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RESEARCH ARTICLE

Spatiotemporal dynamics of water spread areas and vegetation health in the lower Vaigai sub-basin: A multi-sensor analysis using Sentinel-1A SAR and Sentinel-2A MSI (2018-2023)

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Abstract

A spatiotemporal analysis of water spread areas in tanks within the lower Vaigai sub-basin was performed using Sentinel-1A SAR imagery from 2018 to 2023. The analysis revealed a mean water spread area of 275.29 ha, with the highest being 628.29 ha in summer 2023 and the lowest at 5.55 ha in summer 2018. This was influenced by a total rainfall of 5777.06 mm, with an average of 879.14 mm annually. NDVI data from Sentinel-2 categorized crop health across 74.5 thousand ha, showing high no vegetation (20-45 %) and sparse vegetation (24-33 %) during the Kharif season. The Rabi season exhibited improved conditions, with moderate vegetation peaking at 40 % in 2020, while summer consistently showed crop stress with minimal good vegetation (up to 5 %). Given the arid conditions and dependence on irrigation tanks, the study underscores the importance of water availability for crop growth in lower Vaigai sub basin. In this investigation, the identification of poor crop performance during the Kharif and summer seasons can guide researchers and administrators to increase efforts on introduce drought-resistant crops, adjust planting schedules or implement supplemental irrigation over this region. Additionally, the insights gained from the present investigation on water spread dynamics in tanks recommend the development of climate-smart agricultural practices, including water-saving irrigation techniques and hydrological modelling, to enhance resilience. The results can further support government interventions, such as improving tank rehabilitation programs, which are crucial for ensuring sustainable crop production and food security in the Lower Vaigai sub-basin.

Keywords

Adaptive Irrigation Management; Crop Health Analysis; Normalized Difference Vegetation Index; Synthetic Aperture Radar; Water Spread Area

Introduction

Water constitutes a critical resource for agricultural production globally, with the sector representing its largest consumer. Surface water bodies provide freshwater essential for natural ecosystems and human needs, playing a crucial role in the survival of all living organisms (1). The Indian subcontinent, particularly Tamil Nadu, exemplifies this dependence, where agriculture accounts for a substantial proportion of total water consumption. Traditional irrigation systems, such as tanks, have historically supported agrarian livelihoods, especially among small-scale farmers. These water bodies, prevalent in southern India, contribute significantly to rice production. However, the challenges posed by water scarcity and the limitations of conventional water management practices necessitate innovative approaches like precision agriculture, in situ rain water harvesting, Managed Aquifer Recharge (MAR), Climate Smart-Irrigation support system and climate resilient cropping systems

Tanks, which are shallow valleys with low earthen embankments designed to collect rainfall runoff, are crucial traditional irrigation sources in India. Tanks perform several important functions, including collecting, conserving and storing rainfall, which helps reduce soil erosion and provides cost-effective irrigation for crops (2). Approximately 250000 tanks across the country irrigate around 1.7 million ha of land, with southern states contributing about 60 % to this area. These tank-irrigated regions in the south collectively yield about 4.5 million tons of rice annually, accounting for roughly 25 % of the total rice production in Andhra Pradesh, Telangana, Karnataka and Tamil Nadu (3). Tanks constitute a primary irrigation source across numerous districts in Tamil Nadu, significantly contributing to the state's overall net irrigated area (4). The area irrigated by tanks has been steadily declining in recent years, largely due to inadequate maintenance and mismanagement. Many tanks have deteriorated significantly, with some becoming entirely defunct due to several factors. If properly managed and given the required attention, these tank systems could serve as a highly sustainable resource for the future (5).

Accurate assessment of water spread dynamics at the tank level is essential for farmers, especially given the frequent scarcity or unavailability of water. Conventional methods of surveying and estimating water spread are costly and impractical due to the sheer number of tanks, highlighting the need for remote sensing applications. Surface water mapping through remote sensing is crucial for estimating water availability, monitoring changes over time and predicting droughts and floods (6).

Optical remote sensing is commonly used to monitor changes in water surface areas due to its easy accessibility. However, its effectiveness is limited by cloud cover and the inability to capture data at night. Conversely, SAR data from satellites is extensively utilized in surface water investigations due to its all-weather, day-and-night sensing capabilities and ability to detect inundated areas obscured by vegetation. SAR wavelengths are unaffected by cloud cover, lighting, weather and vegetation. Sentinel-1A SAR Ground Range Detected (GRD) in VV polarization offers high accuracy and resolution (10 m) for monitoring surface water (7). SAR technology is effective for monitoring changes in surface water and wetlands both seasonally and annually. Its characteristics make SAR ideal for mapping and monitoring water and wetlands over time, making it a valuable tool for studying water spread dynamics. Utilizing satellite-based remote sensing not only helps in water spread estimation but also presents a viable and economical approach for monitoring crops at both regional and national levels (8). Remote sensing technology offers a robust methodology for estimating crop area and cropping intensity. Through the analysis of satellite imagery and the application of advanced image processing techniques, precise delineation and quantification of crop extents across expansive agricultural landscapes become feasible. Remote sensing data provides invaluable insights into crop types, growth stages and spatial distribution, facilitating highly accurate crop area estimation. Furthermore, temporal analysis of satellite imagery enables the tracking of crop pattern variations throughout the growing season and across multiple years, thereby deepening the comprehension of cropping intensity.

Sentinel-2A plays a pivotal role in advanced crop monitoring and management, utilizing high-resolution multispectral sensors to capture detailed agricultural imagery. This capability allows for precise crop mapping and thorough analysis. The satellite's frequent revisit times and wide coverage enable continuous observation of crop phenology, health metrics and spatial distribution throughout the growing season, ensuring comprehensive monitoring.

The Normalized Difference Vegetation Index (NDVI) is a critical metric derived from multispectral imagery, widely used for vegetation assessment. With values ranging from -1 to +1, NDVI quantitatively reflects vegetation health, where lower values indicate stress and higher values signify optimal growth. As the most prevalent vegetation index for assessing crop phenology and health, NDVI is essential for regional crop area estimation. By analysing crop area and cropping intensity through NDVI and similar indices, researchers and policymakers can devise strategies to boost agricultural productivity and enhance food security.

The present investigation in the lower Vaigai sub-basin aimed to assess water spread dynamics using Sentinel-1A SAR data (2018-2023) and crop conditions through NDVI values from Sentinel-2A and also to evaluate the impact of water spread dynamics on crop conditions throughout the study period.

Materials and Methods

Study area

The Vaigai River, originating from the Varusanadu Hills on the Periyar Plateau of the Western Ghats, flows 258 km northeast through Tamil Nadu, passing through Theni, Madurai and Ramanathapuram. Among Tamil Nadu's 17 river basins, the Vaigai Basin, covering 7009.13 hectares, is divided into 10 sub -basins, including the largest, the Lower Vaigai Basin. This sub -basin, encompassing 1063.88 km^2 of plains, primarily lies in Ramanathapuram and Sivagangai districts. It is bordered by the Kottakaraiyar sub-basin to the North, the Uppar sub-basin to the West, the Uthiragosamangaiyar and Paralaiyar sub-basins to the South and the Bay of Bengal to the East. The Lower Vaigai Sub-Basin contains 143 system and non-system tanks, significant for irrigation and features key structures like the Parthibanur regulator and Ramnad Big Tank. The study area that depicts the parts of Ramanathapuram and Sivagangai and its satellite view were illustrated in Fig. 1 and 2 respectively.

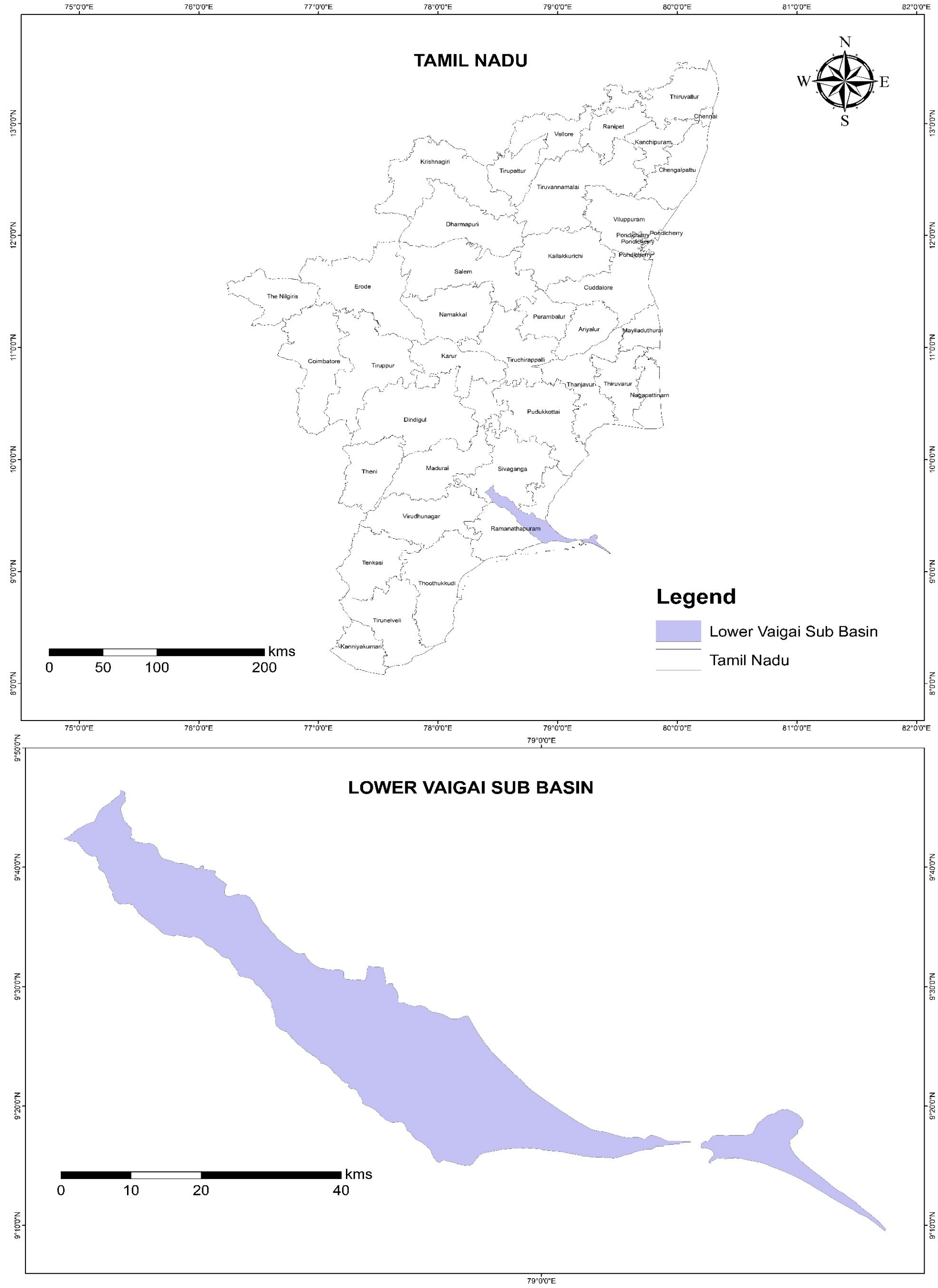

Fig. 1. Lower Vaigai sub basin - Parts of Ramanathapuram and Sivagangai.

Fig. 2. Satellite view of study area.

Satellite data

Various satellite data products such as Sentinel 1A and Sentinel 2A were employed to evaluate water spread areas, crop conditions and cropping intensity over different spatial and temporal scales to meet the study objectives (Table 1). Data acquisition for the study area covered the period from 2018 to 2023, allowing for a 6 years analysis of water spread, crop condition and cropping intensity. These data underwent pre-processing for further analysis.

Sentinel 1A

The European Space Agency's (ESA) Copernicus program plays a pivotal role in Earth observation, providing open and free access to a diverse range of data for scientific, commercial and public use. Sentinel-1A, launched in 2014 as the first satellite within the Copernicus constellation, offers C-band Synthetic Aperture Radar (SAR) data in the Ground Range Detected (GRD) format via the Sentinel Scientific Data Hub (https://scihub.copernicus.eu/dhus/). This sensor's key advantage lies in its ability to acquire high-resolution images irrespective of weather or lighting conditions.

Sentinel-1A boasts a revisit time of 12 days, enabling the monitoring of dynamic Earth processes across various temporal scales. Among the 4 operational modes of Sentinel-1A, the Interferometric Wide (IW) swath mode over land serves as the primary mode for terrestrial applications within the microwave spectrum. Notably, Sentinel-1A offers dual polarization SAR capabilities, transmitting and receiving signals in both horizontal (H) and vertical (V) polarizations. The superior sensitivity of VV polarization in detecting surface water roughness, compared to VH polarization, has been well demonstrated, making it a critical component for water spread analysis in this research (9, 10). Synthetic Aperture Radar (SAR) technology is highly effective for monitoring changes in surface water (11) as well as wetlands on both seasonal and annual scales (12, 13).

Sentinel 2A

Sentinel-2A, a cornerstone of the European Union's Copernicus program, provides high-resolution multispectral imagery for comprehensive Earth observation. Launched in 2015, this satellite carries a Multispectral Instrument (MSI) capable of capturing data across 13 spectral bands, ranging from visible to shortwave infrared wavelengths. With a sun-synchronous orbit at approximately 786 km, Sentinel-2A offers frequent revisit times, enabling detailed monitoring of Earth's surface. The combination of spatial resolution, spectral coverage and temporal frequency makes Sentinel-2A an invaluable asset for a wide range of applications, including but not limited to agriculture, forestry, land use/cover mapping, disaster management and environmental monitoring. The open-access nature of Sentinel-2A data has fostered its widespread utilization in scientific research, commercial endeavours and policymaking, contributing significantly to global sustainability efforts. Sentinel-2 satellite imagery stands out for its frequent coverage, ability to capture multiple spectral bands, wide imaging range and high spatial resolution. This type of imagery is valuable for tasks such as mapping land cover, detecting changes in land use and estimating various geophysical parameters (14).

Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a critical metric for assessing plant health and vigor. Derived from satellite and aerial imagery, NDVI quantifies vegetation conditions based on the differential reflectance of visible and near-infrared light. Higher NDVI values correlate with healthier, denser vegetation, while lower values indicate sparse or stressed plants. By categorizing NDVI into non-vegetation, low vegetation and high vegetation classes, researchers can effectively map and monitor vegetation patterns. The index's robustness to external factors like lighting and topography has solidified its status as a primary tool for agricultural management and ecological studies.

$$\text{NDVI} = \frac{\text{pNIR - pRed}}{\text{pNIR - pRed}}$$

where,

NDVI – Normalised Difference Vegetation Index

pNIR – Near Infra-Red Band

pRed - Red Band

Rainfall Data

Rainfall serves as a vital factor influencing multiple aspects of the study region's water resource and tank water spreads. It was also influence the groundwater recharge, crop cultivation patterns and water availability for both domestic and industrial use (15). To analyse the influence of rainfall on tank water spread area, daily gridded rainfall data with a high spatial resolution of 0.25 x 0.25 degrees was acquired from the India Meteorological Department's website (https://www.imdpune.gov.in/lrfindex.php). This data was subsequently aggregated on a seasonal basis to establish a clear link between rainfall patterns and water level fluctuations within the tanks (16).

Water spread area calculation

The calculation of water spread area is done with following steps.

Preprocessing

Synthetic Aperture Radar (SAR) data from Sentinel-1A, specifically C-band Ground Range Detected (GRD) imagery with 20 m resolution in VV polarization, was sourced from the Google Earth Engine (GEE) for the study area. Effective SAR data utilization requires preprocessing to address geometric and radiometric issues, as specified by the ESA Sentinel-1A toolbox. This includes updating orbit state vectors, removing thermal and border noise, performing calibration, applying

Table 1. Satellite details and data products.

Sl. No.	Data collection	Spatial resolution	Temporal resolution	Use
1.	Sentinel 1A	20 m	12 days	Water spread area assessment
2.	Sentinel 2A	10 m	10 days	Crop conditions and cropping intensity assessment

Range Doppler terrain correction and converting backscatter units to logarithmic decibels (dB). Precise orbit files ensure accurate SAR metadata positioning, while normalization techniques mitigate thermal noise (17). Border noise elimination and calibration enhance image quality and radiometric correction translates data into decibels for precise analysis (18). Range Doppler Terrain correction with SRTM data and Lee's speckle filter (7x7 window) further improve image quality (19). These steps enhance SAR data accuracy for environmental monitoring and resource management.

Reprojection

To ensure precise quantification of water spread area, a coordinate system transformation was imperative. The initial SAR data, acquired from Google Earth Engine, was projected in the WGS 1984 geographic coordinate system, which employs a spherical datum and is inherently unsuitable for accurate area calculations. To address this limitation, the dataset was reprojected into the Universal Transverse Mercator (UTM) Zone 44N projection. This cylindrical projection system provides a more appropriate framework for planimetric measurements. The transformation process was executed using the ArcGIS geoprocessing tool, resulting in a UTM-projected raster dataset suitable for subsequent analysis.

Thresholding

Image thresholding, a fundamental image processing technique, involves classifying image pixels into distinct categories based on intensity values. (20). When applied to Sentinel-1 Synthetic Aperture Radar (SAR) imagery, this method effectively discriminates between various land cover types, including water bodies. By establishing a specific threshold value or range, pixels are categorized into corresponding classes. Due to its computational efficiency, thresholding is widely employed for SAR image analysis. Histogram-based thresholding is a prevalent approach for differentiating water and non-water pixels (21). In this study, a threshold value of -21 dB was adopted to delineate water bodies and track their temporal dynamics and the water area maps were also created using the histogram thresholding method (22). The overall methodology that elaborately explains the flow of procedures for assessing water spread area was illustrated in Fig. 3.

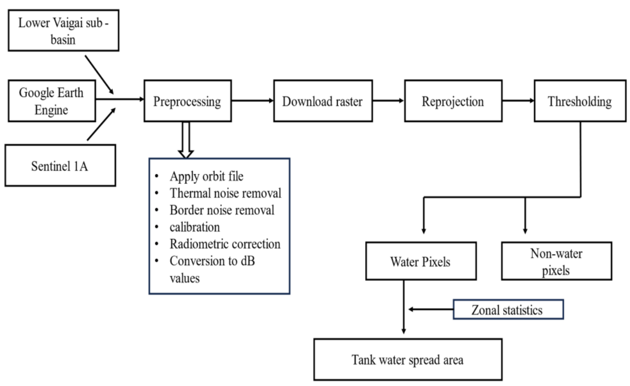

Fig. 3. Flow chart encompassing methodology for estimating water spread area.

Assessment of crop conditions

The Normalized Difference Vegetation Index (NDVI) has emerged as a reliable proxy for assessing crop health and vigor. This spectral index leverages the contrasting reflectance properties of vegetation in the near-infrared (NIR) and red bands of the electromagnetic spectrum. Healthy vegetation exhibits high NIR reflectance and low red reflectance, resulting in elevated NDVI values. Conversely, stressed or sparse vegetation displays lower NDVI values due to increased red reflectance. By employing high-resolution Sentinel-2 imagery, NDVI time series were generated to monitor crop growth and vitality across the study area. NDVI values were categorized into 5 classes - no vegetation (<0.2), sparse (0.2 - 0.4), moderate (0.4 - 0.6), good (0.6 - 0.8) and very good (0.8 - 1) to provide a comprehensive assessment of crop status throughout the growing season. The detailed pathway to understand the procedures to assess the crop conditions was illustrated in Fig. 4.

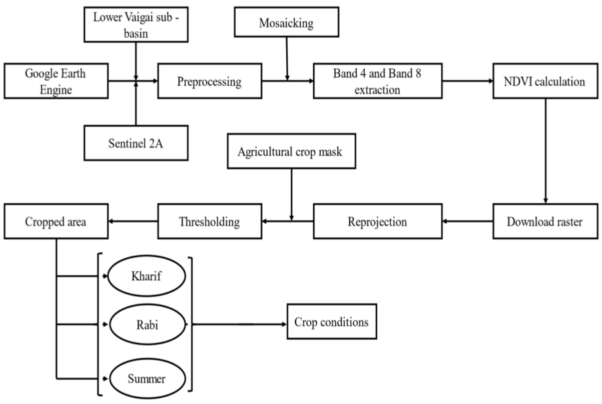

Fig. 4. Flowchart holding methodology for estimating crop conditions.

Results and Discussion

The water spread area of the total 143 tanks in study area was calculated and the contrast crop conditions for the study period of 2018 to 2023 were evaluated. In recent years, remote sensing-based water body mapping has become increasingly prevalent, as evidenced by studies utilizing SAR data for water spread (23, 24).

Crop condition assessment was conducted using NDVI value classification and the area of different conditions was categorized and calculated. The variation in crop conditions was significantly impacted by the timing of the monsoon (25). Low NDVI values, indicating poor crop conditions, suggested that crops experienced water stress, reflected in reduced greenness (26).

Backscattering (dB) Values

SAR data from Sentinel-1A for 2023 was downloaded and processed with Google Earth Engine (GEE) and furthermore processed with ArcGIS software to obtain backscatter values. These values correlate with different land cover types. High backscatter values typically correspond to urban areas, while low values often indicate water bodies. Vegetation, barren land and dry soil generally exhibit intermediate backscatter levels. The backscattering values over Kharif, Rabi and summer seasons from 2018 to 2023 with minimum and maximum values of -35.9211 and 27.4093 respectively were presented in Table 2.

Table 2. Backscattering values - season wise (2018 - 2023).

Season	Backscattering (dB) value
Kharif, 2018	-32.9011 to 25.5504
Rabi, 2018	-33.3257 to 25.2381
Summer, 2018	-35.9211 to 26.2600
Kharif, 2019	-34.0081 to 25.9116
Rabi, 2019	-29.0228 to 27.4053
Summer, 2019	-30.4915 to 26.2916
Kharif, 2020	-27.4296 to 26.4120
Rabi, 2020	-27.2188 to 25.4231
Summer, 2020	-28.0592 to 26.2333
Kharif, 2021	-29.9753 to 26.2435
Rabi, 2021	-27.0840 to 25.3793
Summer, 2021	-27.7750 to 26.0912
Kharif, 2022	-30.7655 to 26.4898
Rabi, 2022	-28.1080 to 25.1458
Summer, 2022	-29.1682 to 26.0110
Kharif, 2023	-29.9237 to 26.2772
Rabi, 2023	-32.4210 to 26.4417
Summer, 2023	-35.8620 to 25.5775

Table 3. Season wise average water spread area in tanks of lower Vaigai sub basin (2018 - 2023).

Season	Water spread area (ha)	Rainfall (mm)
Kharif, 2018	24.39	123.62
Rabi, 2018	180.68	546.67
Summer, 2018	5.55	15.54
Kharif, 2019	11.81	166.87
Rabi, 2019	192.02	834.29
Summer, 2019	205.02	82.97
Kharif, 2020	10.16	250.76
Rabi, 2020	136.73	857.88
Summer, 2020	366.11	64.16
Kharif, 2021	305.44	189.23
Rabi, 2021	327.30	707.75
Summer, 2021	386.46	107.90
Kharif, 2022	438.41	238.93
Rabi, 2022	470.50	430.46
Summer, 2022	478.00	211.70
Kharif, 2023	383.09	133.98
Rabi, 2023	405.28	698.71
Summer, 2023	628.29	115.64

Water Spread Area Estimation

Histogram thresholding is a widely used and efficient method for creating binary images to estimate the water spread area in tanks. Table 3 presents the average seasonal water spread area in tanks within the lower Vaigai sub-basin along with rainfall data from 2018 - 2023. Over the past 6 agricultural years the average estimated water spread area in the tanks was 275.29 ha. The largest water spread area was observed in the summer of 2023, reaching 628.29 ha while the lowest was recorded in the summer of 2018, at just 5.55 ha. The cumulative water spread area of Kharif, Rabi and summer for the study period (2018-2023) were given as water spread area maps in Fig. 5.

A stark disparity in water spread area was observed, with 8.39 % of tanks remaining dry throughout the period and 88.81 % exhibiting a water spread area of less than 10 ha. A mere 2.8 % of tanks displayed a water spread area exceeding 10 ha. The season wise range of water spread area in tanks which was categorized into 0 ha, 0 - 10 ha, 10 - 25 ha and greater than 25 ha is given in Fig. 6.

Rainfall, as the primary water source for these tanks, significantly influenced water spread area dynamics. Annual rainfall in the sub-basin averaged 879.14 mm, with seasonal averages around 320.95 mm. The analysis of water spread area and rainfall data in the lower Vaigai sub-basin from 2018 to 2023 reveals a general positive correlation between rainfall and water spread area, indicating that higher rainfall generally results in a larger water spread area. However, this relationship is not strictly proportional, suggesting that factors such as water retention capacity, soil absorption rates and infrastructure management also play significant roles. For instance, the summer season of 2023 had the highest water spread area of 628.29 ha despite a moderate rainfall of 115.64 mm, indicating effective water management and retention strategies. But the previous season exhibit very good rainfall of 699 mm. Similarly, the Rabi season of 2020 experienced the highest rainfall of 857.88 mm and resulted in a significant increase in water spread area of almost around 1200 times i.e., from just 10 ha to 136.73 ha, showing the direct impact of substantial rainfall on water spread. On the other hand, the summer season of 2018 recorded the worst conditions, with a very low water spread area of only 5.55 ha and the lowest rainfall at 15.54 mm, indicating a drought-like scenario and poor water availability. Another notable low was in the Kharif season of 2020, where despite a moderate rainfall of 250.76 mm, the water spread area was only 10.16 ha, suggesting possible issues with water retention or inadequate infrastructure.

Over the years, the data shows a noticeable improvement in water spread areas, particularly from 2021 onwards, where values consistently increased across all seasons, reflecting better water management practices, infrastructural improvements, or more favourable rainfall patterns. The best results in summer 2023, with a high water spread area despite relatively low rainfall, underscore the importance of efficient water management in achieving optimal water storage outcomes. Conversely, the worst scenario in summer 2018 highlights the challenges of maintaining adequate water levels during periods of low precipitation. Overall, our research findings emphasize that rainfall is a key determinant of water and the tanks always can go through fluctuations in water spread among the seasons due to Indian monsoon which was evident by previous findings (27). Therefore, effective management and infrastructural enhancements are crucial for optimizing water resources in the lower Vaigai sub-basin. Further research is warranted to elucidate the complex interplay of these factors in determining water spread area dynamics in the lower Vaigai sub-basin. The findings of this research were consistent with the findings of previous studies (28, 29). The pictorial illustration that describes the correlation of water spread area and rainfall is presented in Fig. 7.

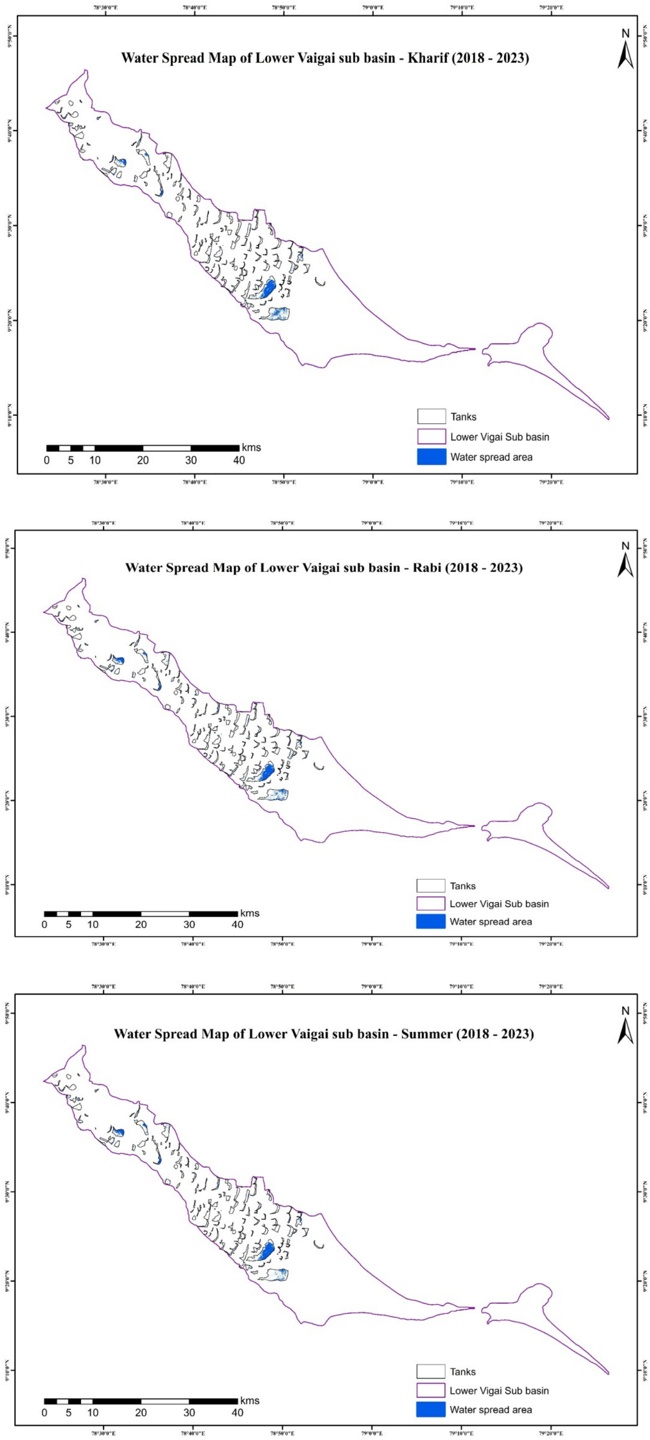

Fig. 5. Cumulative water spread area maps of Kharif, Rabi and summer 2018 - 2023.

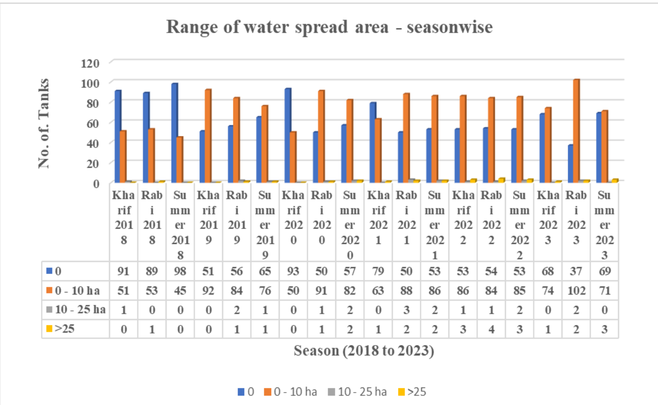

Fig. 6. Range of water spread area in tanks of lower Vaigai sub basin - season wise 2018 to 2023.

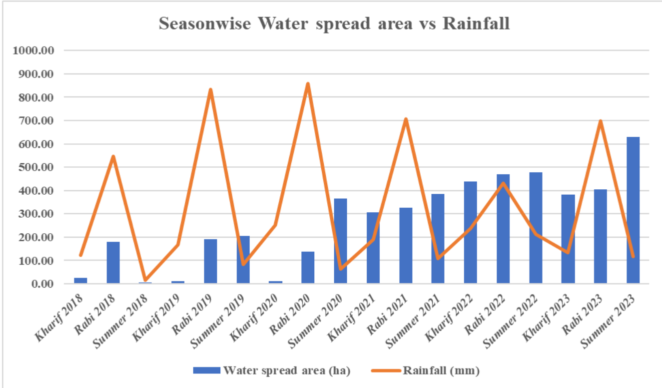

Fig. 7. Water spread area in tanks (ha) and Rainfall (mm) of lower Vaigai sub-basin in 2018 - 2023.

Assessment of crop condition

The analysis from 2018 to 2023 reveals significant seasonal variability in crop conditions in the Lower Vaigai sub-basin, with persistent challenges. The season wise crop condition (in thousand ha) which was categorized into no vegetation, sparse, moderate, good and very good from 2018 to 2023 were given in table 4 and the cumulative crop conditions maps of Kharif, Rabi and summer for the study period (2018 - 2023) were illustrated in Fig 8. In 2018, both Kharif and Rabi seasons resulted in relatively similar vegetation patterns, with a significant portion of the area under moderate vegetation (44.34 %) and sparse vegetation (23.09 %) and minimal areas under good vegetation (4.91 %). However, the summer season of 2018 experienced a noticeable decline in vegetation cover, with 19.84 % of the area having no vegetation and 39.21 % under sparse vegetation, indicating more challenging conditions compared to the Kharif and Rabi seasons. In 2019, the Kharif season faced a significant increase in areas with no vegetation (44.77 %), suggesting a decline in crop conditions. Meanwhile, the Rabi season showed better performance with 39.09 % of the area under moderate vegetation and 18.09 % under good vegetation. The summer season in 2019 also showed some recovery, with 33.43 % under sparse vegetation and 28.49 % under moderate vegetation, slightly better than the previous year.

Table 4. Crop condition of lower Vaigai sub basin - season wise - 2018 to 2023.

Year	Crop condition (in '000 ha)					
	Season	No vegetation	Sparse	Moderate	Good	Very good
2018	Kharif	2.15	23.09	44.34	4.91	0.00
	Rabi	2.15	23.09	44.34	4.91	0.00
	Summer	19.84	39.21	14.65	0.80	0.00
2019	Kharif	44.77	24.58	5.00	0.15	0.00
	Rabi	2.09	15.24	39.09	18.09	0.00
	Summer	9.76	33.43	28.49	2.83	0.00
2020	Kharif	28.13	29.63	15.49	1.26	0.00
	Rabi	2.38	19.88	40.50	11.74	0.00
	Summer	9.90	31.55	27.81	5.25	0.00
2021	Kharif	29.27	25.47	13.85	1.99	0.00
	Rabi	1.37	14.34	37.38	21.40	0.00
	Summer	8.04	34.34	29.71	2.33	0.00
2022	Kharif	23.33	31.92	17.02	2.15	0.00
	Rabi	2.27	24.85	38.76	8.54	0.00
	Summer	7.74	33.36	30.36	2.96	0.00
2023	Kharif	20.35	32.21	19.02	2.84	0.00
	Rabi	3.88	27.25	37.77	5.52	0.00
	Summer	5.85	33.49	31.66	3.50	0.00

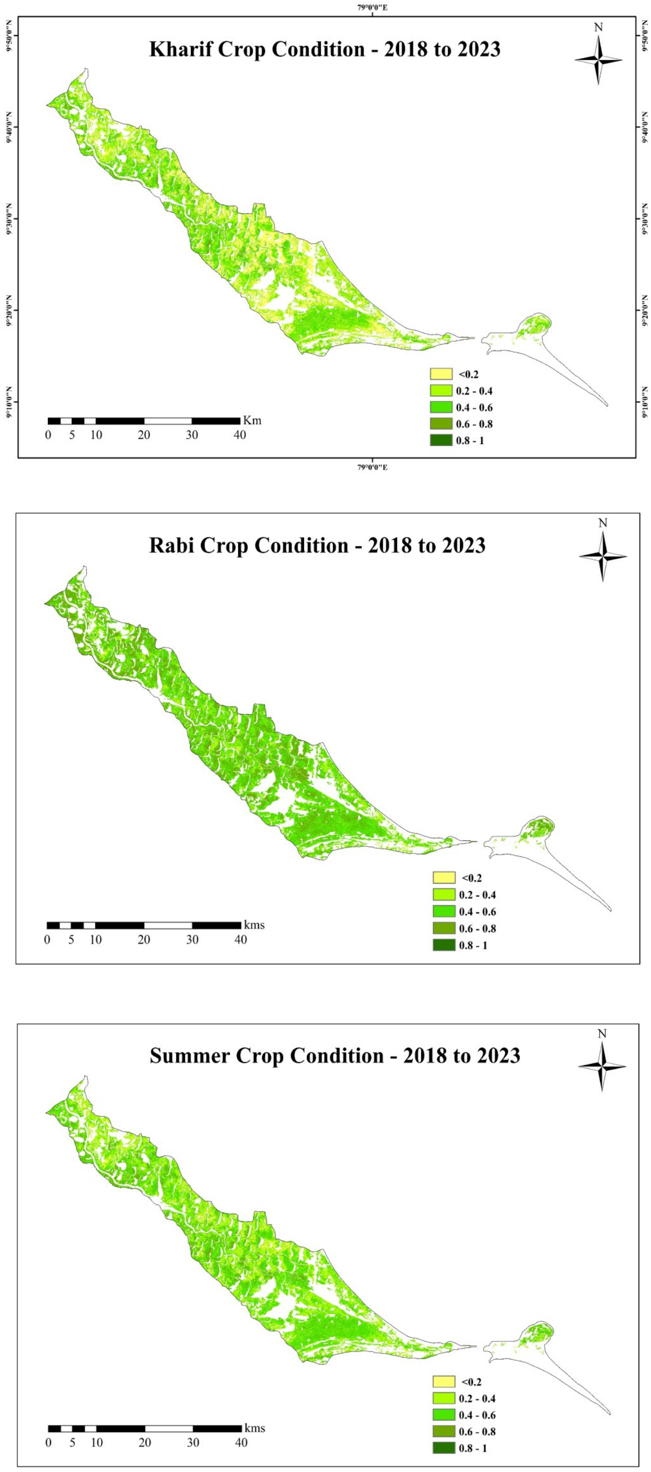

Fig. 8. Cumulative crop condition maps of Kharif, Rabi and summer 2018-2023.

From 2020 onwards, the seasonal variations became more pronounced. The Kharif season in 2020 saw some improvement, with moderate vegetation covering 15.49 % of the area, but sparse vegetation remained high at 29.63 %. The Rabi season performed better, with 40.50 % under moderate vegetation and an increase in good vegetation to 11.74 %, indicating relatively favourable conditions. In contrast, the summer season continued to struggle, with 9.90 % of the area under no vegetation and 32.55 % under sparse vegetation, although there was a slight improvement in areas with good vegetation (5.25 %). In 2021, the Kharif season saw a further increase in areas with no vegetation (29.27 %) and sparse vegetation (25.47 %), while the Rabi season showed mixed results, with a higher proportion of land under good vegetation (21.40 %) but still significant areas under moderate vegetation (37.38 %). By 2022, the Kharif and Rabi seasons both experienced deteriorating conditions, with sparse vegetation increasing to 31.92 % and 24.85 % respectively. The trend continued in 2023, where the Kharif season saw 32.21 % of the area under sparse vegetation, and the Rabi season saw good vegetation drop to just 5.52 %. The results evident that remote sensing technique can help better crop planning (30). These comparisons highlight the varying challenges and crop conditions across different seasons, emphasizing the importance of tailored water management and agricultural practices like sustainable agriculture, precision farming, in situ moisture conservation, zero/reduced tillage, etc. to address the specific needs of each season and also the results aligning with previous works (31).

The overall decline in vegetation cover, especially from 2021 onwards, underscores the need for effective water management and sustainable agricultural practices like climate smart crop models, introduction of drought resistant varieties, incorporation of usage ideas of anti-transpirants, development of short duration varieties so as to enhance crop productivity and address these ongoing issues. The proportion of crop condition towards the cent % is presented season wise in Fig. 9.

Impact of Water spread on crop conditions

The analysis of water spread area and crop conditions in the lower Vaigai sub-basin from 2018 to 2023 reveals a strong relationship between water availability and vegetation health. Generally, larger water spread areas positively correlate with improved crop conditions, while smaller areas lead to higher instances of sparse or no vegetation. For example, in 2018, the Kharif and summer seasons had limited water spread areas (24.39 ha and 5.55 ha respectively), resulting in 88 % of Kharif and 98 % of summer areas experiencing sparse or no vegetation. Conversely, the Rabi season, with a larger water spread of 180.68 ha, showed 74 % of the area with moderate to good vegetation. In 2019, despite the Kharif season having a mere 11.81 ha of water spread, which led to 83 % of the area with no vegetation, the Rabi season improved significantly with a water spread of 192.02 ha, leading to 57 % of the area having moderate to good vegetation.

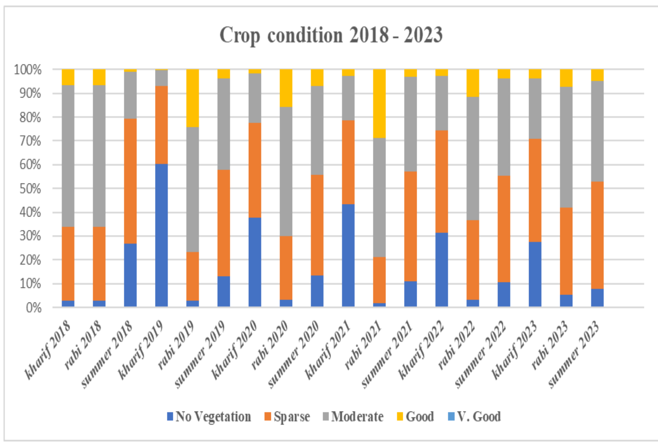

Fig. 9. Crop condition (%) of lower Vaigai sub basin - season wise - 2018 to 2023.

From 2020 to 2023, increased water spread areas during Rabi and summer generally corresponded to improved crop conditions. In 2020, the summer season with a water spread of 366.11 ha had 40 % of the area under moderate to good vegetation, compared to only 21 % in Kharif with a water spread of 10.16 ha. In 2021, water spread areas surged in Kharif (305.44 ha) and summer (386.46 ha), resulting in better crop conditions, particularly in Rabi, where 43 % of the area had moderate to good vegetation. By 2022 and 2023, water spread areas peaked in summer (478.00 ha in 2022 and 628.29 ha in 2023), correlating with improved crop conditions; however, challenges remained during Kharif seasons where 36 % of the area still had no vegetation in 2023, underscoring the need for balanced water management and other agronomic interventions to optimize crop productivity.

The research also finds that rainfall and water spread area directly impact on crop growth and conditions which was supported by previous findings (32, 33) and evident that decrease in water in tanks cause decrease in crop area (34).

Conclusion

This study on water spread area estimation in the lower Vaigai sub-basin from 2018 to 2023 using Sentinel-1A SAR and IMD rainfall data underscores the vital connection between water availability and agricultural sustainability. The results demonstrate that water spread areas are significantly influenced by rainfall, with notable peaks in summer 2023 (628.29 ha) and troughs in summer 2018 (5.55 ha) and Kharif 2020 (10.15 ha). NDVI analysis reveals variability in crop conditions, showing improved vegetation during the Rabi and summer seasons of 2019 and 2020 but increasing scarcity in 2022 and 2023. The findings of this research concluded the reduction of crop area in the Kharif and summer seasons because of lower water spread in tanks and insisted the need for adaptive strategies such as drought-resistant crops, adjusted planting schedules and supplemental irrigation, along with climate-smart agricultural practices and enhanced tank rehabilitation programs in future. These initiatives are crucial for boosting agricultural productivity, ensuring food security and fostering resilience in the face of climate variability within the lower Vaigai sub basin region.

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Authors' contributions

All the authors have contributed equally to data collection, analysis, writing the original manuscript draft, editing and reviewing.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Chat GPT in order to improve the language. After using this tool/ service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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