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Evaluating Biophysical Impacts of Watershed Interventions Using Time-Series Satellite Data: A Study in Semi-Arid Andhra Pradesh

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ABSTRACT

This study demonstrates the critical role of satellite data in monitoring and evaluating NRM interventions in semi-arid, rain-fed agricultural regions. This study evaluates the biophysical impacts of Watershed level interventions in Bandlapalle village, Anantapur district, Andhra Pradesh, using time-series satellite data. Landsat-TM data (2006–2022) was utilized for seamless temporal analysis, with 2006 as the base year due to the commencement of MGNREGA and IWMP projects during this period. The study focused on the analysis of Land Use Land Cover (LULC), Vegetation Condition Index (VCI), Normalized Difference Water Index (NDWI), and Soil Moisture Index (SMI) across three cropping seasons - Kharif, Rabi, and Zaid. LULC analysis shows an increase in agricultural land from 1839.21 ha in 2006 to 2041.45 ha in 2022, alongside a decrease in scrubland from 464.39 ha to 268.79 ha, indicating shifts in land use patterns. VCI values improved significantly, reflecting healthier vegetation over time, particularly in the Rabi season, where the high vegetation class increased from 287.12 ha in 2007 to 1539.11 ha in 2022. NDWI analysis shows an overall improvement in water availability, with high NDWI class areas expanding notably during the Kharif season, from 214.78 ha in 2006 to 2046.13 ha in 2021. Similarly, SMI analysis indicates enhanced soil moisture levels, especially during the Rabi and Zaid seasons, with medium and high moisture areas showing considerable growth. The results reflects the positive influence of watershed management and water harvesting structures, such as check dams and farm ponds, on improving land use patterns, vegetation health, water availability, and soil moisture retention.

INTRODUCTION

Roughly 80% of the global agricultural land is under rain-fed agriculture, with over 60% in South Asia alone (Wani *et al.,* 2009). These rainfed areas are identified with generally low yield levels and high on-farm water losses (Rockstrom *et al*., 2003). Their water demands are further exacerbated by the uncertainty in rainfall occurrences and its distribution in a growing population and changing climate context (Mall *et al*., 2017). Climate change is estimated to reduce agricultural income by 15-25 percent. Rain-fed arable land in the drylands is also subject to; a range of degradation hazards (Stroosnijder, 2007). Rainfed croplands' main land degradation problems, especially in central Asia, are soil erosion and soil fertility depletion (Mirzabaev, 2016). Ensuring water availability is critical for developing these dryland regions for food production and building resilience to cope with future water-related risks and uncertainties (Rockstrom *et al*., 2003).

India has 60% of the total geographical area under the rainfed area contributing 44 percent of food grains and supporting 40 percent of the population, the largest in the world, both in terms of area and value of production (Sharma *et al*., 2010). 27.7% of its total geographic area is also identified as degraded land (Sreenivas *et al*., 2021). Given the complex and diverse factors underlying watershed development, such as the social, ecological, institutional, and economic factors, besides the regional variations, the rain-fed agriculture area development in India presents a wide range of challenges as well opportunities (Venkateswarlu, 2010). Considering the strong link between land and water productivity, it is thus necessary to ensure adequate mitigation measures for preventing land degradation in addition to water management in rainfed areas. In biophysical terms, watershed management involves blending productive and protective uses of the land and water resources in an area delineated by watershed boundaries (Hamilton & Pearce, 1986). The role of watershed development is widely studied in terms of improvement and livelihoods and successfully controlling soil erosion and runoff reduction (Kerr *et al*., 2002) by a large number of researchers from both social sciences and science (Palanisami & Suresh, 2014). The conventional approaches to studying the impacts on soil and water aspects are mainly rapid reconnaissance surveys, study area profiling, and household surveys. The studies deploying automatic runoff recorder and guging stations are instrumentation intensive, and have less diligent efforts in terms of time and cost. Another, limitation of these methods is that the rigor of the individual reports varies with the capacities and understanding of the organizations involved (Wani *et al*., 2009). Thus, more evidence-based scientific studies

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are needed to address the bio-physical impacts linkable to enhancing ecosystem services.

Water, vegetation, and soil represent the three most crucial bio-physical components of the terrestrial environment and an important indicator of ecosystem health and ecosystem services. These features or biophysical characteristics are essential for studying the watershed's resource availability, utilization, and management (Rapport, 2001). The study of spatial arrangement of patches with remote sensing-derived information provides a scale-explicit context and contributes to the impacts of watershed interventions. Vegetation Indices (VIs) are effective algorithms for quantitative and qualitative evaluations of vegetation cover, vigor, and growth dynamics, among other applications (Xue & Su, 2017). Time-series satellite data analysis further provides a basis for monitoring the watershed level changes in the bio-physical variables and their quantification.

Several studies have analyzed time-series satellite data for monitoring the land use land cover changes in the watersheds (Singh *et al.*, 2021; Munoth *et al.*, 2020), their relationship with the groundwater quality (Maurya *et al.*, 2021), vegetation condition (Kumar *et al.*, 2014) and soil erosion (Mekuriaw, 2019). Thakkar *et al.* (2017) used time series data to study the watershed management programs on land use/land cover dynamics using remote sensing and GIS in the part of Khan-Kali watershed in the semi-arid region Gujarat, India. Halder *et al.* (2021) carried out the monitoring and impact assessment of the Narwa project in terms of LULC and vegetation in Kasdol block in Baloda Bazar district, Chhattisgarh. Reddy *et al.* (2022) used satellite images and GIS tools for the evaluation of nine watershed projects implemented under the Pradhan Mantri Krishi Sinchayee Yojana (PMKSY) in Chittoor District of Andhra Pradesh.The popularity of time-series analysis in various domains is substantially increased in recent years due to open access, freely available satellite images, and cloud computation platforms, such as the Google Earth Engine (GEE) (Gorelick *et al.*, 2017). This study thus aims to evaluate the effects of ongoing watershed development interventions on three critical biophysical resources viz, water, and soil by utilizing spectral indices derived from time-series satellite images, in a semi-arid village in Andhra Pradesh, India.

Study Area

The study is carried out in the Bandlapalle village is located between 14°9'2.2 N latitude and 77°43'53.64 E longitude, having total geographical area of 2261 hectares (Figure 1). It is also one of the four villages forming a part of the Anantapur-IWMP-33/2010-11 watershed project in KothacheruvuMandal in the Anantapur district of Andhra Pradesh State, India.As per the 2011 census, the total population of the village is 3895. The region is formed byhard-rock terrain of semi-arid climatic conditions with high runoff and evapotranspiration potentials. Due to the influence of geological structures, the drainage pattern is dendritic, rectangular to sub-rectangular. The area is drained Vengaperu, a tributary of the lower Thungabadra River and by few other ephemeral streams. The average rainfall in the Mandal is 622 mm. The normal temperature ranges from 15ºC in December-January to 40º C in May-June. The major agricultural commodity in the study area is paddy, groundnut and red gram.

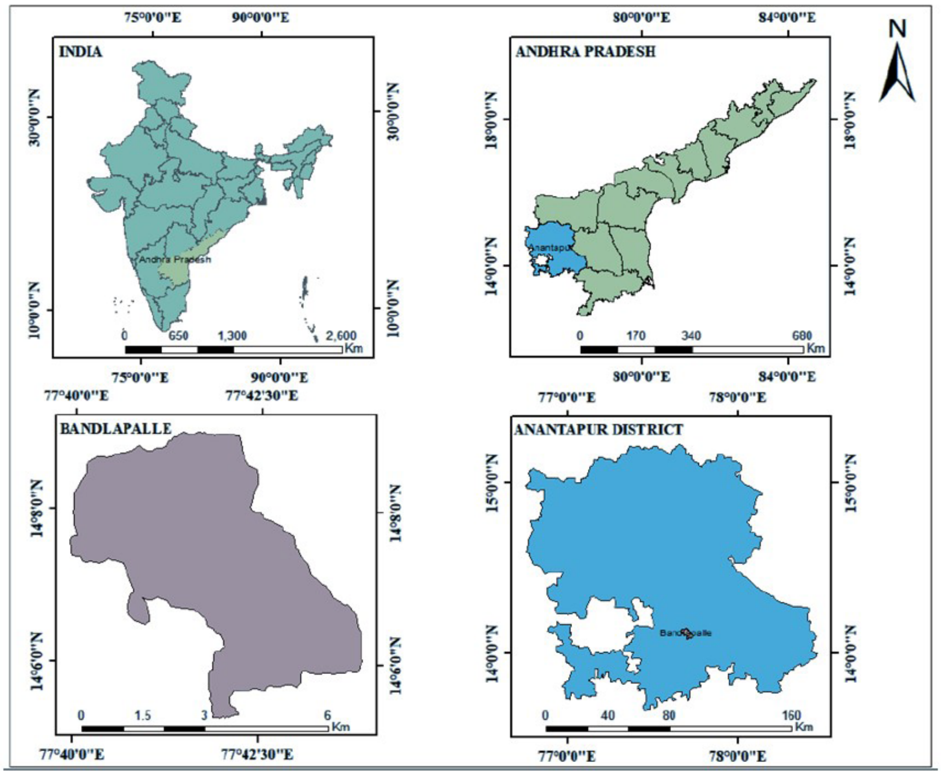

Figure 1: Study Area-Location Map

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MATERIALS AND METHODS

Satellite Data

While selecting the satellite data major considerations made included, seasonal represenation of cahnges, selection of base year and the seamless availability for temporal comparison. The rainfed regions across the globe present a juxtaposition of land use land cover patches predominantly agriculture under different cropping stages. Their temporal nature in a given region manifests as intra and interannual processes and changes (Crews-Meyer, 2004), as influenced by prevailing agriculture practices and cropping cycles depending on the agro-ecological, agro-climatic conditions. Thus, selection of satellite data also taken into consideration the coverage of three cropping season's viz., Kharif (June/July-September/October), Rabi (November/December-February/March), and Zaid (April-May) as prevalent in India. The selection of base year for monitoring the impacts of NRM works is taken up as 2006 as they are majorly taken up under Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) and PMKSY, earswhile Integrated Watershed Development Project (IWMP) since 2006 and 2009 onwards, respectively. Over 758 water conservation water harvesting structures (SWCS), mainly farm ponds, have been created in Bandlapalli under the MGNREGA, and under IWMP 58 such works; mainly the check dams have been created. Since the MGNREGA was launched in 2006, with the peak number of SWCS created in 2016-17, the selection of the base year and subsequent years for evaluating the biophysical impacts of these interventions using time-series satellite data has been considered accordingly. Although Sentinel offers better spatial resolution (10 meters), its absence during earlier periods, particularly as our study's base year is 2006, restricts its use for historical, seamless observations. Therefore, we used Landsat-TM, which ensures a consistent comparison with recent years, facilitating seamless temporal analysis (Li *et al.*, 2020).

Land Use Land Cover Mapping (LULC)

LULC mapping has been carried outfor 2006, 2016 and 2021 using the Landsat-TM satellite data. We used on-screen visual interpretation-based mapping and detection. It involves manually comparing satellite from different time periods to identify changes in land cover and land use in a given area. Visual change detection is particularly useful in regions with high spatial heterogeneity or in cases where historical data lacks the resolution or consistency needed for automated methods (Lu *et al.*, 2004). Although, it is considered to be time-consuming and may be prone to human error or subjectivity it remains particularly useful for identifying subtle changes that automated algorithms might miss (Janga *et al.*, 2023).

Table 1: Satellite data used

Satellite	Sensor	Date of Acquisition
Landsat-5	TM	01-Sep-06
Landsat-5	TM	08-Feb-07
Landsat-5	TM	29-Apr-07
Landsat-8	OLI	12-Oct-15
Landsat-8	OLI	01-Feb-16
Landsat-8	OLI	21-Apr-16
Landsat-8	OLI	18-Sep-18
Landsat-8	OLI	25-Feb-19
Landsat-8	OLI	30-Apr-19
Landsat-8	OLI	09-Aug-21
Landsat-8	OLI	17-Feb-22
Landsat-8	OLI	06-Apr-22

Spectral Indices

Spectral indices are the equations derived from satellite data that combines pixel value from two or more bands in a multispectral image. They are used to highlight particular biophysical phenomena or features depending on their interaction with a particular wavelength with the electromagnetic spectrum as manifested in the satellite data, individual bands. Aligning with to study requirement of studying the impacts of watershed interventions in the study area, the spectral indices used are:

Vegetation Condition Index

The Vegetation Condition Index (VCI) relates the current decadal Normalized Difference Vegetation Index (NDVI) to its long-term minimum and maximum, normalized by the historical range of NDVI values for the same decade (Kogan, 1990). It is derived as follows:

VCI = (NDVI-NDVImin)/(NDVImax- NDVImin) ...(1)

The NDVI is the most basic and widely used spectral index for assessing vegetation condition, mainly in terms of its vigor and health. It quantifies vegetation by measuring the difference between the near-infrared band which vegetation strongly reflects and the red wavelength band which vegetation absorbs (Rouse, 1974). It is calculated as follows:

NDVI= (NIR-R)/(NIR+R) ...(2)

The table 2 shows the statistics of input NDVI Images from 2006/7 to 2021/22 across the seasons as used in the study.

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Table 2: NDVI statistics from 2006/7 to 2021/22 across the seasons

Kharif				
Year	**Min**	**Max**	**Mean**	**SD**
2006	0.02	0.75	0.27	0.08
2015	-0.08	0.73	0.46	0.09
2021	0.14	0.75	0.50	0.10
Rabi				
Year	**Min**	**Max**	**Mean**	**SD**
2007	0.05	0.60	0.17	0.08
2016	0.05	0.80	0.32	0.11
2022	-0.04	0.66	0.31	0.08
Zaid				
Year	**Min**	**Max**	**Mean**	**SD**
2007	0.02	0.53	0.12	0.05
2016	0.07	0.69	0.23	0.08
2022	-0.02	0.64	0.28	0.09

Normalized Difference Water Index

The Normalized Difference Water Index (NDWI) is known to be strongly related to plant water content and is therefore considered a reliable proxy for plant water stress. Different studies have demonstrated its usefulness for drought monitoring and early warning (Gu *et al.*, 2007; Ceccato *et al.*, 2002). It is computed using near-infrared (NIR) and short-wave infrared (SWIR) reflectance (GAO, 1996).

NDWI = (NIR-SWIR)/(NIR+SWIR) ...(3)

Soil Moisture Index

Soil moisture is a critical land surface variable affecting various climatological, agricultural, and hydrological processes.It influences the exchange of water and energy fluxes at the land surface/atmosphere interface. It can be derived using various methods, including in situ monitoring, remote sensing, and numerical modeling (Wang & Qu, 2009). For this study, we calculated soil moisture index (SMI) using the Land Surface Temperature (LST) as a proxy (eq 4). Determining LST is complex as it is more sensitive to changes in vegetation density and captures additional information on the biophysical controls on surface temperatures, such as surface roughness and transpirational cooling (Oyler *et al.*, 2016). We followed the method given by Janani *et al.* (2024) for computing LST. The output map was classified into three class viz. 0 to 0.25: Low; 0.25 to 0.5: Medium; 0.5 to 1: High.

SMI = (LSTmax-LST)/(LSTmax-LST) ...(4)

The table 3 shows the statistics of input LST images from 2006/7 to 2021/22 across the seasons as used in the study.

Table 3: LST statistics (in Celsius) from 2006/7 to 2021/22 across the seasons

Kharif				
Year	**Min**	**Max**	**Mean**	**SD**
2006	24.97	33.66	30.57	1.26
2015	21.25	30.39	26.24	1.18
2021	21.20	30.30	26.38	1.29
Rabi				
Year	**Min**	**Max**	**Mean**	**SD**
2007	24.54	36.04	32.15	1.75
2016	17.72	36.04	29.08	2.92
2022	23.53	34.59	29.72	1.85
Zaid				
Year	**Min**	**Max**	**Mean**	**SD**
2007	30.82	39.92	36.87	1.28
2016	33.19	42.96	40.33	1.38
2022	29.31	42.48	37.39	2.35

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RESULTS AND DISCUSSION

Results

Land Use Land Cover (LULC)

The LULC analysis for the years 2006, 2015, and 2022 demonstrates notable changes across different classes in the study area (Figure 2, Table 4). Agricultural land, which accounted for 1839.21 ha in 2006, increased to 1906.14 ha in 2015 and further expanded to 2041.45 ha by 2022, reflecting a steady rise in cultivated areas over time. Forest cover, however, remained constant throughout the period, occupying 66.44 ha, indicating the preservation of forest areas. Similarly, river areas remained unchanged at 26.16 ha across the years. The area classified as rocky decreased from 82.41 ha in both 2006 and 2015 to 61.06 ha in 2022, potentially due to land use conversion or erosion processes. Scrubland experienced a significant decline from 464.39 ha in 2006 to 397.45 ha in 2015, and further reduced to 268.79 ha by 2022, suggesting land degradation or a shift in land use patterns. Settlement areas showed a slight increase from 34.63 ha in 2006 and 2015 to 37.24 ha by 2022, reflecting urban growth. Water bodies exhibited a notable expansion from 3.62 ha in 2006 and 2015 to 15.71 ha by 2022, likely due to the creation of artificial reservoirs or the restoration of natural water bodies. These LULC changes indicate dynamic land use patterns, with expansion in agricultural, settlements and shifts in natural land cover being the dominant trends over the 16-year period.

Table 4: Change in Land Use Land Cover area (in ha)

LULC Class	**Year- 2006**	**2015**	**2022**
Agriculture	1839.21	1906.14	2041.45
Forest	66.44	66.44	66.44
River	26.16	26.16	26.16
Rocky	82.41	82.41	61.06
Scrub	464.39	397.45	268.79
Settlements	34.63	34.63	37.24
Waterbody	3.62	3.62	15.71
Total Geographic Area	**2516.85**		

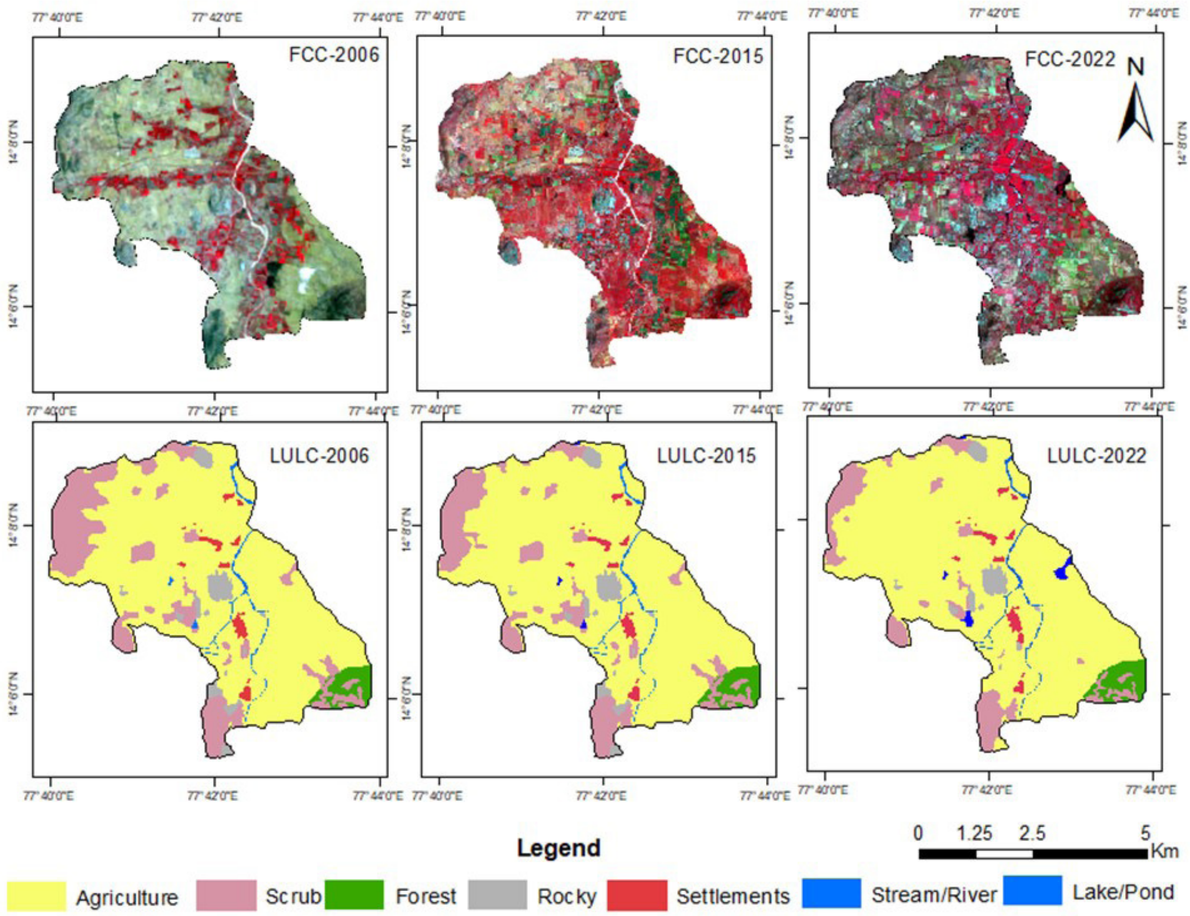

Figure 2: False Color Composite Image & Land Use Land Cover Maps (2006, 20015 and 2022)

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Vegetation Condition Index (VCI)

The Vegetation Condition Index (VCI) from 2006/07 to 2021/22 across the Kharif, Rabi, and Zaid seasons show an overall improvement in vegetation health over time (Figure 3, Table 5). In the Kharif season, the mean VCI increased from 0.35 in 2006 to 0.68 in 2015, though it slightly decreased to 0.57 in 2021. Similarly, the Rabi season shows a consistent rise in the mean VCI from 0.21 in 2007 to 0.59 in 2022, indicating better vegetation conditions. The Zaid season also reflects an improvement, with the mean VCI increasing from 0.20 in 2007 to 0.38 in 2022 (Table 5).

Table 5: VCI image statistics from 2006/7 to 2021/22 across the seasons

Kharif				
Year	**Min**	**Max**	**Mean**	**SD**
2006	0	1	0.35	0.11
2015	0.07	1	0.68	0.11
2021	0	1	0.57	0.17
Rabi				
Year	**Min**	**Max**	**Mean**	**SD**
2007	0	1	0.21	0.14
2016	0	1	0.35	0.14
2022	0	1	0.59	0.14
Zaid				
Year	**Min**	**Max**	**Mean**	**SD**
2007	0	1	0.20	0.09
2016	0	1	0.26	0.12
2022	0.02	1	0.38	0.15

The VCI class-wise area across the Kharif, Rabi, and Zaid seasons indicates a trend of decreasing areas in the low and medium classes, with a corresponding increase in the high and very high classes over the years (Table 6). In the Kharif season, the low class area decreased dramatically from 7.84 ha (0.31%) in Sep 2006 to 0.95 ha (0.04%) in Aug 2021, while the high class area increased significantly from 1050.16 ha (41.73%) to 1534.95 ha (60.99%). Similarly, in the Rabi season, the low class area dropped from 339.84 ha (13.50%) in Feb 2007 to 0.78 ha (0.03%) in Feb 2021, with the high class area rising from 287.12 ha (11.41%) to 1539.11 ha (61.16%). The Zaid season follows the same pattern, with the low class area decreasing from 78.61 ha (3.12%) in Apr 2007 to 0.52 ha (0.02%) in Apr 2022, and the high class area increasing from 189.84 ha (7.54%) to 1641.66 ha (65.23%).

Table 6: VCI Classes Area (in ha) from 2006/7 to 2021/22 across the seasons

Kharif				
Year	**Low**	**Medium**	**High**	**Very High**
2006	7.84	1409.14	1050.16	49.49
2015	0.87	279.53	1218.73	1017.50
2021	0.95	144.91	1534.95	835.82
Rabi				
Year	**Low**	**Medium**	**High**	**Very High**
2007	339.84	1820.72	287.12	68.95
2016	3.38	1337.23	1022.77	153.25
2022	0.78	683.15	1539.11	293.58
Zaid				
Year	**Low**	**Medium**	**High**	**Very High**
2007	78.61	2235.07	189.84	13.11
2016	50.50	1949.47	472.35	44.32
2022	0.52	626.69	1641.66	247.75

Normalized Difference Water Index (Normalized Difference Water Index)

The Normalised Difference Water Index from 2006/07 to 2021/22 across the Kharif, Rabi, and Zaid seasons also showed an overall improvement over time (Figure 4, Table 7). The NDWI statistics for Kharif, Rabi, and Zaid seasons across the years reveal notable trends in water content in the studied region (table 9). The Kharif season demonstrates a positive trend, with the mean NDWI rising from -0.03 in 2006 to 0.2 in 2021, suggesting enhanced water content during this period. In the Rabi season, the mean NDWI shows a steady increase from -0.13 in 2007 to -0.02 in 2021, indicating a gradual improvement in water availability during this season. In contrast, the Zaid season shows a slight improvement in mean NDWI, moving from -0.15 in 2006 to -0.08 in 2021. Across all seasons, the standard deviation (SD) values indicate increasing variability over the years, reflecting more fluctuating water conditions. These trends may be influenced by various factors such as changing climatic patterns and irrigation practices.

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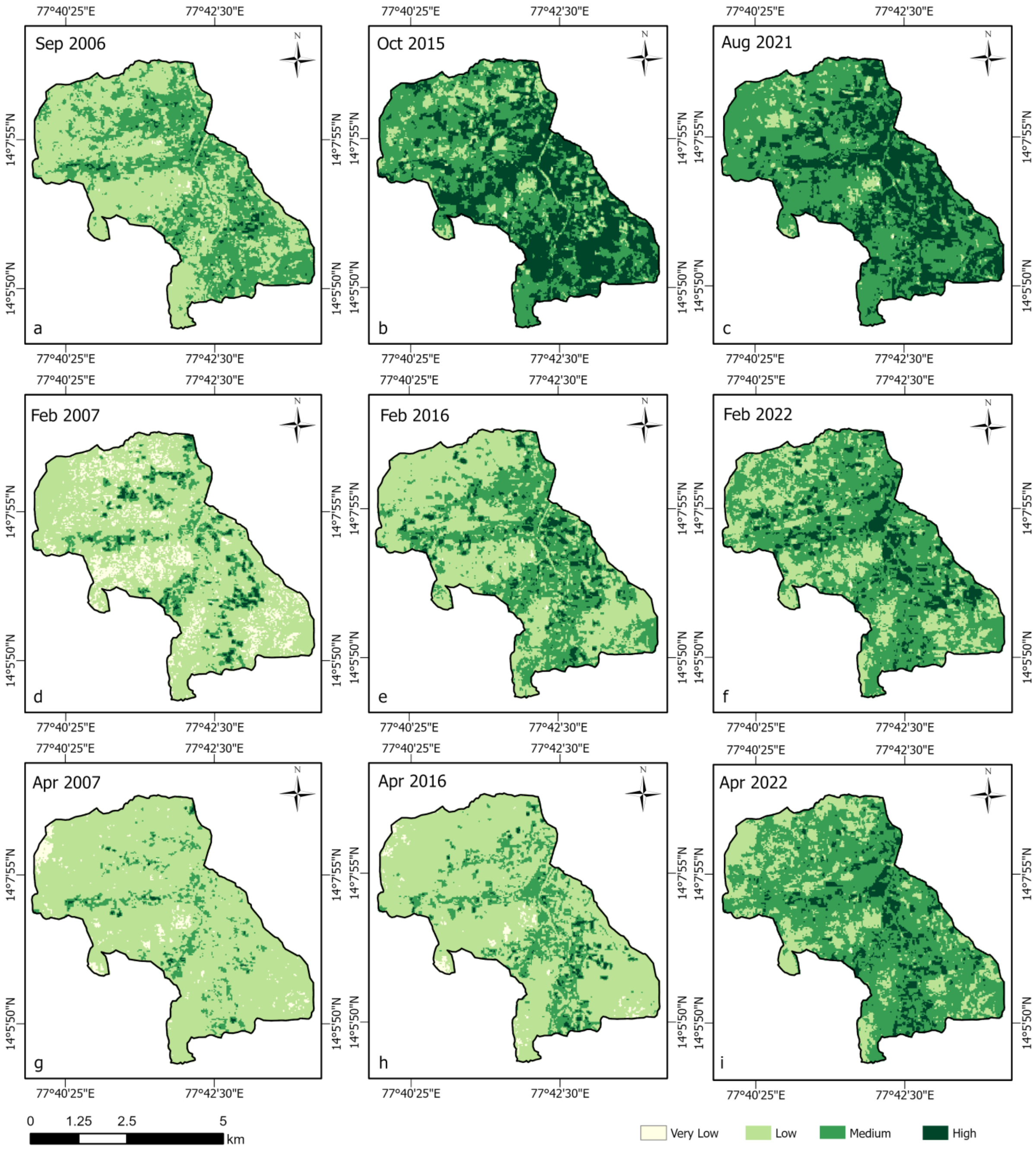

Figure 3: VCI maps from 2006/7 to 2021/22 across the seasons

Table 7: NDWI image statistics from 2006/7 to 2021/22 across the seasons

Kharif				
Year	**Min**	**Max**	**Mean**	**SD**
2006	-0.19	0.44	-0.03	0.08
2015	-0.14	0.45	0.17	0.1
2021	-0.07	0.46	0.2	0.1
Rabi				
Year	**Min**	**Max**	**Mean**	**SD**
2007	-0.26	0.38	-0.13	0.1
2016	-0.23	0.59	-0.04	0.12
2022	-0.65	0.55	-0.02	0.16
Zaid				
Year	**Min**	**Max**	**Mean**	**SD**
2006	-0.24	0.3	-0.15	0.05
2015	-0.24	0.46	-0.1	0.08
2022	-0.22	0.42	-0.08	0.1

The analysis of area under NDWI classes also shows significant changes across the Kharif, Rabi, and Zaid seasons (Table 8). In the Kharif season, the "Low" NDWI class dropped from 171.14 ha (6.59%) in 2006 to just 1.52

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ha (0.06%) in 2015, disappearing completely by 2021. The "Medium" class also declined from 2120.97 ha (81.64%) in 2006 to 460.77 ha (18.36%) by 2021, while the "High" class increased from 214.78 ha (8.27%) to 2046.13 ha (81.64%) over the same period, reflecting improved water retention. In the Rabi season, the "Low" class reduced from 1919.07 ha (72.91%) in 2007 to 781.68 ha (30.46%) by 2022. Meanwhile, the "Medium" class grew from 467.47 ha (17.76%) to 1316.40 ha (51.31%), and the "High" class expanded from 120.36 ha (4.57%) to 408.81 ha (15.93%), indicating improved water availability. For the Zaid season, the "Low" class dropped from 2231.49 ha (84.76%) in 2007 to 1660.83 ha (64.00%) by 2022. The "Medium" class initially rose from 262.35 ha (9.96%) in 2007 to 754.95 ha (28.66%) in 2016 but decreased to 570.39 ha (21.98%) by 2022. The "High" class saw a substantial increase from 13.05 ha (0.50%) to 275.67 ha (10.62%), reflecting better water conditions in this off-season.

Table 8: NDWI Classes Area (in ha) from 2006/7 to 2021/22 across the seasons

Kharif			
Year	**Low**	**Medium**	**High**
2006	171.14	2120.97	214.78
2015	1.52	659.72	1845.66
2021	0.00	460.77	2046.13
Rabi			
Year	**Low**	**Medium**	**High**
2007	1919.06	467.47	120.35
2016	939.95	1238.60	328.33
2022	781.68	1316.39	408.81
Zaid			
Year	**Low**	**Medium**	**High**
2007	2231.50	262.35	13.06
2016	1668.34	754.95	83.60
2022	1660.83	570.39	275.67

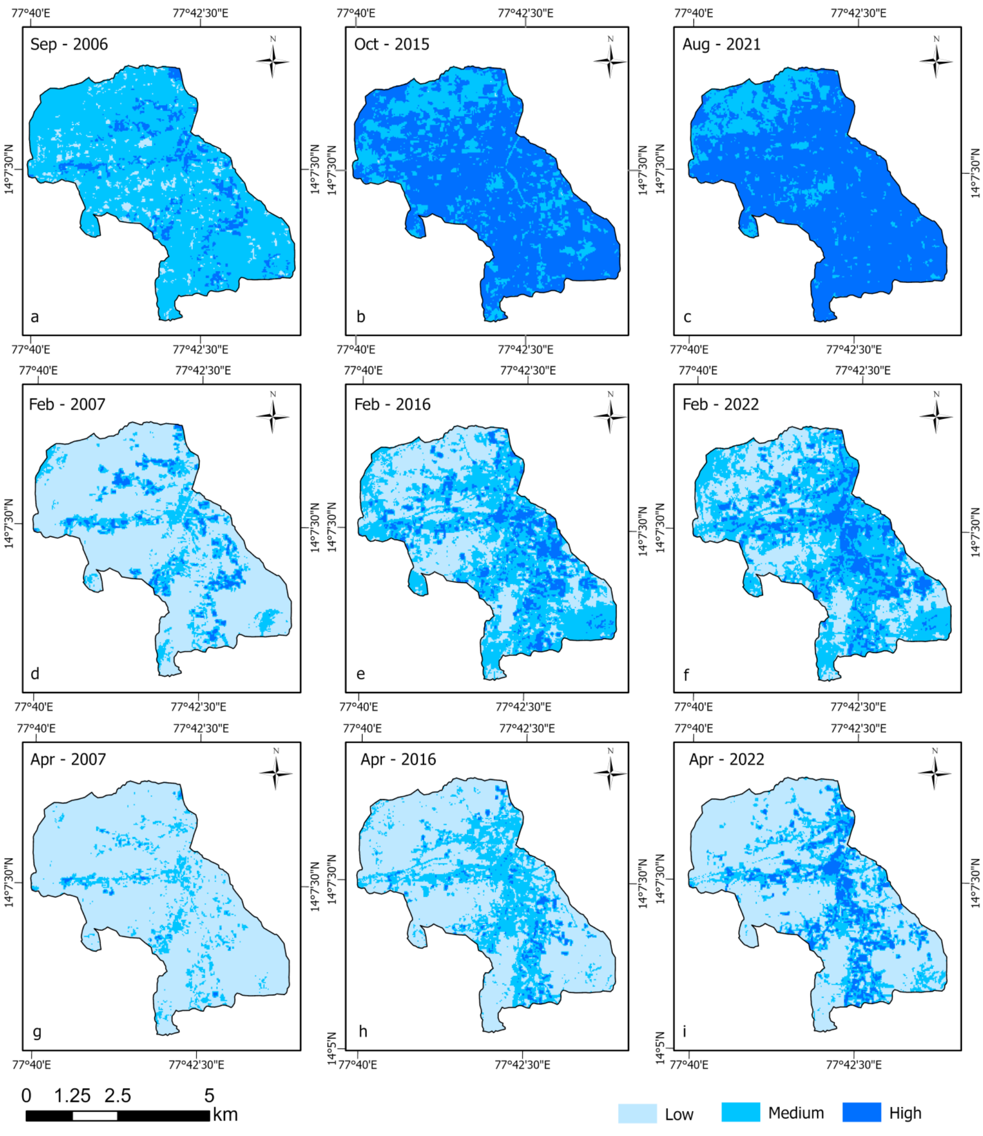

Figure 4: NDWI maps from 2006/7 to 2021/22 across the seasons

Soil Moisture Index (SMI)

Temporal variation in the soil moisture index from 2006/07 to 2021/22 is presented in Figure 5 and Table 9. During the Kharif season, in 2006, 659.90 ha (31%) of the area had low moisture, 1411.90 ha (66%) had medium moisture, and 435.09 ha (20%) had high moisture. By 2015, the low moisture area dropped to 94.57 ha (4%), while the medium moisture area increased to 1742.83 ha (73%), and the high moisture area rose to 669.49 ha (28%). In 2021, 278.05 ha (10%) had low moisture, 1600.25 ha (61%) had medium moisture, and 628.59 ha (24%) had high moisture.For the Rabi season, in 2007, 898.29 ha (35%) of the area had low moisture, 1286.80 ha (51%) had medium moisture, and 321.79 ha (13%) had high moisture. By 2016, the low moisture area decreased to 462.59 ha (17%), while medium moisture rose to 1551.46 ha (57%) and high moisture increased to 492.84 ha (18%). In 2022, low moisture covered 330.57 ha (13%), medium moisture accounted for 1297.18 ha (52%), and high moisture expanded to 879.13 ha (35%). In the Zaid season, in 2007, 603.56 ha (25%) of the area was under low moisture, 1590.05 ha (65%) under medium moisture, and 313.27 ha (13%) under high moisture. By 2016, the low moisture area slightly decreased to 466.93 ha (18%), medium moisture increased to 1645.06 ha (63%), and high moisture covered 394.90 ha (15%). In 2022, low moisture accounted for 620.78 ha (28%), medium moisture for 1246.88 ha (56%), and high moisture for 639.23 ha (29%). The SMI results thus indicate a general shift towards higher moisture areas in recent years, especially in the Rabi and Zaid seasons.

Table 9: SMI class area (in ha) from 2006/7 to 2021/22 across the seasons

Kharif			
Year	**Low**	**Medium**	**High**
2006	659.90	1411.90	435.09
2015	94.57	1742.83	669.49
2021	278.05	1600.25	628.59
Rabi			
Year	**Low**	**Medium**	**High**
2007	898.29	1286.80	321.79
2016	462.59	1551.46	492.84
2022	330.57	1297.18	879.13
Zaid			
Year	**Low**	**Medium**	**High**
2007	603.56	1590.05	313.27
2016	466.93	1645.06	394.90
2022	620.78	1246.88	639.23

Discussion

The transformation of rain-fed rural landscapes in India, particularly through watershed interventions, is a critical area of study given the predominance of rain-fed agriculture in the region. This study underscores the importance of spatio-temporal evidence in evaluating the effectiveness of watershed management programs in transforming these landscapes. The use of spatio-temporal data, particularly from satellite sources like Landsat and Sentinel-2, has provided invaluable insights into the changes in vegetation and land use patterns over time. The VCI and NDVI reveal significant improvements in vegetation health across the Rabi, Kharif, and Zaid seasons from 2007 to 2021. These indices have shown an overall positive trend, indicating successful implementation of watershed interventions and better agricultural practices The increase in their values across seasons highlights the enhanced vigor and productivity of vegetation, which is a direct result of improved water management and soil conservation practices (Singh *et al.*, 2021).

The NDWI data further support the positive impact of watershed interventions on water availability. The increasing variability in water content, as indicated by the rising standard deviation values across seasons, suggests that while overall water availability has improved, there are fluctuations that may be attributed to seasonal climatic variations and differential water retention capacities of the soil (Kundu *et al.*, 2020). The soil moisture index derived from LST data corroborates these findings, showing a shift towards higher soil moisture levels, which is critical for sustaining agriculture in semi-arid regions (Naga Rajesh *et al.*, 2023). .

Moreover, farm pond interventions have contributed to temperature stabilization and moderation in the local microclimate. The relatively stable variation in mean temperatures across most seasons suggests that these ponds help buffer temperature fluctuations by improving moisture retention (Riley *et al.*, 2018). Notably, years like Rabi 2016 and Zaid 2022 saw higher temperature variability, possibly due to external factors. Over time,

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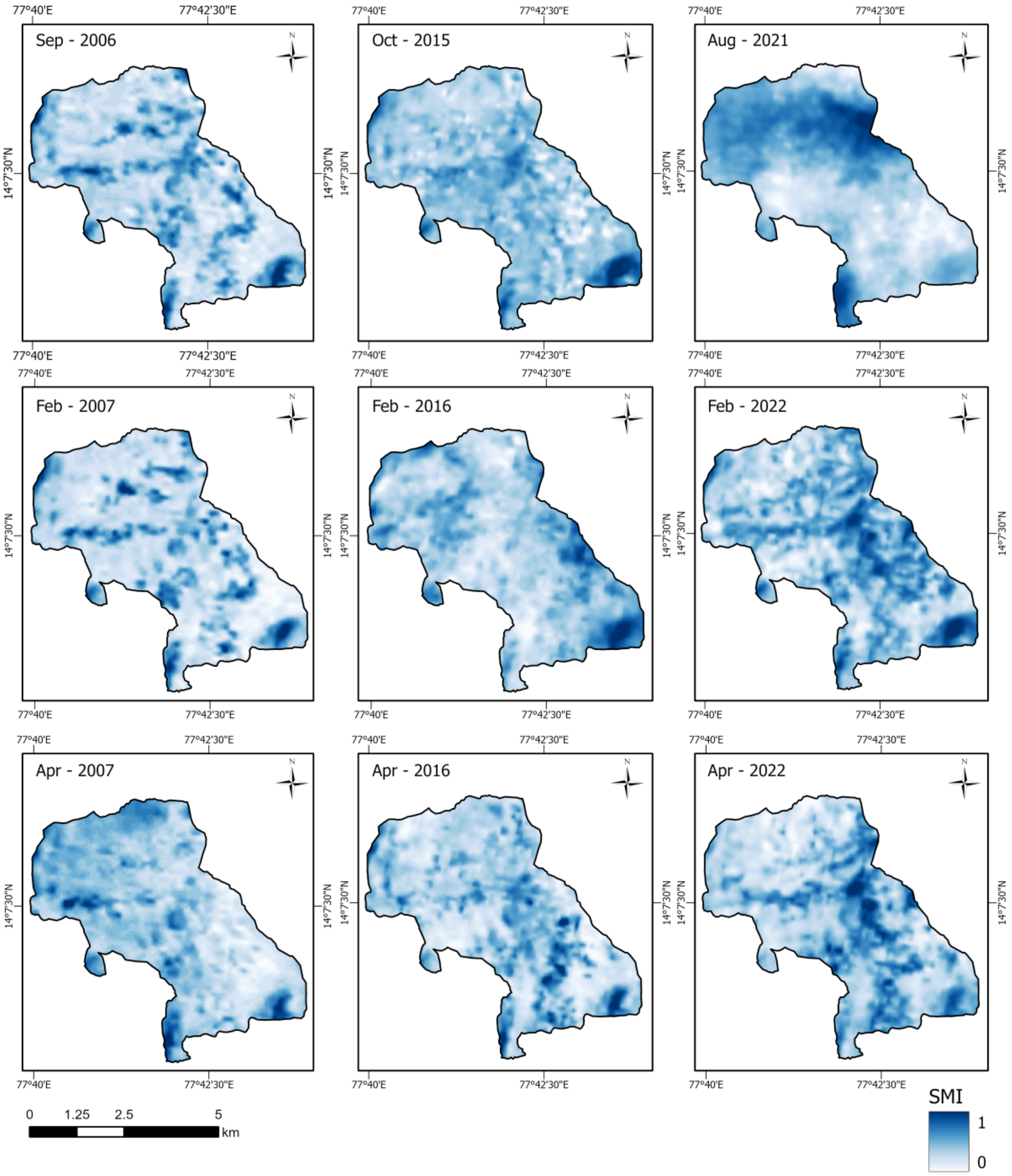

Figure 5: SMI maps from 2006/7 to 2021/22 across the seasons

there's a slight cooling trend in Kharif and Rabi seasons, with mean temperatures decreasing, likely due to the cooling effect of farm ponds. Additionally, the presence of these ponds has contributed to a more regulated microclimate, particularly in the Rabi and Zaid seasons. The LULC analysis shows only a slight increase in agricultural areas, which could be due to the conversion of scrubland into farmland as water availability improved. The dominance of agriculture in the study area, with 78% coverage, reflects the successful transition of marginal lands into productive agricultural zones. These findings suggest that while the overall increase in agricultural land may be modest, the quality and productivity of these lands have significantly improved, contributing to better livelihoods for the rural population.

CONCLUSION

This study demonstrates the effectiveness of watershed interventions in transforming rain-fed rural landscapes in India. The use of spatio-temporal data and spectral indices has provided robust evidence of improvements in vegetation health, water availability, and land use patterns. These changes are crucial for enhancing agricultural productivity and building resilience against climate change in rain-fed regions. Future studies should focus on integrating more advanced remote sensing technologies and ground-truthing methods to further refine the understanding of these transformations and guide policy decisions for sustainable rural development.

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