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Coal Mining And Environmental Degradation: A Study Of Vegetation Dynamics And Land Surface Temperature Of Paschim Bardhaman, India

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Abstract

The growth of mining is a significant contributor to environmental change, especially in the coal mining area, where large-scale land transformation takes place. This paper analyses how mining activities have changed land use/land cover (LULC), vegetation dynamics, and land surface temperature (LST) in Paschim Bardhaman, India, between 1990 and 2020 through remote sensing and GIS. The LULC maps were created by utilizing multi-temporal Landsat data, whereas NDVI and LST were obtained to determine the state of vegetation and thermal conditions. The findings show that the mining areas have grown significantly, such as Hansdiha colliery that had a size of 577,800 m^2 in 1990 but had a size of 4,497,300 m^2 in 2020, and 1,206,000 m^2 in 2020 but 3,052,80 The values of NDVI indicate a decreasing tendency in most collieries that means the vegetation is being degraded, but LST has been growing significantly, with the surface temperatures rising by about 25°C in areas with mining activity. Statistical analysis indicates that there is a strong negative relation between mining expansion and NDVI (r =0.6 to 0.8) and a positive relation between mining and LST (r = 0.5-0.7). Transect analysis further supports the fact that there is a higher temperature in the mining and built-up areas than in vegetated areas. The paper finds that mining activities have caused considerable loss of vegetation and thermal increase, and thus, there is an urgent requirement to adopt sustainable mining methods, ecological recovery, and ongoing environmental monitoring.

Keywords: Open Cast Coal Mining, Environmental Degradation, Paschim Bardhaman, LST, Transect Profile

1. Introduction

There has been a growing trend in mining activities that have changed patterns of land use and land cover (LULC) with tremendous effects on the environment across the globe. These changes have necessitated the use of remote sensing, especially techniques that make use of satellite imagery because of its availability, spatial scale, and temporal reliability (Chatterjee et al., 2022). The growth in mining zones is usually accompanied by vegetation loss, a rise in land surface temperature (LST), and general fragmentation of the landscape, which may have severe ecological and socio-economic effects.

This paper aims to examine multi-temporal satellite images between 1990 and 2020 in order to evaluate mining activity, vegetation changes, and LST changes in the study area. The study utilizes Landsat data and thermal products of MODIS to classify the data using a supervised classification technique with a maximum likelihood algorithm to produce LULC maps and calculate vegetation indices like the Normalized Difference Vegetation Index (NDVI). The combination of these datasets allows a detailed assessment of mining-related changes in the environment in terms of space and time.

The issues with mixed pixels in moderate-resolution satellite imagery have been noted in previous research, and the need to measure accuracy using ground truth verification and statistical measures (such as Kappa statistics) to guarantee quality classification results (Biswas et al., 2024; Lu and Weng, 2005; Anderson et al., 1976). Through the quantification of changes in the decadal period and the association of the growth of mining with the vegetation cover and LST, this research will explain the impacts of mining activities on the environment and give insight into the processes of land degradation and recovery trends in the area.

Although much has been done in research on the environmental changes that have been brought about by mining, there are several gaps that are critical. Past research has mainly concentrated on the change of land use/ land cover (LULC) or on an individual environmental measure like NDVI or LST. Nevertheless, there is still a lack of integrated analysis it is possible to make concerning the mining expansion, vegetation dynamics, and thermal characteristics, mostly at the regional scales. The majority of papers focus on the short-term or local effects, without long-term (i.e., multi-decadal) spatio-temporal evaluation, which is needed to learn about the cumulative environmental degradation. The other gap is that there is no spatially explicit analysis, i.e. transect-based or zone-based analysis, which can provide a more detailed explanation of the environmental gradient affected by mining activities. The current research will thus fill these gaps by performing a thorough spatio-temporal investigation into mining development and its environmental effects through a multi-temporal satellite data. This research uses a combination of LULC, NDVI analysis, and LST estimation to understand the interrelation between mining activities, vegetation dynamics, and thermal conditions in the period 1990-2020. This study offers an enhanced perspective on the environmental dynamics in mining-dominated landscapes by integrating spatial, temporal, and statistical analysis.

The primary aim of the research is to examine how mining expansion affects the environmental conditions with the help of geospatial methods. To examine land use/land cover (LULC) variations in the study area over the time span of 1990-2020; to determine how mining activity affects land degradation and thermal conditions; and to assess how mining activity, NDVI, and LST are statistically related.

2. Study area

The area of study is in Paschim Bardhaman, which is in the tropical climate of eastern India and is geographically situated between a latitude of about 22 56 N to 23 53 N and a longitude of 86 48 E to 88 25 E. This geographical position situates the area in the Damodar Valley coal belt, which is one of the most significant mining-industrial areas of the country. It is an arid, desolate, and developing republic with the highest point standing at about 227 m of rocky origin, with laterite soil developing to hang onto the rocky hillocks. Ajoy-Barakar division is a curvilinear plateau (Halder et al., 2024) that has an average elevation of about 150 m. The climate of the study area is tropical monsoon (Koeppen Aw), which is characterized by hot summers, moderate to heavy rainfall, and mild winters. The temperature is approximately 2526 C/year on average, with temperatures occasionally reaching 4445 C in the summer and -6-10 C in the winter. The average yearly rainfall in the region amounts to about 1300-1474 mm, most of which falls during the southwest monsoon season (June-September).

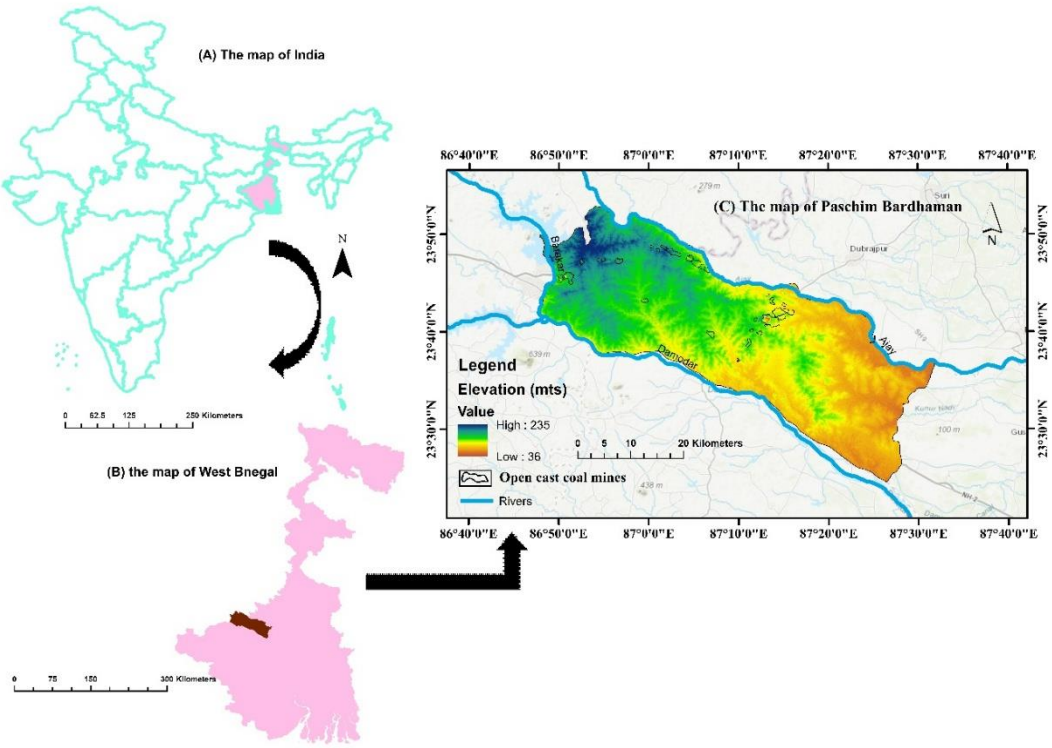

Figure 1: Physical and Environmental Characteristics and Location of the Study Area

3. Data used

The present study uses multi-temporal satellite datasets and secondary data sources to analyze mining expansion, vegetation dynamics, and land surface temperature (LST) in the study area. Both spatial and temporal datasets were used for the period 1990–2020.

Table 1: Description of Data Sources and their Characteristics

Data Type	Dataset / Source	Satellite / Product	Spatial Resolution	Temporal Coverage
Satellite Data	USGS Earth Explorer	Landsat 5 TM	30 m	1990, 2000
Satellite Data	USGS Earth Explorer	Landsat 7 ETM+	30 m	2010
Satellite Data	USGS Earth Explorer	Landsat 8 OLI/TIRS	30 m	2020
Thermal Data	NASA Earth data	MODIS (MOD11A1 / MOD11A2)	~1 km	2000–2020
Vegetation Index	Derived from Landsat	NDVI	30 m	1990–2020
Mining Data	Extracted from classified images	Digitized mining area	Variable	1990, 2000, 2010, 2020

4. Methodology

Multi-temporal Landsat data (1990–2020) were used for spatio-temporal analysis. LULC classification was conducted to measure the mining expansion. To measure vegetation and thermal conditions, NDVI and LST were computed. Spatial and transect analyses were used to analyze land cover and temperature.

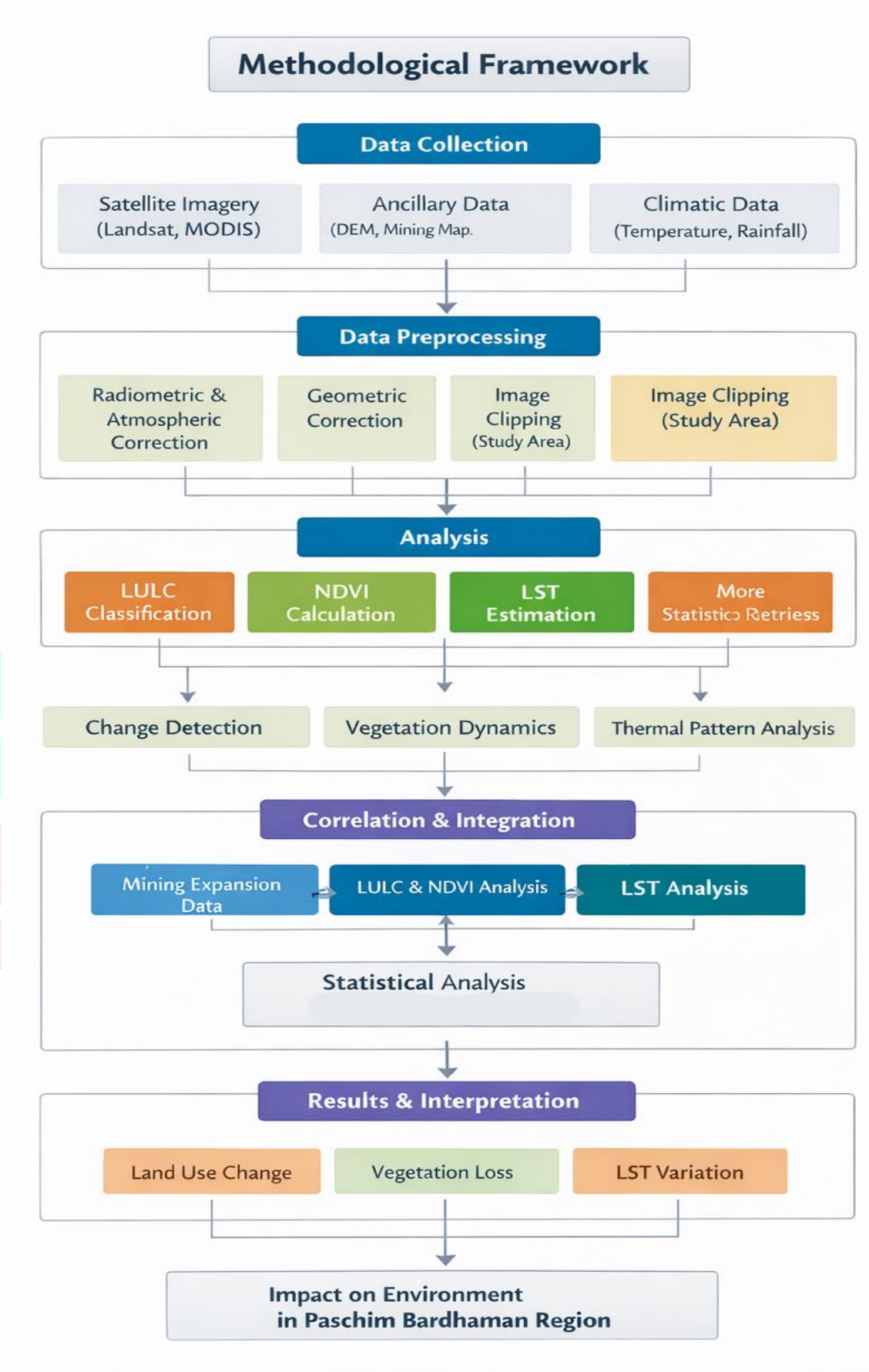

Figure 2: Methodological flow chart of the study

4.1. LULC classification

Remote sensing using satellite images is now commonly recognized as the best practice for detecting LULC since it is more accessible in any geographical location, provides real-time data, and is widely applicable in other scientific researches (Chatterjee et al.,2022). Supervised classification technique with the maximum likelihood algorithm has been employed in preparing the LULC map. Selection of

training site is another essential component of supervised classification image processing. In this case, some pixels have been selected as training sites that share similar DN values (Biswas et al.,2024). On average, 100 training sites have been established for each class in different portions of the area. In line with the available training sample, the computer has been programmed to classify the entire image based on the maximum likelihood image classification algorithm. Post-classification corrections have been done in order to increase the quality of the results. During the image classification process, mixed pixels pose another challenge as a result of the moderate spatial resolution of the Landsat datasets (Lu and Weng.,2005). Mixed pixels have been adjusted in the post-classification correction through Semi-Automatic-Classification-Plugin and several Plugin in QGIS.

Accuracy assessment in terms of ground truth verification is a vital element of image classification to get a higher precision level of the outcome, which suggests more than 85% correct classification for a healthier explanation and recognition (Anderson et al., 1976; Monserud and Leemans, 1992; Rwanga and Ndambuki, 2017). For this study, 178 points for 1990, 181 points for 2000, 243 points for 2010 and 177 random points for 2020 are generated over the classified LULC maps used for cross-validation using Google Earth-provided data. Based on these random points, ' Kappa Statistics' (Lea and Curtis., 2010) are computed to calculate the accuracy level of the classified image (Biswas et al.,2024).

Kappa analysis is a discrete multivariate technique used in accuracy assessments. Kappa analysis yields a Khat statistic (an estimate of Kappa) that measures agreement or accuracy (Rwanga et al., 2017). The Khat statistics are computed using Eq.-1.

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_i + Xx_{+1}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{ii} Xx_{+1}\right)} \quad (1)$$

Where **N** indicates the sum of pixels; r is the total count of rows in matrix. **xii** = number of observations in row **i** and column **i**; $\mathbf{x_i}+$ and **x+i** are the marginal for row **i** and column **i,** respectively.

LULC of the study area changes substantially due to different factors, including mining activities. To obtain quantitative changes of the land cover classes during the study period, i.e., from 1990 to 2000, from 2000 to 2010 and from 2010 to 2020, the change matrix is generated by cross-tabulation analysis on a pixel-by-pixel basis as suggested by (Munsi et al.,2009). Land Use Land Cover area distribution results were used to compute the trend, net change, percent change and rate of LULC change between 1990 and 2000, 2000 and 20010, and 2010 and 2020.

4.2. Calculation of NDVI, LST

The normalized differential vegetation index (NDVI) was chosen to reflect vegetation coverage and growth, which is calculated as follows:

$$NDVI = \frac{\rho_{nir} - \rho_{mir}}{\rho_{green} - \rho_{mir}} \quad (2)$$

where ρNIR and ρR represent the near-infrared and red bands of Landsat 5 TM and Landsat 8 OLI/TIRS, respectively.

Land surface temperature (LST), which can be retrieved by the inversion of thermal infrared remote sensing, was selected to represent heat. The formula is:

$$L_\lambda = M_L \times DN + A_L$$

$$T_B = \frac{K_2}{ln(\frac{K1}{L\lambda}+1)} \quad (3)$$

$$LST = \frac{TB}{1+(\frac{\lambda \cdot T_B}{\rho}) \cdot ln(\varepsilon)}$$

Where, L_λ TOA spectral radiance (W/(m²·sr·µm), M_L Band-specific radiance multiplicative scaling factor, DN Digital number of the thermal band pixel, A_L Band-specific radiance additive scaling factor (Twumasi et al.,2021)

$$T_B = \frac{K_2}{ln(\frac{K1}{L\lambda}+1)} \quad (4)$$

Where, T_B Brightness Temperature (Kelvin), $L\lambda$ TOA spectral radiance (from step 1), K_1, K_2= Calibration constants specific to the thermal sensor band (Moisa et al, 2022).

$$LST = \frac{TB}{1+(\frac{\lambda \cdot T_B}{\rho}) \cdot ln(\varepsilon)} \quad (5)$$

Where, LST Land surface temperature (Kelvin), T_B= Brightness temperature (Kelvin), ε= Surface emissivity (dimensionless, typically 0.95–0.99 for vegetated/urban surfaces), λ= Wavelength of the thermal band (e.g., ~10.9 µm for Landsat TIRS), $\rho = \frac{h \cdot c}{k}$(with Planck's constant **h**, speed of light **c**, and Boltzmann's constant **k**) (Li et al., 2023).

4.3. Association between mining expansion, vegetation dynamics, and LST

The association between mining expansion, vegetation dynamics, and LST was analyzed using multi-temporal Landsat data (1990–2020). LULC classification was performed to extract mining areas and assess their expansion. NDVI was calculated to evaluate vegetation conditions, while LST was derived from thermal bands to analyze surface temperature. A transect profile (A–B) was used to examine spatial variation in LST across different land cover types. Finally, Pearson's correlation analysis was applied to quantify relationships among mining area, NDVI, and LST, where mining expansion showed a negative relation with NDVI and a positive relation with LST.

5. Result

5.1. LULC areal distribution

The Land Use Land Cover (LULC) maps for 1990, 2000, 2010, and 2020 show big changes in land cover patterns over time and space in the study area. Satellite images are often used to classify LULC, which is a way to keep an eye on changes in the landscape and the environment that people cause.

The landscape in 1990 is mostly made up of plants and farmland, which means that the environment is pretty stable. There aren't many mining areas, and they are spread out, which means there isn't much

industrial activity. Settlement areas are also smaller.

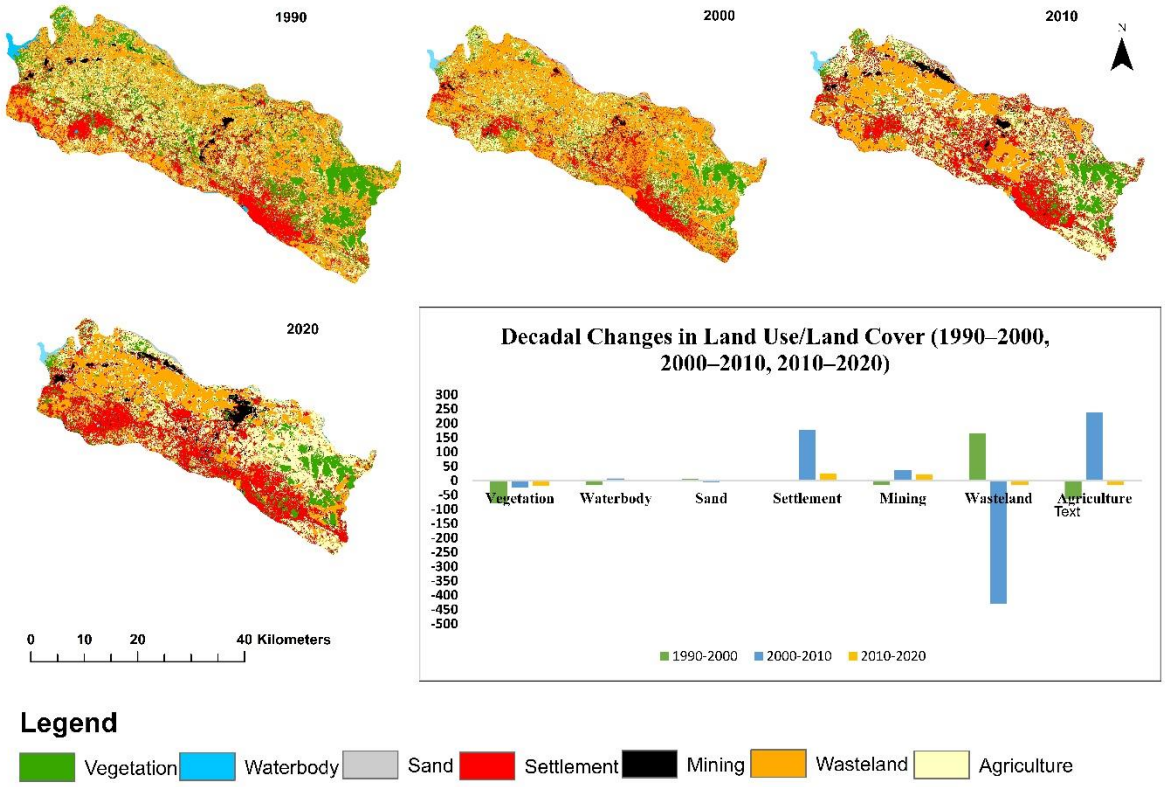

Figure 3: Spatio-temporal changes in land use/land cover (LULC) from 1990 to 2020, showing the transformation of vegetation and agricultural land into mining, settlement, and wasteland areas, along with decadal change analysis

Beginning from the year 2000, a definite transformation takes place. In this regard, it can be seen that an expansion of both the settled areas as well as wasteland occurs. There is also a reduction in vegetation cover in certain specific areas, which means that there is an indication of initial land disturbance. Mining areas start expanding, although geographically they remain limited in extent. In 2010, there is a more pronounced shift taking place. Here, one can observe significant expansion of mining areas (black patches) and settlements (red). Fragmentation of vegetation as well as agricultural lands shows increasing anthropogenic pressure on the land. Wastelands also continue expanding, signifying land degradation resulting from mining and mining-related activities.

During the year 2020, one finds there have been extensive changes made to the landscape. For instance, mining area expands significantly, creating larger black patches. Vegetation cover reduces considerably, as does the wastelands areas. The area of settlement increases significantly, denoting urbanization resulting from mining.

In terms of the decadal bar graph from 1990 to 2000, 2000 to 2010, and 2010 to 2020, the observations made regarding the various transitions can be better understood through quantification of data. In particular, there is an evident decline in vegetation cover, especially from the later periods. In the same way, settlements exhibit an increase, particularly for 2000-2010.

5.2. Mining expansion

The study of mining expansion shows that the areas where mining takes place have grown a lot between 1990 and 2020 at all of the chosen collieries. The results show that mining has grown over time, which is consistent with rising demand for extraction and more land transformation in the study area. Mining expansion is a major cause of changes in how land is used, which leads to big changes in the landscape and damage to the environment.

Table 2: Areal calculation of LULC of five mines in square meters of 1990, 2000, 2010, and 2020

Name of the mines	1990	2000	2010	2020
Hansdiha	577800	1290600	3308400	4497300
Kumardihi	5400	0	18900	986400
Ramnagar	1206000	1125900	1890000	3052800
Rashunpur	297900	0	1989000	1675800
Sonpur	2700	1800	38700	2489400

Hansdiha showed a big increase in mining area among the chosen collieries, going from 577,800 in 1990 to 4,497,300 in 2020. The mining area at Ramnagar colliery also grew steadily, going from 1,206,000 to 3,052,800 during the same time. These trends show that open-cast mining operations are getting bigger all the time, which means clearing a lot of land and removing a lot of overburdens.

A striking trend in collieries like Kumardihi and Sonpur is that mining operations were virtually absent in the early days, only to experience rapid growth after 2000. For example, the mining area in Kumardihi was virtually non-existent in 2000, expanding to 986,400 in 2020, whereas that of Sonpur has shown tremendous expansion from 2,700 in 1990 to 2,489,400 in 2020. It demonstrates the emergence and fast development of mining areas in recent decades.

On the other hand, Rashunpur colliery has an irregular trend, starting from no mining areas in 2000, then increasing significantly to 1,989,000 in 2010 and slightly decreasing to 1,675,800 in 2020. The fluctuations could be due to operational issues, exhaustion of natural resources, or even regulatory pressures.

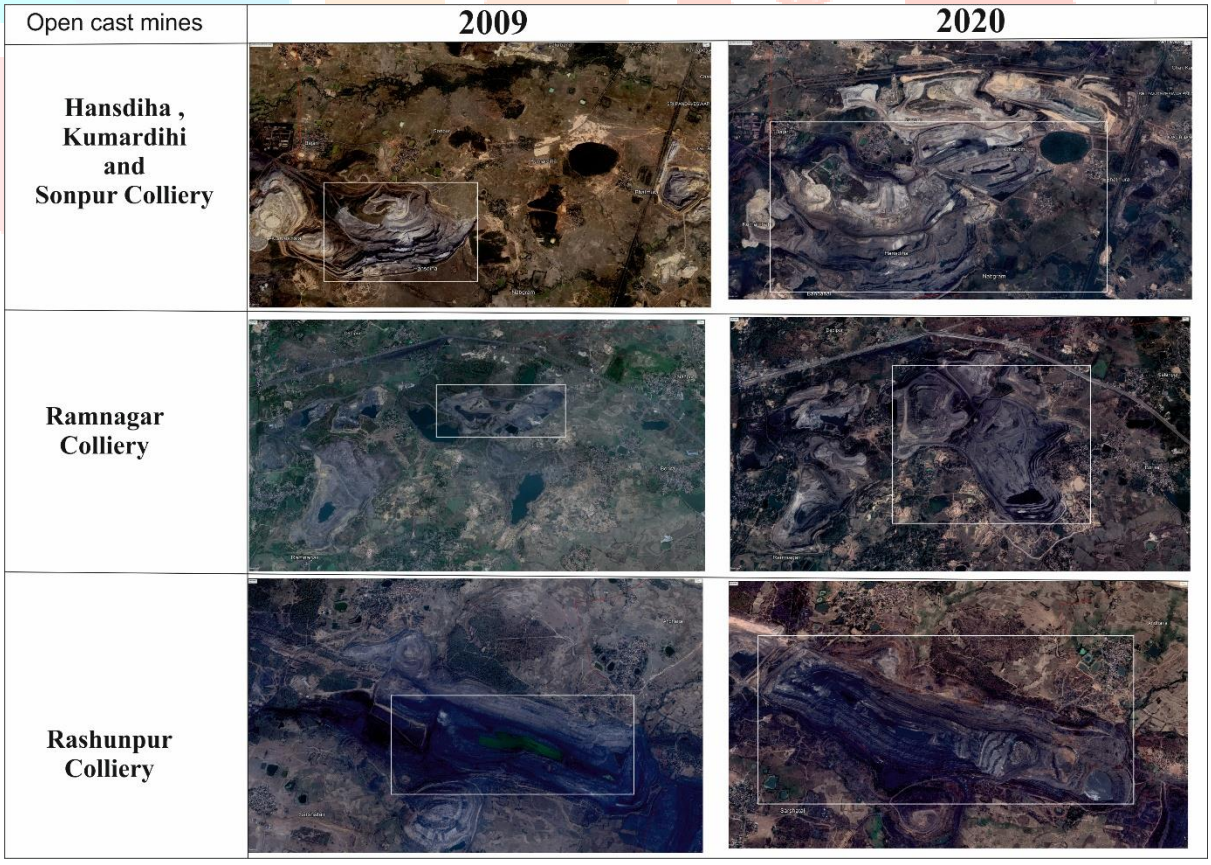

Figure 4: Spatio-Temporal Expansion of Open-Cast Coal Mines (2009 and 2020)

In these defined zones for Hansdiha and Ramnagar collieries, there is always a continued outward extension of mining boundaries. It is evident that these areas show an increasing trend in mining areas in all the four time spans, demonstrating extended mining activities in these zones. The process of extension is brought about by expansion through lateral spread of open-cast mining and the development of overburden dumps which replace the nearby vegetation and arable lands.

The marked sections in these two collieries represent the new mining zones. The marked regions show very little or no mining activity in these zones before the year 2000. However, after 2000, there is an increasing trend in mining in these marked sections. There is an indication of rapid expansion from the year 2000 onwards due to recent industrialization and mineral resource exploitation.

On the other hand, in this case, there is an evident fluctuation of the area rather than the constant increase. There is an observable expansion around the year 2010 followed by a slight reduction or stabilization of the marked section by 2020.

5.3. Vegetation dynamic

The NDVI maps for the years 1990, 2000, 2010, and 2020 represent how vegetation cover varies temporally and spatially in the study area. NDVI is a commonly used indicator that helps to determine how healthy and dense the vegetation cover is. Areas with high NDVI indicate healthy dense vegetation while low NDVI represents poor vegetation or even the absence of vegetation.

From the NDVI map for the year 1990, one can clearly see a moderate vegetation cover within most parts of the study area, and the few areas that have low NDVI levels represent bare ground, poor vegetation cover, or areas of disturbance due to minimal impact from mining activities.

From the NDVI map in the year 2000, there is an indication of increased vegetation cover in comparison with the NDVI in 1990, but there are also some areas of disturbed vegetation cover as indicated by low NDVI levels. This change is probably caused by increased mining activities.

The NDVI map for the year 2010 shows vegetation degradation in the study area. Most of the study area has low NDVI values, meaning that vegetation degradation has occurred.

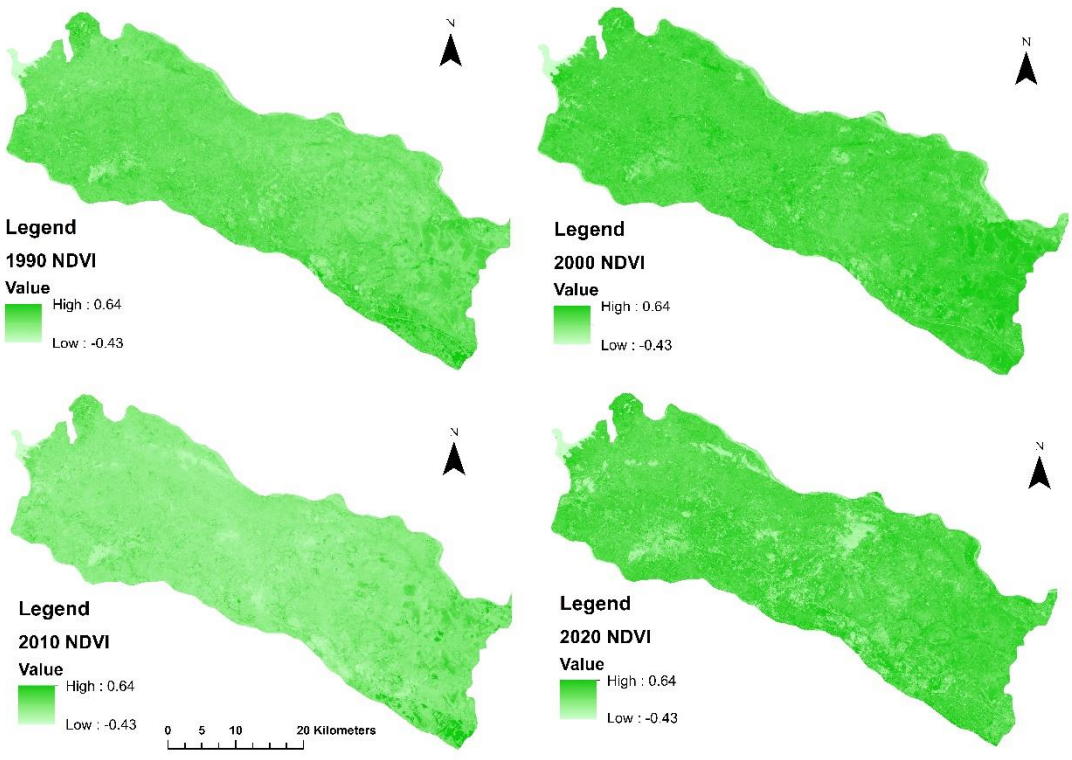

Figure 5: Spatio-Temporal Analysis of Vegetation Dynamics Using NDVI (1990–2020)

The spatial pattern in the year 2020 reveals heterogeneity in nature. Although some areas show moderate levels of recovery or have maintained vegetation cover, there are patches that still maintain their low NDVI levels due to environmental stressors. The maintenance of low NDVI patches means that the level of mining is still high coupled with no ecological restoration measures in specific places.

A graph shows an undulating decrease in NDVI values in many collieries implying vegetation cover degradation overtime. This means that vegetation is not permanently degraded since it experiences disturbances from mining processes and subsequent regrowth. Time series NDVI is very crucial when measuring long-term environmental impacts of collieries.

Hansdiha shows moderate values of NDVI during the early years (1990s). Fluctuations were recorded thereafter until there was a slight increase of NDVI in the mid-2000s. However, a decreasing trend starts to be evident post-2010 implying that mining activities in Hansdiha have been expanding thereby vegetation cover destruction. The fluctuations imply that though there is some recovery in vegetation, the environment is under stress. On the other hand, Kumardihi shows a constant yet low level of NDVI in most years. Lack of clear peaks indicates the low level of dense vegetation. Possible increases in certain years can be attributed to some growth of vegetation.

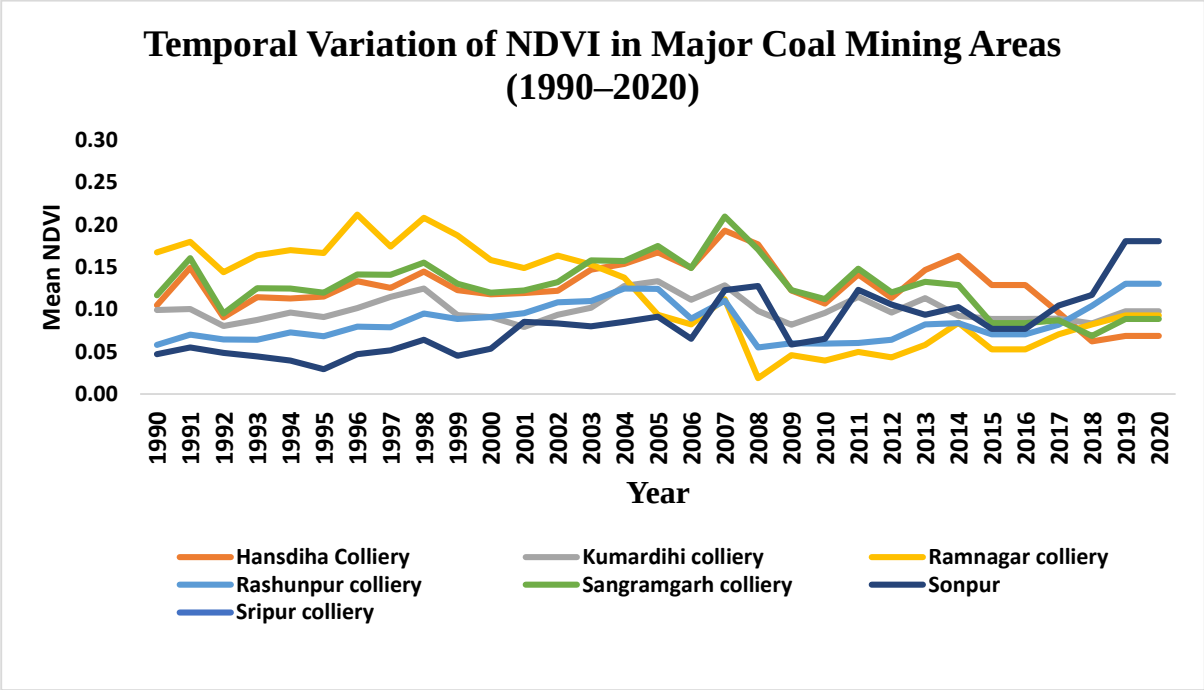

Figure 6: Temporal Variation of NDVI in Major Coal Mining Areas (1990–2020)

There is a notable trend towards a decrease for Ramnagar, especially from the early 2000s onwards. During the first period, the NDVI values are quite high, which signifies that the condition of vegetation is quite good in this area. On the contrary, there is a significant fall with respect to time, which suggests that there has been considerable deterioration in the vegetation due to continuous mining in this region. For Rashunpur, there are fluctuations with some improvement during the middle period but followed by further fall after that. The fluctuation suggests a change in the intensity of mining operation or some reclamation activities; nevertheless, the level of NDVI values is quite low, which is suggestive of environmental disturbance. It is observed that the NDVI value is relatively moderate with fluctuations, suggesting a balance between the loss and gain of vegetation. The maximum value of NDVI indicates phases of temporary recovery of vegetation, which can be attributed to seasons or any other reason. Sonpur shows an increasing trend in recent years, unlike the other two collieries.

5.4. Association between mining expansion and environmental conditions

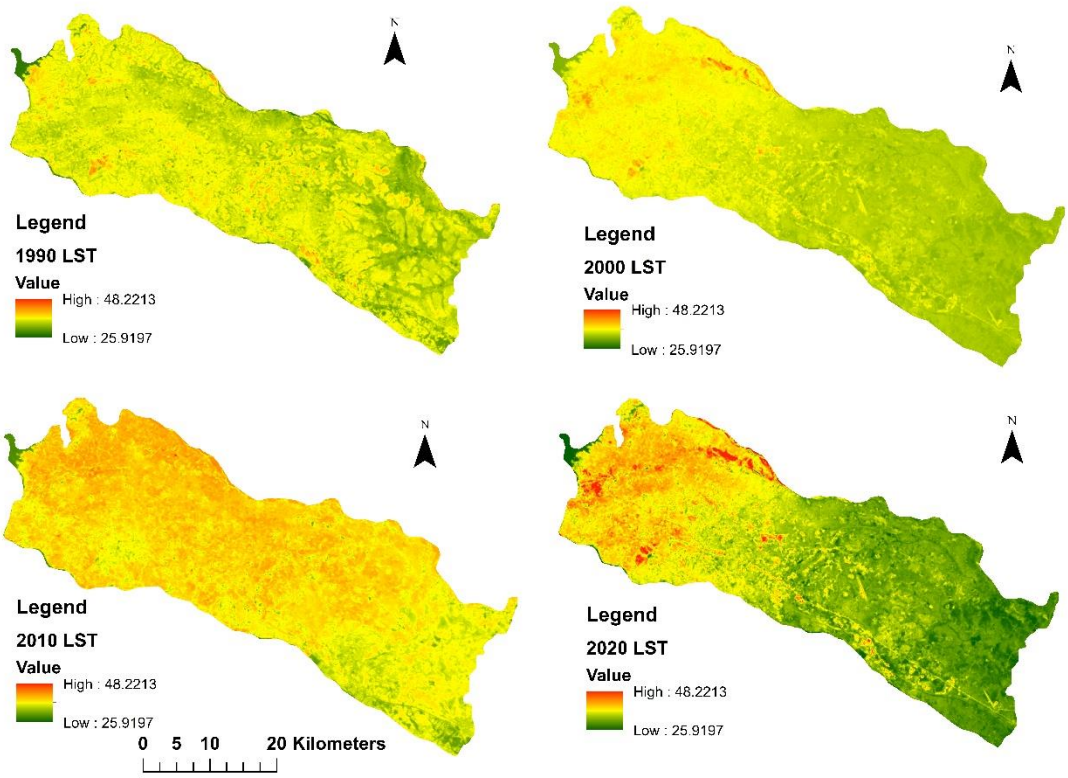

Figure7: Spatio-Temporal Analysis of surface temperature Using LST(1990–2020)

This spatial distribution of Land Surface Temperature (LST) in 1990, 2000, 2010 and 2020 indicates a lot of temporal and spatial changes in the study area. The LST map of 1990 indicates a fairly average distribution of temperatures with the majority of both regions being in the lower-to-mid-temperature range (green to yellow). The warmer spots are those that have vegetation cover whereas those that are a bit warmer are those that are exposed or less vegetated. This shows a relatively less disturbed and calm landscape. A small rise in temperature is witnessed by 2000, especially in localized areas. The introduction of additional yellow and light orange coloration indicates the initial land surface alteration, which may have been caused by the early mining development and decrease in vegetation cover. Nevertheless, there is a comparatively uniform distribution of temperature.

The 2010 map reveals a high percentage of change in LST and also a lot of domination of orange and red colors, which means surface temperatures are higher. The time is associated with the peak levels of anthropogenic disturbance, in which the alteration of the surface of the land causes an increase of heat uptake. Experiments validate that bare soil and mining lands absorb more solar radiation, leading to increased LST. The LST pattern was even more heterogeneous in 2020. High temperatures are still experienced in some areas, especially those that are dominated by mining. Elsewhere, there is a lower temperature, suggesting potential vegetation recovery or stable land cover.

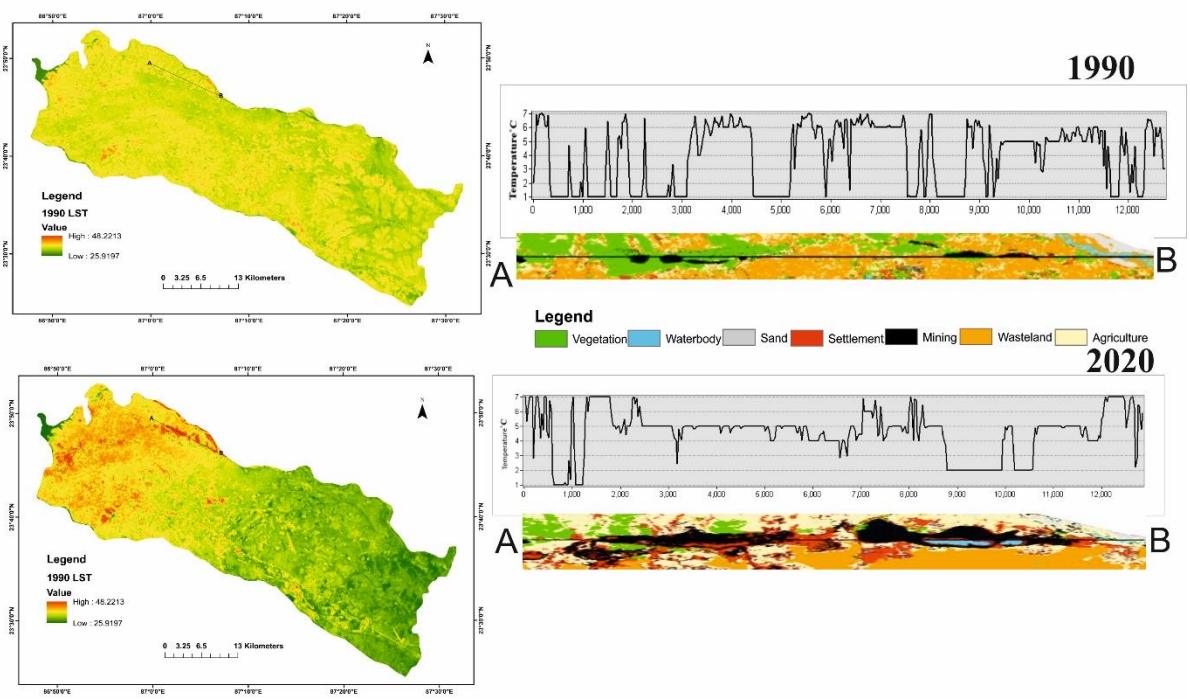

Figure 8: Spatio-Temporal Variation of Land Surface Temperature (LST) with Transect Profile Analysis (1990–2020):

The figure provides a comparative study of the Land Surface Temperature (LST) of 1990 and 2020 and a transect profile (A -B) and land use/land cover (LULC) distribution. In the 1990 LST map, there is a fairly even and moderate distribution of temperature. In the 2020 LST map, it is evident that the temperature has risen considerably, with more yellow and red areas. Barren and mining surfaces have a higher amount of solar radiation since they are scientifically more absorptive and result in increased LST, whereas vegetation cools down temperatures by shading and providing moisture.

The LST variation along the transect in the 1990 profile is moderately smooth and shows moderate fluctuations. The temperature rates are relatively stable with small peaks and saddles which shows the existence of a more homogeneous land surface, predominantly vegetation and farmland. The fact that there were no sharp temperature spikes indicates that there was little anthropogenic disturbance in the period. Areas where there is vegetation and water bodies have lower temperature values because of evapotranspiration and water retention that regulate the surface temperature.

Conversely, the 2020 transect profile is much more irregular and has stronger peaks and troughs, meaning that the spatial variability in LST is higher. The occurrence of extreme temperatures is associated with mining and developed land areas and bare surfaces, which have a greater heat absorbing capacity. On the other hand, lower temperature segments are associated with vegetation patches and water bodies. This added variability indicates the heterogeneity of land cover as a result of mining growth and urban growth. Studies have shown that such variations in LST along transects are directly controlled by land surface characteristics and changes in vegetation cover. Moreover, as it can be seen in the comparison of 1990 and 2020 profiles, the number and intensity of high-temperature peaks in 2020 are evidently bigger and more frequent. This indicates that there will be an increase in the average LST along with an increase in thermal contrast in the study area. The fact that the relatively homogeneous thermal profile in 1990 changed to a highly variable profile in 2020 underscores the effect of land use change, especially mining activities, on the thermal environment.

The links between mining growth and the environment were studied by combining the mining area data with vegetation indices (NDVI) and land surface temperature (LST). The findings indicate that there is strong and statistically significant association between environmental degradation and anthropogenic land transformation. It is well known that mining expansion is one of the greatest contributors to land

use change, which has a direct effect on the changes in the vegetation cover and the thermal features of the surface.

6. Discussion

The current research gives a detailed evaluation of the effect of mining growth on the land use/ land cover (LULC), vegetation dynamics (NDVI), and land surface temperature (LST) between the years 1990 and 2020. The findings have shown clearly that mining activities have been a leading cause of environmental change which has resulted into great changes in landscape structure and ecological conditions. In the LULC analysis it is shown that the study area is undergoing a significant change, with vegetation and agricultural land decreasing, and mining, settlement and wasteland increasing correspondingly. This change indicates the transformation of natural land to anthropogenic land uses, mainly as a result of open-cast mining activities. The temporal NDVI analysis shows a great variability with general decreasing tendency in vegetation cover. Regions with high mining activities are always showing a low NDVI value which validates the negative effects of land disturbance on the health of vegetation. The decrease in NDVI can be directly linked to vegetation clearance, soil erosion, and overburden dumping.

The LST analysis reveals that there is a significant rise in surface temperature over the years especially in the mining and barren land dominated regions. The peak temperatures in the later years are associated with areas with less vegetation cover and more exposure of the soil and rock surfaces. This observation is in line with the scientific knowledge available that the built-up and bare land surfaces have higher thermal values than vegetated surfaces. The heterogeneity of the LST in space in 2020 also demonstrates the unequal distribution of land covers and the level of disturbance of the environment.

The combination of NDVI and LST values demonstrates that vegetation cover and the surface temperature have a high inverse correlation. High NDVI areas have lower LST because of evapotranspiration and shading effects but low NDVI areas have high temperatures. This adverse association between NDVI and LST has been extensively recorded in literature on remote sensing and is one of the primary indicators of stresses on the environment.

Environmentally, mining activities cause various types of degradation such as loss of biodiversity, soil erosion, and air and water resources pollution. These effects are not only limited to the mining locations but they also affect the overall ecology. The trend of wasteland which is on the rise also means that land is degraded long-term and become less productive. Comprehensively, the conclusion of this paper corresponds with the already existing studies and supports the fact that the land use change caused by mining has profound environmental impacts. The trends observed underscore the need to adopt sustainable land management practices such as mine reclamation, afforestation, and environmental monitoring in order to reduce the negative effects of mining activities.

7. Conclusion

The current research examined the effects of mining development on land use/land cover (LULC), vegetation (NDVI) and land surface temperature (LST) between 1990 and 2020. The findings clearly show that mining activities have greatly transformed the landscape and environmental environment of the study area.

The LULC analysis showed that there is a significant change in natural land cover into anthropogenic land use. There was an uninterrupted decline in vegetation and agricultural land, and there was a significant expansion of mining, settlement and wasteland areas over time. This change is indicative of the intensifying mining operations and related infrastructural growth. This sort of land conversion is an established impact of mining, which frequently causes land degradation and deforestation.

The NDVI analysis showed that there was a general decreasing trend in the health and density of vegetation especially in the mining areas. The LST analysis revealed a significant rise in surface temperature with time with a peak of thermal conditions recorded in regions with mining and barren land. The negative correlation between NDVI and LST in this research is in line with other scientific literature where a low cover of vegetation results in a high surface temperature. These findings were

further confirmed by the transect profile analysis where the temperature peaks were more in the mining and built-up regions and less in vegetated regions.

The LULC analysis shows clearly that there has been a significant growth in the mining, settlement, and wasteland areas with a loss of vegetation and agricultural land. The NDVI analysis shows that the vegetation cover has been generally decreasing, especially in areas where mining is the norm. Reduced NDVI values are a measure of a decrease in vegetation health, biomass, and ecological disturbance. The experiment validates the hypothesis that a decrease in vegetation cover causes a rise in the surface temperature since bare soil absorbs more heat.

The recommendations that can be given to reduce environmental degradation and achieve sustainable development based on the findings are Adoption of scientific and controlled mining methods, Ongoing monitoring of LULC, NDVI and LST through remote sensing and GIS, Control of soil erosion and sedimentation, Strict implementation of environmental regulations and mining laws and Development of sustainable land use planning strategies.

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