Quaternary Science Advances 15 (2024) 100214

Contents lists available at ScienceDirect

Quaternary Science Advances

journal homepage: www.sciencedirect.com/journal/quaternary-science-advances

Variation of ecosystem resilience across the anthropogenic biomes of India: A comprehensive analysis

Subhojit Shaw [a,*], Aparajita Chattopadhyay [a], Karikkathil C. Arun Kumar [b]

[a] Department of Population and Development, International Institute for Population Sciences, Mumbai, India
[b] L&T Technology Services, Hyderabad, Telangana, India

ARTICLE INFO

Keywords:
Anthropogenic biome
Ecosystem resilience
Drought
Net primary productivity
India

ABSTRACT

Quantifying ecosystem resilience under drought is crucial for sustainable development strategies. This study aims to investigate the spatial and temporal variability of Net Primary Productivity (NPP) across anthropogenic biomes in India (2000 to 2020) and to understand the post-drought long-term ecosystem resilience. A time series study of monthly precipitation, standardized precipitation index (SPI), and NPP were applied to understand ecosystem resilience across twenty anthropogenic biomes. Mann-Kendall test was used to quantify the magnitude and direction of the trend. In addition, bivariate raster maps of mean precipitation and soil moisture were presented in relation to ecosystem resilience in India. The forested areas in the Himalayan region and the Western Ghats of India were identified with resilient ecosystem that can withstand climate change. However, the croplands and rangelands were non-resilient to drought, making them vulnerable to climate change. Northern and western part of India falls under catastrophic to critical non-resilient ecosystem. Soil moisture availability in the biome, forest cover, type of land use, agricultural practices, and climate shocks are mainly influencing the resilience of the anthropogenic biomes in India. The resilience assessment can be used by policymakers to plan anthropogenic interventions in harmony with nature.

1. Introduction

Drought is one of the most complex hydrological and climate disasters, causing damage to ecosystem structure and function (Vicente-Serrano et al., 2020; Orimoloye et al., 2022). During the last three decades, the per cent area affected by the serious climatic hazard of drought has doubled, severely affecting natural ecosystems, global food production, and human livelihoods (Hu et al., 2019). When an ecosystem experiences a drought, it can lead to a variety of ecological changes that may affect the elasticity or resilience of the natural system (Chambers et al., 2019; Sandi et al., 2020). In other words, ecological resilience is the ability of an ecosystem to maintain its normal patterns of nutrient cycling and biomass production after being subjected to damage caused by drought. Recovery time, as an important measure of resilience. It has been widely used to assess ecosystem resilience to drought. However, distinguishing the difference in recovery time under various drought intensities is difficult (Falk et al., 2019; Ndayiragije and Li, 2022). In recent times, the impact of recurring droughts on crop yields has been further exacerbated by climate change and anthropogenic activities (Ali et al., 2017; Ray et al., 2018; Vogel et al., 2019). The period, frequency, and degree of droughts varied from region to region. It can disrupt the economic and ecological systems that disturbes the livelihoods of the people (Reddy and Singh, 2016).

In India, agricultural drought risk is higher because of a prolonged dry spell during the monsoon season, which has an impact on groundwater and food security to feed 1.3 billion people (Arun Kumar et al., 2021). Nearly 60% of India's population relies on the agricultural sector for their livelihood and contributes about 17% of the nation's gross domestic product (Maruti, 2013). Crop stress due to droughts has a direct impact on crop production and the nation's overall economy (Malhi et al., 2021). Jha et al. (2019) conducted a study to understand the relationship between extreme climate conditions and terrestrial ecosystem productivity using a copula-based probabilistic model over India and found that 8 out of 25 river basins were resilient to extreme climatic conditions. This is concerning, as it suggests that many areas may be unable to adapt to the changing climate.

Effective assessment of droughts requires frequent and internally consistent records of information on a variety of biophysical variables (Kogan, 2001). Remote sensing can play a crucial role in the assessment of ecosystem resilience by providing a wealth of information on the

* Corresponding author. Department of Population and Development, International Institute for Population Sciences, Deonar, Mumbai, 88, India.
E-mail addresses: subhojitshaw93@gmail.com (S. Shaw), aparajita@iipsindia.ac.in (A. Chattopadhyay), arunkumar.kc@yahoo.com (K.C.A. Kumar).

https://doi.org/10.1016/j.qsa.2024.100214
Received 25 May 2024; Received in revised form 24 June 2024; Accepted 24 June 2024
Available online 27 June 2024

biophysical and environmental conditions of the ecosystem at various scales (Senf, 2022). Globally, vegetation indices derived from temporal remote sensing data are widely applied to monitor ecosystem stress and health (Frappart et al., 2020). Normalized difference vegetation index (NDVI) data is a widely used technique that can provide valuable insights into the health and productivity of vegetation in an ecosystem (Huang et al., 2021). The Moderate Resolution Imaging Spectroradiometer (MODIS) data products have been widely used in time series analysis and change detection studies, especially to measure crop conditions (Zheng et al., 2016). Shahzaman et al. (2021) explored the performance of the evaporative stress index (ESI), vegetation health index (VHI), enhanced vegetation index (EVI), and standardized anomaly index (SAI) based on satellite remote sensing data for agricultural drought assessment in South Asia and found that ESI is a good agricultural drought indicator, being quick and having greater sensitivity. Martínez et al. (2022) analysed a spatiotemporal study of ecosystem functioning in Spain with a time series study of daily GPP, NPP, mean air temperature, and monthly SPI. Based on long-term observed data, SPI, and the Biome-BGC process model, Lei et al. (2015) proposed a new method of estimating NPP loss under various drought conditions in different grassland ecosystems. Fu et al. (2021) focused on the effects of the resilience of an extremely drought-prone desert riparian forest ecosystem in the Tarim River basin of China. They found that ecological resilience has increased significantly from 2013 to 2015, following the implementation of ecological water transfer projects, river regulation, and natural vegetation enclosure projects. Liu et al. (2021) analysed the global response of vegetation activity to drought at different time scales using the Standardized Precipitation Evapotranspiration Index (SPEI) and NPP and concluded that the water balance was the most predominant factor affecting the response of vegetation to drought. Another study examined the relationship between spatiotemporal gradients and the response of vegetation productivity under both dry and wet conditions (Khatri-Chhetri et al., 2021). According to a study by (Xu et al., 2018), drought trends in most parts of northern China are associated with changes in the response of different land cover classes, as indicated by the link between NDVI and SPEI. In a study conducted by (Gouveia et al., 2017), the impact of drought on vegetation across the entire Mediterranean basin was investigated. The findings of the study demonstrated that a considerable portion of the region encountered severe drought during the research period, exhibiting notable variations in both spatial distribution and seasonality.

Although these studies have significantly contributed to the understanding of the mechanisms by which drought impacts vegetation, it is yet unknown what elements may be capable of influencing how the plant reacts to drought in various climatic regions around the globe. The main objective of this study is to use SPI3 to estimate the quantitative effects of ecosystem resilience under different anthropogenic biomes in India. To achieve this objective, the study has three specific goals: (1) to identify the temporal variation of drought across different anthropogenic biomes in India between 2000 and 2020; (2) to quantify the NPP across different anthropogenic biomes in India and identify vulnerable regions at risk of ecosystem resilience; and (3) to evaluate the correlation of different climatic determinants for ecosystem resilience.

2. Data and methods

2.1. Study area

India, with a population of over 1.4 billion people as of 2021, is projected to hold 1.6 billion by 2050 (United Nations, 2017). Southern part of India is surrounded by water: the Indian Ocean in the south, the Bay of Bengal in the southeast, and the Arabian Sea in the southwest. While all along the northern boundary- we have Himalayas. India is a diverse country with a varied geography and a total area of 3.29 million square kilometres, which includes the Himalayan Mountain range in the north, the Indo-Gangetic Plain, the Thar Desert in the northwest, and the Deccan Plateau in the south. The climate in India varies from tropical in the south to more temperate in the north. The country experiences three distinct seasons: summer, monsoon, and winter. The summer months are from March to May, with temperatures ranging from 32 °C to 45 °C. The monsoon season, which brings most of the country's rainfall, is from June to September. The winter season is from December to February, with temperatures ranging from 10 °C to 15 °C in the north and 20 °C to 25 °C in the south (Krishnan et al., 2020). Agriculture is an important sector of the Indian economy, contributing to around 17% of the country's GDP and employing more than 50% of the population (Gulati and Juneja, 2022). India is one of the largest agricultural producers in the world, producing a wide range of crops such as rice, wheat, sugarcane, cotton, tea, coffee, and spices (Pathak et al., 2022). The majority of the agricultural land in India is rainfed and prone to weather-related risks, such as droughts and floods. As climate change continues to alter global weather patterns, it is becoming increasingly important to prioritize resilience by promoting biodiversity and reducing human impact on natural resources.

2.2. Datasets and methods

2.2.1. Anthropogenic biome

The Anthropogenic Biome offers a novel perspective by addressing the human effect on Indian ecosystems when taking into consideration the terrestrial biosphere. The term "anthropogenic biome" or "human biome" refers to a biome that has been modified by humans in terms of its functional depth and geographic range, and the input variables include population (urban and non-urban), land use (per cent area of pasture, crops, irrigation, rice, and urban land), and land cover (per cent area of trees and bare earth). A novel approach to mapping the global patterns of human interaction and the transformation of the terrestrial biosphere was introduced by (Ellis and Ramankutty, 2008). The datasets were acquired from Dataverse at Harvard University (https://dataverse.harvard.edu/). Tere are six major and twenty sub-categories of anthropogenic biomes in India, i.e., dense settlements, villages, croplands, rangelands, seminatural lands, and wildlands (Ellis et al., 2020).

2.2.2. Net Primary Productivity

Gross Primary Productivity (GPP) is the amount of organic substance synthesized by the producers/plants in a given period and area. NPP is the amount of organic matter produced during photosynthesis minus autotrophic respiration. In other terms, NPP reflects the health status of vegetation affected by climate, soil, CO_2, and other minerals. It is one of the most useful measurements for the regional and global carbon cycle of the terrestrial ecosystem (Sun et al., 2021). To access the ecosystem health of India, remote sensing estimation of NPP has been used. It is a key indicator for measuring vegetation growth status and ecosystem health through the carbon cycle. NPP is a commonly used index that reflects ecosystem response to climate change and has shown a significant correlation with precipitation, temperature, soil moisture, and several other climatic factors (Li et al., 2015; Lei et al., 2015). The present study has used remotely sensed data from MODIS (MOD17A2H.061) acquired from Land Processes Distributed Active Archive Center (https://lpdaac.usgs.gov/). In the present study, we used the NPP as a proportion of 0.5 * GPP (Collalti and Prentice, 2019).

2.2.3. Precipitation and soil moisture datasets

The rainfall data has been acquired from the IMD gridded dataset. This data is prepared from daily rainfall data and archived at the National Data Centre, IMD, Pune (https://www.imdpune.gov.in/), using the Shepard method. The data is arranged in a 135 x 129 grid with a spatial resolution of 25 km and a one-day temporal resolution (1950 to 2020). In addition, we have also used soil moisture data extracted from the Climate Prediction Center, prepared by the Earth System Research Laboratory of the National Oceanic and Atmospheric Administration

(ESRL NOAA). The Climate Prediction Center Soil Moisture data is prepared from a bucket water balance model using global precipitation at 17,000 gauge stations worldwide available at 0.5° global grids (https://psl.noaa.gov/).

2.2.4. Computation of standardized precipitation index (SPI3) at a three-month time scale

In the study, gridded monthly mean precipitation data has been used to compute a three-month SPI (SPI3). (McKee et al. 1993, 1995) proposed the SPI3 as a drought monitoring index to define drought intensities. The SPI3 is used in the study as it is useful for monitoring and managing agricultural impacts, short-term water resource management, and responding to immediate changes in precipitation patterns (Mohammed et al., 2022). SPI3 was defined as the number of standard deviations that the observed cumulative rainfall at a given time scale would deviate from the long-term mean for that same time scale over the entire length of the record (McKee et al., 1993). The positive SPI values indicate greater than mean precipitation, and the negative values indicate less than mean precipitation.

$$SPI3 = \frac{Xi - Xi_{mean}}{\sigma}$$

where, Xi = rainfall, Xi_{mean} = long term average rainfall, σ = standard deviation. Based on the intensities of the values the drought classes have been classified as seven classes accordingly, extremely dry (−2 and less), severely dry (−1.5 to −1.99), moderately dry (−1.0 to −1.49), near normal (−0.99 to 0.99), moderately wet (1.0 to 1.49), very wet (1.5 to 1.99) and extremely wet (2.0 and more) conditions.

2.2.5. Computation of ecosystem resilience

Biodiversity stabilizes over time following any extreme climate event, which is becoming more common due to anthropogenic intervention worldwide. To quantify the Indian subcontinent's ecosystem resilience to climate shocks (drought), we have used NPP as an ecosystem response indicator. A drought event was marked when the SPI3 was negative and reached an intensity of −1.0 or less during the study period. Initially, the driest year was identified for every anthropogenic biome (NPP_d). Then the mean NPP_m was also calculated for the study period to calculate ecosystem resilience (R_i) expressed as a ratio of (NPP_d) in the driest year to its temporal mean (NPP_m) value calculated from 2000 to 2020. If R_i is ≥ 1, the ecosystem was resilient to climatic shock (drought), and <1 was non-resilient.

$$Ri = \frac{NPP_d}{NPP_m}$$

Where, R_i is classified into five categories 0.7 ≤ catastrophic non-resilient ecosystem; 0.8 ≤ R_i < 0.9 critical non-resilient ecosyatem; 0.8 ≤ R_i < 0.9 moderate resilient ecosystem; 0.9 ≤ R_i < 1 marginal non-resilient ecosystem and R_i ≥ 1 resilient ecosystem.

3. Result

3.1. Spatial distribution and land cover area of the anthropogenic biome

India is a home of 1.4 billion plus people residing in cities, towns, suburbs, villages (Fig. 1a). Rainfed villages occupy the largest portion of the land area, covering over 38%. Following closely are irrigated villages, which account for approximately 19% of the land area. Additionally, there are rice villages, covering about 8% of the total area.

Despite their limited coverage, croplands including residential irrigated croplands, residential rainfed croplands, populated rainfed croplands, and remote croplands play a crucial role in India's agricultural landscape (Fig. 1b). These areas primarily support subsistence farming and provide livelihoods for millions of rural families. However, their productivity is often constrained due to reliance on rainfall and a lack of irrigation infrastructure. Followed by villages, croplands are the most dominant biomes in India, covering over 11% of the total land area. Interestingly, even the rangelands which include forests and woodlands are home to a substantial human population. These highly productive areas support diverse crops such as rice, wheat, and pulses. However, rangelands are the least populated regions, with livestock, forests, and minimal crop fields covering only 2% of India's total land area. The seminatural biome, accounting for 18% of India's land area, includes forests and woodlands with smaller per cent of human populations. In contrast barren lands, have very limited human occupancy and cover just 10% of India's land (Fig. 1b). Lastly, the wildlands, which are

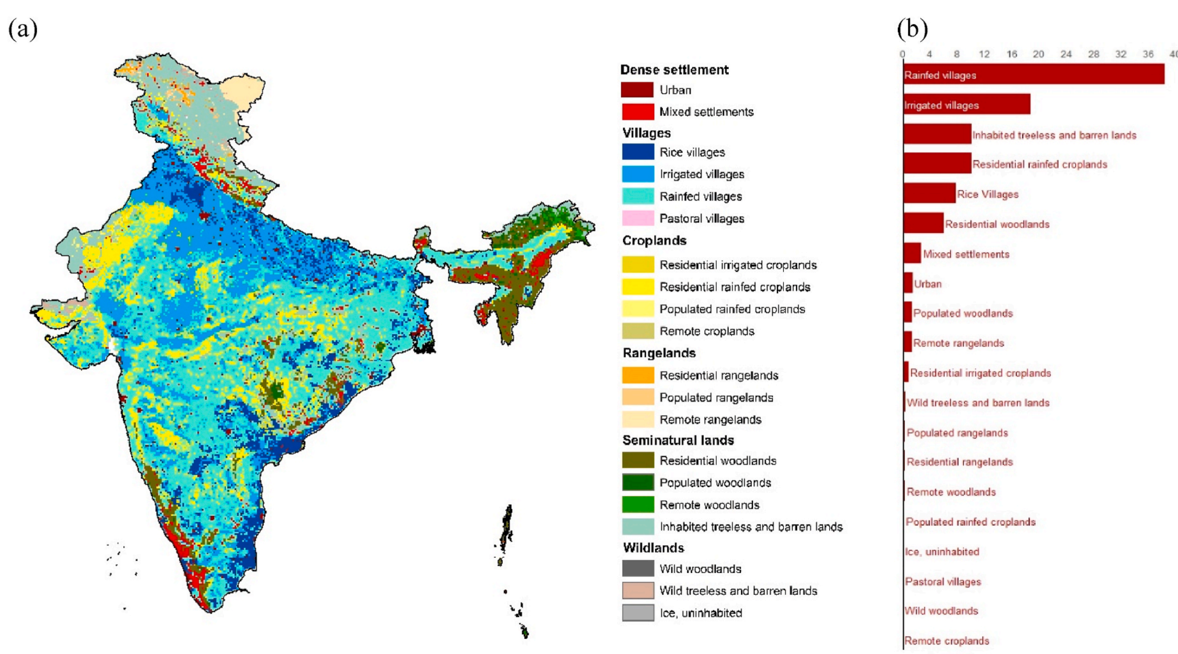

Fig. 1. (a) Anthropogenic biomes of India, organized into groups and sorted in order of population density; (b) Percentage of land area under twenty anthropogenic biomes.

uninhabited and characterized by harsh environmental conditions such as extreme temperatures, low precipitation, and high winds support specialized plant and animal species.

3.2. Trend of NPP

The findings for statistical significance and magnitude measures of NPP are presented in Table 1. NPP quantifies the carbon stored in plant biomass through photosynthesis and is evaluated across various anthropogenic biomes, which refer to human-influenced landscapes. Z-values indicate the deviation of each biome from the mean. Higher Z-values indicate a greater deviation. In Table 1, we observe that the Z-values range from 0.436 to 2.681. Croplands like residential irrigated croplands, rice villages, irrigated villages and rainfed villages have higher Z-values, indicating a substantial deviation from the mean compared to remote croplands with a lower Z-value. The p-value indicates the statistical significance of the relationship between variables, p-value <0.001 suggests a highly significant relationship. Most biomes have p-values below 0.001, except the rangelands, populated, remote and wild woodlands. Sen's slope (Q) measures the trend or change in a variable over time. Higher Sen's slope values indicate a stronger trend. For example, villages like irrigated and rainfed have higher Sen's slope values (0.281 and 0.278, respectively), indicating a relatively strong trend compared to pastoral villages with a lower Sen's slope value of 0.008. It is observed that the largest percentage share of irrigated village biome and rainfed village biome is 38% and 19% respectively (Fig. 1b) with significant NPP values due to their sheer size. Tau (τ) is Kendall's tau correlation coefficient, representing the strength and direction of the association between two variables. Higher Tau values indicate a stronger correlation. τ - value ranges from -1 to +1, with values closer to -1 indicating a negative trend, values closer to +1 indicating a positive trend, and values closer to 0 indicating no trend. Rice villages (0.108), irrigated villages (0.112), rainfed villages (0.112) and residential irrigated cropland (0.113) have higher Tau values, indicating a fair correlation. In contrast, inhabited treeless and barren lands have a lower τ-value of 0.066, suggesting a weak correlation. Additionally, all Sen's slopes and τ-values are positive with little to no trend, indicating an overall positive trend in the variables across time. The study shows that rice villages, irrigated villages, rainfed villages and residential irrigated croplands are becoming increasingly productive over time, while other biomes show mixed results.

Table 1
Summary of Mann-Kendall trend test for net primary productivity (2000–2020).

Anthropogenic biomes	Z	p-value	Sen's slope (Q)	Tau (τ)
Dense settlements				
Urban	1.703	<0.001	0.137	0.072
Mixed settlements	2.211	<0.001	0.238	0.094
Villages				
Rice villages	2.553	<0.001	0.232	0.108
Irrigated villages	2.650	<0.001	0.281	0.112
Rainfed villages	2.640	<0.001	0.278	0.112
Pastoral villages	1.778	0.002	0.008	0.075
Croplands				
Residential irrigated cropland	2.681	<0.001	0.249	0.113
Residential rainfed croplands	2.049	<0.001	0.223	0.087
Populated rainfed cropland	1.744	<0.001	0.126	0.074
Remote croplands	0.436	0.317	0.000	0.018
Rangeland				
Residential rangelands	1.290	0.019	0.002	0.055
Populated rangelands	1.173	0.027	0.008	0.050
Remote rangelands	1.091	0.032	0.005	0.046
Seminatural lands				
Residential woodlands	1.592	<0.001	0.231	0.067
Populated woodlands	1.021	0.023	0.127	0.043
Remote woodlands	0.772	0.087	0.097	0.033
Inhabited treeless and barren lands	1.567	<0.001	0.136	0.066
Wildlands				
Wild woodlands	0.541	0.230	0.073	0.023
Wild treeless and barren lands	1.635	<0.001	0.022	0.069
Ice, uninhabited	/	/	/	/

3.3. Net primary productivity across different anthropogenic biomes

The present study highlights the importance of extreme climatic conditions in influencing the variation in NPP, which poses a substantial risk to ecosystem stability. Precipitation variations can alter soil moisture and could aggravate biomass reduction. Fig. 2 illustrates the average NPP in 20 distinct anthropogenic biomes. During the period from 2000 to 2020, ice, uninhabited biome recorded the lowest NPP (0 g*C/m^2) due to negligible vegetation cover, followed by remote rangelands (47 g*C/m^2) and wild treeless and barren lands (39 g*C/m^2). While water-abundant biomes such as irrigated and rainfed land had higher NPP values, arid and semi-arid regions with limited water availability had lower NPP values, indicating the importance of water availability in determining an ecosystem's productivity (Fig. 2). Similarly, the mean NPP of the biomes in the woodlands/forests and irrigated cropland have higher mean NPP values than barren and rangeland over time.

3.4. Ecosystem resilience across anthropogenic biomes

Table 2 represents the variation in ecosystem resilience calculated as the ratio of the driest NPP, identified during the driest SPI3 condition, by the mean NPP over the study period. The ecological indicators, such as NPP and SPI3, provide insights into the productivity, climate, and water availability in each anthropogenic biome, human-made landscapes that have been significantly altered by human activities, such as agriculture, urbanization, and land-use changes. It is observed that across the dense settlement, urban biomes have lower resilience (R_i) (0.704) compared to the mixed settlements biome. In terms of village biomes, rice villages exhibit the highest R_i value (0.721) followed by irrigated, rainfed and pastoral villages, suggesting an adequate level of soil moisture. Among the croplands, remote croplands have the lowest R_i (0.493). The rangeland biome has a lower R_i compared to all other biomes. The most overwhelming resilience ecosystem is the woodlands/forests with a Ri value close to 1. On the other hand, the barren biome has a R_i value of less than 1, indicating less productivity than most of the biomes.

3.5. Ecosystem resilience across anthropogenic biomes

The spatial variation in the distribution of the ecosystem shows that (Fig. 3) a large part of the northern and western part of India falls under catastrophic to critical non-resilient ecosystem. This could be due to ecosystem vulnerability in terms of lower NPP. Central and western India shows a mixed pattern of non-resilient ecosystems. The western parts of northern India are also having non-resilient ecosystems, which signifies the seriousness of anthropogenic-induced and climate-driven vulnerability. The northeastern part of India has moderate non-resilient to resilient ecosystems due to its forest cover. Although the valley region of Brahmaputra is non-resilient. The highlight of the study is the western part of southern India is more slightly resilient due to good canopy cover and soil moisture.

3.6. Association of ecosystem resilience with precipitation and soil moisture

The links between ecosystem resilience and other environmental variables like precipitation, and soil moisture are complex (Fig. 4a and b). The study has identified a correlation between different variables at a 95% significance level with the spatial Spearman's correlation between precipitation and soil moisture. North-eastern, southwestern coastal and a few pockets of eastern India have higher ecosystem resilience with

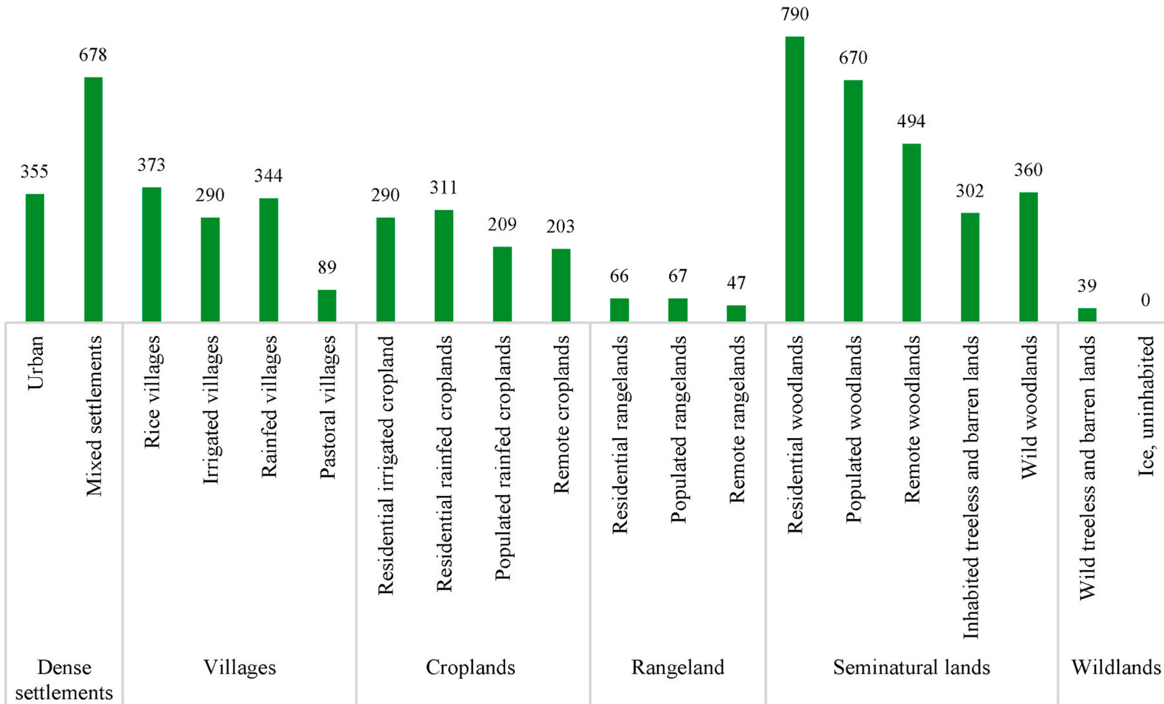

Fig. 2. Mean NPP across anthropogenic biomes in India over 2000–2020.

Table 2
Ecosystem resilience across the anthropogenic biome region of India, 2000–2020.

Anthropogenic biomes	Year	Driest SPI3	NPP_d	NPP_m	$R_i = \frac{NPP_d}{NPP_m}$
Dense settlements					
Urban	2012	−1.325	250	355	0.704
Mixed settlements	2016	−1.687	529	678	0.780
Villages					
Rice villages	2018	−1.187	269	373	0.721
Irrigated villages	2002	−2.078	201	290	0.693
Rainfed villages	2002	−1.324	245	344	0.712
Pastoral villages	2007	−2.615	62	89.5	0.693
Croplands					
Residential irrigated cropland	2002	−2.017	233	290	0.803
Residential rainfed croplands	2002	−1.869	212	311	0.682
Populated rainfed cropland	2002	−2.108	173	209	0.828
Remote croplands	2001	−2.814	100	203	0.493
Rangeland					
Residential rangelands	2007	−2.267	32	66	0.485
Populated rangelands	2007	−1.964	38	67	0.567
Remote rangelands	2007	−1.755	33	47	0.702
Seminatural lands					
Residential woodlands	2009	−1.419	716	790	0.906
Populated woodlands	2009	−1.763	587	670	0.876
Remote woodlands	2014	−2.726	395	494	0.800
Inhabited treeless and barren lands	2012	−1.464	252	302	0.834
Wildlands					
Wild woodlands	2014	−3.100	272	360	0.756
Wild treeless and barren lands	2012	−1.647	30	39.1	0.767
Ice, uninhabited	/	/	/	/	/

higher soil moisture and precipitaion. Although, the north-western states of India have soil moisture, resilience is significantly low. In contrast, western and northern India have low soil moisture and low resilience. The Western Ghats of India also have a better resilient ecosystem with higher precipitation.

4. Discussion

The spatial pattern of the anthropogenic biome was derived from Ellis et al. (2020), who disintegrated the human influence on land use for agriculture and settlement patterns (Ellis et al., 2020). In recent years, India's anthropogenic biomes have undergone significant changes due to human activities. India has experienced rapid urbanization, leading to the expansion of cities and towns characterized by high population density, infrastructure development, and altered land cover (Mandal et al., 2019). In the agricultural sector, intensive farming practices have also transformed land with the use of agricultural modernization. Studies have found that agricultural land has expanded, while wetlands, lakes, and rivers have depleted, affecting water quality and wildlife habitats (Singh et al., 2020). Our study has also observed that semi-natural lands such as woodlands, are decreasing due to overwhelming deforestation and forest land encroachment. Studies from India has shown that high population density, road construction and introduction of cash crops are principal factors behind probable deforestation (Giriraj et al., 2008; Bera et al., 2020). It has also been observed that over time, government initiatives and agricultural modernization, including improvement in irrigation, fertilizers and other artificial inputs have led to increased agricultural production (Bera et al., 2020). A global study from 2000 to 2014 also suggests that NPP has improved in India over the years (Peng et al., 2017). However, factors like water unavailability, frequent droughts and land use change contributes to the decrease in NPP. This analysis provides valuable insights into the current state and trends of these biomes, which can inform decision-making regarding land use and management practices. Biome with substantial populations, like rangelands, have a lower mean NPP, while biomes with limited populations and more agricultural fields such as croplands have a higher mean NPP. These findings suggest that water availability is a key factor in determining the productivity of an ecosystem and that land use practices such as irrigation can significantly impact NPP values (Sharma and Goyal, 2018). This underscores the importance of preserving forests and other high NPP biomes for their role in carbon sequestration and climate regulation. Human activities such as deforestation and urbanization, can have significant impacts on the NPP of an

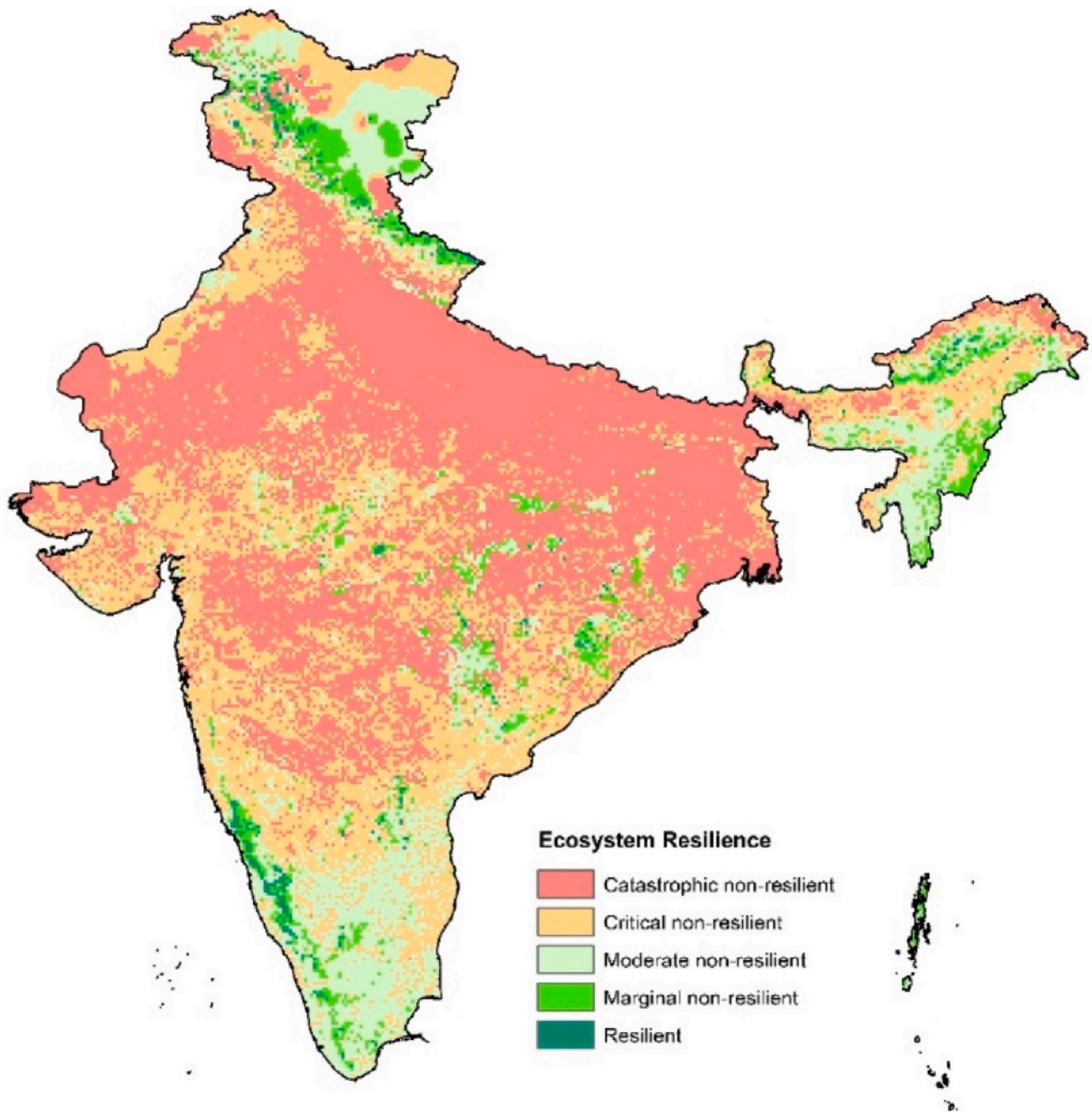

Fig. 3. Spatial distribution of ecosystem resilience at anthropogenic biome scale of India, 2000 to 2020.

ecosystem. However, it is important to balance these activities with the need to preserve natural ecosystems and their biodiversity.

Another highlight of this study is the spatial variation of ecosystem resilience, It shows that a large part of the northern and western part of India falls under catastrophic to critical non-resilient ecosystem. This could be due to ecosystem vulnerability in terms of lower NPP and low precipitation. A similar pattern can be observed in a study conducted by (Sharma and Goyal, 2018), where moderate NPP values were recorded in the agricultural lands of the Indo-Gangetic plains and lower Himalayas. It is also observed the coastal areas of the Eastern Ghats and the Konkan region are critically non-resilient while the deltaic region of the Sundarbans of India falls under a catastrophic non-resilient ecosystem. The land use change from mangroves to aquaculture and rapid urbanization is a major challenge in these regions (Saha and Paul, 2021; Sinha et al., 2023). Central and western India shows a mixed pattern of non-resilient ecosystems. The western parts of northern India are also having non-resilient ecosystems, which signifies the seriousness of anthropogenic-induced and climate-driven vulnerability. Previous studies have suggested that overuse of groundwater has led to depletion of water table in these region (Swain et al., 2022). Groundwater recharge in northwestern region is also less due to low rainfall (Taloor et al., 2022; Taloor et al., 2022). Other studies from India align with this finding indicating that these areas have low water use efficiency, indicating crop production in these areas will not be able to withstand climatic shocks (Hatfield and Dold, 2019; Wang et al., 2020). The northeastern part of India has moderate non-resilient ecosystems to resilient ecosystems due to its forest cover. The valley region of Brahmaputra is non-resilient due to settlements and recurring floods and crop failures (Pandey et al., 2022). Overall, it can be suggested that the soil moisture availability in the biome, forest cover, type of land use, agricultural practices, and climate shocks are influencing the resilience of the anthropogenic biomes in India.

The linkage between ecosystem resilience and the most proximate environmental variables like precipitation, and soil moisture have identified interesting correlations. The correlation between precipitation and soil moisture is the strongest. Previous studies have shown that soil moisture retention can last up to 10 months (Hoover et al., 2021) and therefore with the porosity and percolation capacity of any soil type, the ecosystem resilience varies. Ecosystem resilience and soil moisture go hand in hand, which can be studied at the micro level for regional planning.

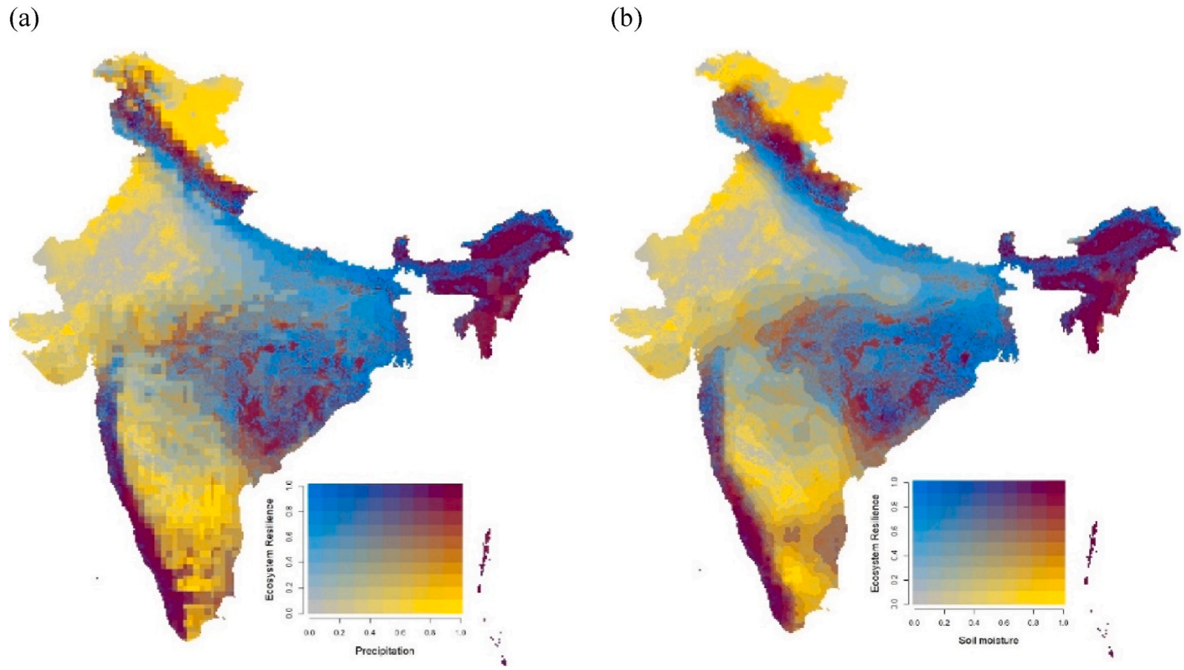

Fig. 4. Bivariate map of (a) precipitation and (b soil moisture combined with ecosystem resilience.

5. Conclusion

Different biomes have varying levels of resilience in India. Rangelands and cropland biomes have the lowest levels of resilience, while woodlands have the highest level. It is crucial to consider the costs of adaptive measures (like irrigation and groundwater recharge) to maintain productivity. Research on the functioning of ecosystems and their capacity to handle environmental stressors is essential to take mitigating actions. As ecosystem resilience and soil moisture support each other, it is necessary to take care of soil moisture for saving the ecosystem. In urban areas, rainwater harvesting could be helpful in reducing runoff and recharge the ground water while in the agricultural land, over pumping of groundwater should be checked. Further, it is important to develop sustainable land management practices that can consider the impact of climate change, mainly in terms of drought and temperature rise in India.

Ethical approval

As the study is based on secondary data available in public domain for research; no ethical approval was required from any institutional review board (IRB).

Consent for publication

Not applicable.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

CRediT authorship contribution statement

Subhojit Shaw: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Aparajita Chattopadhyay:** Writing – review & editing, Writing – original draft, Validation, Supervision. **Karikkathil C. Arun Kumar:** Writing – review & editing, Writing – original draft, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

Not applicable.

References

Ali, S., Liu, Y., Ishaq, M., Shah, T., Abdullah, Ilyas A., Din, I.U., 2017. Climate change and its impact on the yield of major food crops: evidence from Pakistan. Foods 6 (6), 39. https://doi.org/10.3390/foods6060039.

Arun Kumar, K.C., Reddy, G.P.O., Masilamani, P., Turkar, S.Y., Sandeep, P., 2021. Integrated drought monitoring index: a tool to monitor agricultural drought by using time-series datasets of space-based earth observation satellites. Adv. Space Res. 67 (1), 298–315. https://doi.org/10.1016/j.asr.2020.10.003.

Bera, B., Saha, S., Bhattacharjee, S., 2020. Forest cover dynamics (1998 to 2019) and prediction of deforestation probability using binary logistic regression (BLR) model of Silabati watershed, India. Trees, Forests and People 2, 100034. https://doi.org/10.1016/j.tfp.2020.100034.

Chambers, J.C., Allen, C.R., Cushman, S.A., 2019. Operationalizing ecological resilience concepts for managing species and ecosystems at risk. Frontiers in Ecology and Evolution [Internet], 2023 Jun 15] 7. https://www.frontiersin.org/articles/10.3389/fevo.2019.00241.

Collalti, A., Prentice, I.C., 2019. Is NPP proportional to GPP? Waring's hypothesis 20 years on. Tree Physiol. 39 (8), 1473–1483. https://doi.org/10.1093/treephys/tpz034.

Ellis, E.C., Beusen, A.H.W., Goldewijk, K.K., 2020. Anthropogenic biomes: 10,000 BCE to 2015 CE. Land 9 (5), 129. https://doi.org/10.3390/land9050129.

Ellis, E.C., Ramankutty, N., 2008. Putting people in the map: anthropogenic biomes of the world. Front. Ecol. Environ. 6 (8), 439–447. https://doi.org/10.1890/070062.

Falk, D.A., Watts, A.C., Thode, A.E., 2019. Scaling ecological resilience. Frontiers in Ecology and Evolution [Internet], 2023 Jun 15] 7. https://www.frontiersin.org/articles/10.3389/fevo.2019.00275.

Frappart, F., Wigneron, J.-P., Li, X., Liu, X., Al-Yaari, A., Fan, L., Wang, M., Moisy, C., Le Masson, E., Aoulad Lafkih, Z., et al., 2020. Global monitoring of the vegetation dynamics from the vegetation optical depth (vod): a review. Rem. Sens. 12 (18), 2915. https://doi.org/10.3390/rs12182915.

Fu, A., Li, W., Chen, Y., Wang, Y., Hao, H., Li, Y., Sun, F., Zhou, H., Zhu, C., Hao, X., 2021. The effects of ecological rehabilitation projects on the resilience of an extremely drought-prone desert riparian forest ecosystem in the Tarim River Basin, Xinjiang, China. Sci. Rep. 11 (1), 18485 https://doi.org/10.1038/s41598-021-96742-5.

Giriraj, A., Irfan-Ullah, M., Murthy, M.S.R., Beierkuhnlein, C., 2008. Modelling spatial and temporal forest cover change patterns (1973-2020): a case study from south western Ghats (India). Sensors 8 (10), 6132–6153. https://doi.org/10.3390/s8106132.

Gouveia, C.M., Trigo, R.M., Beguería, S., Vicente-Serrano, S.M., 2017. Drought impacts on vegetation activity in the Mediterranean region: an assessment using remote sensing data and multi-scale drought indicators. Global Planet. Change 151, 15–27. https://doi.org/10.1016/j.gloplacha.2016.06.011.

Gulati, A., Juneja, R., 2022. Transforming Indian agriculture. In: Chand, R., Joshi, P., Khadka, S. (Eds.), Indian Agriculture towards 2030: Pathways for Enhancing Farmers' Income, Nutritional Security and Sustainable Food and Farm Systems [Internet]. Springer Nature, Singapore, pp. 9–37. https://doi.org/10.1007/978-981-19-0763-0_2, 2023 Jun 15].

Hatfield, J.L., Dold, C., 2019. Water-use efficiency: advances and challenges in a changing climate. Front. Plant Sci. 2023 Jun 15] 10 https://www.frontiersin.org/articles/10.3389/fpls.2019.00103.

Hoover, D.L., Pfennigwerth, A.A., Duniway, M.C., 2021. Drought resistance and resilience: the role of soil moisture–plant interactions and legacies in a dryland ecosystem. J. Ecol. 109 (9), 3280–3294. https://doi.org/10.1111/1365-2745.13681.

Hu, X., Ren, H., Tansey, K., Zheng, Y., Ghent, D., Liu, X., Yan, L., 2019. Agricultural drought monitoring using European Space Agency Sentinel 3A land surface temperature and normalized difference vegetation index imageries. Agric. For. Meteorol. 279, 107707 https://doi.org/10.1016/j.agrformet.2019.107707.

Huang, S., Tang, L., Hupy, J.P., Wang, Y., Shao, G., 2021. A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. J. Res. 32 (1), 1–6. https://doi.org/10.1007/s11676-020-01155-1.

Jha, S., Das, J., Goyal, M.K., 2019. Assessment of risk and resilience of terrestrial ecosystem productivity under the influence of extreme climatic conditions over India. Sci. Rep. 9 (1), 18923 https://doi.org/10.1038/s41598-019-55067-0.

Khatri-Chhetri, P., Hendryx, S.M., Hartfield, K.A., Crimmins, M.A., Leeuwen, WJD van, Kane, V.R., 2021. Assessing vegetation response to multi-scalar drought across the mojave, sonoran, chihuahuan deserts and Apache highlands in the southwest United States. Rem. Sens. 13 (6), 1103. https://doi.org/10.3390/rs13061103.

Kogan, F.N., 2001. Operational space technology for global vegetation assessment. Bull. Am. Meteorol. Soc. 82 (9), 1949–1964. https://doi.org/10.1175/1520-0477(2001)082<1949:OSTFGV>2.3.CO;2.

Krishnan, R., Gnanaseelan, C., Sanjay, J., Swapna, P., Dhara, C., Sabin, T.P., Jadhav, J., Sandeep, N., Choudhury, A.D., Singh, M., et al., 2020. Introduction to climate change over the Indian region [Internet]. In: Krishnan, R., Sanjay, J., Chellappan, Gnanaseelan, Milind, Mujumdar, Kulkarni, A., Chakraborty, S. (Eds.), Assessment of Climate Change over the Indian Region: A Report of the Ministry of Earth Sciences (MoES), Government of India. Springer, Singapore, pp. 1–20. https://doi.org/10.1007/978-981-15-4327-2_1, 2023 Jun 15].

Lei, T., Wu, J., Li, X., Geng, G., Shao, C., Zhou, H., Wang, Q., Liu, L., 2015. A new framework for evaluating the impacts of drought on net primary productivity of grassland. Sci. Total Environ. 536, 161–172. https://doi.org/10.1016/j.scitotenv.2015.06.138.

Li, S., Lü, S., Liu, Y., Gao, Y., Ao, Y., 2015. Variations and trends of terrestrial NPP and its relation to climate change in the 10 CMIP5 models. J. Earth Syst. Sci. 124 (2), 395–403. https://doi.org/10.1007/s12040-015-0545-1.

Liu, Y., Zhou, R., Wen, Z., Khalifa, M., Zheng, C., Ren, H., Zhang, Z., Wang, Z., 2021. Assessing the impacts of drought on net primary productivity of global land biomes in different climate zones. Ecol. Indicat. 130, 108146 https://doi.org/10.1016/j.ecolind.2021.108146.

Malhi, G.S., Kaur, M., Kaushik, P., 2021. Impact of climate change on agriculture and its mitigation strategies: a review. Sustainability 13 (3), 1318. https://doi.org/10.3390/su13031318.

Mandal, J., Ghosh, N., Mukhopadhyay, A., 2019. Urban growth dynamics and changing land-use land-cover of megacity Kolkata and its environs. J Indian Soc Remote Sens 47 (10), 1707–1725. https://doi.org/10.1007/s12524-019-01020-7.

Martínez, B., Sánchez-Ruiz, S., Campos-Taberner, M., García-Haro, F.J., Gilabert, M.A., 2022. Exploring ecosystem functioning in Spain with gross and net primary production time series. Rem. Sens. 14 (6), 1310. https://doi.org/10.3390/rs14061310.

Maruti, A.K., 2013. Indian agriculture- status, importance and role in Indian economy. Int. J. Agric. Food Sci. Technol. 4 (4), 343–346.

McKee, T.B., Doesken, N.J., Kliest, J., 1993. The relationship of drought frequency and duration to time scales. In: Proceedings of the 8th Conference of Applied Climatology. American Meterological Society, Boston, MA, pp. 179–184.

McKee, T.B., Doesken, N.J., Kliest, J., 1995. Drought monitoring with multiple time scales. In: Proceedings of the 9th Conference of Applied Climatology. American Meterological Society, Boston, MA, pp. 233–236.

Mohammed, S., Alsafadi, K., Enaruvbe, G.O., Bashir, B., Elbeltagi, A., Széles, A., Alsalman, A., Harsanyi, E., 2022. Assessing the impacts of agricultural drought (SPI/SPEI) on maize and wheat yields across Hungary. Sci. Rep. 12 (1), 8838. https://doi.org/10.1038/s41598-022-12799-w.

Ndayiragije, J.M., Li, F., 2022. Effectiveness of drought indices in the assessment of different types of droughts, managing and mitigating their effects. Climate 10 (9), 125. https://doi.org/10.3390/cli10090125.

Orimoloye, I.R., Belle, J.A., Orimoloye, Y.M., Olusola, A.O., Ololade, O.O., 2022. Drought: a common environmental disaster. Atmosphere 13 (1), 111. https://doi.org/10.3390/atmos13010111.

Pandey, A.C., Kaushik, K., Parida, B.R., 2022. Google earth engine for large-scale flood mapping using SAR data and impact assessment on agriculture and population of ganga-brahmaputra basin. Sustainability 14 (7), 4210. https://doi.org/10.3390/su14074210.

Pathak, H., Mishra, J., Mohapatra, T., 2022. Indian Agriculture after Independence [Internet]. Indian Council of Agricultural Research, New Delhi.

Peng, D., Zhang, B., Wu, C., Huete, A.R., Gonsamo, A., Lei, L., Ponce-Campos, G.E., Liu, X., Wu, Y., 2017. Country-level net primary production distribution and response to drought and land cover change. Sci. Total Environ. 574, 65–77. https://doi.org/10.1016/j.scitotenv.2016.09.033.

Ray, R.L., Fares, A., Risch, E., 2018. Effects of drought on crop production and cropping areas in Texas. Agricultural & Environmental Letters 3 (1), 170037. https://doi.org/10.2134/ael2017.11.0037.

Reddy, G.P.O., Singh, S.K., 2016. Role of Remote Sensing and Geospatial Technologies in Climate Smart Agriculture. The Indian Society of Agronomy, New Delhi.

Saha, J., Paul, S., 2021. An insight on land use and land cover change due to tourism growth in coastal area and its environmental consequences from West Bengal, India. Spat Inf Res 29 (4), 577–592. https://doi.org/10.1007/s41324-020-00368-0.

Sandi, S.G., Rodriguez, J.F., Saintilan, N., Wen, L., Kuczera, G., Riccardi, G., Saco, P.M., 2020. Resilience to drought of dryland wetlands threatened by climate change. Sci. Rep. 10 (1), 13232 https://doi.org/10.1038/s41598-020-70087-x.

Senf, C., 2022. Seeing the system from above: the use and potential of remote sensing for studying ecosystem dynamics. Ecosystems 25 (8), 1719–1737. https://doi.org/10.1007/s10021-022-00777-2.

Shahzaman, M., Zhu, W., Bilal, M., Habtemicheal, B.A., Mustafa, F., Arshad, M., Ullah, I., Ishfaq, S., Iqbal, R., 2021. Remote sensing indices for spatial monitoring of agricultural drought in South asian countries. Rem. Sens. 13 (11), 2059. https://doi.org/10.3390/rs13112059.

Sharma, A., Goyal, M.K., 2018. District-level assessment of the ecohydrological resilience to hydroclimatic disturbances and its controlling factors in India. J. Hydrol. 564, 1048–1057. https://doi.org/10.1016/j.jhydrol.2018.07.079.

Singh, S., Bhardwaj, A., Verma, V.K., 2020. Remote sensing and GIS based analysis of temporal land use/land cover and water quality changes in Harike wetland ecosystem, Punjab, India. J. Environ. Manag. 262, 110355 https://doi.org/10.1016/j.jenvman.2020.110355.

Sinha, R.K., Eldho, T.I., Subimal, G., 2023. Assessing the impacts of land use/land cover and climate change on surface runoff of a humid tropical river basin in Western Ghats, India. Int. J. River Basin Manag. 21 (2), 141–152. https://doi.org/10.1080/15715124.2020.1809434.

Sun, J., Yue, Y., Niu, H., 2021. Evaluation of NPP using three models compared with MODIS-NPP data over China. PLoS One 16 (11), e0252149. https://doi.org/10.1371/journal.pone.0252149.

Swain, S., Taloor, A.K., Dhal, L., Sahoo, S., Al-Ansari, N., 2022. Impact of climate change on groundwater hydrology: a comprehensive review and current status of the Indian hydrogeology. Appl. Water Sci. 12 (6), 120. https://doi.org/10.1007/s13201-022-01652-0.

Taloor, A.K., Goswami, A., Bahuguna, I.M., Singh, K.K., Kothyari, G.C., 2022. Remote sensing and GIS applications in water cryosphere and climate change. Remote Sens. Appl.: Society and Environment 28, 100866. https://doi.org/10.1016/j.rsase.2022.100866.

United Nations, 2017. World Population Prospects the 2017 Revision. Key Findings and Advance Tables. Department of Economic and Social Affairs Population Division, New York. Working Paper No. ESA/P/WP/248.

Vicente-Serrano, S.M., Quiring, S.M., Peña-Gallardo, M., Yuan, S., Domínguez-Castro, F., 2020. A review of environmental droughts: increased risk under global warming? Earth Sci. Rev. 201, 102953 https://doi.org/10.1016/j.earscirev.2019.102953.

Vogel, E., Donat, M.G., Alexander, L.V., Meinshausen, M., Ray, D.K., Karoly, D., Meinshausen, N., Frieler, K., 2019. The effects of climate extremes on global agricultural yields. Environ. Res. Lett. 14 (5), 054010 https://doi.org/10.1088/1748-9326/ab154b.

Wang, W., Wang, J., Cao, X., 2020. Water use efficiency and sensitivity assessment for agricultural production system from the water footprint perspective. Sustainability 12 (22), 9665. https://doi.org/10.3390/su12229665.

Xu, H., Wang, X., Zhao, C., Yang, X., 2018. Diverse responses of vegetation growth to meteorological drought across climate zones and land biomes in northern China from 1981 to 2014. Agric. For. Meteorol. 262, 1–13. https://doi.org/10.1016/j.agrformet.2018.06.027.

Zheng, Y., Wu, B., Zhang, M., Zeng, H., 2016. Crop phenology detection using high spatio-temporal resolution data fused from SPOT5 and MODIS products. Sensors 16 (12), 2099. https://doi.org/10.3390/s16122099.