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Unveiling Nature's Resilience: Exploring Vegetation Dynamics during the COVID-19 Era in Jharkhand, India, with the Google Earth Engine

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Abstract: The Severe Acute Respiratory Syndrome Coronavirus Disease 2019 (COVID-19) pandemic has presented unprecedented challenges to global health and economic stability. Intriguingly, the necessary lockdown measures, while disruptive to human society, inadvertently led to environmental rejuvenation, particularly noticeable in decreased air pollution and improved vegetation health. This study investigates the lockdown's impact on vegetation health in Jharkhand, India, employing the Google Earth Engine for cloud-based data analysis. MODIS-NDVI data were analyzed using spatio-temporal NDVI analyses and time-series models. These analyses revealed a notable increase in maximum vegetation greenery of 19% from April 2019 to 2020, with subsequent increases of 13% and 3% observed in March and May of the same year, respectively. A longer-term analysis from 2000 to 2020 displayed an overall 16.7% rise in vegetation greenness. While the maximum value remained relatively constant, it demonstrated a slight increment during the dry season. The Landsat data Mann–Kendall trend test reinforced these findings, displaying a significant shift from a negative NDVI trend (1984–2019) to a positive 17.7% trend (1984–2021) in Jharkhand's north-west region. The precipitation (using NASA power and Merra2 data) and NDVI correlation were also studied during the pre- and lockdown periods. Maximum precipitation (350–400 mm) was observed in June, while July typically experienced around 300 mm precipitation, covering nearly 85% of Jharkhand. Interestingly, August 2020 saw up to 550 mm precipitation, primarily in Jharkhand's southern region, compared to 400 mm in the same month in 2019. Peak changes in NDVI value during this period ranged between 0.6–0.76 and 0.76–1, observed throughout the state. Although the decrease in air pollution led to improved vegetation health, these benefits began to diminish post-lockdown. This observation underscores the need for immediate attention and intervention from scientists and researchers. Understanding lockdown-induced environmental changes and their impact on vegetation health can facilitate the development of proactive environmental management strategies, paving the way towards a sustainable and resilient future.

Keywords: COVID-19 pandemic; lockdown; vegetation health; Mann–Kendall; NDVI; Jharkhand

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Citation: Ahmad, T.; Gupta, S.K.; Singh, S.K.; Meraj, G.; Kumar, P.; Kanga, S. Unveiling Nature's Resilience: Exploring Vegetation Dynamics during the COVID-19 Era in Jharkhand, India, with the Google Earth Engine. *Climate* **2023**, *11*, 187. https://doi.org/10.3390/cli11090187

Academic Editor: Eldar Kurbanov

Received: 16 June 2023
Revised: 30 August 2023
Accepted: 6 September 2023
Published: 8 September 2023

1. Introduction

Forests cover approximately one third of the Earth's total land area, and play a vital role in providing essential services to human societies [1]. Besides acting as a natural habitat and supplying raw materials for various industries, forests also regulate the environmental setup by balancing climatic parameters, conserving soil quality, maintaining water quality, facilitating pollination, controlling diseases, and preventing floods [2]. The global forest cover has faced significant challenges, with the Asia-Pacific region experiencing notable forest loss [3]. This region encompasses a vast area, and is home to diverse ecosystems, rich biodiversity, and millions of people who depend on forests for their livelihoods.

The emergence of the COVID-19 pandemic in 2019 has had profound and far-reaching effects on social and economic activities worldwide, leading to a severe health crisis in numerous countries. On 11 March 2020, the World Health Organization (WHO) declared the COVID-19 outbreak a global pandemic, highlighting the urgent need for international cooperation and coordinated responses [4,5]. The pandemic has caused widespread disruptions across various sectors, including travel, tourism, manufacturing, retail, and services, resulting in a significant impact on the global economy. Governments around the world have implemented various measures such as lockdowns, social distancing guidelines, and travel restrictions to contain the spread of the virus and mitigate its impact on public health systems.

India experienced a relatively low number of COVID-19 cases and deaths in the early stages of the pandemic compared to some other countries [6,7]. The Indian government took proactive measures to prevent the rapid spread of the virus and protect its citizens. On 24 March 2020, India implemented a nationwide lockdown, one of the most extensive and stringent measures taken globally at the time [8]. The lockdown aimed to break the chain of transmission by imposing restrictions on movement, suspending non-essential activities, and promoting social distancing. The nationwide lockdown in India had significant implications for the country's economy and society. Industries and businesses, especially those in non-essential sectors, faced disruptions in their operations, leading to layoffs, reduced incomes, and economic contraction. Daily wage workers and informal sector workers were particularly affected, as they often lacked social security benefits and faced challenges in meeting their basic needs.

As the initial phase of the lockdown brought the number of COVID-19 cases under control to some extent, the Indian government began implementing phased unlocking measures from 8 June 2020 [9,10]. The unlocking process aimed to balance the need to revive economic activities with the necessity of continuing precautionary measures to prevent a resurgence of the virus. The unlocking phases were implemented gradually, with the government providing guidelines and protocols for different sectors to ensure safety and prevent the spread of the virus.

During the unlocking phases, various sectors started resuming their operations, with businesses adopting preventive measures such as sanitization protocols, social distancing norms, and work-from-home arrangements wherever possible. The unlocking process faced challenges as localized outbreaks occurred in different parts of the country, leading to localized lockdowns and restrictions to contain the spread of the virus.

During the COVID-19 lockdown, when industrial activities halted and travel restrictions were implemented worldwide, there were significant changes observed in the global environment, particularly in terms of air pollution reduction [11]. Forests play a crucial role in mitigating air pollution, as they act as natural filters, absorbing and sequestering pollutants. Therefore, they serve as important bio-indicators of air quality [12].

The period of lockdown witnessed notable changes in forest ecosystems due to the reduction in air pollutants such as sulfur (S) and nitrogen (N) deposition, as well as surface ozone [12,13]. These pollutants, emitted primarily from industrial processes and transportation, have detrimental effects on both human health and the environment. High levels of sulfur and nitrogen deposition can lead to acidification of soil and water bodies, negatively impacting plant and aquatic life. During the lockdown, the reduced emission of air pollutants resulted in improvements in forest soil recovery and overall environmental health. Long-term monitoring and analysis are essential to assess the movement of acid radicals and subsequent precipitation and acidification in the environment, particularly in transboundary regions where pollution can travel across borders [14]. These studies help in understanding the complex interactions between air pollution, forest ecosystems, and the broader environment.

Air quality monitoring conducted in the Jharkhand state during the lockdown period revealed positive changes in forest soil recovery. There were notable declines in carbon monoxide (CO) and fine particulate matter (PM 2.5) levels, indicating a reduction in combustion-related pollutants and airborne particles [15]. Additionally, there were slight reductions in sulfur dioxide (SO_2) levels, a major contributor to acid rain and air pollution. These improvements in air quality can have beneficial effects on the health and well-being of both humans and ecosystems, which has been observed in the many regions of India, especially in the Himalayan region [16,17].

It is important to note that the positive changes observed during the lockdown were temporary and influenced by the specific circumstances of reduced human activity. As restrictions eased and economic activities resumed, the levels of air pollutants gradually returned to pre-lockdown levels in many regions. Therefore, sustained efforts are required to address the long-term challenges of air pollution and promote sustainable practices in industries, transportation, and energy production to maintain improved air quality and support the recovery of forest ecosystems.

The Normalized Difference Vegetation Index (NDVI) has widely been used throughout the world in the geospatial method which helps to understand the periodical changes in health and spatial extent of vegetation [18–20]. Previous studies have harnessed NDVI for evaluating forest cover changes, including global-scale assessments using Landsat 7 data (30 m spatial resolution) on the Google Earth Engine platform [21]. While some research has indicated a consistent negative trend in NDVI for various Indian forest types, utilizing MODIS/TERRA-derived data [22,23], the Eastern Indian Himalayan region has exhibited a significant NDVI increase [24]. Worldwide assessments have determined that approximately 34% of continents have experienced greening, primarily in the Sahel, Europe, India, and South China. Conversely, a mere 10% of global land regions have experienced browning, most notably in Canada, South America, Central Africa, and Central Asia [25]. The ongoing monitoring of vegetation's evolutionary patterns through NDVI is crucial for the development of robust conservation and restoration practices.

The major cities of India like Delhi, Kolkata, Mumbai, and Chennai also represented improvement in their vegetation quality index [26]. Numerous studies are currently in progress to evaluate COVID-19's impact on various environmental aspects [27,28]. In this paper, we investigate the significant NDVI changes from 2000 to 2020 and from 2019 to 2020 using MODIS data. Additionally, we apply the Mann–Kendall correlation test (Kendall Tau) to the Landsat time series for the periods 1984 to 2019 and 1984 to 2021, in order to understand the variation in Jharkhand state's vegetation.

2. Materials and Methods

2.1. Study Area

Jharkhand, the state considered for this study, covers a total area of 79,710 km^2 and lies between 21°58′02″ N to 25°08′32″ N latitude and 83°19′05″ E to 87°55′03″ E longitude (Figure 1). A significant portion of Jharkhand is situated on the Chota Nagpur plateau. The state is renowned for the Saranda forest, which is Asia's largest Sal forest [29]. Jharkhand is a landlocked state bordered by five other states: Bihar, Uttar Pradesh, Chhattisgarh, and West Bengal. Ranchi is the capital of Jharkhand, while Jamshedpur is its major industrial city. Key rivers flowing through the state include the Damodar, Barakar, Son, North Koel, South Koel, Subarnarekha, and Sankh. The state receives an average annual rainfall of 1386 mm, which is predominantly erratic and temporal, observed mainly from June to September [30]. May is the hottest month, with daily temperatures reaching a maximum of 38 °C and a minimum of 25 °C, while winter temperatures can drop to a minimum of 6 °C.

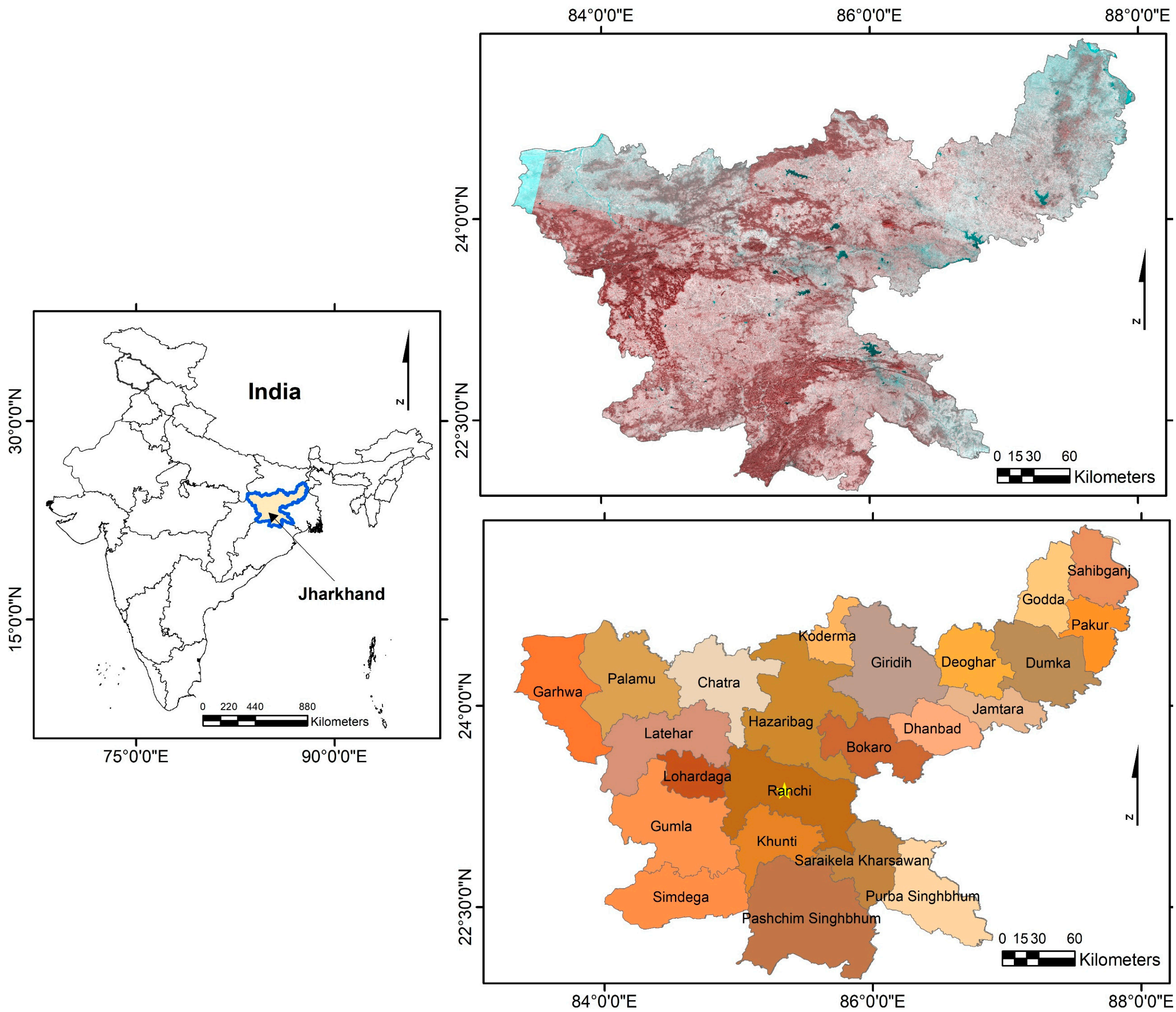

Figure 1. Location of study area (starred) in the Jharkhand state of India represented using Landsat 8 OLI satellite images (November–December 2020), along with the district boundaries.

2.2. Methodology and Data Used

In this study, time series modelling was performed using MODIS-NDVI (MOD13Q1) and Landsat data for vegetation change analysis. The Google Earth Engine (GEE) platform was utilized for this analysis, providing a cloud computing environment capable of storing and processing vast amounts of geographic information on a petabyte scale [31]. MODIS data were downloaded from GEE and processed using ArcGIS software, thereby enabling spatial analysis and visualization. Further, the Power global data, which has a resolution of 0.5 × 0.5 degree, was obtained from NASA's online public database (https://power.larc.nasa.gov, accessed on 21 December 2021) [32] to understand the relationship between NDVI and precipitation. This data has been used by researchers to understand climatic impact, and in this research, the Inverse Distance Weightage (IDW) interpolation method was applied to observe precipitation variability in Jharkhand [17,33].

The MODIS vegetation index (MOD13Q1) employed in this study provides information on vegetation greenness based on leaf area, chlorophyll content, and canopy structure. The index is derived from 16-day composites at a spatial resolution of 250 m, enabling both spatial and temporal analysis of vegetation dynamics. Linear trend calculation (Mean and Max) for the period of 2000–2020 and NDVI during the period of 2019–2020 was performed using these data.

For further assessment of vegetation change trends, the Mann–Kendall test was applied on the retrieved NDVI values from Landsat data for the period of 1984–2019 and 1984–2021. NDVI is indicative of greenness and density and, thus, is useful for evaluating the health of vegetation on the Earth's surface [18–20,34]. The Mann–Kendall test is a non-parametric statistical test used to identify monotonic trends in data [35]. It calculates the Kendall Tau, reflecting the strength and direction of the trend, and the Sen's Slope, quantifying the magnitude of temporal change [36–38]. Calculations of the Kendall Tau and Sen's Slope were performed using the Google Earth Engine, leveraging the capabilities provided by the platform (https://developers.google.com/earth-engine/tutorials/community/nonparametric-trends, accessed on 15 January 2022). The formula of calculating the NDVI is:

$$\mathrm{NDVI} = \frac{\mathrm{Near\ IR} - \mathrm{Red}}{\mathrm{Near\ IR} + \mathrm{Red}} \tag{1}$$

where Near IR is the reflectance value in the near-infrared band and Red is the reflectance value in the red band.

The use of Kendall Tau in trend analysis offers certain advantages compared to linear regression and developed by Kendall represented in Equation (2) [39]. Unlike linear regression, Kendall Tau is not affected by the presence of outliers and data errors, making it robust for detecting monotonic patterns in the data [36–38]. The formula of calculating Kendall Tau is:

$$\tau = (\mathrm{P} - \mathrm{Q})/\sqrt{}((\mathrm{P} + \mathrm{Q} + \mathrm{T}) \times (\mathrm{P} + \mathrm{Q} + \mathrm{U})) \tag{2}$$

where τ represents the Kendall Tau coefficient, P denotes the number of concordant pairs (pairs that have the same order in both variables), Q denotes the number of discordant pairs (pairs that have different orders in the two variable), T denotes the number of tied pairs in the first variable, and U denotes the number of tied pairs in the second variable. It must be noted that tied pairs occur when there are multiple instances of the same value in either variable. The formula considers both the concordant and discordant pairs, as well as the tied pairs, to compute the Kendall Tau coefficient. The coefficient ranges between -1 and 1, where -1 indicates a perfect negative correlation, 1 indicates a perfect positive correlation, and 0 indicates no correlation between the variables.

The slope estimator method is used to calculate the magnitude of the trend anticipated by Theil [40] and Sen [41], represented as Sen's slope (Ti) mentioned in Equation (3).

$$\mathrm{Ti} = \frac{\mathrm{xj} - \mathrm{xk}}{\mathrm{j} - \mathrm{k}}\ for\ i = 1,\ 2,\ \ldots,\ N, \tag{3}$$

where (xj − xk) represents the data values at time j, k (j > k) consequently.

The flow chart of the present work, illustrating the methodology and steps followed in the study, is presented in Figure 2. This flow chart provides a visual representation of the process undertaken to analyze vegetation change using MODIS-NDVI and Landsat data, with the support of the Google Earth Engine platform.

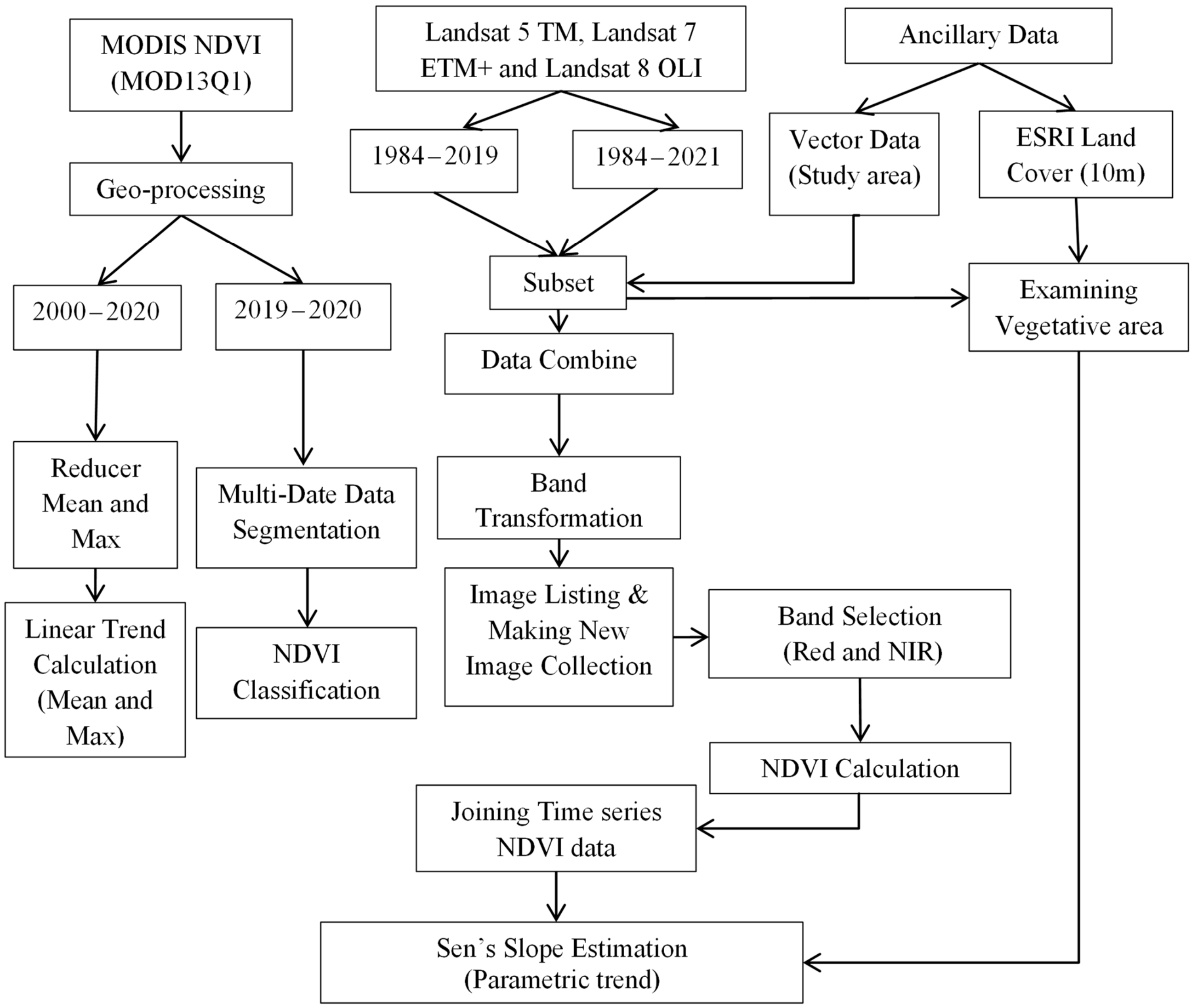

Figure 2. Flow chart of present methodology.

3. Results

3.1. Long Term Changes in Vegetation of Jharkhand

The state land in Jharkhand is full of greenery, with 27% of the area being forest and the majority (52%) being cropland, as studied here. The p–resent analysis showed that there was an accelerated increase in forest greenness during the COVID-19 lockdown period (2019–2020) (Figure 3, Table 1). Interestingly, it has been observed that many areas of the forest have improved in health since the year 2000, while a substantial portion remained unchanged during the period from 2000 to 2020 (Figure 4).

The vegetation in Jharkhand has been steadily increasing since 2000, with a significant growth observed in 2019–2020 due to the COVID-19 lockdown and subsequent restrictions. Though, the vegetation returned to its previous levels in 2019 after the lockdown measures were lifted, indicating a reversion to the original environmental conditions. The analysis indicated that all areas with the highest NDVI values remained unchanged from 2000 to 2020 during the months of November and October (Figure 4). These months, following the end of the rainy season, exhibit the highest level of vegetation vigor. Additionally, the maximum NDVI value during other seasons has also shown an increasing trend, particularly from 2016 to 2020, with a notable acceleration between 2019 and 2020. This finding suggests that areas with already high vegetation quality maintained their status over the two-decade period.

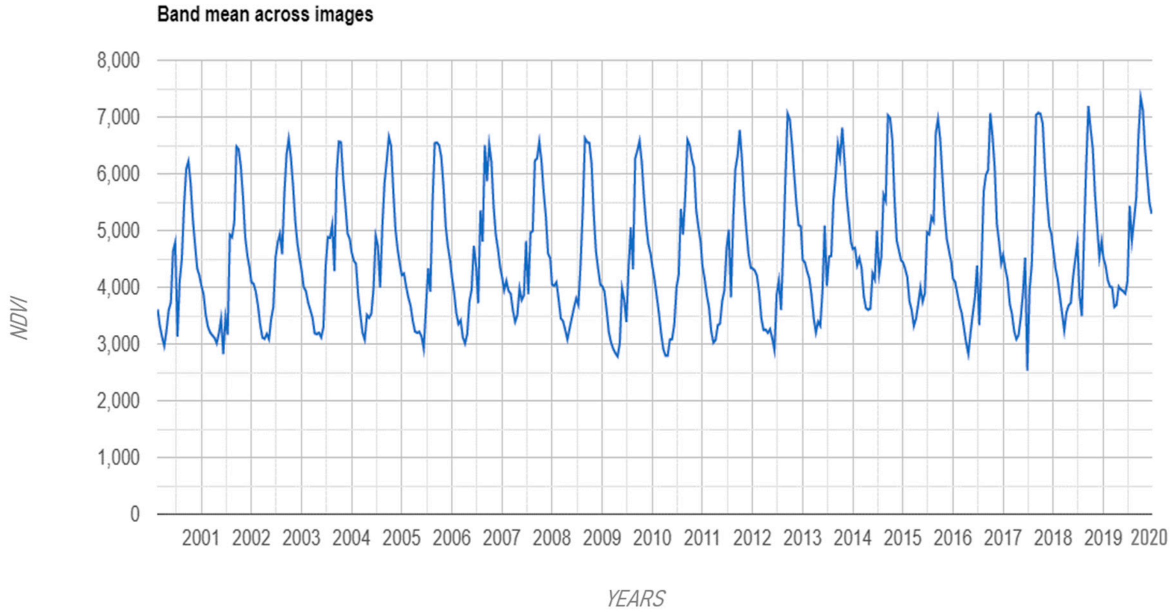

Figure 3. MODIS NDVI mean value from 2000–2020; NDVI value is not scaled, thus a factor of 0.0001 should be used for scaling (X: year and Y: value).

Table 1. Data used and sources mentioned as below used in this study.

Data Used	Characteristics	Sources	Resolution	Date Acquisition	Path/Row
MODIS-NDVI (MOD13Q1)	NDVI	USGS	250 m	18 February 2000 to 31 January 2022	103/54, 103/55, 104/54, 104/55, 104/56, 105/54, 105/55, 105/56, 105/57, 106/54, 106/55, 106/56, 106/57, 107/54, 107/55
Landsat 5 TM	Mann–Kendall Tau	USGS	30 m	1 January 1985 to 1 January 2012	
Landsat 7 ETM+	Mann–Kendall Tau	USGS	30 m	28 May 1999 to 31 December 2021	
Landsat 8 OLI	Mann–Kendall Tau	USGS	30 m	18 March 2013 to 31 January 2022	
Vector data	Map Preparation	https://www.igismap.com, accessed on 10 January 2022	30 m	-	
Sentinel 2A/ESRI 10 m land cover	Land Use and Land cover	ESRI [42]	10 m	2021	

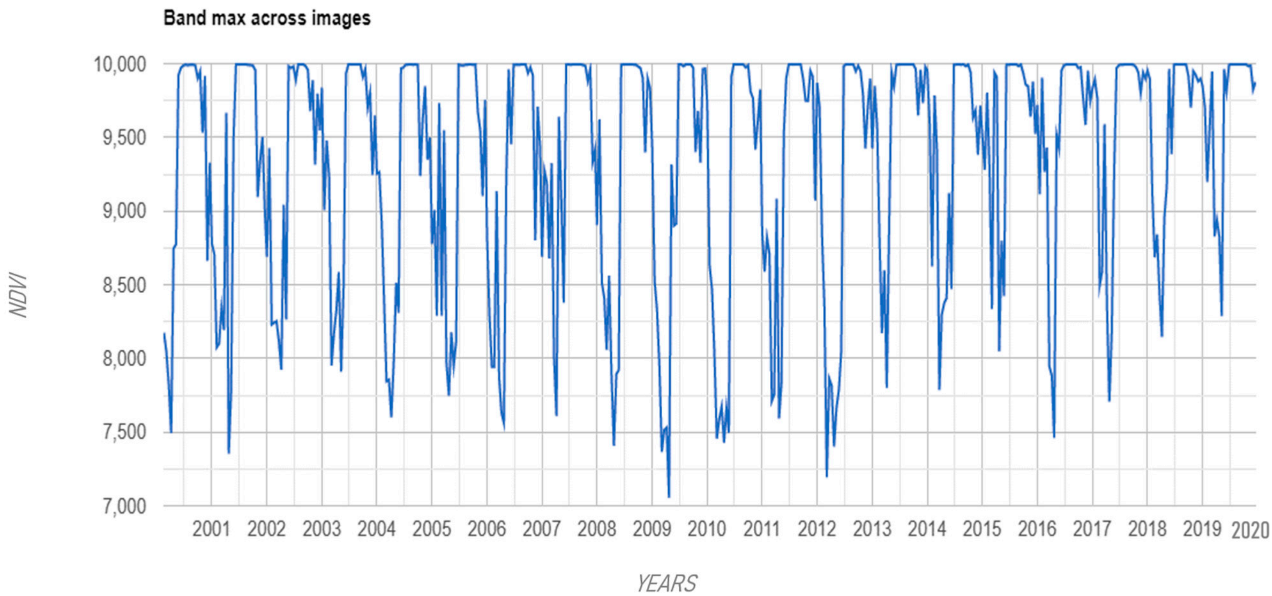

Figure 4. MODIS NDVI maximum value from 2000–2020; NDVI value is not scaled, thus a factor of 0.0001 was used for scaling (X: year and Y: value).

3.2. COVID-19 Lockdown and Unlock Impacts on Vegetation

The analysis presented herein explores the state of vegetation in both forests and croplands in Jharkhand, using various figures for illustration. The mean NDVI value, a measure of vegetation greenness, corresponds to croplands with scant forest cover, while the highest NDVI value is attributed to forest vegetation. These figures offer insights into the shifts in vegetative greenness during different periods, with particular emphasis on the impact of the COVID-19 pandemic and the ensuing lockdown measures [43–46].

In April 2020, compared to April 2019, there was a 19% increase in the maximum vegetative greenness and a 9% increase across half of the area (Figure 5), suggesting a significant rise in vegetation during that period. Likewise, in May 2020, a 13% increase in maximum vegetative greenness was observed compared to May 2019, and a substantial 27% increase across approximately 35,872.2 km^2 of Jharkhand. These findings indicate a noteworthy boost in vegetation during May 2020.

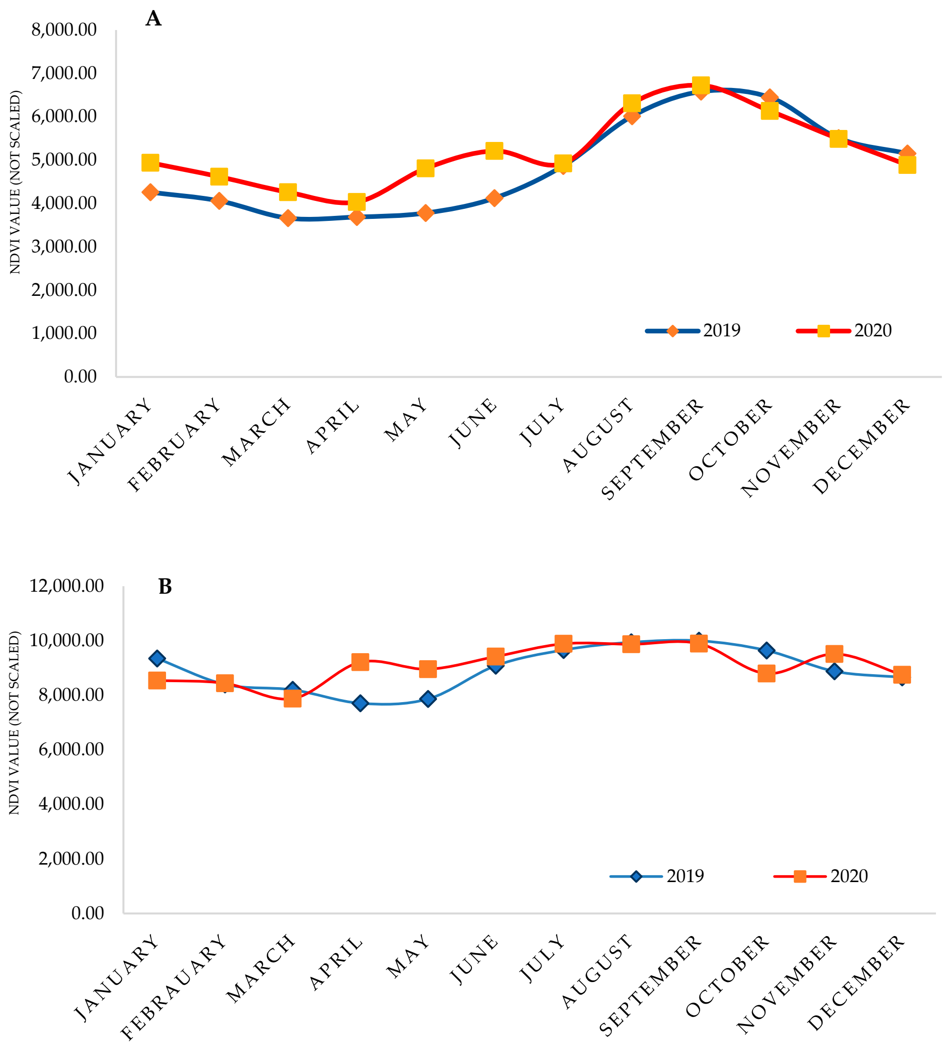

Figure 5. Representation of statistical chart of NDVI (**A**) mean and (**B**) maximum values during 2019 and 2020 period.

In June 2020, a 3% rise in maximum vegetative greenness was observed compared to June 2019, but a more significant 26% increase was seen across 39,858 km^2 of Jharkhand (Figure 6). Although there was a slight dip in maximum greenness from Unlock 2.0 to Unlock 5.0, it is important to note that approximately half of Jharkhand still experienced a modest increase in vegetation greenness (Figures 7 and 8).

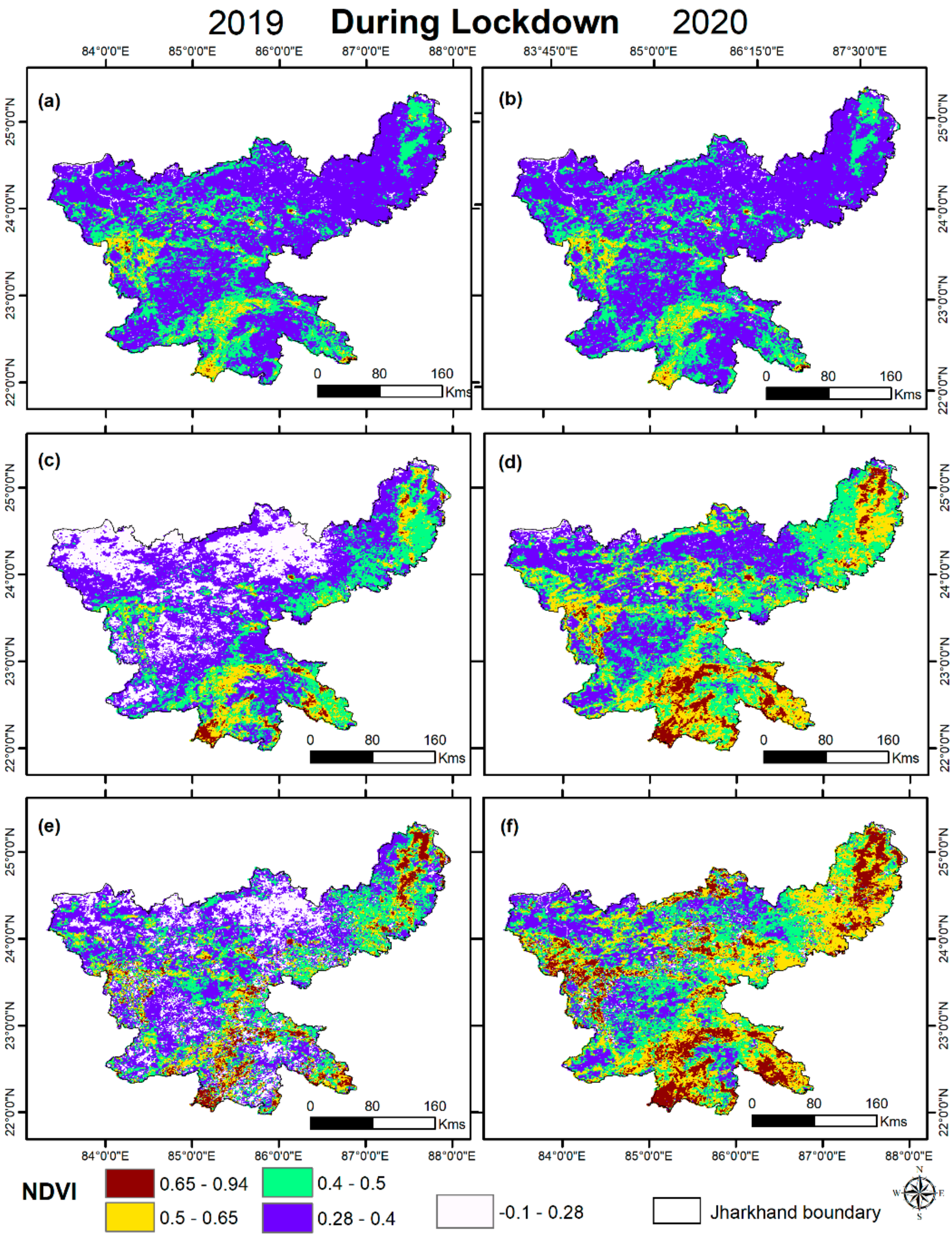

Figure 6. Vegetation condition of Jharkhand state observed in the month of April (**a**,**b**), May (**c**,**d**), and June (**e**,**f**) during 2019 and 2020, respectively, of pre- and lockdown period.

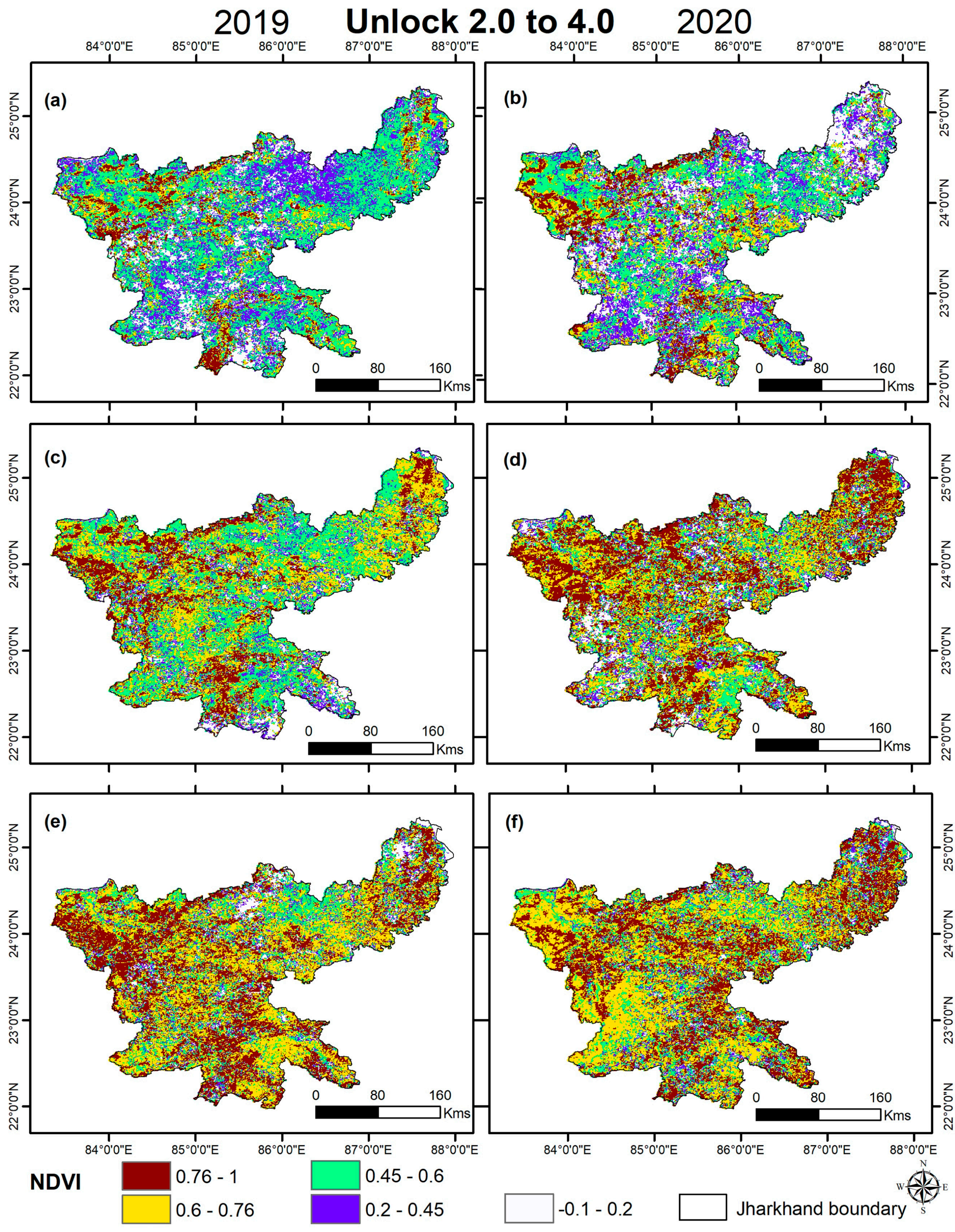

Figure 7. Vegetation condition of Jharkhand state observed in the month of July (**a**,**b**), August (**c**,**d**), and September (**e**,**f**) during 2019 and 2020, respectively, of pre-lockdown period and Unlock 2.0 to 4.0.

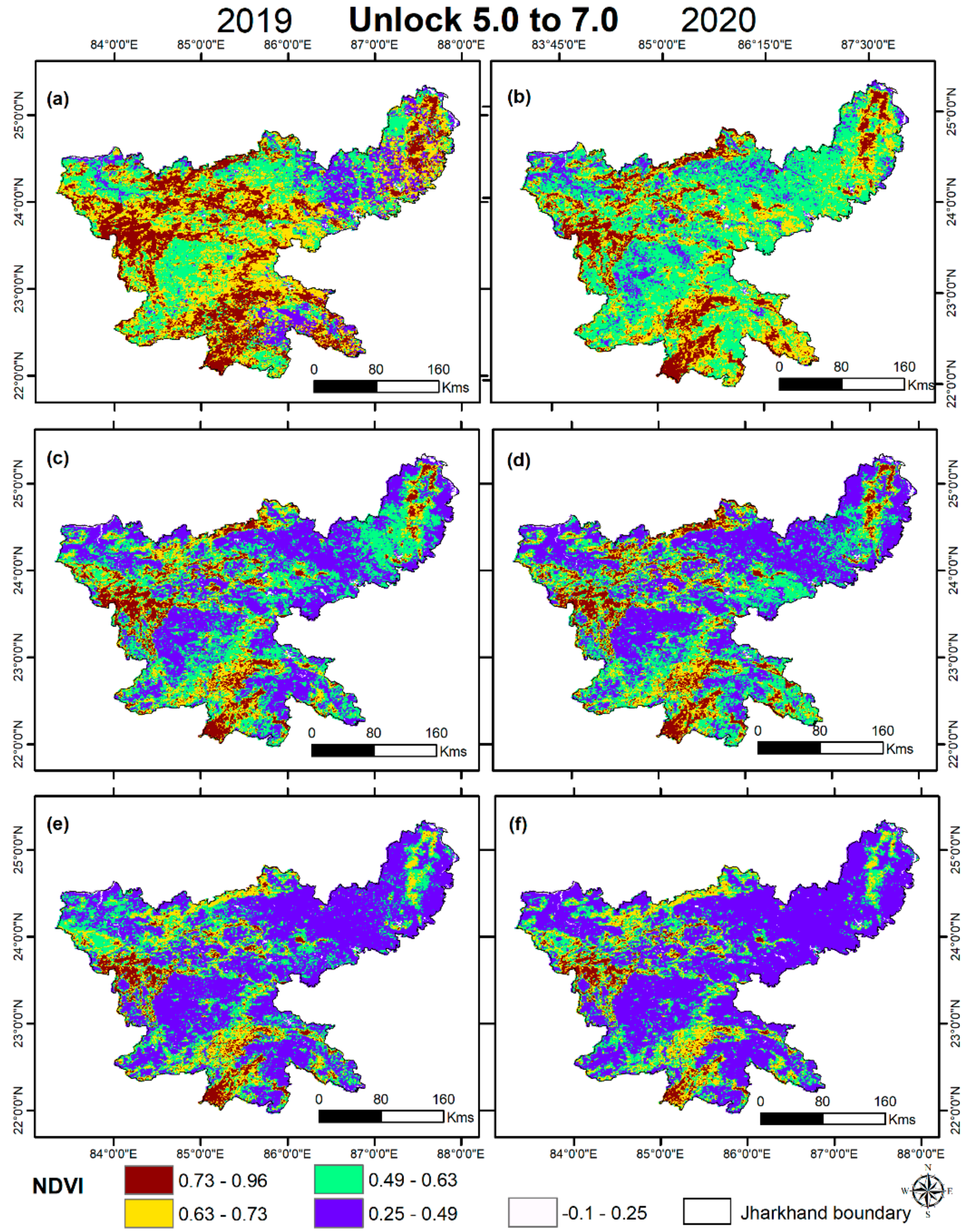

Figure 8. Vegetation condition of Jharkhand state observed in the month of October (**a**,**b**), November (**c**,**d**), and December (**e**,**f**) during 2019 and 2020, respectively, of pre-lockdown period and during Unlock 5.0 to 7.0.

During Unlock phases 5.0 to 7.0, there was a minor drop in the maximum percentage of greenness across 39,858 km^2 of the area, except in November, when a slight rise in the highest value of greenness was observed, albeit with a small decrease in nearly half of the Jharkhand area (Figure 8). These findings suggest that while overall greenness experienced some fluctuations during the unlocking phases, certain periods exhibited slight increases or decreases in vegetative greenness across various parts of Jharkhand [47–53].

To further comprehend the spatial distribution of NDVI during the COVID-19 phase, NDVI spatial maps are depicted in Figures 6–8. These maps offer visual representations of changes in vegetation greenness across the region during specific periods, facilitating a more detailed analysis of vegetation dynamics.

3.3. Precipitation and NDVI Relationship during Pre and Post Lockdown Period

The precipitation analysis was conducted for the months of April through November during the pre-lockdown and lockdown periods from 2019 to 2020, to establish a relationship between precipitation and vegetation. This study reveals that during the pre-lockdown and lockdown months of April to June (2019 and 2020), maximum precipitation of 350–400 mm was primarily observed in the southwestern and north-eastern regions of Jharkhand in June 2020 (Figure 9a–f). Conversely, the maximum rainfall recorded in June 2019 was only 150 mm. Furthermore, vegetation conditions were found to be favorable during the lockdown, as per NDVI observations. In April and May, the western region received less precipitation (0–50 mm) in 2019. In 2020, precipitation up to 100 mm was observed in most parts of Jharkhand.

In July, rainfall of about 300 mm dominated approximately 85% of Jharkhand's area, whereas the north-eastern part received up to 450 mm. Interestingly, in 2020, the central region recorded the highest precipitation of 400 mm. The month of August saw precipitation of 400 mm in 2019, whereas up to 550 mm of rainfall was observed in 2020, primarily in the southern part of Jharkhand (Figure 9g–l). Coinciding with this, NDVI values also peaked during this month, ranging between 0.6–0.76 and 0.76–1 throughout Jharkhand.

In September, precipitation ranged between 350–400 mm, observed in the southern and north-eastern regions during 2019, whereas up to 550 mm was recorded in the north-western region. The most significant increases in NDVI were observed in the western, eastern, and southern parts of Jharkhand. In October 2019, 200 mm of rainfall was recorded, a similar observation was made in 2020, NDVI values were exceptionally higher in many parts in 2019 compared to 2020 (Figure 9m–p). The month of November recorded precipitation ranging from 0–50 mm only in 2019 and 2020. These observations suggest that the most significant impact on vegetation health occurred in June, July, August, and September, as these months received ample rainfall during the lockdown period.

As seen in Figure 10, the north western part of Jharkhand demonstrated significant improvement during the lockdown. The relationship between NDVI and precipitation during the pre-lockdown period (1984–2019) reveals a positive linear relationship across all vegetation regions. Figure 11 depicts the COVID-19 era, where a stronger positive relationship is observed between rainfall and NDVI values. This is because rainfall has increased, leading to an increase in NDVI values. Extrapolating these observations to the entire area of Jharkhand revealed similar scenarios throughout the region.

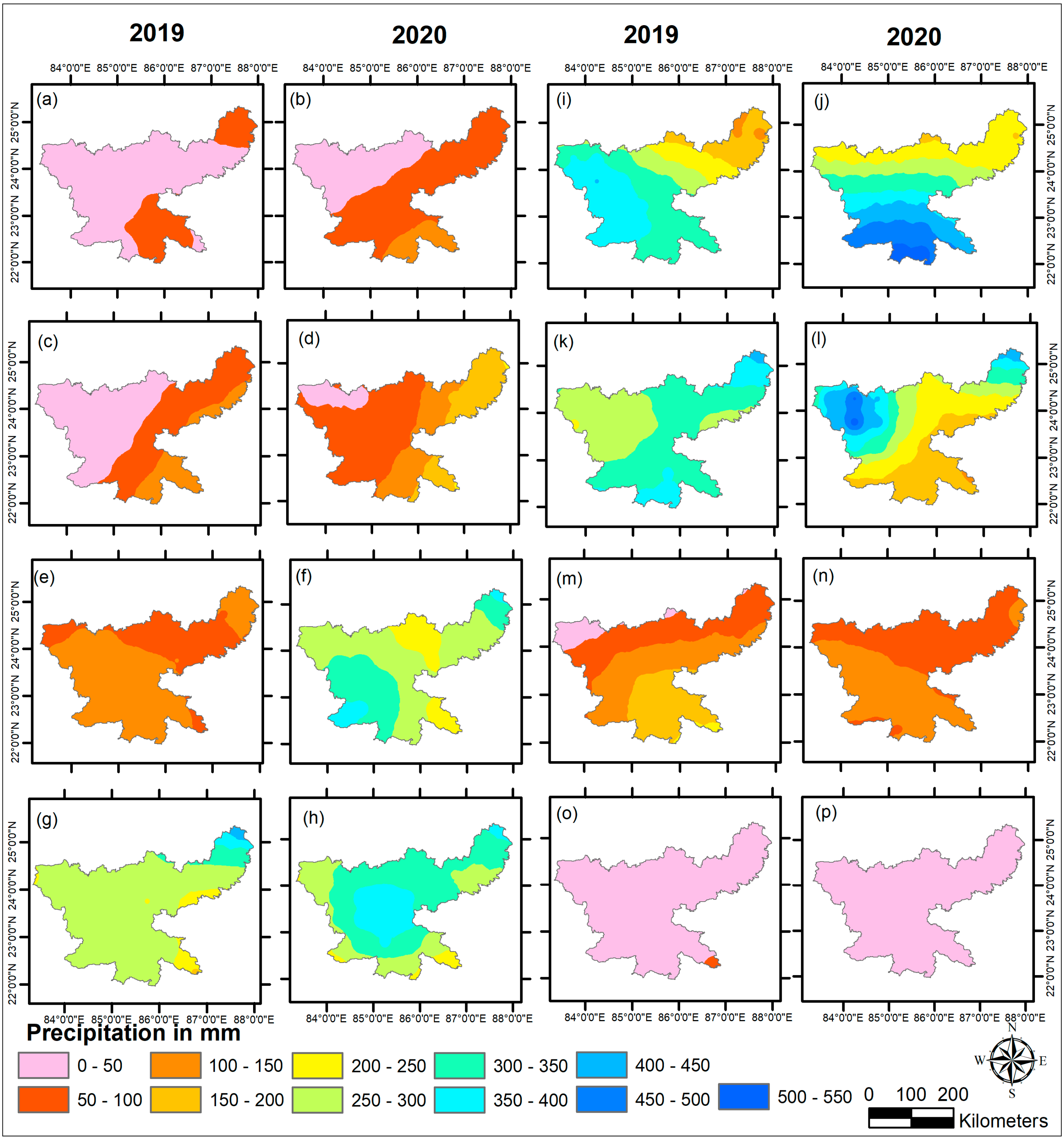

Figure 9. Precipitation distribution in Jharkhand state during the pre-lockdown and lockdown period 2019 and 2020 in the months of April (**a**,**b**), May (**c**,**d**), June (**e**,**f**), July (**g**,**h**), August (**i**,**j**), September (**k**,**l**), October (**m**,**n**), and November (**o**,**p**).

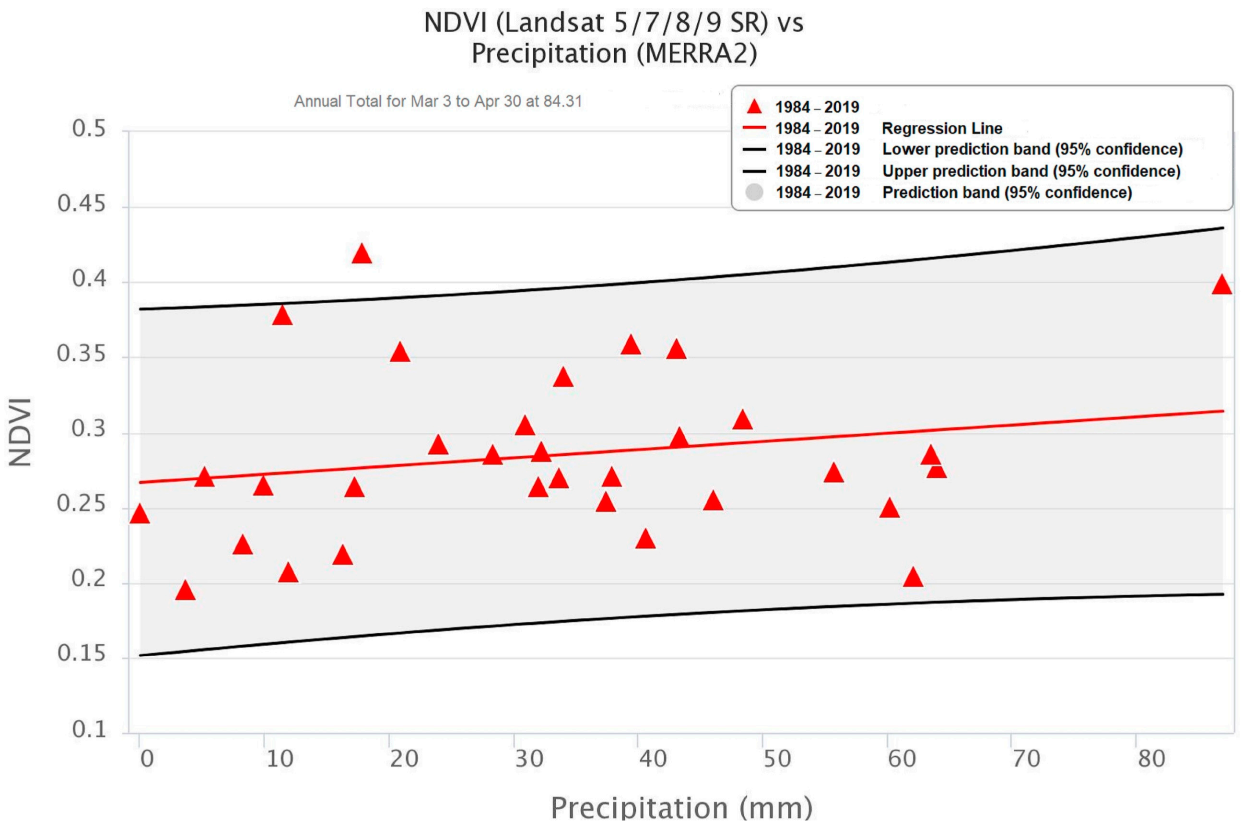

Figure 10. Relationship of NDVI and precipitation over north west part of Jharkhand (pre-COVID).

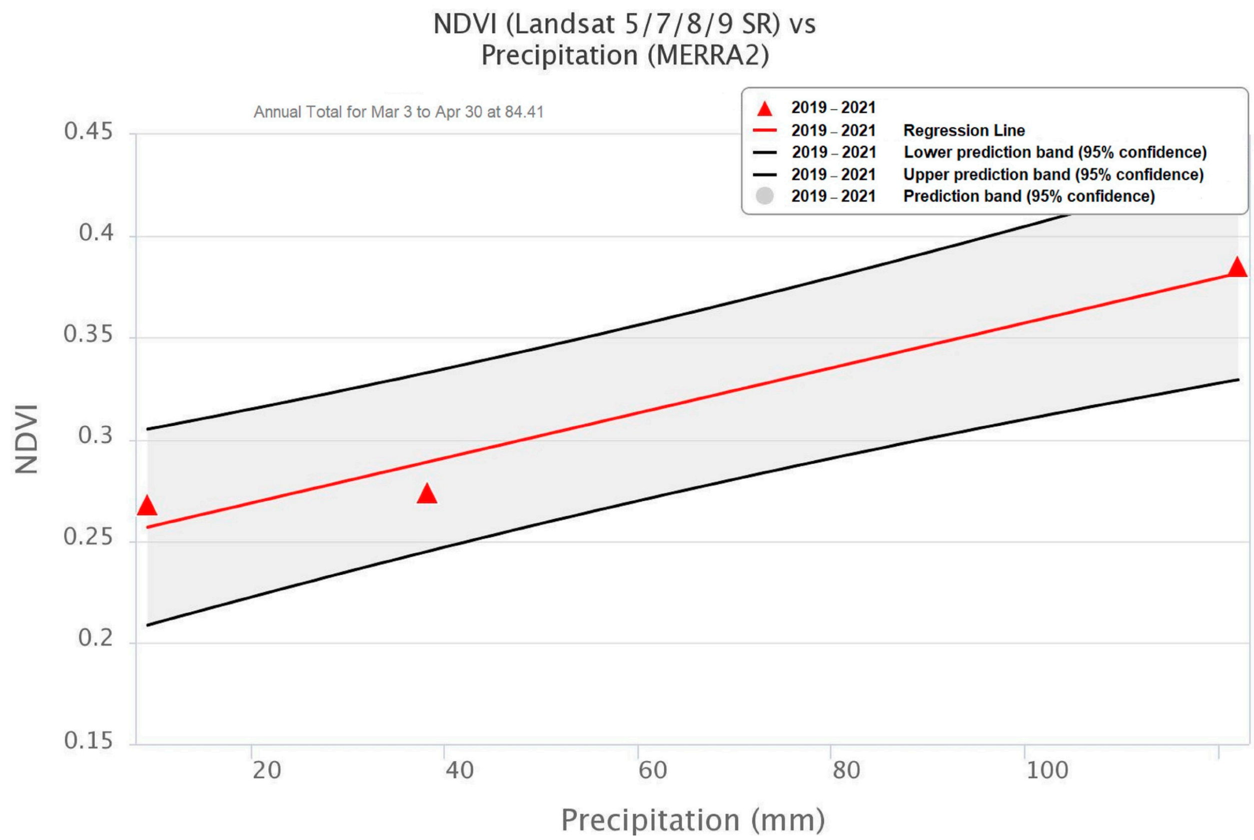

Figure 11. Relationship of NDVI and precipitation over north west part of Jharkhand (post-COVID).

3.4. Mann–Kendall Trend Analysis during 1984–2021

The application of the Mann–Kendall test was used to analyze multi-temporal Landsat data spanning from 1984 to 2019 in Jharkhand (Figure 12). The Mann–Kendall test is a statistical test used to detect trends in data over time. In this case, it was employed to assess the trend of vegetation based on the NDVI, which is a measure of vegetation greenness.

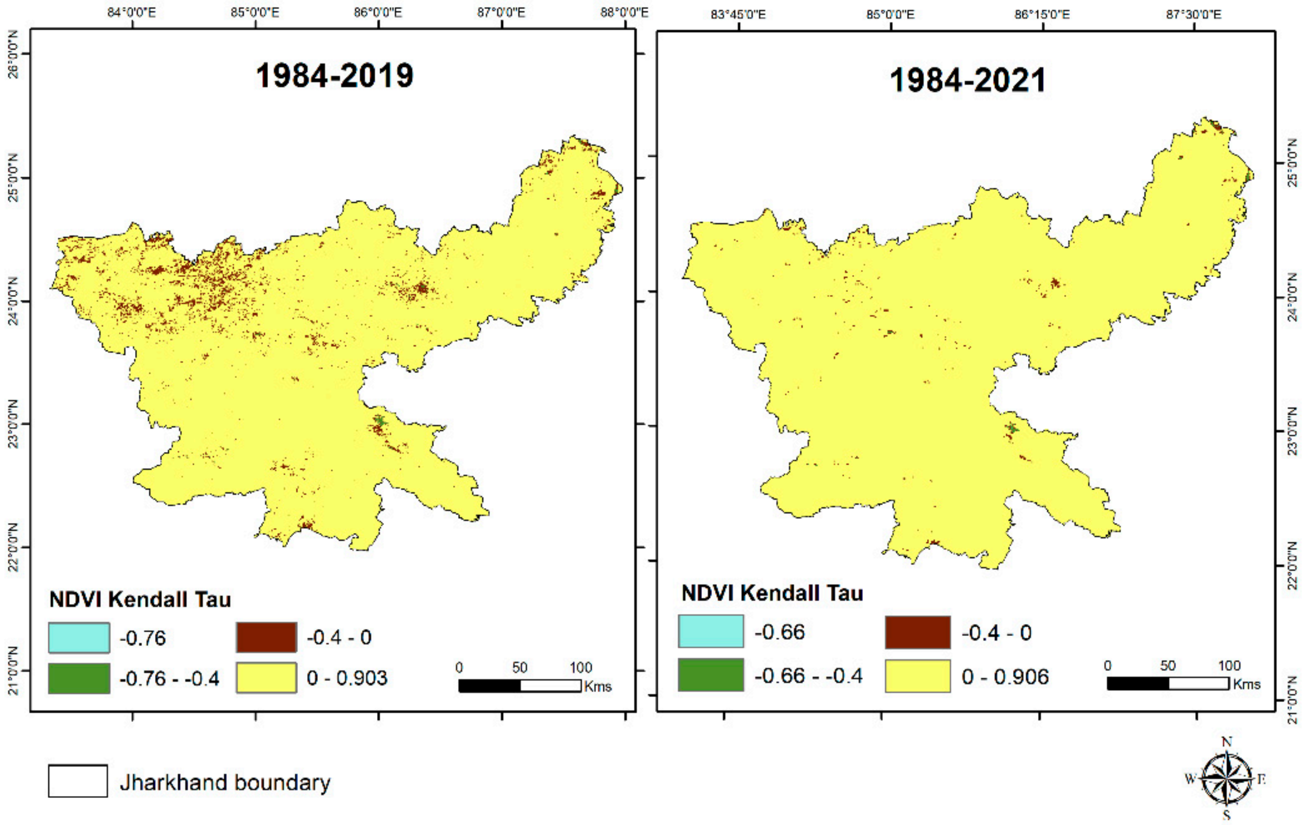

Figure 12. NDVI Kendall Tau values from the period of 1984 to 2019 and 1984 to 2021.

At a 95% confidence level with a significance level of 0.05 (*p*-value), the Mann–Kendall test was performed on the Landsat data. The Kendall Tau statistic, derived from this test, represents the trend of the NDVI values over time. The analysis revealed that the majority of Jharkhand exhibited an increasing trend in NDVI values, indicating an improvement in vegetation cover. The northwestern part of the region showed a decreasing trend in NDVI values, suggesting a decline in vegetation.

Furthermore, when analyzing the data from 1984 to 2021, it was observed that there was an acceleration and negative trend in most parts of the northwestern region. This indicates a worsening vegetation condition in that particular area over the analyzed period.

Moreover, the passage mentions that there was a difference in the correlation of trend values between two periods. Specifically, the Tau value, which represents the strength and direction of the trend, increased by 0.03 due to the COVID-19 phases. This suggests that the COVID-19 pandemic and associated lockdowns might have had a slight positive impact on vegetation, leading to a small improvement in NDVI values.

4. Discussion

The research findings shed light on the profound influence of human activities on the health and vitality of vegetation and ecosystems on a larger scale [54–59]. This emphasizes the urgency of adopting comprehensive and sustainable practices to mitigate environmental damage, while also potentially enabling nature's recovery [60–62]. By illuminating the temporary yet significant positive impacts resulting from reduced pollution during the COVID-19 lockdown, this study offers invaluable insights that can be harnessed in the development of proactive environmental policies. These revelations underscore the immediate need for well-planned and strategic action, informing both local and global efforts aimed at achieving a sustainable future [63,64]. In this way, this research stands as a critical contribution to our comprehension of ecosystem dynamics, serving as a pivotal foundation for crafting effective and sustainable strategies for environmental management.

To delve into the research results, the study explores the effects of the COVID-19 lockdown measures on vegetation health in Jharkhand, particularly in relation to reduced human activity and industrial operations. These measures led to a significant reduction in air pollution levels, subsequently yielding positive effects on the region's forests and vegetation. This positive impact was notably manifested by a distinct greening effect observed in both forested and cultivated lands. The greening phenomenon in Jharkhand's croplands can be attributed to a combination of advanced agricultural practices, such as enhanced irrigation, hybrid cultivation, efficient pest management, and the use of high-quality seeds [44–46]. Financial support, crop insurance, and agricultural automation also played contributing roles.

The research reveals a nuanced picture across different regions of Jharkhand, with some areas exhibiting positive ecological shifts, while others necessitate focused conservation efforts [47]. Remarkably, the lockdown measures had a discernible positive influence on the health of Jharkhand's forests, leading to visible greening effects [48]. However, the study observes that with the cessation of lockdown in 2020, the vegetation levels in Jharkhand reverted to their pre-lockdown state, mainly due to the resumption of human activities that tend to escalate air pollution levels [49,50].

The research's reliance on spatial representations of the Normalized Difference Vegetation Index (NDVI) provided critical insights into the fluctuations in vegetation greenery during the COVID-19 lockdown, which was subsequently followed by observable increments and subsequent decrements during the unlocking phases [49]. This approach aligns with various studies that have addressed the environmental impact of lockdown measures [52–55]. Notably, similar improvements in vegetation health and productivity were observed across India, even in mining areas [51]. Nonetheless, divergent outcomes were noted in certain countries like Egypt, where adverse effects on agricultural production were reported [20]. The utilization of NDVI was crucial in highlighting the improvements in air quality and vegetation resulting from reduced pollution [56].

The study conducted Mann–Kendall trend tests on Landsat data, uncovering temporal vegetation trends in Jharkhand [58]. Most of the region exhibited an increasing NDVI trend, except for the north western part, which displayed a decline. Notably, the analysis revealed an increase in the Tau value during the COVID-19 lockdown period, hinting at potential positive effects of the pandemic-related restrictions on Jharkhand's vegetation. However, the researchers emphasize the necessity for further extensive research to substantiate this assumption.

Furthermore, the research delves into the relationship between precipitation and vegetation, as measured by NDVI, during the pre-lockdown and lockdown periods of 2019 and 2020. The study identifies significant impacts on vegetation health during the lockdown months of June, July, August, and September, which coincide with periods of high rainfall. An affirmative correlation is noted between NDVI and precipitation across Jharkhand. Notably, the increment in NDVI was more pronounced post-COVID, potentially attributable to increased global atmospheric circulation and decreased atmospheric pollution resulting in unforeseen consequences.

In conclusion, the research effectively navigates the nexus between human activities, vegetation health, and ecosystem dynamics in Jharkhand. By focusing on the tangible impacts of COVID-19 lockdown measures, the study provides a basis for proactive environmental policies and strategies. It underscores the significance of sustainable practices in mitigating environmental degradation and propelling the restoration of natural systems. Through the exploration of NDVI data and a comprehensive analysis of long-term vegetation changes, the research contributes valuable insights that resonate both locally and globally, guiding efforts towards a sustainable future [63,64].

5. Conclusions

This study represents a novel endeavor that harnesses MODIS and Landsat data to deliver a comprehensive assessment of vegetation health dynamics in Jharkhand from 2000 to 2020. Leveraging the Normalized Difference Vegetation Index (NDVI), our analysis unveils a substantial increase in vegetation health within this timeframe. Particularly during the 2019–2020 period, our investigation spotlights remarkable improvements in vegetation health during May and June, with significant enhancements also observed in April. These NDVI fluctuations closely align with periods of peak precipitation, yielding intriguing insights into the intricate connection between precipitation and vegetation health. Of significant note is the positive impact of the COVID-19 lockdown measures on vegetation health, owing to reduced pollution levels. This observation underscores the potential effectiveness of strategically timed reductions in human activity as a means of environmental rejuvenation. However, it is important to recognize the transient nature of these improvements as vegetation reverted to its pre-lockdown state after restrictions were lifted.

While our findings hold profound environmental implications, certain limitations must be acknowledged. Factors such as local agricultural practices and varying weather conditions, which can influence vegetation health, were not fully considered. Moreover, we did not delve into the specific effects of different types of pollution reductions during the lockdown on vegetation health. These limitations notwithstanding, our research underscores the critical need for robust pollution control strategies, holistic water management policies that account for vegetation's pivotal role, and comprehensive air quality regulations. This study also highlights the instrumental role of remote sensing data in shaping environmental policies. Despite its constraints, our research points to the potential for enhancing vegetation health and mitigating air pollution through evidence-based environmental measures, not only in Jharkhand but on a global scale. Future research should delve deeper into the distinct influences of various pollution types on vegetation health and explore how shifts in these pollutants impact ecosystems more broadly.

Author Contributions: Conceptualization, G.M., S.K., T.A. and S.K.S.; Methodology, G.M., S.K., S.K.S., S.K.G., P.K. and T.A.; Software, S.K.G. and T.A.; Validation, G.M., S.K., P.K., T.A. and S.K.G.; Formal Analysis, G.M., S.K., T.A., P.K. and S.K.G.; Investigation, G.M., S.K. and S.K.G.; Resources, S.K. and P.K.; Data Curation, G.M., S.K. and P.K.; Writing—Original Draft Preparation, G.M., S.K., T.A. and S.K.G.; Writing—Review and Editing, G.M. and S.K.S.; Visualization, G.M. and S.K.S.; Supervision, S.K. and S.K.S.; Project Administration, G.M. and S.K.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data shall be available from the first author on request.

Acknowledgments: We extend our gratitude to the United States Geological Survey (USGS) for supplying the indispensable Landsat data, and to Google Earth Engine for the provision of their robust analytical platform, which greatly facilitated our research. Furthermore, we sincerely appreciate the valuable insights and constructive feedback provided by four anonymous reviewers, whose diligent work and thoughtful suggestions have significantly enriched the quality and depth of this manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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