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Assessing Drought Risk in Forest Zones Near Coal Mines with Temperature Vegetation Dryness Index

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Abstract

This study is quantitative research employing survey techniques and spatial modeling. In the research area, particularly in forested areas, the Normalized Difference Vegetaton Index (NDVI) values range from 0.25 to 0.55 with Land Surface Temperature (LST) values of 29°C to 37°C. Cooler temperatures below 34°C were observed in the southwest (outside the mining area). The LST values indicate high temperatures above 37°C in the coal mining area, with effects extending up to 6 km. The linear regression equation between NDVI and LST in the coal mining area, with a regression equation of $y = -20.888x + 40.458$; $R^2 = 0.83$; $r = -0.91$, shows an inverse relationship between NDVI increase and ground surface temperature, indicating a good model fit with the data and a strong negative linear relationship between the two variables. The Urban Heat Island (UHI) effect in the mining area, especially at the mining center, shows a UHI with a temperature difference of more than 0.6 degrees Celsius compared to the cooler surrounding area. At the center of the coal mining area, the TVDI value is 0.6-0.8 (high-very high), but in the eastern part of the mine in forested areas with a certain soil type, the TVDI value is 0.2-0.6 (moderately dry - dry), while in other parts of the forested area with a different soil type, the NDVI value is < 0.2 (moist). There is a difference in response to different soil types. Drought increases in the forested areas around the mining site, affecting ecosystem productivity and soil moisture.

Keywords: NDVI, LST, UHI, TVDI, Coal Mining

1. Introduction

Climate change, driven by both natural processes and human activities such as fossil fuel emissions, is altering Earth's average climate conditions [1], [2]. Greenhouse gases such CO_2, CH_4, and N_2O are raising global temperatures [3], with CO_2 emissions reaching 36.44 gigatons in 2019, primarily from industry and fossil fuels. This leads to a warming greenhouse effect and contributes to species extinction. Urbanization and trade exacerbate biodiversity loss, while climate change impacts ecosystems, agricultural yields, and production costs. Global warming, intensified by wildfires, affects all life and is heavily influenced by the transport and industrial sectors [3], [4]. Global studies indicate that global warming increases natural disaster risks, with floods, landslides, droughts, and tropical storms becoming more likely at 4°C warming compared to 1.5°C. Sea levels have risen 20 cm since 1900 and could increase by up to 110 cm by 2100 [5]. The relationship between global warming and natural disasters is complex, with human activities linked to increased disasters, affecting millions in coastal regions, while soil plays a role in CO_2 absorption.

Coal mining contributes to carbon emissions, increased LST, drought, and affects water and air quality, with closed mines releasing harmful emissions [6]. The steel industry, a major coal consumer, significantly adds to emissions [7]. Reclamation and mine ventilation emit methane, but CO_2 capture technologies like mineral carbonation face challenges in deep seams [8]. Indonesia is working to lower emissions across multiple sectors [9]. Mining impacts LST and ecosystems, with revegetation and green spaces as mitigation strategies [10]. TVDI research reveals its effectiveness

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in monitoring soil moisture and drought in mining areas [11], supported by satellite observations of drought's ecological effects. Studies affirm TVDI's correlation with microclimate and soil moisture [12].

Plant-based carbon reduction efforts help normalize LST and TVDI values and aim for carbon neutrality to mitigate emission impacts, involving multiple stakeholders [13]. Plant-based carbon removal, or carbon sequestration, reduces greenhouse gas concentrations, especially CO2 [14]. Biogeophysical and economic limits exist for plant-based negative carbon removal [15]. Biomass, the living vegetation mass, has a direct correlation with carbon absorption potential [16]. The role of forest restoration in carbon absorption is crucial [17]. Over 10 years (2001-2012), emission reductions in South Kalimantan's forest and peat lands reached 2,030,500 tCO2-eq/year [18].

Climate change impacts, particularly from mining operations, have led to increased soil dryness and vegetation stress (TVDI) in forested areas surrounding mines. This situation underscores the urgent need for research to determine whether the elevated TVDI levels are primarily due to the direct impacts of mining activities, the inherent characteristics of the soil, or a combination of both factors. Understanding the root causes of increased TVDI is crucial for devising effective mitigation strategies. Such research could provide vital insights into how mining activities and soil types interact to exacerbate the effects of climate change, offering a foundation for developing targeted interventions to mitigate these impacts, enhance soil and vegetation health, and contribute to more sustainable mining practices.

In connection with this narrative, researchers have formulated a critical problem: What are the spatial patterns of changes in LST and levels of soil dryness and vegetation stress (TVDI) that occur in mining areas, particularly in forested regions? The aim of this research is to create a spatial model of changes in LST, soil dryness, and vegetation stress (TVDI) in forested areas resulting from open-pit coal mining activities.

2. Method

This research uses a quantitative method where the research location encompasses both the mining areas and the surrounding regions. As shown in figure 1, the research location map includes not only the mining areas but also the surrounding regions. This approach is taken to better understand the conditions of vegetation, temperature, humidity, and other aspects before and after mining activities. Additionally, another supporting aspect is the social and institutional conditions around the mining area, which are taken into consideration when determining future strategies for emission control and carbon sequestration.

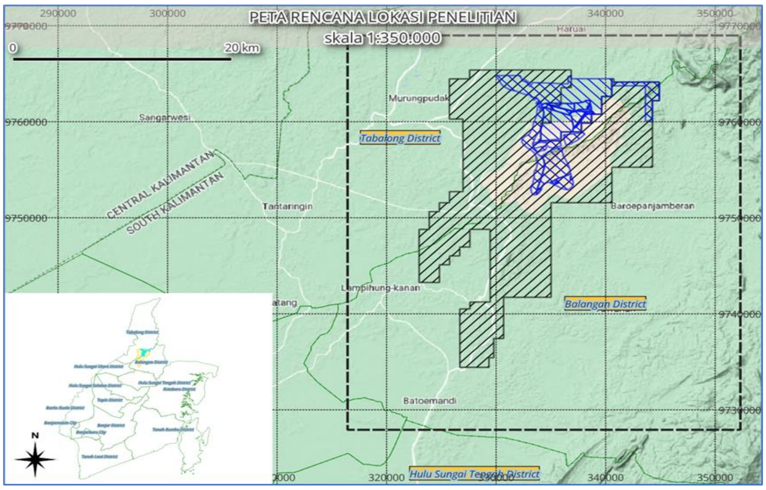

Figure 1. Map of Research Locations in Mining Companies

Figure 1 presents the research location map. The research location is not only within mining areas but also includes the surrounding areas. This is done to assist in understanding the vegetation conditions, temperature, humidity, and other aspects before and after mining activities are conducted. Another supporting aspect is the social and institutional conditions around the mining area, which serve as considerations for determining future emission control and carbon sequestration strategies.

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2.1. Types of Research Data

Primary data, both in the form of satellite images and field data, are analyzed to obtain research results. The data analysis process for this research includes the type of data required during the research is presented in table 1. This table presents the data name, data type, data usage, types of analysis and formulas used, sources, and explanations. The explanation section in the table also presents the data requirements tailored to the research objectives.

Table 1. Required Data Characters

Data Name	Data Type	Utility	Type Analysis and formula	Source	Description
LST	Numeric	Sentinel-2 satellite data comparison	Field data	Field survey	Processing results Data
LST and UHI	Numerical Raster	land surface temperature map	LST and UHI $TS = TB\ [1+\lambda TB\ \partial]ln(\varepsilon)$ UHI = LSTmean –(0.5*α)	Download and correct with field results	https://earthexplorer.usgs.gov/
Humidity	Numeric	For comparison with Sentinel-2 satellite data	Field Data	Field survey	Processing results Data
TVDI	Numeric Raster	Vegetation moisture maps	TVDI = (LST - LSTref) / (NDVI - NDVIref)	Download and correct with field results	https://earthexplorer.usgs.gov/

2.2. Data Collection Technique

This research involves a multi-stage process comprising several key activities: initially, data collection is undertaken to gather relevant information. Subsequently, pre-processing of the data is conducted to ensure its quality and suitability for analysis. The core phase of data processing follows, wherein the data is systematically analyzed using appropriate methodologies. Concurrently, field activities are carried out to validate and complement the collected data. Finally, a thorough data analysis is performed, culminating in the creation of a comprehensive research report that encapsulates the findings and insights derived from the entire research process.

2.2.1. Data Collection

The collected data is categorized into primary and secondary data. Primary data consists of data obtained directly through internet downloads such as Sentinel-2 imagery, field data through surveys of stand potential, soil temperature, humidity, and other necessary information. Meanwhile, secondary data refers to pre-existing information specifically gathered to complement research needs, such as units for borrowing and using forest areas (PPKH) region data.

2.2.2. Pre-Processing of Imagery

This stage includes image correction and cropping based on the study area. Radiometric correction is conducted to minimize atmospheric disturbances during image acquisition using the NDVI Analysis. It is then followed by cropping the study area according to the administrative boundaries of the coal mining region to obtain detailed data.

2.2.3. Image Processing

Data processed at this stage include the greenness index using NDVI by utilizing the Infrared and Near-Infrared channels. The NDVI values are classified based on greenness index ranges, which are then used to place sample plot points for field observation activities. Additionally, surface soil temperature and urban heat island indices are processed.

2.2.4. Determining Sample Size Sample Plot Placement is Done using Purposive Sampling Per NDVI and LST Class

Sample plots are presented on a sample plot map, which serves as a reference for field surveys. To facilitate tracking of sample points in the field, the sample plot map is integrated into Garmin GPS or the Avenza app on smartphones.

The sampling intensity used in determining the number of plots complies with Regulation Number 44 of 2004, which is 0.1% of the total area of each NDVI class. The plot shape used in this research is square-shaped pixels measuring 20 x 20 m in size, consistent with the resolution of 4 Sentinel-2 Satellite image pixels, as shown in figure 2 below.

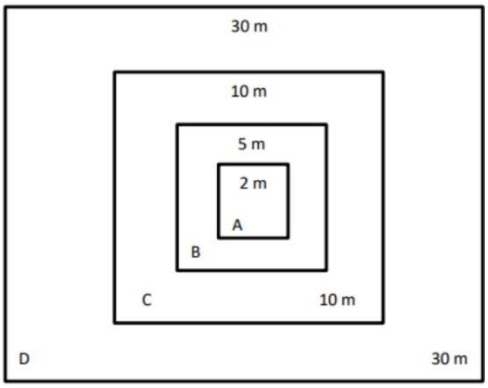

Figure 2. Sample square plot shape

The locations of surface soil temperature sample points, humidity, and other supporting parameters are synchronized with the NDVI sample point observation locations.

2.2.5. Field Activities

The initial phase of field activities involves observing or ground-checking the research locations. This is done to cross-verify the consistency of image analysis data with field conditions to obtain real data.

1) Using Garmin GPS and/or Avenza to navigate to sample plots
2) Creating sample plots
3) Sketching tree positions within the plot, recording plant species, measuring diameter and height of trees, measuring surface soil temperature, light intensity, and humidity levels
4) Capturing aerial photos with a drone in each plot area sample
5) Data Porcessing and analysis after returning from the field
6) Capturing aerial photos with a drone in each plot area sample.

2.2.6. Data Processing and Analysis

Upon returning from the field, several activities are conducted. These include data processing and analysis such:

1) Double-checking the sketch of tree positions within the plot to aid position correction using drone photos
2) Checking the quality of survey data results

Calculating tree volume, Biomass, and carbon potential. Wood Volume Formula (tons): V = 0.253.14D2*T Biomass Potential Formula (tons), Tree Volume * Wood Density * BEF Carbon Potential Formula (tons): C = Biomass * 0.47 The plant dimension field data is presented per plot unit and converted to per hectare units. For surface soil temperature and humidity data, a direct relationship can be established between field and Sentinel-2 satellite data.

2.2.7. Data Analysis

This analysis is the final stage and involves correcting survey results to build regression equation models and their validation. This model is used to derive overall area results using the obtained and validated model. Analysis methods used include NDVI, LST, UHI, and TVDI. Furthermore, overlays of these parameters are conducted to obtain a spatial model guiding carbon emission/absorption control, simultaneously reducing LST and TVDI.

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2.2.8. Final Output Presentation

The final output includes land cover class maps, carbon potential prediction maps per pixel and per hectare, LST maps, UHI maps, and NDVI maps

3. Result and Discussion

3.1. Land Surface Temperature

To obtain information based on the results of LST analysis on satellite data and field measurement results are presented in figure 3.

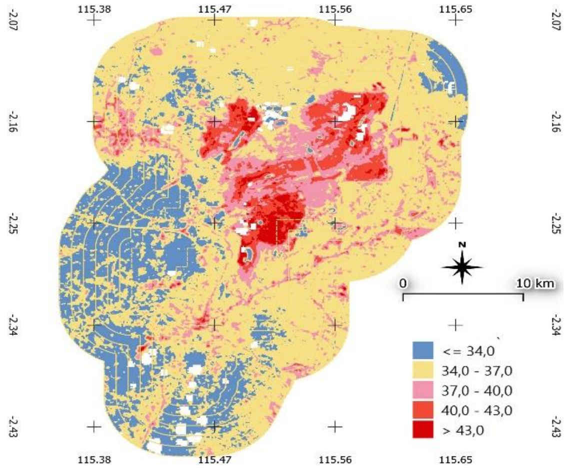

Figure 3. Condition of distribution LST Result in Coal Mining Area

Figure 3 depicts the results of LST analysis in the coal mining area and its surroundings within a buffer distance of 6 km, from LANDSAT-9 image data coverage in September 2023. The open coal mining area is clearly visible with very high temperatures, above 37°C, marked in dark red. This intense heat is most likely caused by the open ground surface and direct exposure to sunlight, as well as mining activities which increase local temperatures.

The zone around the mining area, within a radius of up to 6 km, has temperatures ranging from 34 to 37°Celsius, marked by shades of pink to yellow. These conditions indicate that the high temperatures from mining activities still affect this distance, potentially impacting the surrounding ecosystem and community with increased average temperatures.

Interestingly, in the southwest direction from the mining area, temperatures appear to be below 34 degrees Celsius, indicated by blue and green colors. This region may have more vegetation or sufficient ground cover that provides a cooling effect and reduces the UHI impact, or there could be geographical features like bodies of water helping maintain lower temperatures.

From figure 3, it's also evident that forested areas around or outside the mining area have high ground surface temperatures. Based on the analysis of the relationship between NDVI values and ground surface temperatures from 98 sample points, after stepwise analysis to obtain a high correlation relationship, the results are as presented in figure 4.

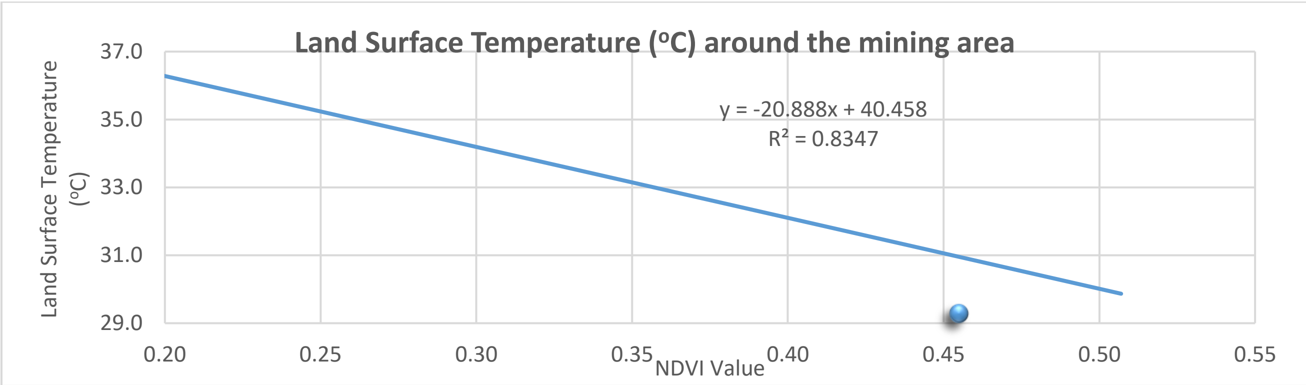

Figure 4. Relationship between NDVI values and LST In the Research Area

3.2. Urban Heat Island

Based on the description of land surface temperature above, it is necessary to determine the highest temperature concentration and its distribution. This is necessary to ensure a heat area island which is usually called the UHI Urban Heat Island. In this case, the urban area in question is the location of an open-pit coal mine. The results are presented in figure 5.

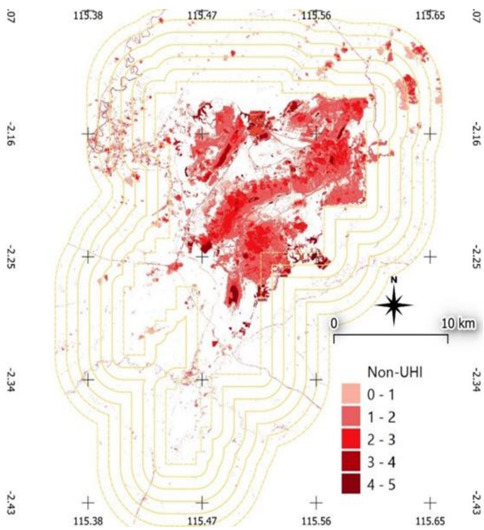

Figure 5. UHI Analysis Result in a Coal Mining Area

Figure 5 displays the distribution of the UHI in a coal mining area. In this image, there is a sharp contrast between areas with high UHI intensity and surrounding areas with lower UHI intensity. Zones marked in shades of light pink to dark red indicate areas with UHI values ranging from 1 to 5, reflecting a significant increase in surface temperature compared to non-UHI areas shown in pale colors.

The darkest red zone indicates the highest UHI values, dominating the central part of the coal mining area, indicating extremely high surface temperatures in that area. This is likely due to a combination of extensive soil exposure, lack of vegetation, and intensive mining activities, all contributing to reduced surface albedo and heat accumulation. Figure 5 can serve as important visual evidence supporting research on the impacts of mining on local microclimate changes. By using UHI data, researchers can assess and respond to challenges posed by coal mining, particularly in ecological terms.

3.3. Temperature Vegetation Dryness Index (TVDI)

The hot surface temperature conditions and their distribution resulting from mining activities in locations such as those presented above can have an impact on the health of vegetation in the surrounding area and the thermal comfort of humans living nearby. This study focuses on the impact on vegetation. The type of analysis used for this purpose is the TVDI analysis. The results of the analysis are presented in figure 6.

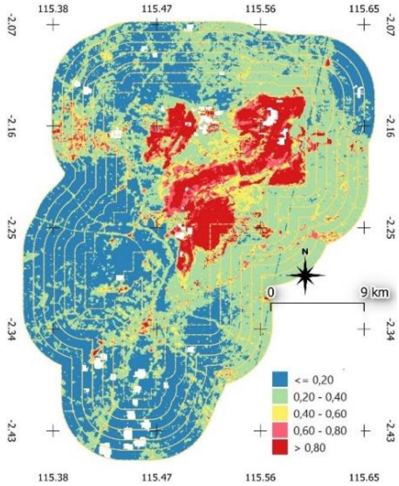

Figure 6. TVDI and the level ff stress vegetation

Figure 6 presents the condition of the Soil Moisture Stress Index and vegetation stress levels in the research area. From the image, the Middle Part with TVDI 0.6-0.8 represents the coal mining area. The right-hand side tends to be more affected by mining, with a dominance of TVDI values ranging from 0.2 to 0.4 compared to its surrounding areas.

TVDI is a useful indicator for assessing the level of soil moisture and vegetation stress. Low TVDI values (0 to 0.2) indicate very moist soil conditions without drought. This is typically associated with healthy vegetation and minimal stress due to sufficient water availability. TVDI values increasing from 0.2 to 0.4 indicate still moist soil conditions but with low levels of drought, possibly indicating the onset of vegetation stress. TVDI values between 0.4 and 0.6 are associated with normal or moderate conditions, where vegetation stress ranges from low to moderate. However, higher TVDI values, such as between 0.6 and above, indicate dry soil with high levels of drought. Lastly, very high TVDI values, above 0.8, indicate extremely dry soil with severe drought. These highest TVDI values correspond to active coal mining areas.

TVDI was chosen for this study because of its ability to combine information from two important parameters: LST and vegetation index NDVI. The advantage of TVDI compared to other drought indices is its ability to provide a more comprehensive picture of drought conditions by integrating these two parameters, allowing for a deeper analysis of the relationship between soil moisture and vegetation health. Additionally, TVDI is more sensitive to small changes in soil moisture and vegetation compared to other indices such as the Standardized Precipitation Index or the Palmer Drought Severity Index, which focus more on meteorological or hydrological drought conditions. However, the limitation of TVDI is that it heavily depends on the quality and resolution of the satellite data used, and it may not be fully accurate in regions with high cloud cover or complex topographic variations. Despite this, in the context of this study, TVDI offers an effective method for identifying and monitoring drought conditions and their impact on vegetation around coal mining areas.

Based on figure 6 above, it is observed that higher TVDI values (0.2-0.4) predominantly occur in the eastern part, values below 0.2 are concentrated in the west, and values from 0.4 to 0.6 are generally found around mining centers with values exceeding 0.6. To determine the causes, this study focuses on the eastern section and delves deeper with the support of a Soil Map. The map used is the semi-detailed soil map from 2016. The results of overlaying the eastern area and the soil map are presented in the following table 2.

Table 1. Condition of area (ha) and distribution of Parent Material in areas with a TVDI

Soil Map Unit	Limestone	Claystone and Sandstone	Sandstone	Clay Deposits	Total
2				336.0	336.0
3				1587.4	1587.4
4				1612.6	1612.6

5				306.5	306.5
10	331.1				331.1
11	46.9				46.9
12		2219.6			2219.6
13			1628.2		1628.2
14		2352.2			2352.2
15			1264.9		1264.9
16		2081.7			2081.7
17			341.4		341.4
19		52.8			52.8
	377.9	**6706.3**	**3234.6**	**3842.5**	**14161.3**

The result presents the extent and distribution of soil parent materials in forest areas characterized by moderate vegetation health, as indicated by NDVI values ranging from 0.3 to 0.5, and moderate dryness or water stress, represented by TVDI values between 0.2 and 0.4. Specifically, soil map units 10 and 11, encompassing 331 ha and 47 ha respectively, are predominantly comprised of limestone, which reflects more sunlight and thus contributes less to temperature increases. In contrast, soil map units 12, 14, and 16, covering a total of 6,706 ha, are primarily composed of clay and sand, which significantly influence water retention and infiltration rates, thereby affecting vegetation growth. Additionally, soil map units 13 and 15 are characterized by sandstone, which provides good drainage but is low in nutrients. Furthermore, soil map units 2, 3, 4, 5, and 17, which contain extensive clay deposits, demonstrate a high potential for water retention; however, these clay soils may restrict root growth and subsequently impact NDVI and TVDI values. Notably, these clay soils also exhibit slow heating and prolonged warmth retention.

Anomalies where temperatures outside open coal mining areas do not decrease despite the presence of vegetation can be attributed to various factors. One significant factor is the UHI effect, wherein urban regions experience higher temperatures compared to rural areas due to human activities and heat-retaining materials in buildings [18]. In the context of coal mining, operations and the use of heavy equipment generate substantial heat, contributing to localized temperature increases [19]. Studies have demonstrated that vegetation can lower land surface temperatures, as observed in the southern part of Majalengka Regency [20]. Remote sensing data underscores the importance of natural surfaces, particularly vegetation cover, in mitigating UHI effects across various spatial scales [21].

Moreover, climate change can also contribute to temperature anomalies. Studies have shown that climate change can cause shifts in rainy and dry seasons, subsequently affecting temperature and vegetation patterns in a region [22]. These shifts can lead to changes in vegetation distribution and plant growth patterns, ultimately impacting temperatures around the coal mining area. Such alterations in climate patterns and their effects on vegetation underscore the complex interplay between natural and anthropogenic factors influencing local temperature anomalies. Apart from internal factors such as mining activities and climate change, external factors like wind patterns and topography can also influence temperature distribution in the mining area. Consistent wind patterns can transport hot air to specific locations, while complex topography can create unique air circulation patterns that affect temperature distribution. These external factors interact with the local environment, further complicating the temperature dynamics in and around the mining area [23].

Relevant studies reveal a significant relationship between the NDVI and LST, consistently showing a negative correlation between LST and NDVI, with this correlation being more pronounced during the summer months. For instance, research by [24] observed opposite spatial distribution patterns of NDVI and LST, indicating areas with high NDVI values tend to have lower LST values. Another study by [25] noted that NDVI values are highest in winter, followed sequentially by the rainy, post-rainy, and pre-rainy seasons. Furthermore, [26]determined that the negative correlation between NDVI and LST is strongest in Baquba and weakest in Muqdadiya. Contrarily, [27] found that increases in LST can sometimes correlate with increases in NDVI over certain periods, suggesting a complex and variable relationship influenced by specific regional and temporal factors.

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Research indicates that in Taiga ecosystems, NDVI values range between 0.41-0.51 and LST values between 20-24°C, while in Forest Steppe ecosystems, NDVI ranges from 0.3-0.4 and LST from 24-29°C C [27], [28]. In contrast, our findings, as shown in figure 6, reveal NDVI values of 0.25-0.51 and LST values of 29.3-36.5°C. These findings align more closely with the Desert Steppe and Desert ecosystems, where NDVI values range from 0.05-0.15 and LST from 31-43°C, indicating sparser vegetation and higher surface temperatures. This suggests unusually high surface temperatures for what are typically forested ecosystems, pointing to significant deviations likely influenced by local factors such as land use changes and climate variations.

Urban heat islands are a significant concern in mining areas due to their potential to exacerbate heat-related issues. The phenomenon of urban heat islands refers to urban areas experiencing higher temperatures compared to their rural surroundings [29]. Mining activities, particularly open-pit coal mining, have been shown to contribute to the urban heat island effect, requiring urgent attention and mitigation to address health-related impacts [30]. Additionally, mining areas can act as heat islands themselves, further intensifying the overall heat index in these regions [27].

Studies have utilized various indices to assess urban heat hazards and urban heat islands. The Universal Temperature Climate Index has been used to evaluate urban heat hazards in urban areas [27]. Furthermore, the Urban Heat Island Ratio Index has been employed to characterize the spatial distribution of high temperatures within cities [31]. UHI Ratio Index has also been found to be interrelated with urban land area in different zones, indicating its relevance in assessing heat-related issues in urban environments [32].

Moreover, the impact of urban expansion on urban surface temperature has been studied extensively, with indices like the Heat Islands Distribution Index being used to describe the contribution of different areas to the thermal environment of urban areas [33]. These studies highlight the complex relationship between urban development, land use changes, and the resulting urban heat island effect.

TVDI values between 0.2 and 0.4 suggest vegetation stress from water scarcity, indicating drier conditions as values rise. Research links soil drought to reduced global ecosystem productivity and emphasizes soil moisture's critical role in terrestrial carbon fluxes [34]. Soil moisture affects light utilization and primary productivity [18], with implications for ecosystem water and carbon dynamics when considering vapor pressure deficit stress [35]. Moreover, soil moisture's interaction with the atmosphere alters evapotranspiration, precipitation, and water cycles [36].

Open-pit coal mining significantly affects soil dryness and vegetation stress in forested areas with limestone, clay, sandstone, and shale. Large-scale operations disrupt fragile forest ecosystems 30] and ecological health, especially in semi-arid regions [32]. Moreover, it impacts groundwater distribution, with decreases up to 60 m and major disruptions within an 8 km radius of mining sites [33].

Open-pit coal mining has been observed to have various environmental impacts. The process of open-pit coal mining can degrade soil quality, disturb soil nematode communities, and impact ecosystem functions [31]. Alterations to the local microclimate, increased soil dryness, and stress on vegetation are also reported consequences of open coal mines [33].

Moreover, open-cast mining activities can directly change the land surface, affecting ecosystems both directly and indirectly, leading to ecological and environmental problems such as land and vegetation degradation [34]. The economic benefits of open-pit coal mining are acknowledged, especially in arid and semiarid regions, but the practice may induce ecological issues in these areas [33].

4. Conclusion and Recommendations

4.1. Conclusion

The quantitative research employing survey techniques and spatial modeling highlighted significant environmental impacts of coal mining activities, particularly on temperature, vegetation, and soil moisture levels. It was observed that in forested research areas, NDVI values ranged from 0.25 to 0.55, while LST varied between 29°C to 37°C. Significantly, temperatures above 37°C were noted in the coal mining area, with these elevated temperatures affecting areas up to 6 km away. The study’s linear regression analysis revealed a strong inverse relationship between NDVI and LST ($y = -20.888x + 40.458$; $R^2 = 0.83$; $r = -0.91$), This formula describes the relationship between an independent

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variable (x) and land surface temperature (LST) as the dependent variable (y): $y = -20.888x + 40.458$. The coefficient of -20.888 indicates a negative relationship, meaning as x increases, y decreases. The intercept of 40.458 represents the value of y when x is zero. An R^2 value of 0.83 signifies that 83% of the variation in LST can be explained by this model, indicating a very good fit. The correlation coefficient $r = -0.91$ denotes a very strong negative correlation between x and y, indicating that increases in surface temperature are associated with decreases in vegetation health and density. Moreover, the UHI effect was pronounced in the mining area, with temperatures around the mining centers being more than 0.6°C higher than surrounding areas.

In terms of soil moisture, the TVDI varied across the study area, with values ranging from 0.6 to 0.8 (high-very high) in the center of the mining area and 0.2 to 0.6 (moderately dry - dry) in forested areas with specific soil types to the east of the mine. Elsewhere, NDVI values below 0.2 (moist) indicated differing soil moisture conditions, underlining the impact of soil type on environmental responses to mining. The increased drought in forested areas surrounding the mine underscores the broader ecological implications, affecting both ecosystem productivity and soil moisture levels.

4.2. Recommendations

1) Implementation of Green Infrastructure: To mitigate the UHI effect and improve vegetation health, the implementation of green infrastructure such as urban forests, green roofs, and vegetated buffer zones around mining areas is recommended. These measures can help reduce surface temperatures and improve soil moisture retention.

2) Reforestation and Revegetation: Active reforestation and revegetation programs should be initiated in areas affected by mining activities. These programs should focus on planting native species that are well-adapted to local soil and climate conditions to restore ecological balance.

3) Monitoring and Regulation: Regular monitoring of LST, NDVI, and TVDI should be conducted to assess the ongoing impact of mining activities on local ecosystems. Implementing stricter regulations to control mining operations and their environmental impacts is essential.

4) Community Involvement and Education: Engaging local communities in environmental management efforts and educating them about the importance of vegetation and soil health can foster better stewardship of natural resources.

5) Further Research: Additional research should be conducted to explore the long-term effects of mining on soil and vegetation health, and to develop innovative strategies for mitigating these impacts. This research should also examine the potential benefits of integrating traditional ecological knowledge with modern conservation practices.

By adopting these recommendations, it is possible to minimize the adverse environmental impacts of coal mining, promote sustainable land use practices, and enhance the resilience of local ecosystems.

5. Declarations

5.1. Author Contributions

Conceptualization: L.T., S., I.S., and A.J.; Methodology: L.T.; Software: L.T.; Validation: L.T., S., I.S., and A.J.; Formal Analysis: L.T., S., I.S., and A.J.; Investigation: L.T.; Resources: S.; Data Curation: I.S.; Writing Original Draft Preparation: I.S. and A.J.; Writing Review and Editing: I.S. and A.J.; Visualization: A.J.; All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. 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.

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