Original Research Article

CROP DIVERSIFICATION ASSESSMENT IN TANK AYACUT AREAS OF LOWER PALAR SUB-BASIN OF CHENGALPATTU DISTRICT, TAMIL NADU USING GEO-SPATIAL TECHNIQUES

Abstract

For the assessment of crop diversification in the major tank ayacut area of the Lower Palar sub-basin in Chengalpattu district of Tamil Nadu, research works were carried out using sentinel 2, optical data by relating with ground truth data, to identify the crops in pixel-based classification and further classified the crops using Random Forest machine learning algorithms. The total area estimated under crop classification was 58018and 58060 ha respectively for the summer seasons of 2018 and 2021. The water spread area and water volume of tanks estimated were 612.31 and 1177.89 ha and 6,39,248 and 14,06,056 m^3 respectively for 2018 and 2021. The accuracy assessment of ground truth points by confusion matrix reveals an overall classification accuracy of 94.9 % (2021) and 96.8% (2018)with kappa scores of 0.94 and 0.96 respectively. The crop diversification assessments were estimated using the Simpson Index of Diversity and values of 0.63 and 0.68 were accounted for in 2018 and 2021 respectively. The diversified pattern of crops is significantly correlated with tank water availability which increased the cropping area in 2021 as confirmed by the Crop Diversification factor.

Keywords: Crop diversification, SAR data, Random Forest Classification, Water spread, Simpson Index of Diversity.

1. Introduction

India's overall population is estimated to surpass 1.62 billion by 2050, as a result, the challenge that must be resolved is how to use fast diminishing per capita land resources in a sustainable manner(Bhumika et al. 2019).Crop diversification is the process of introducing new crops or cropping methods into an existing farm's agricultural production while taking into account the various returns from value-added crops with complementary marketing prospects. For rural people, diversification, or focusing on associate activity, is important

Comment [RK1]: Review results:
1.This manuscript is written in a very good English structure
2.The content of this paper has fully complied with the rules of scientific writing
3.This paper accepted with minor revision
4. Good paper

because it gives an opportunity to earn extra income and overcome poverty (Dimov et al. 2016). Addressing the diverse cropping patterns might aid in the adaptation of agricultural systems by way of enhancing potential production and resilience to water scarcity.

Choudhury et al. (2013) stated that crop area diversification encourages farmers to grow multiple types of crops on the same plot of land rather than just one crop (food or non-food grains). (Sharma et al. 2021) conferred a successful tactic for meeting the goals of food and nutritional security, income growth, smart use of land and water resources, increasing external input usage efficiency and sustainable agricultural development and environmental improvement. Compared to monoculture farming, diverse agricultural methods yield superior crops and are more tolerant to climate change.

Crop diversification allows farmers to plant a greater variety of crops in a given region, utilizing resources for several crops while also lowering risk. To reduce the chance of crop failure due to emphasized droughts, crop diversification and the planting of a significant amount of crops are exploited in dryland areas (Panneerselvam et al. 2022).

In Tamil Nadu, tank water is mostly used as a source of irrigation. Low Earthen bunds called tanks are built along the terrain or in a valley to store rainwater. There are 39,202 tanks scattered throughout Tamil Nadu and a tank system is comprised of components viz., catchment area, main channel, sub-channels, tank bund, water spread area, sluice outlets, command area, field distributaries, and surplus weir. Tank storage structures are the best way to store rainwater, support farmers during the growing season, and be accountable for sustainable agricultural production. By performing the on-Farm Developmental activities in the command area, the resources are must be used effectively (Krishnaveni and Rajeswari 2014)

Remote sensing has shown to be an effective and useful method of acquiring crop mapping information (Tian et al. 2022). Remote sensing encourages climate-resilient farming techniques, reduces climatic risks, improves food security, and stimulates economic development in rural areas. Crop identification through remote sensing is primarily reliant on all available imagery captured throughout the growth period and the diversified crop types possess various phenological and seasonal rhythm capabilities, as well as differing rates of growth at different seasons (Wei et al. 2023). The spatial and temporal resolution of remote sensing imagery is continuously intensifying for making raw data of crop type maps (Wang et al. 2019). Crop discrimination abilities were enhanced by combining optical pictures with single polarization images. The abilities of optical and SAR imageries to differentiate 16 different land cover categories, including 9 agricultural classes (Michelson et al. 2000). A strategy for agricultural area diversification has been created using maps of agricultural areas and crop rotations derived from remote sensing data (IRS P6-AWiFS and RADARSAT ScanSAR) together with agro-physical characteristics in a GIS context (Choudhury et al. 2013).

Crop diversity is essential for sustainable agriculture and remote sensing helps farmers and policymakers to monitor and evaluate agricultural landscapes, discovering the possibilities for diversification by utilizing satellite imagery and cutting-edge technologies (Kamble et al. 2020). Using information from several satellites and sensors are function in the visible, near-infrared, and microwave spectrum (India's RISAT-1 SAR), the crop rotation and cropping systems were mapped using data from Advanced Wide Field Sensor (AWiFS) of RESOURCESAT-2. Crop diversification was measured using the Multiple Cropping index (MCI), Area Diversity Index (ADI), and Cultivated Land Utilization Index (CLUI) (Kritika et al. 2021).

Satellite pictures are widely used to identify land use, and crop categorization has become increasingly significant in the context of precision agriculture in recent years (Viskovic et al. 2019). Several machine learning methods are used to create crop categorization models from multi-spectral and multi-temporal satellite imageries used in agricultural fields to identify the current land usage classification.

Tetteh et al. (2021) compared the Sentinel-1 and Sentinel-2 imageries of various agricultural landscapes for the accuracy assessment of agricultural fields to identify crops during the growing season by evaluating best feature set from S1 and S2 using supervised classification based multi resolution segmentation technique. Multi-temporal Landsat and Rapid Eye satellite data were used to generate yearly and multi-annual crops and Simpson index of diversity (SID) used to reveal the pattern of spatial distribution of different crops at both the local and landscape scales (Dimov et al. 2016).

In Lower Palar sub-basin area of Chengalpattu district have a major source of irrigation by PWD tanks and rice and sugarcane were major crops in Kharif and Rabi seasons and in the summer season, watermelon, groundnut, gourds and vegetables were predominant. The ~~Hence, a research work was carried out with an~~ objective of this study is to assess the crop classification and diversification for the summer seasons of 2018 and 2021 and correlation between tank water availability and its influence on cropping area and crop diversification.

2. Materials and Methods

2.1 Study area

The Chengalpattu district extends from 12° 41' 33.86" NLatitude and 79° 58' 38.28" Elongitude. The district is situated on the north east coast of Tamil Nadu with total geographic area of 2945 sq. km with an elevation from 25 to 219 m above MSL and is bounded north by Chennai district, West by Kancheepuram and Thiruvanamalai districts, and south by Vilupuram district. The coastal length of 57 km is bounded in the east by Bay of Bengal and the coastal regions prevent extreme variation in the seasonal temperature. The average annual rainfall of the district is about 1400 mm and gets most of its annual seasonal rainfall from northeast monsoon during October and November.

The river Palar is one of the major rivers in the state of Tamil Nadu traversing through Chengalpattu district for a length of 54 km. The district has 528 major irrigation tanks each having ayacut area of more than 40 ha. The total area and number of tanks in the Lower Palar sub-basin is 1044.7 sq. km and 253 respectively, out of which 581 sq. km area and 153 tanks are occupies in Chengalpattu district and the study area was depicted in the figure 1.

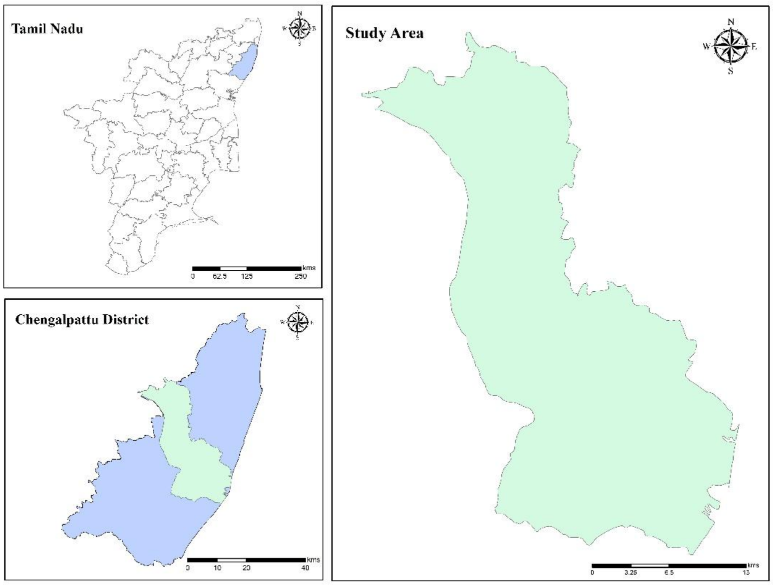

Fig. 1. Study area map of Lower Palar sub-basin of Chengalpattu district

2.2 Satellite Data

Sentinel 2 is a high resolution multi-spectral sensor operating in four spectral bands (B2 490 nm, B3 560 nm, B4 665 nm and B8 842 nm) (Table 1), provides a ground resolution of 10 m (at nadir). Sentinel 2 data is downloaded from Copernicus open access hub ESA (European Space Agency) and Google Earth Engine. The data was optimized through a series of pre-processing techniques (Fig.2) for obtaining composite bands of RGB image, Mosaic to new raster to get a single image of different passes and mask to get a Sentinel 2 images of Lower Palar sub basin of Chengalpattu district. Sentinel 1 Synthetic Aperture Radar (SAR) 10 m resolution data downloaded using python script codes in Google Earth Engine with Lower Palar sub-basin tank boundary shape files to measure the water spread in SAR data using VV polarization.

Table 1. Sentinel 2 Bands and their corresponding wavelengths

Sentinel 2 Bands	**Wavelength (µm)**	**Resolution (m)**
Band 2 – Blue	490	10
Band 3 – Green	560	10
Band 4 – Red	665	10
Band - 8 VNIR	842	10

Source: sentinels.copernicus.eu

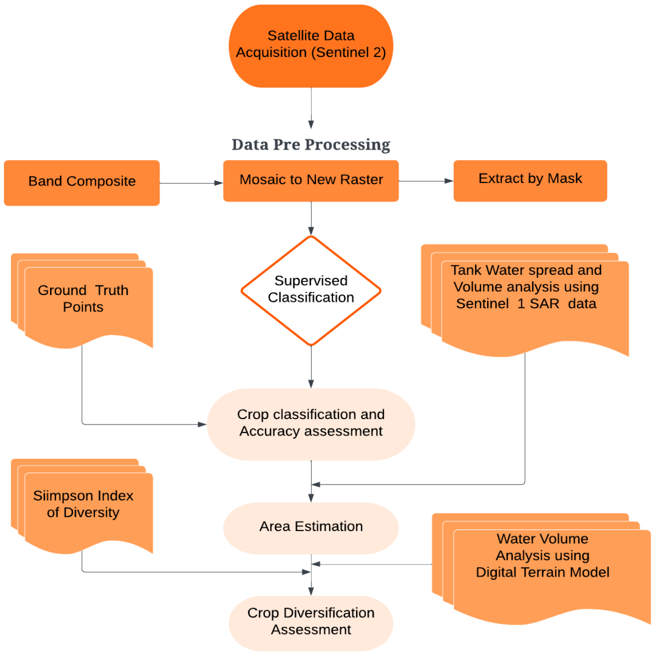

Fig.2. Methodology for mapping of crop diversification from Sentinel 2 data

2.3 Ground truth data collection

During the summer (Zaid) seasons of 2018 and 2022, a total of 530 points (262 and 268 points respectively for both years) were collected with crop details in the study area through the ground truth survey for training and validation purposes.

2.4 Crop classification using Machine learning techniques

A series of satellite imagery acquired over the period of the year, to utilize the multi-temporal aspects of satellite images and use machine learning algorithms on 15 distinct indices of the same region to identify various crops (Viskovic et al. 2019)

2.5 Accuracy assessment

The accuracy of the classification is evaluated using the error matrix and Kappa statistics. According to Kiefer et al. (1994) the pixels of agreement and disagreement are used to generate an error matrix. The Kappa Coefficient, producer accuracy, user accuracy and total accuracy were determined using this Error matrix (Congalton 1991)

3. Results and Discussion

3.1 Crop Classification and Area Estimation

Crop classification was assessed using Machine Learning algorithms like Random Forest Classifier technique. The estimated crop classification area including Forest, Barren land, Settlements and Fallow lands in Lower Palar sub basin of Chengalpattu district was 58018 and 58060 ha respectively for 2018 and 2021 summer seasons using Arc GIS (Fig.3) and the area occupies in different classes are given in table 2. The total cropped area estimated in Lower Palar sub basin of Chengalpattu district was 15768 and 28818 ha respectively in 2018 and 2021 summer season. Rice crop was distributed in an area of 8685.48 followed by sugarcane (3081.43 ha), groundnut (1901.97 ha), watermelon (1556.70), casuarina (476.24 ha) and mango (66.24 ha) for 2018, while in 2021, rice occupies an area of 14603.43 ha followed by watermelon (5191.68 ha), sugarcane (4499.34 ha), groundnut (2089.86 ha), mango (1032.10 ha) and casurina (1401.75 ha).

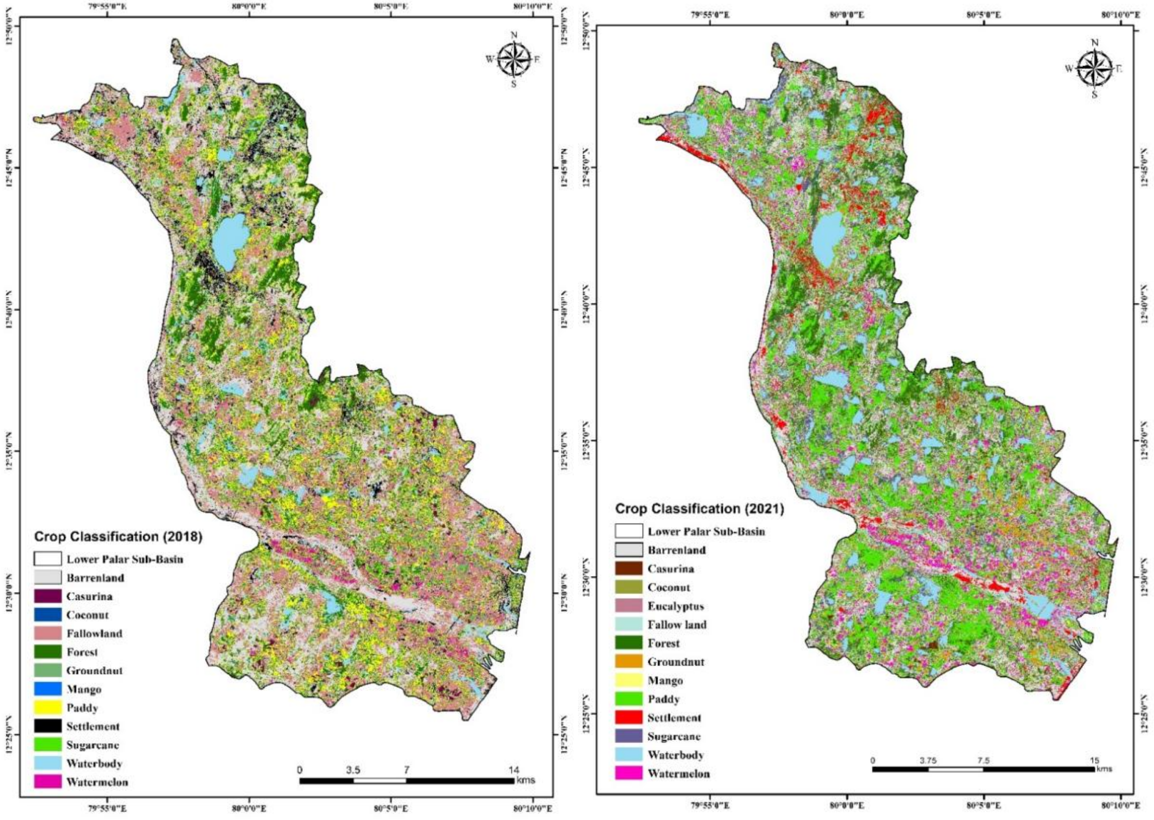

Fig. 3. Crop classification map for 2018 and 2021 summer season

Table 2.Classified Crop classes for 2018 and 2021 summer season

S.No	Class Name	Area (ha)	
		Summer 2018	Summer 2021
1	Barrenland	13772.70	12522.64
2	Casurina	476.15	1401.75
3	Coconut	804.37	1007.74
4	Fallowland	12884.46	3202.24
5	Forest	7701.33	5307.09
6	Groundnut	1901.97	2089.86
7	Mango	66.24	1032.10
8	Paddy	8685.48	14603.43
9	Settlement	3434.71	2441.38
10	Sugarcane	3081.43	4499.34
11	Water body	3652.45	4727.04
12	Watermelon	1556.70	5191.68
13	Eucalyptus	-	33.81
Total		**58018.00**	**58060.12**

3.2 Water Spread area analysis using Sentinel 1 SAR Data

3.2.1 SAR Backscattering Thresholding:

By using negative values, which are typical of water pixels, SAR backscattering intensity was examined to map water features (Fig 4). These features result from the potential of surface waters to serve as mirrors, reflecting nearly all incoming energy in the specular direction (Pham-Duc et al. 2017). In contrast to most land or vegetation characteristics, are extremely low backscatter intensity (Shen et al. 2022)

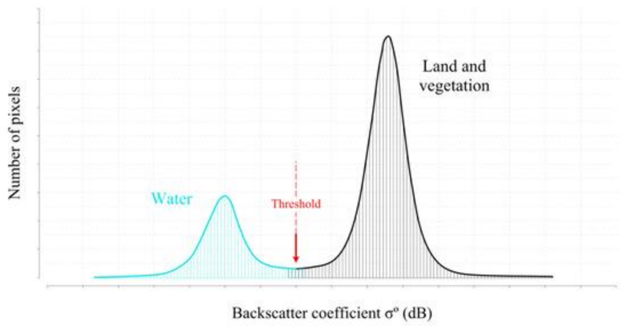

Fig 4. SAR Backscattering for Water Detection

Many research have used Google Earth Engine (GEE) algorithms to extract water bodies over lengthy periods of time because of its data storage and processing capabilities (Shen et al. 2022). Composite imageries of January to April, 2018 and 2021 (Summer season) extracted through Google Earth Engine platform and analyzed water spread area for ha using dB values -21, pixel count and spatial resolution. The estimated water spread area was 612.3 and 1177.9 ha for 2018 and 2021 summer seasons respectively (Fig.5).The estimatedwater spread area was reported as maximum in the summer 2021 season compared to 2018 summer season.

Prasad et al. (2018) extracted water pixels using VV (Vertical Vertical) and VH (Vertical Horizontal) polarization using sentinel 1 SAR data. The threshold was discovered to be -15 for VV and -21 for VH. The water image was exported to ArcGIS for vectorization and water spread area was computed by multiplying the number of water pixels by pixel area since the SAR data was resolved at a spatial resolution of 10 m, mapped maximum and minimum of water spread area in month of October and May respectively in Ghataprabha Reservoir of Karnataka.

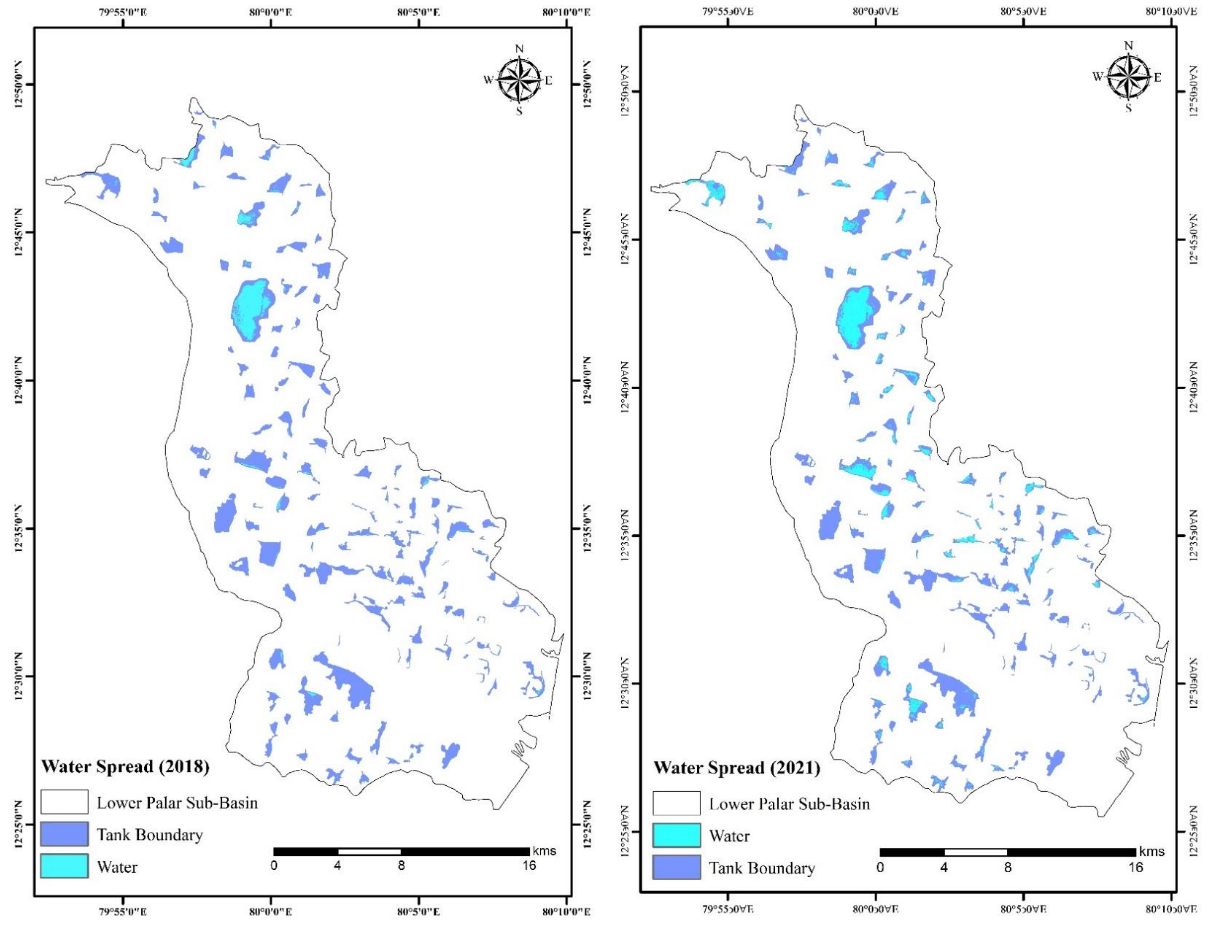

Fig. 5. Water spread area Map for 2018 and 2021 summer season

3.2.3 Water Volume Estimation

The assessment of water volume by water pixel values of tanks extracted by Sentinel 1 SAR data and Digital Terrain Model (DTM) of 143 tanks using Arc GIS software version 10.8 (Fig 6). The total water volume of 6,39,248 m^3 and 14,06,056 m^3 estimated respectively for 2018 and 2021 summer seasons and estimated water volume and DTM of Chengalpattu tankwasshown in (Fig 7). The estimated cropping area was 15767.97 ha and 28818.17 ha in 2018 and 2021 summer seasonrespectively. Based on results of volume estimation of tanks, the water availability highly influenced by the increasing cropping area by 13,050.2 ha in 2021 compared to 2018 for irrigation purposes of crops in ayacut areas of study area.

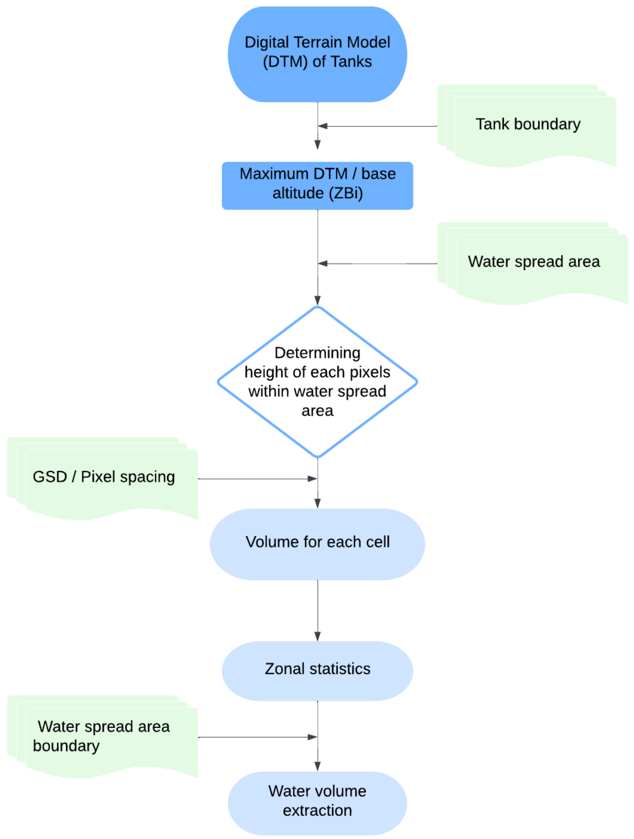

Fig.6. Methodology for Tank Water volume estimation using SAR data and DTM

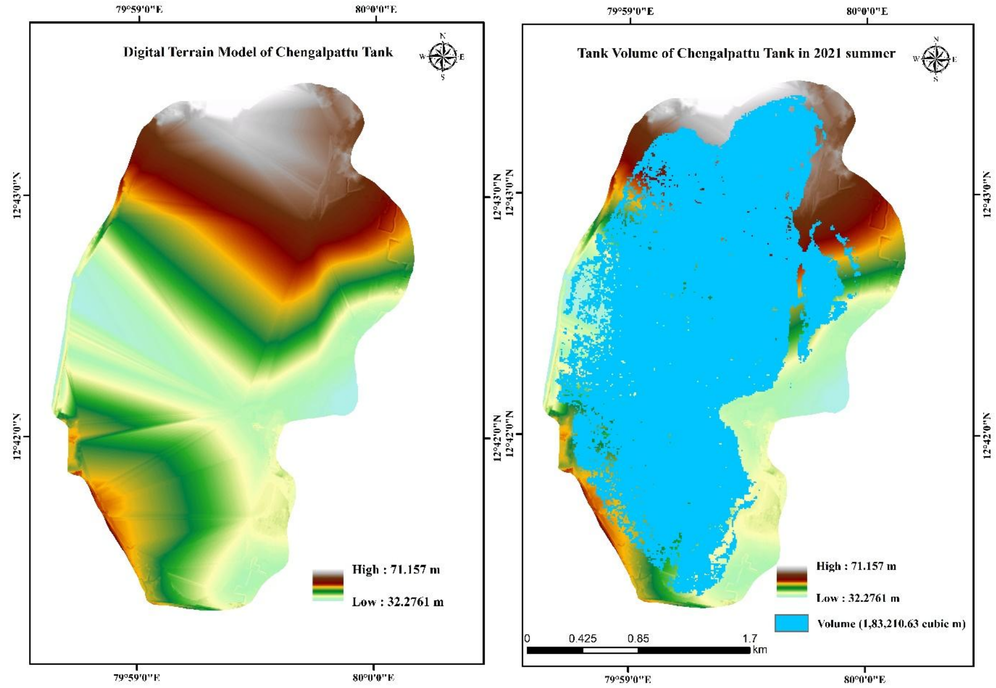

Fig. 7.DTM and Estimated Water volume of Chengalpattutank in 2021 summer

3.4 Crop Diversity Assessment

Panigrahy et al. (2003) generated the Area Diversity Index for Kharif and Rabi seasons as well as for the entire growing cycle of 2004–2005 and compared with already available cropping seasons of 1998–1999 to observe the change in the diversity of crops across the periods. Different Indexes are used for estimating the Crop Diversification over a season.

3.4.1 Simpson Index of Diversity

The Simpson Index of Diversity (Simpson, 1949) is a popular ecological indicator that measures the likelihood that the next observed plant or animal belongs to a different species. It reflects the abundance and uniformity of species within a particular region (Magurran, 2005; Dimov et al. 2016))

$$\text{SID} = 1 - \frac{\sum_{m=1}^{M} n(n-1)}{N(N-1)}$$

M is the number of classes, N is the area that is being observed, and n is the area of one class (Crop). Values around 1 implies a more diversified and heterogeneous cropping pattern, whereas a value of 0 implies monoculture in contrast. Based on classified crop areas of both summer seasons (2018 and 2021) the major agricultural crop areas viz., rice, groundnut, watermelon, sugarcane, mango and casuarina were taken for assessment of crop diversity using Simpson Index of Diversity and crop diversity values of 0.63 and 0.68 were obtained respectively for both seasons (Table 3).

The decreasing the fallow land area in 2021 (3202.24 ha)as compared to 2018 (12884.46 ha), resulting higher crop diversification (0.68) due to higher tank water availability (14,06,056.05 m^3) which ensures the use of irrigation water to middle and distal ends of ayacut and subsequently enhances the cropping area of rice, sugarcane, groundnut, watermelon, Mango and casuarina crops.

The results are mirrored to Conrad et al. (2017) generated yearly crop maps with an ' overall accuracy ranged from 0.84 to 0.86, and estimated SID values varied between 0.1 and 0.85 and the results revealed that the higher crop diversity occurred in the more distal parts of irrigation system and sparsely settled areasand patches of diversified crops area with monocultures in surrounding areas. Dimov et al. (2016) assessed crop diversity in summer crop fields, garden and orchard plots in Fergana Valley in Uzbekistan with mean SID value of 0.65 was noticed and concluded that these areas are having a relatively high cropping system diversity.

Table 3. Simpson Index of Diversity (SID) and Tank water spread

S.No	Crop	Area (ha)	
		Summer 2018	Summer 2021
1.	Paddy	8685.48	14603.43
2.	Sugarcane	3081.43	4499.34
3.	Groundnut	1901.97	2089.86
4.	Watermelon	1556.70	5191.68
5.	Mango	66.24	1032.10
6.	Casuarina	476.15	1401.75
Total		**15767.97**	**28818.17**
Fallow land		**12884.46**	**3202.24**
Tank Water Spread		**612.31**	**1177.89**
Tank Volume (m^3)		**6,39,247.95**	**14,06,056.05**
Simpson Index of Diversity		**0.63**	**0.68**

3.4 Accuracy Assessment

Crop and other non-crop validation points collected during ground truth with the classified output of crop classes. The typical confusion matrix was used to assess the accuracy level and a total accuracy of 96.8 and 94.9 % in 2018 and 2021 was obtained in summer seasons respectively. The Kappa index of 0.96 and 0.94 was attained, which shows a field level good accuracy value (Table 4 & 5). The findings were similar to Sentinel-2 satellite imagery was used to map wetlands (Kaplan and Avdan 2017), with a kappa score of 0.95 and an overall accuracy of 99%. Although (Belgiu and Csillik 2018) reported that cropland mapping under three distinct climatic conditions produced accuracy ranging from 78.08 to 96.19% using high-resolution satellite data.

Table 4. Confusion Matrix for accuracy assessment for 2018 summer season

Class	Barren land	Casurina	Coconut	Fallow land	Forest	Groundnut	Mango	Paddy	Settlement	Sugarcane	water body	Watermelon	Total	User Accuracy
Barren land	13	0	0	0	0	0	0	0	0	0	0	0	13	1
Casurina	0	5	0	0	0	0	0	0	0	0	0	0	5	1
Coconut	0	0	4	0	0	0	0	0	0	0	0	0	4	1
Fallow land	0	0	0	13	0	0	0	0	0	0	0	0	13	1
Forest	0	1	0	0	7	0	0	0	0	0	0	0	8	0.88
Groundnut	0	0	0	0	0	4	0	0	0	0	0	0	4	1
Mango	0	0	0	0	0	0	1	0	0	0	0	0	1	1
Paddy	0	0	0	0	0	0	0	12	0	0	0	1	13	0.92
Settlement	0	0	0	0	0	0	0	0	9	0	0	0	9	1
Sugarcane	0	0	0	0	0	0	0	0	0	4	0	0	4	1
Water body	0	0	0	0	0	0	0	1	0	0	9	0	10	0.9
Watermelon	0	0	0	0	0	0	0	0	0	0	0	10	10	1
Total	13	6	4	13	7	4	1	13	9	4	9	11	91	

Producer Accuracy	1	0.83	1	1	1	1	1	0.92	1	1	1	0.91		96.8

Table 5. Confusion Matrix for accuracy assessment for 2021 summer season

Class	Barren land	Casurina	Coconut	Eucalyptus	Fallow land	Forest	Groundnut	Mango	Paddy	Settlement	Sugarcane	water body	Watermelon	Total	User Accuracy
Barren land	15	0	0	0	0	0	0	0	0	0	1	0	0	16	0.94
Casurina	0	7	0	0	0	0	0	0	0	0	0	0	0	7	1
Coconut	0	0	6	0	0	0	0	0	0	0	0	0	0	6	1
Eucalyptus	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1
Fallow land	0	0	0	0	7	0	0	0	2	0	0	0	0	9	0.78
Forest	0	0	0	0	0	9	0	0	2	0	0	0	0	11	0.82
Groundnut	0	0	0	0	0	0	7	0	0	0	0	0	0	7	1
Mango	0	0	0	0	0	0	0	6	0	0	0	0	0	6	1
Paddy	0	0	0	0	0	0	0	0	20	0	0	0	0	20	1
Settlement	0	0	0	0	0	0	0	0	0	4	0	0	0	4	1
Sugarcane	0	0	0	0	0	0	0	0	0	0	8	0	0	8	1
Water body	0	0	0	0	0	0	0	0	0	1	0	10	0	11	0.91
Watermelon	0	0	0	0	0	0	0	0	0	0	0	0	12	12	1
Total	15	7	6	1	7	9	7	6	24	5	9	10	12	112	
Producer Accuracy	1	1	1	1	1	1	1	1	0.83	0.80	0.89	1	1		94.9

4. Conclusion:

The Sentinel 2 satellite data and machine learning approach was used to map the Crop classification and Sentinel 1 (SAR) was used to extract the Tank water spread area and Tank water availability influencing cropping areas and Crop diversification in Lower Palar region of Chengalpattu District. The area of different crop was spatially estimated as 58018and 58060 ha for the year 2018 and 2021 of summer season respectively. The overall accuracy attained for 2018 summer season was 91.4 *per cent* with a kappa index of 0.90 while in 2021 summer season 94.9 *per cent* with a kappa index of 0.94. The estimated area is found to be in good agreement with variety of crops. The estimated Crop Diversification (Simpson Index of Diversity) was 0.63 and 0.68 which shows the significant impact on Tank water availability which is highly influenced the cropping area of different agricultural crops and Crop Diversification in 2021 summer season as compared to 2018. The assessment of the crop diversity helps farmers and policymakers to monitor and evaluate agricultural landscapes, crop health, assisting in decision-making to utilise the land and resources.

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