI. illustrated all districts of Karnataka have low MAPE value, *i.e* less than 10%, indicating highly precise prediction of NDVI values by 3-year WMA model. NDVI time series analysis proved vegetation of 25 districts has increased during 2000-2023, which includes 12 districts showing decreasing vegetation between 2019 to 2023 and 5 districts vegetation has not varied much. District Dakshina kannada's raster NDVI data is not available from MODIS. The WMA predicted NDVI values for the year 2023 proved model accuracy exceeding 95.5% for all 31 districts, including accuracy of 99% -100% for 15 districts. The NDVI forecast for 2023, also indicates that all districts exhibit NDVI values surpassing 0.75, with 9 districts registering values between 0.95 and 1.0, signifying robust vegetation for the year 2023.

ACKNOWLEDGEMENT

The authors sincerely acknowledge the valuable support and assistance provided by the PAHER University personnel during the experimental phase of this work

Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article. No funding or sponsorship influenced the design of the study, data collection, analysis, decision to publish, or preparation of the manuscript.

REFERENCES

Ahlawat, S. and Kaur, D. (2015). Climate change and food production in North West India. *Indian Journal of Agricultural Research*. **49(6):** 544-548. doi: 10.18805/ijare.v49i6.6683.

Bombe, D.D. (2023). Assessment of vegetation cover of palghar taluka using NDVI technique. *Plant Science Biospectra.* **18(1):** 241-250. https://doi.org/10.13140/RG.2.2.31393.83042.

Buraka, T., Elias, E. and Lelago, A. (2022). Analysis and prediction of land-use and land-cover changes and driving forces by using GIS and remote sensing in the coka watershed, Southern Ethiopia. *Indian Journal of Agricultural Research.* **56(5):** 581-587. doi: 10.18805/IJARe.A-699.

Chen, D., Hu, H., Liao, C., Ye, J., Bao, W., Mo, J., Wu, Y., Dong, T., Fan, H. and Pei, J. (2023). Crop NDVI time series construction by fusing Sentinel-1, Sentinel-2 and environmental data with an ensemble-based framework. *Computers and Electronics in Agriculture.* **215:** 108388. https://doi.org/10.1016/j.compag.2023.108388.

Dehghanisanij, H., Emami, H., Emami, S. and Rezaverdinejad, V. (2022). A hybrid machine learning approach for estimating the water-use efficiency and yield in agriculture. *Scientific Reports.* **12(1).** https://doi.org/10.1038/s41598-022-10844-2.

Dey, A., Sarkar, S., Mondal, A. and Mitra, P. (2025). Spatio-temporal NDVI prediction for rice crop. *SN Computer Science.* **6(3).** https://doi.org/10.1007/s42979-025-03767-y.

Janarth, S., Jagadeeswaran, R., Pazhanivelan, S., Kannan, B., Ragunath, K.P. and Sathiyamoorthy, N.K. (2025). Assessment of agricultural drought in Tamil Nadu using remote sensing techniques. *Agricultural Science Digest.* **45(1):** 178-186. doi: 10.18805/ag.D-6007.

Jeyasingh, I.A.R., Devakumari, S.M., Poonguzhali, S.R., Katharine, P.S. and Jeeva, C.S. (2023). Evaluating the soil nutrient status using GIS and remote sensing technology-A case study at Coimbatore District. *Agricultural Science Digest.* **43(3):** 319-323. doi: 10.18805/ag.D-5698.

Judith, J., Tamilselvi, R., Beham, M.P., Sathiya, S., Lakshmi, P., Panthakkan, A., Al Mansoori, S. and Al Ahmad, H. (2025). Remote Sensing Based Crop Health Classification Using NDVI and Fully Connected Neural Networks.

Kumar, A., Singh, I., Kashyap, M., Kumar, A., Devi, N.B., Singh, S., Sharma, S. and Pradhan, R. (2025). Integration of machine learning and 9remote sensing in crop yield prediction: A review. *International Journal of Research in Agronomy.* **8(1S):** 549-562. https://doi.org/10.33545/2618060x.2025.v8.i1sh.2496.

Kaushalya, R., Kumar, V.P. and Shubhasmita, S. (2014). Assessing agricultural vulnerability in India using NDVI data products. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XL.* **8:** 39-46.

Lemenkova, P. (2020). Hyperspectral vegetation indices calculated by qgis using landsat Tm image: A case study of Northern Iceland. *Advanced Research in Life Sciences.* **4(1):** 70-78. https://doi.org/10.2478/arls-2020-0021 M.

Li, X., Yuan, W. and Dong, W. (2021). A machine learning method for predicting vegetation indices in China. *Remote Sens (Basel).* **13:** 1147. https://doi.org/10.3390/rs130611.

Nandy, A. and Kumar, A. (2025). Spatio-temporal assessment of land surface temperature, vegetation and crop water stress for sustainable land management in upper Brahmaputra Valley, Assam. *Indian Journal of Agricultural Research.* **59(Special Issue):** 141-148. doi: 10.18805/IJARe.A-6415.

Nie, J., Wu, K., Li, Y., Li, J. and Hou, B. (2024). Advances in hyperspectral remote sensing for precision fertilization decision-making: A comprehensive overview. *Turkish Journal of Agriculture and Forestry.* **48(6):** 22. https://doi.org/10.55730/1300-011X.3243.

Nalina, C. and Kumar, A., Kokkuvayil, M., Chandrakala, R., Sujata, K., Hegde, R.and Singh, S. (2016). Soil nutrient status mapping of Nagenahalli micro-watershed under eastern dry zone of Karnataka by remote sensing, detailed soil survey and GIS techniques. *Indian Journal of Agricultural Research.* **50:** 389-397. doi: 10.18805/ijare.v0iOF.3762.

Raza, A., Fahmeed, R., Syed, N.R., Katipoğlu, O.M., Zubair, M., Alshehri, F. and Elbeltagi, A. (2023). Performance evaluation of five machine learning algorithms for estimating reference evapotranspiration in an arid climate. *Water (Switzerland).* **15(21).** https://doi.org/10.3390/w15213822.

Sarwar, S., Aziz, G. and Balsalobre-Lorente, D. (2023). Forecasting accuracy of traditional regression, machine learning and deep learning: A study of environmental emissions in Saudi Arabia. *Sustainability.* **15(20):** 14957. https://doi.org/10.3390/su152014957.

Thimmegowda, M.N., Manjunatha, M.H., Lingaraj, H., Soumya, D.V., Jayaramaiah, R., Sathisha, G.S. and Nagesha, L. (2025). Comparative analysis of machine learning and statistical models for cotton yield prediction in major growing districts of Karnataka, India. *Journal of Cotton Research.* **8(1).** https://doi.org/10.1186/s42397-024-00208-8

Yadav, M. and Patil, P., Prasad, V. and Devi, V.V.R. (2024). Suitability evaluation for cultivation of cotton in ganjigatti sub-watershed of Karnataka using GIS, remote sensing and detailed survey. *Agricultural Science Digest-A Research Journal.* doi: 10.18805/ag.D-5954.