Spatiotemporal monitoring of ground cover changes (NDVI and LST) in the Bozshakol Mine Kazakhstan using integrated Remote Sensing and geospatial approach

by

Zahid Shah

THESIS SUPERVISOR

Emil Bayramov

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Declaration

I hereby declare that this thesis on the topic "Spatiotemporal monitoring of ground cover changes (NDVI and LST) in the Bozshakol Mine Kazakhstan using integrated Remote Sensing and geospatial approach" is the result of my own work it contains no materials previously published or written by another person and all sources of information including figures, tables and other materials contained within the paper have been duly acknowledged.

Abstract

Mining activities have significant negative environmental impacts, particularly in terms of land cover degradation and temperature changes. This study assesses these environmental impacts associated with Bozshakol open pit mine in Northeastern part of Kazakhstan through remote sensing geospatial approach. The methodology incorporates the use of Normalized Difference Vegetation Index (NDVI), and Land Surface Temperature (LST) data extracted from Landsat 8/9 database to assess land cover changes and surface temperature variations from 2013 to 2023. Climatic factors, that include precipitation, air temperature, and relative humidity, are also evaluated and correlated to differentiate between mining-induced changes and natural climate variability.

The findings show significant decrease in NDVI values post-2016, correlating with increased mining activities. The vegetation loss, which is lower NDVI values, has also resulted LST rising significantly in different section of study area. In terms of climate data, the result shows that higher precipitation years (2016 and 2018) has led to temporarily stabilization of NDVI values, however, overall vegetation decline continued, suggesting that land degradation from mining outweighed the benefits of rainfall. Likewise, the decreasing relative humidity trend and increasing air temperature trend correlate with the land surface warming.

The spatiotemporal analysis of mine section of the study area showed an increased pit boundary, waste dump and tailing area between the years 2017 and 2024 which is the period of post-mining. Mine tailings increased from 7 km² to more than 14 km² and waste dumps from 1 km² to 4.5 km². This growth is directly linked to vegetation loss, increased land surface temperature, and landcover changes.

The findings from this study highlights the need for sustainable mining practices, land rehabilitation, vegetation restoration, and improved waste management associated with Bozshakol mine. Stricter environmental regulations and climate adaptation strategies must be integrated to mitigate long-term environmental damage. Environmental monitoring and responsible mining operations are essential to balancing resource extraction with environment preservation.

Aknowledgement

I would like to express my sincere gratitude to my supervisor, Professor Emil Bayramov, for his guidance, immense support and kind advice throughout my thesis research. I highly appreciate his expertise and knowledge which have been instrumental in the timely completion of this work. I would also like to express my gratitude for the opportunity to work with him as a Research Assistant, which enabled us to collaboratively publish our work in a Q1 journal on the topic Determination of Geospatial Criteria and Prediction of Potential Areas for Porphyry Copper Deposits in Kazakhstan.

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1 Introduction

1.1 Background

Rapid industrialisation, especially in emerging economies and rising demand for raw materials for technology and urbanisation have resulted in an exponential growth in global demand for minerals. Critical minerals like copper, lithium, iron, and rare earth elements are the main components for the production of electronics, batteries, and infrastructure (Jowitt, Mudd et al. 2020). Thus, the corresponding pressure on mining mineral resources increases the global economy to increase mining activities all over the world. While mining is fundamental to economic growth, it also has a detrimental effect on landscapes, contributes to biodiversity loss, and pollutes the environment. Hence, appropriate monitoring strategies are required to reduce these effects and protect the environment from degradation.

Kazakhstan is endowed with rich mineral resources and is one of the major suppliers in the world of uranium, copper, chromite and other valuable minerals. Due to the vast scope for future exploration and extraction of minerals in the country sustainable monitoring of mining operations is necessary in order to balance economic growth with environmental conservation. Structured environmental impact assessment is essential for preventing land degradation, water contamination, and loss of biodiversity which result from unregulated or poorly managed mining practices prevalent around the globe. With a commitment to expanding its mining sector over the coming years, Kazakhstan also needs the systematic methods available to monitor and mitigate the negative effects of mining on the environment. A case study of Bozshakol mine is presented in this research, estimating the ecological impacts of a copper mine in Kazakhstan, using remote sensing techniques. So, the goal of this research is to analyze satellite data to observe changes or alterations that can occur in land use, vegetation coverage, and land surface temperature due to mining activities. The findings of this research can be enhanced in the future research through ground investigations to validate remote sensing results. (Abdulraheem, Zhang et al. 2023)

There are many environmental impacts in mining operations that include deforestation, habitat destruction, soil erosion, water pollution, and air pollution. Unplanned handling of waste including overburden and tailings can create risk to soil and water contamination due to mining activities. The land degradation or land cover change due to mining activities is an environmental concern, as it could lead to the releases of many metals and toxic chemicals into adjacent sources of water in mining area that could result in serious health problems in the community. Improper mining could also destroy local ecosystems and impede rehabilitation following the end of mining. Therefore, there is a need the mining activities should be monitored in a systematic and careful manner for minimizing environmental degradation and impacts and at the same time allowing for the sustainable extraction of resources.

The Remote Sensing data has been very useful for monitoring the environmental impact of Mining activities. Satellite Imageries from different satellite and space agencies could be utilized to monitor the vegetation loss, land cover change and temperature variation in specific region over time. The remote sensing approach can also be used to monitor the expansion of mine pits, tailing and waste dump areas. Remote sensing techniques can help identify signs of environmental stress, including loss of vegetation cover, water pollution, and land subsidence, through spectral signature analysis. Also, the determination and quantification of contaminations in soils and water bodies near mining sites can be done using multispectral and hyperspectral imaging. Researchers and policy makers use remote sensing and Geographic Information System to crate spatial model for environmental impact assessment and decision making.

Monitoring the Environmental impact of mining through remote sensing can help decision makers take necessary corrective measures to minimize the hazardous effects of mining. Sustainable monitoring is useful in timely detection of environmental degradation and impacts, thus facilitating timely actions. Additionally, mining rehabilitation programs could also be monitored for performance and compliance with environmental regulations through satellite imagery. This will lead to balance global demand of mineral extraction with environmental sustainability. Over time, this integration of remote sensing-based monitoring systems into mining regulations and environmental policies is crucial for sustainable mining practices and long-term ecological conservation.

1.2 Motivation

This research is motivated by the increasingly high demand to monitor and asses environmental impacts of mining activities through publicly available remote sensing data. The Bozshakol mine, which has started its operations recently (2016) and is planned to be operated for many years, needed a proper system to monitor the environmental impacts of its mining activities. Application of various environmental indices using remote sensing technology can continuously assess the changes in the land surface. However, negative environmental impacts are not only caused by the mining operations, but climate change is also a factor that contributes to causing negative environmental conditions. The objective of this study is to separate and distinguish the influences of mining activities from the effects of regional climatic factors through anlyzing both remote sensing indices and the climate data from local station. By providing information on the changing trends of remote sensing indices used in this research such as NDVI (Normalized Difference Vegetation Index) and LST (Land Surface Temperature) over time, this research will help to determine the land cover change patterns, thus enabling decision-makers to implement mitigation strategies in a timely manner. Understanding these trends is very important for ensuring sustainable mining practices and minimizing long-term ecological damage in the Bozshakol region.

1.3 Problem Statement

Mining activities have many negative impacts on the environment, affecting land use, vegetation, and contaminating water sources. The long-term environmental impact of the Bozshakol mine, which has recently been operational, raising concerns about its long-term mining activities and impact on the environment. But still it was not possible to disentangle environmental changes attributable to mining from changes attributable to climate change. However, because there are relatively few monitoring efforts, a systematic, data-informed approach is needed to fully assess and mitigate these impacts. The following key problems are addressed in this research:

1. The Bozshakol mine has not been monitored continuously and on a large scale for environmental changes. Indices of remote sensing, including NDVI and LST, can be used to monitor changes in land surface conditions.
2. It’s uncertain if the environmental shifts around the Bozshakol mine stem from mining activity or the regional climate change. To separate these aspects, remote sensing information needs to be united with climate information.
3. The Bozshakol mining and adjacent areas had not been systematically studied for the long-term dynamics of the indices applied from remote sensing. Monitoring what drives these indices over time is critical for recognizing trends in degrading environments and deploying successful remediation.
4. This will support, with timely and data-driven insights, decision-makers to implement effective strategies to mitigate the mine's environmental footprint. Analysis of remote sensing and climate data can support sustainable mining practices in a systematic way.

The goal of this research, therefore, is to create a reliable technique for monitoring the environmental effects of mining. By addressing these problems, proactive mitigation strategies can be ensured and sustainable resource management supported.

1.4 Research Objectives

Following are the main research objectives of this study;

1. Spatio-temporal Analysis using NDVI and LST remote sensing indices, land degradation, vegetation cover, and climate variability will be analysed to determine the environmental impacts of the Bozshakol mine.
2. Integrating remote sensing-based data with climatic records gives a broader sense of the main drivers of environmental change in the region, which aids in distinguishing between environmental changes caused by mining and those caused by climate change.
3. Understanding the long-term changes in land surface conditions and their correlation with mining activities by temporal trends of remote sensing indices throughout the Bozshakol mine area.
4. To develop a framework that utilizes remote sensing to monitor the environment and give decision-makers actionable insights to reduce environmental impacts related to mining and ensure sustainable resource management

1.5 Project Significance to the Industry

This study utilizes public access remote sensing data then incorporated into a GIS environment to assess mining-induced environmental changes and to separate climate change effects from mining eactivities This research contributes to establishing a framework for continuous monitoring of the environment by integrating remote sensing indices such as NDVI and LST with climatic data. By adopting this approach, the industry can move toward sustainable mining practices through proactive decision-making and early mitigation of environmental impacts.

The findings of this study will assist regulatory bodies and mining companies in creating policies that promote responsible resource extraction. The ability to track environmental changes over time ensures compliance with environmental regulations and company sustainability goals. This research aims to enhance industry practices while minimizing long-term ecological damage by aligning mining operations with global sustainability standards.

1.6 Scope of the Work

The research is based on the use of open-access satellite imagery from various databases accessible through Google Earth Engine. Through its API code editor, it offers a platform for remote sensing analysis with efficient processing capabilities. The study uses various remote sensing techniques to evaluate environmental changes caused by mining operations, and ArcGIS Pro software is utilized for further spatial analysis. Due to its recent operational status and the need for long-term environmental monitoring, the Bozshakol mine was selected for study. However, the research methodology is applicable to other open-pit mining operations and surface tailings monitoring studies, and it is not restricted to this specific location only. The objective of this research is to establish a framework that can be scaled and adapted to monitor environmental changes caused by mining, using satellite-based environmental assessments.

2 Study Area

Bozshakol mine is one of the biggest coppers mine located in the northern part of Kazakhstan (Figure 1). It is porphyry Cu deposit that was first discovered by R.A. Borukaev in 1930. The deposit contains mixture of volcanogenic sedimentary rocks of Cambrian and Ordovician age. According to (Kudryavtsev 1996) the deposit contains proven reserves of 0.28 g/t of Au and and 0.72% of Cu. Mineralization is associated with middle Cambrian Ordovician rocks mostly tonalite. These host rocks are mostly covered by Ordovician sediments. The mining and production of Cu has started in 2016, and the predicted Mine life is 40 years.

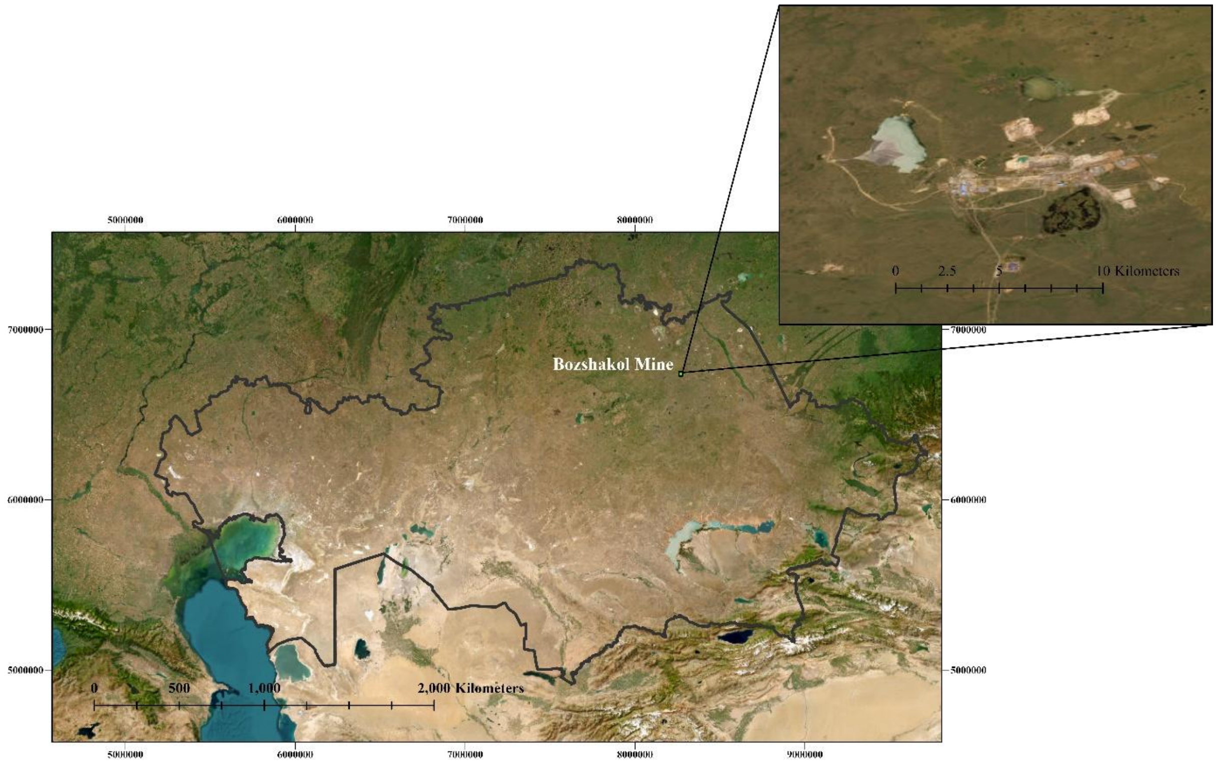

Figure 1. Showing location of the mine in Kazakhstan

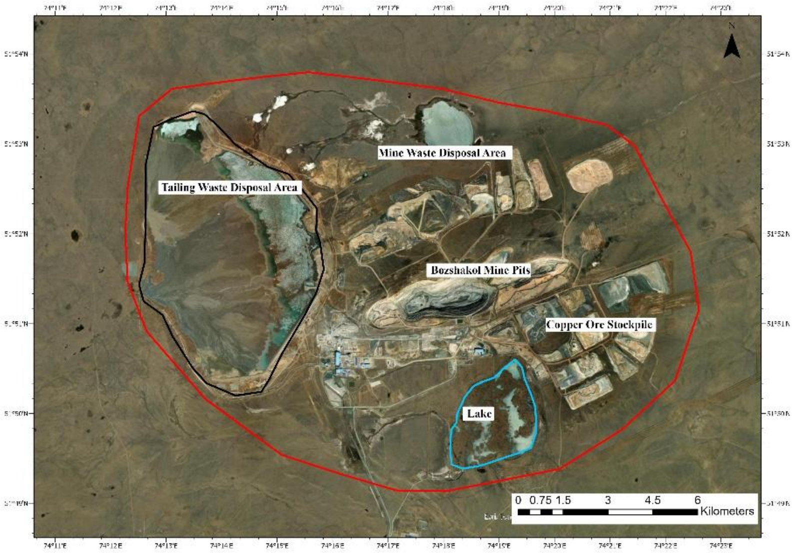

Figure 2. showing the Mine, tailing and waste boundaries

The study area has been divided into three main section (Figure 3) to analyse the extent of impacts of Mine on its surrounding and to correlate these finding with climate data to identify trends.

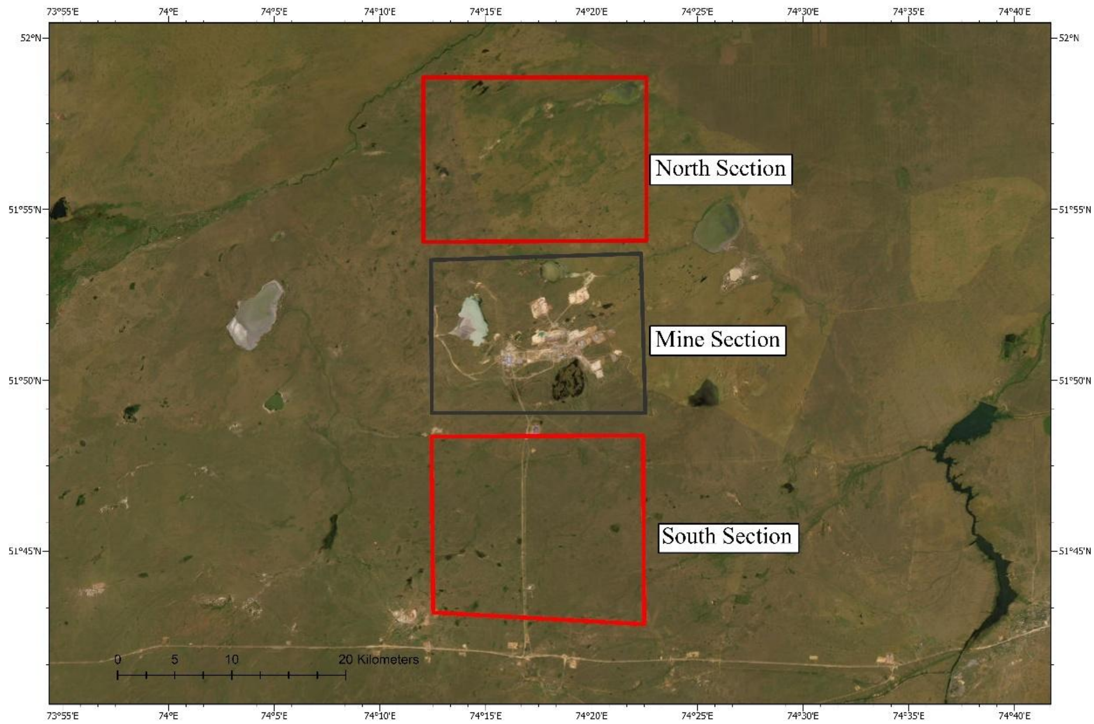

Figure 3 showing three sections of the study area

To obtain the accurate assessment of land cover changes, three summer months were chose, considering Kazakhstan's landscape remains predominantly covered in snow for most of the year (Figure 4). So, the months selected are June, July, and August, and their average values were used for analysis of NDVI and LST. These months are selected considering the high Mean NDVI values (Figure 5).

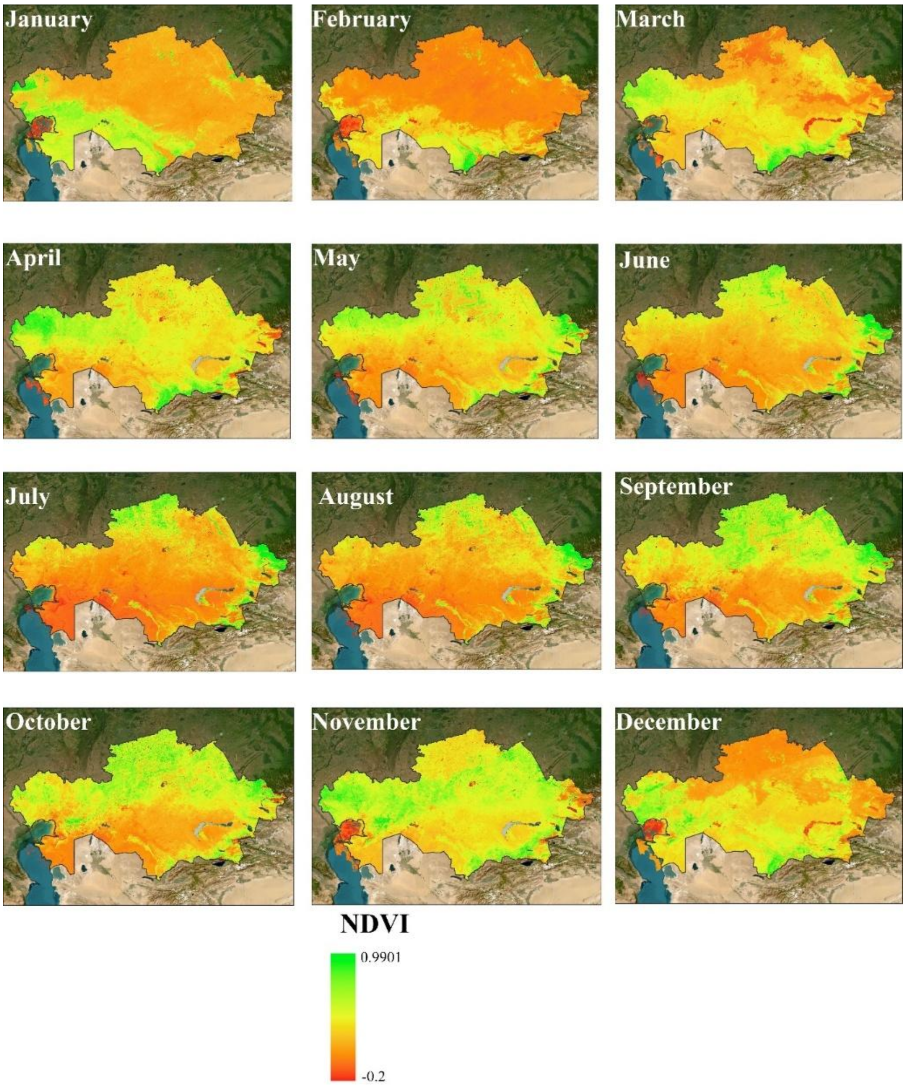

Figure 4. Showing NDVI of Kazakhstan for year 2023 at resolution of 250m

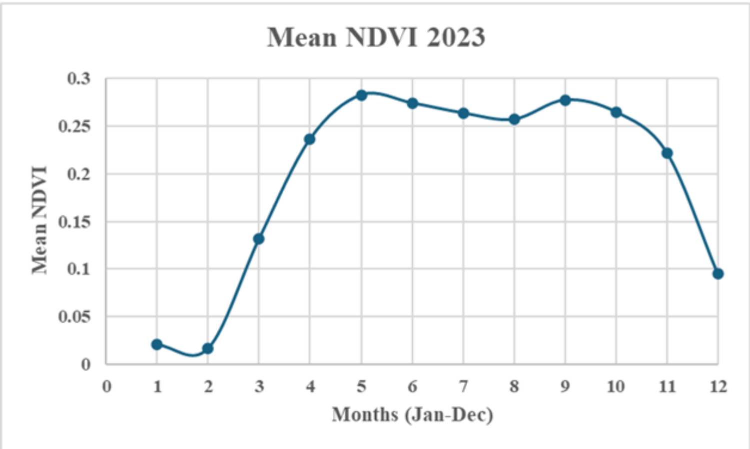

Figure 5. Monthly Mean NDVI graph based on MODIS database for the year 2023

3 Literature Review

3.1 Remote Sensing

The ability of human eye is limited to very minute portion of electromagnetic spectrum. It is in the range between 0.4μm and 0.7μm wavelength and whole spectrum range from 10^{-6} μm (gamma rays) to 10^{7} μm wavelength (Radio waves) (Figure 6). However, human being has developed ways to artificially augment the vision sensory system to detect all range of electromagnetic spectrum to study the nature and environment through use of technological advanced detector and sensors. Remote Sensing is the techniques and processes of studying electromagnetic spectrum as mean of exploring the target objects. The advancement in the remote sensing technologies comes with the development of space exploration and increasing concern of protecting our natural environment. (Navalgund et al. 2007).

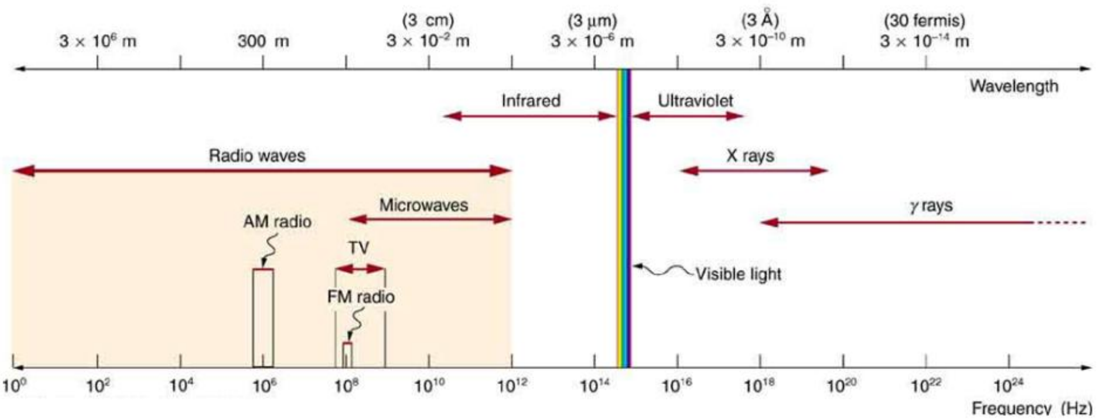

Figure 6. Electromagnetic waves after (Urone et al. 2012)

The remote sensing is based on the radiation source and sensing system as illustrated in (Figure 7). The radiation when enters to the atmosphere can be subjected to range of attenuative processes that include scattering or absorption. It depends on wavelength of radiation, particle matter in the atmosphere and its density and absorptivity. Every substance absorb radiation based on its composition and wavelength of radiation. The loss of radiation energy to the atmosphere depends on its constituents. These are comprised of water vapour, carbon dioxide, ozone, nitrogen and other atmospheric gases. The fraction electromagnetic radiation when pass through the atmosphere are reflected, absorbed or transmitted. These fractions' values will be based on the nature of the earth's materials. Moreover, the proportion of energy that is reflected, absorbed, and transmitted by a given feature will vary based on wavelength. Thus, in one spectral range, two features may be unidentifiable, but they can be very different in another wavelength band. Colour is a visual effect caused by spectral variations within the visible spectrum. So, A composite image is created by the combination of bands in multi-spectral remotely sensed imagery, which can then be used for interpretation and analysis (Huang et al. 2021). Different formulas are applied to these bands to use them for various purpose such as environmental studies, geology, urban planning. In this study focus is on two major environmental indices that is Normalized difference vegetative index NDVI and Land Surface Temperature LST.

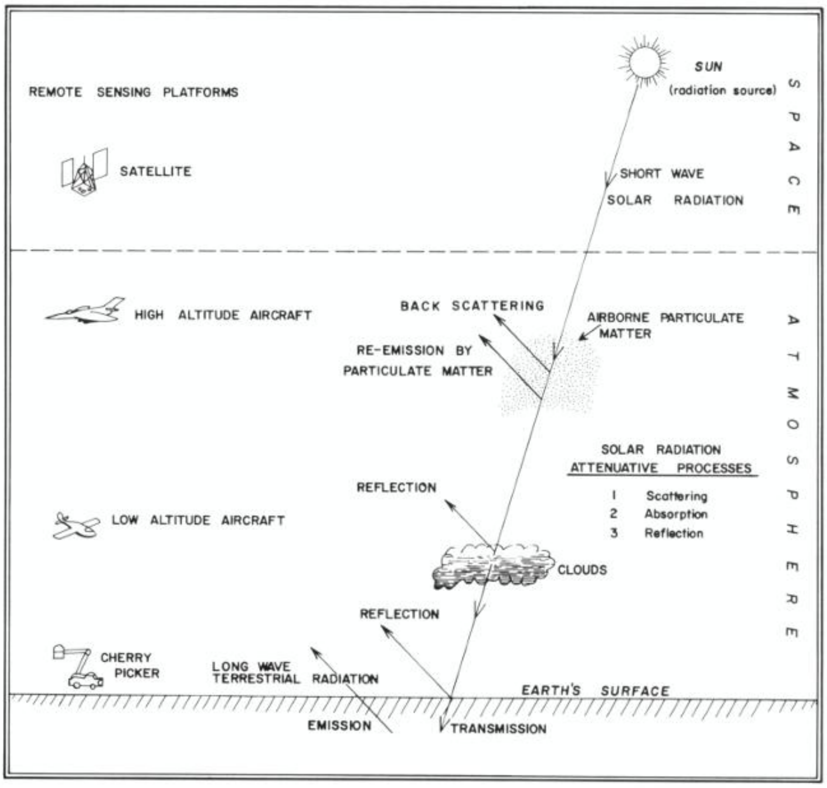

Figure 7. General model of remote sensing after(Navalgund et al. 2007)

3.2 Normalize Difference Vegetative Index

Normalized difference Vegetative Index (NDVI) was first proposed by (KRIEGLER 1969) which is a simple band transformation of the difference of near infrared radiation(NIR) and red radiation (RED) divided by addition of near infrared radiation(NIR) and red radiation(RED). This results in totally different image called Normalised Difference Vegetative Index (NDVI)

$$NDVI = \frac{NIR - RED}{NIR + Red}$$

This index is widely used across many fields of studies to delineate the coverage of vegetation. The value ranges from -1 to +1. The higher value is indicating the dense vegetation and vice versa. Water bodies, rocks, sands, or concrete surfaces have negative values, but vegetation, including crops, shrubs, grasses, and forests, has positive values in general (Jones et al. 2010). The overall objective of employing NDVI is to enhance the evaluation of vegetation data through the use of remotely sensed data. Vegetation affects environmental quality and desertification conditions in arid and semi-arid regions (Zhang et al. 2003).). It has been clearly shown in various studies that NDVI can be used to separate savannah, dense forest, non-forest and agricultural fields, as well as differentiate between evergreen and seasonal forest types (Pettorelli et al. 2005) fraction of vegetation cover (Dutrieux et al. 2015). Numerous different vegetation indices exist, each with their own advantages and limitations (Loranty et al. 2018). The most commonly used index for vegetation assessment is NDVI (Jones et al. 2010).

3.3 NDVI and Mining Activities

NDVI time series has been widely used to monitor land surface change and vegetation cover in mining areas (Lei et al. 2016). A number of researchers have used vegetation indices to evaluate post-mine reclamation vegetation (Dogan et al. 2008); (Karan et al. 2016); (Chen et al. 2017).(Liu et al. 2019) studied vegetation variation in arid and semiarid mining regions, examining the impact of geomorphology, groundwater depth, climate conditions, and mining operations on vegetation, and found vegetation ecology is negatively impacted by mining activities. (Sun et al. 2022) studied 3 main central mining areas of China, which are the Liaoning Nanfen iron mining area, the Inner Mongolia Sanheming iron mining area, and the Sichuan Hongge iron mining area, aiming to identify the factors that control the phenology of vegetation and quantify the impact of mining activities using Sentinel-2 time series. Their results shows that mining activities had an exponential effect on vegetation phenology with the increase in distance to the mines. (Nursaputra et al. 2021) utilizes NDVI using google earth engine platform to study the change in the forest density around the mining area and found significant decline over the time.

3.4 Land Surface Temperature (LST)

The temperature that is experienced when long-wave radiation and turbulent heat fluxes interact at the surface-atmosphere interface is defined as land surface temperature (LST).The radiative energy budget of the surface of the earth is determined by Land Surface Temperature

(LST), which is a critical variable (Hulley et al. 2019). The partitioning of energy into latent and sensible heat fluxes is controlled by LST, which is one of the most important climate system variables on various time scales (Schneider et al. 2010). At the interface between the land and atmosphere, the LST is responsible for the outgoing longwave radiation and turbulent heat fluxes (Anderson et al. 2011); (Hain et al. 2011). LST remote sensing is based on the theory that the ground surface emits a concentrated amount of radiative energy when temperatures increase, Plank's Law. LST is commonly known as the 'skin' temperature or radiometric temperature, but it's not the same as near surface air temperature which is the temperature of the air near the surface and is regularly monitored. The temperature of the top few micrometres of bare soil surfaces and the temperature of the leaves of dense vegetation is what LST measures. Two infrared spectrumal 'window' regions contain the highest radiometric emission for the typical range of Earth surface temperatures, which exclude fires and volcanic eruptions. The midwave infrared (3.5–5 µm) and the thermal infrared (TIR, 8–13 µm) regions are not affected by atmospheric absorption and scattering, so these ranges are used in LST calculation by Remote Sensing.

3.5 LST and Mining

Many researchers have studied the effects of Mining on the land surface temperature (LST) of nearby mining areas. (Bhagat et al. 2024) Investigated the effect of land use and land cover changes on land surface temperature, particularly mining operations in Chhattisgarh, India and found that LST increased significantly in the summer month in the mining areas. (Singh et al. 2018) studied the impact of changing land use land cover (LULC) on land surface temperature (LST) in Jharia Coalfield India and their results shows that the rate at which the LST increased was 1.05°C from 2005 to 2013 and there exist a strong correlation between land use land change and LST values. (Sánchez 2020); (Millán et al. 2013) and (Padmanaban et al. 2017) observed that when in proximity to open pit mining activity, the exposed environment is even more critical due to the anthropic activities that have the most negative impacts on the environment this leads to negative environmental impacts and geological changes that are visible on the surface. According to (Li et al. 2022) practically obtaining LST data is crucial due to the dispersed ore characteristics in mining areas that affect the use and occupation of the area. In this regards, (Ogunro et al. 2023) in their spatial-temporal analysis, found that the mean LST values in a mining area in Nigeria consistently increased from 23.98 °C in 1984 to 29.46°C in 2020.

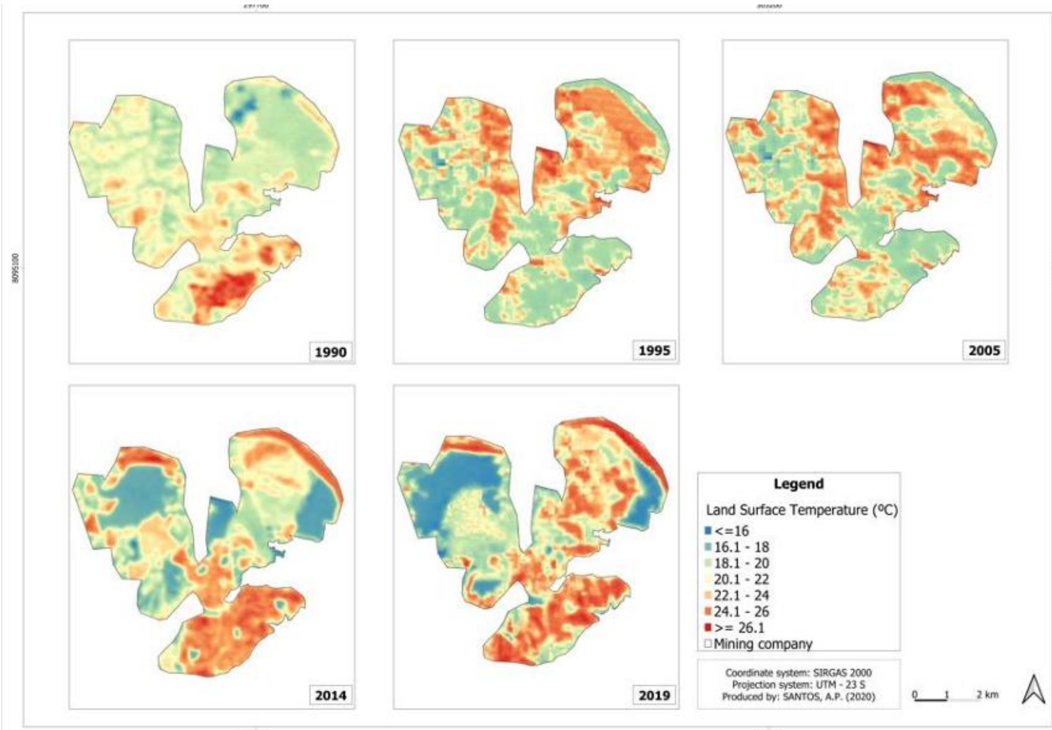

Figure 8. Temporal Variation of LST in Mining Areas after (Santos et al. 2022)

3.6 Effect of Mining on Climate

Recently there has been much research on climate and its relationship with mining activities (Pearce et al. 2011); (Nelson et al. 2010) . It is because the local environment and communities where mining operations are located may face new impacts or exacerbate existing ones due to climate change. (Phillips 2016) extensively reviewed the effects of surface mining and climate change in a regional context focusing on the case studies across the globe. In term of Surface mining operations, Acid Mine Drainage (AMD) is the impact that mining activities have on the most well-known and established level. Metal sulphides, particularly pyrite, are oxidized in this process and due to precipitation and infiltration, water usually reacts with exposed rocks to cause oxidation (Cervantes 2012); (Sierra et al. 2013). The process happens with increased in surface temperature and could lead to potential health risk and ecological impacts (Mphephu et al. 2002); (Bae et al. 2010). (Lin 2012) Increased temperatures and precipitation can lead to rapid oxidation and acid production in waste stockpiles. Therefore, change in climate could increase AMD phenomena poses significant threat to environment.

4 Methodology

In this study, the Bozshakol mine area is divided into three sections: Mine Section, North Section, and South Section. The division facilitates a more precise and exact evaluation of environmental changes by preventing the generalization of findings over a large area. The **Mine Section** represents the area directly affected by mining activities, while the **North** and **South Sections** are used as reference zones to assess how far and how intensely these changes extend beyond the mine. For each section, the study examines multiple environmental indicators from 2013 to 2023 to ensure that mining-related impacts are assessed comprehensively. The two major environmental indicators selected for analysis are:

1. **Remote Sensing-Based Indicators**
2. **Climatic-Based Indicators**

The generalised workflow of the methodology is shown below (Figure 9)

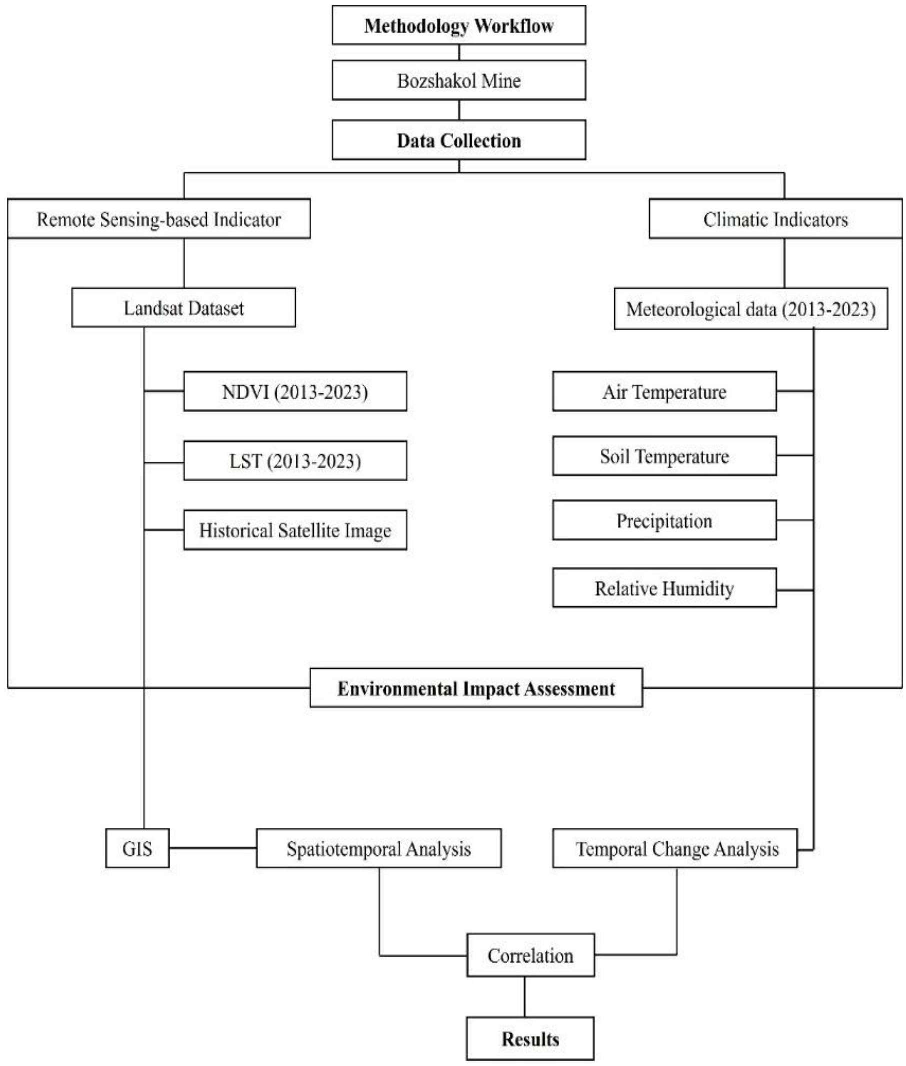

Figure 9. Methodology workflow

Remote Sensing-Based Indicators

The remote sensing-based indicators used in this study include:

- Normalized Difference Vegetation Index (NDVI)
- Land Surface Temperature (LST)
- Mining boundary change detection

Climatic-Based Indicators

The climatic-based indicators used in this study include:

- Air Temperature
- Soil Temperature
- Humidity
- Precipitation

4.1 Data Collection

4.1.1 Remote Sensing Data Collection

Remote sensing data is collected using the Google Earth Engine (GEE) platform. NDVI and LST data are extracted focusing on the summer months (June-August) of each year from 2013 to 2023 using Landsat 8/9 Collection 2 Level 2 imagery database. The primary reason for choosing summer months is that other months are largely covered by snow in the study region, which could cause inconsistencies in vegetation and surface temperature analysis.

The spatial resolution of the Landsat data used is **30 meters**. Separate NDVI and LST maps are produced for each section of the study area (Mine Section, North Section, and South Section).

4.1.2 NDVI Calculation

The calculation of NDVI was done using Google Earth Engine (GEE) and processed Landsat 8/9 surface reflectance imagery at a 30m resolution for the three summer months (June, July, and August) for 2013-2023. Using the standard formula, the NDVI was computed: NDVI = (NIR - RED) / (NIR + RED), where the NIR (Band 5) and RED (Band 4) bands were used. The QA bands were used to mask clouds and shadows, resulting in cloud-free composite images. The average of the available cloud-free images was used to create monthly NDVI composites, and the mean NDVI across three months was used to generate a seasonal composite. NDVI values are categorized into five classes considering minimum and maximum value in the study region**:** (Figure 10); (Figure 11); (Figure 12)

- **Class 1:** 0.01 – 0.1
- **Class 2:** 0.1 – 0.2
- **Class 3:** 0.2 – 0.3
- **Class 4:** 0.3 – 0.4
- **Class 5:** 0.4 – 0.5

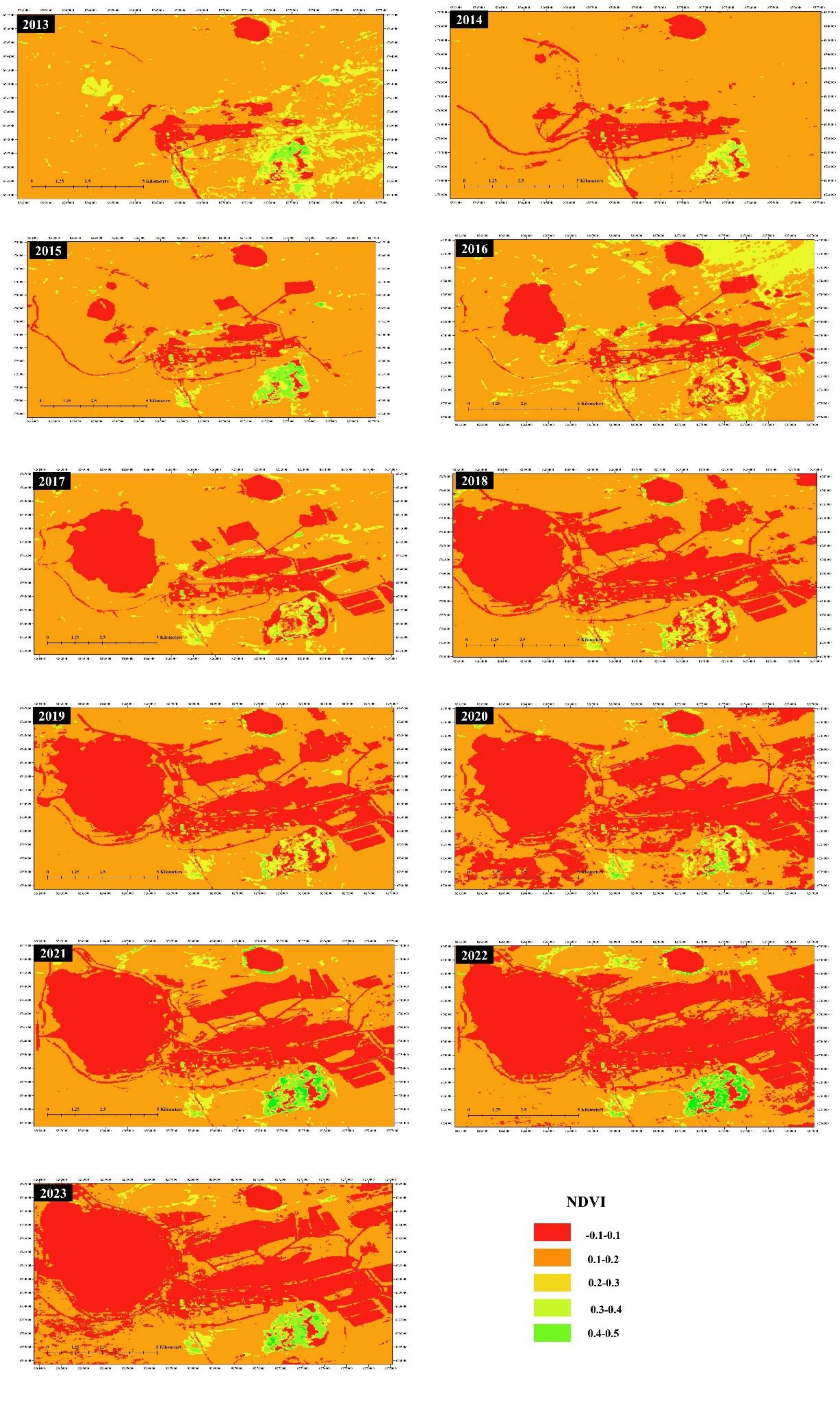

Figure 10. NDVI of Mine Section for year 2013 to 2023 (Pixel graphs appendix A)

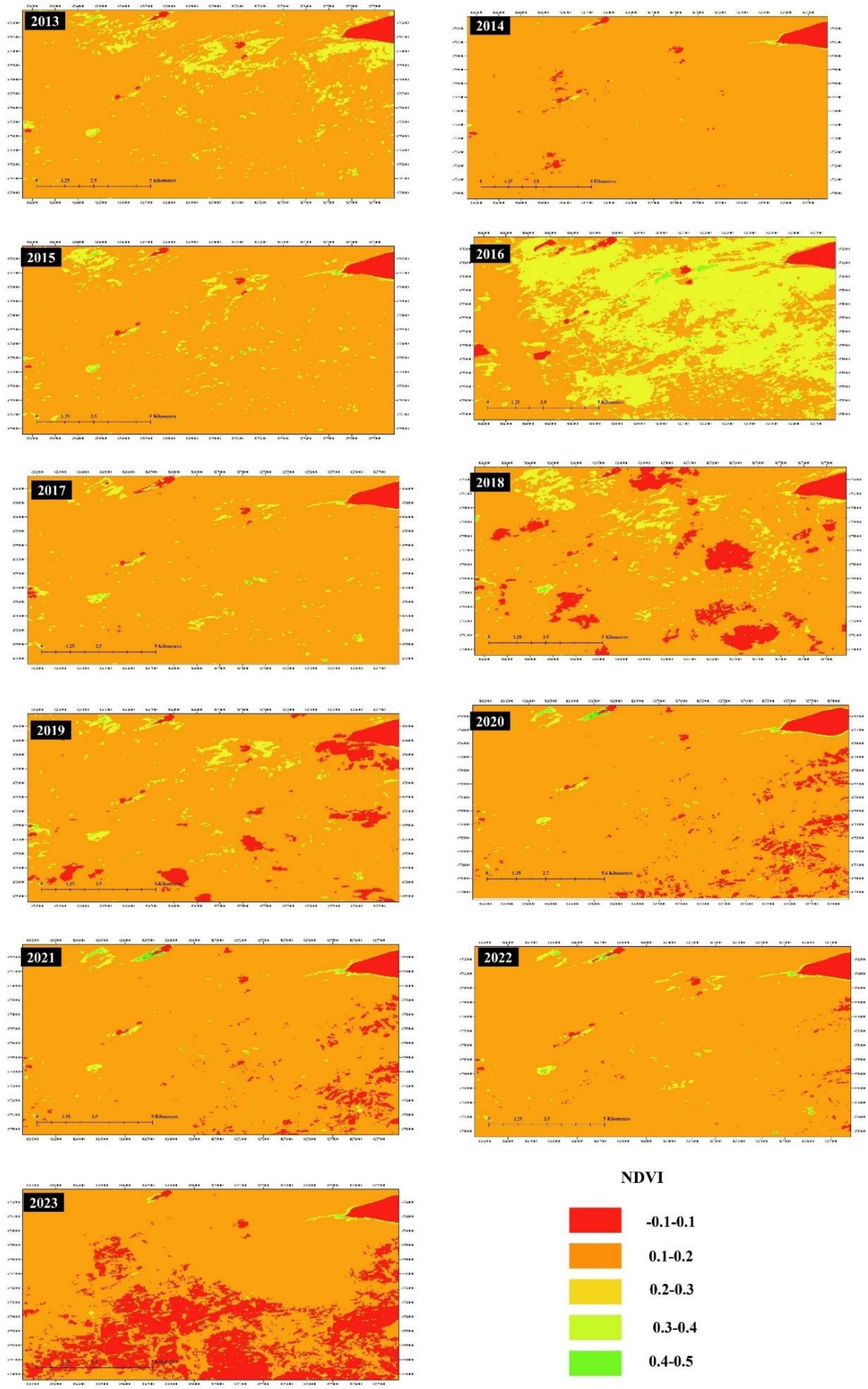

Figure 11. NDVI of North Section for year 2013 to 2023 (Pixel graphs appendix A)

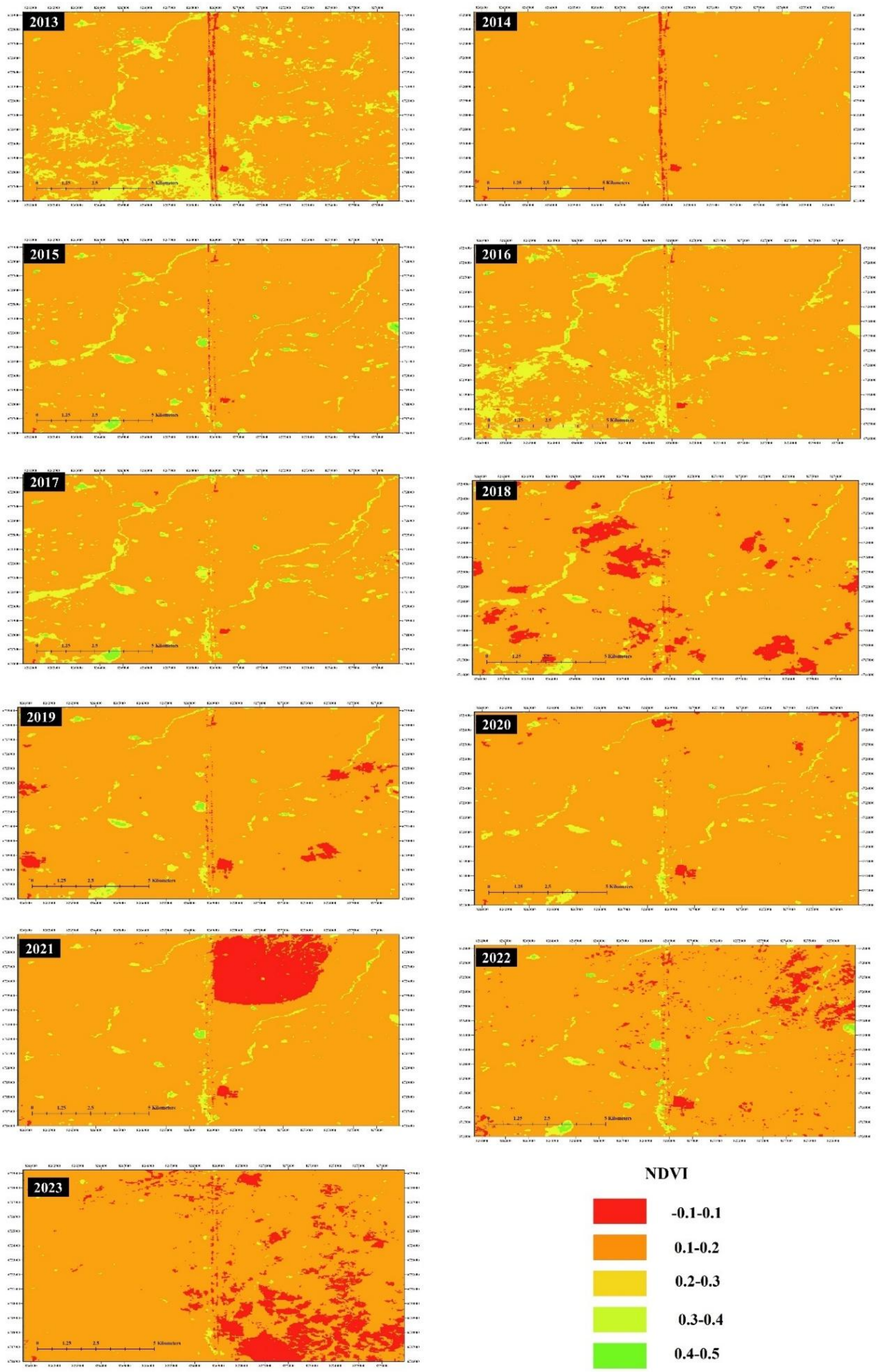

Figure 12. NDVI of South Section for year 2013 to 2023 (Pixel graphs appendix A)

4.1.3 LST Calculation

Google Earth Engine (GEE) was used to process surface reflectance images from Landsat 8 and Landsat 9. Only summer months (June, July, and august) were included in the study period after filtering the dataset. The Quality Assurance (QA) band was utilized to apply cloud masking and keep only clear pixels. Based on the radiative transfer equation, the LST was obtained from the thermal infrared band (B10), where Top of Atmosphere (TOA) brightness temperature was computed and corrected for land surface emissivity based on the Normalized Difference Vegetation Index (NDVI). Kelvin to Celsius conversion was done for the resulting LST values. LST values are categorized into five classes considering the minimum and maximum value in the study region**: (**Figure 13); (Figure 14); (Figure 15)

- **Class 1:** -1°C – 10°C
- **Class 2:** 10°C – 18°C
- **Class 3:** 18°C – 26°C
- **Class 4:** 26°C – 34°C
- **Class 5:** 34°C – 42°C

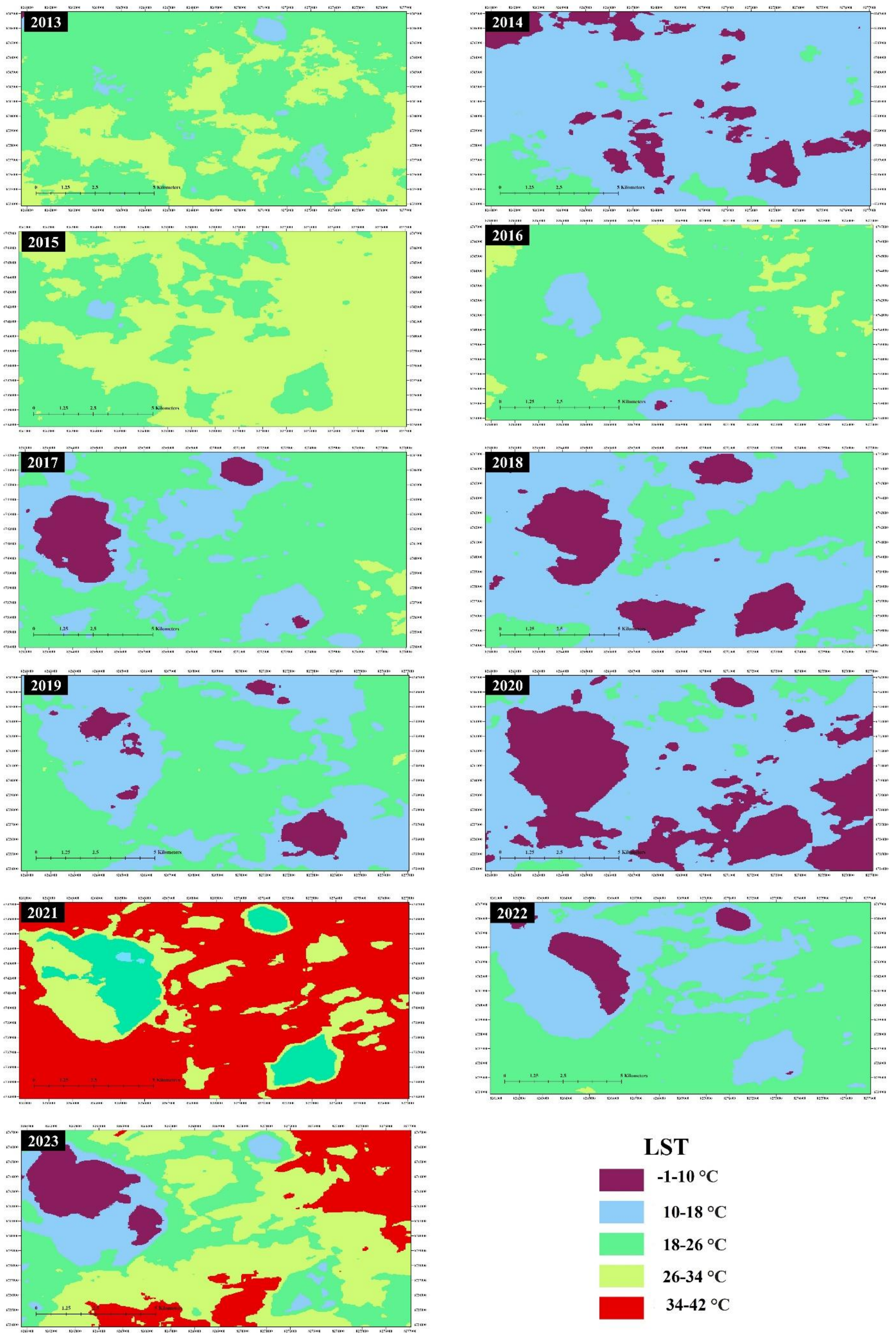

Figure 13. LST of Mine Section for year 2013 to 2023 (Pixel graphs appendix B)

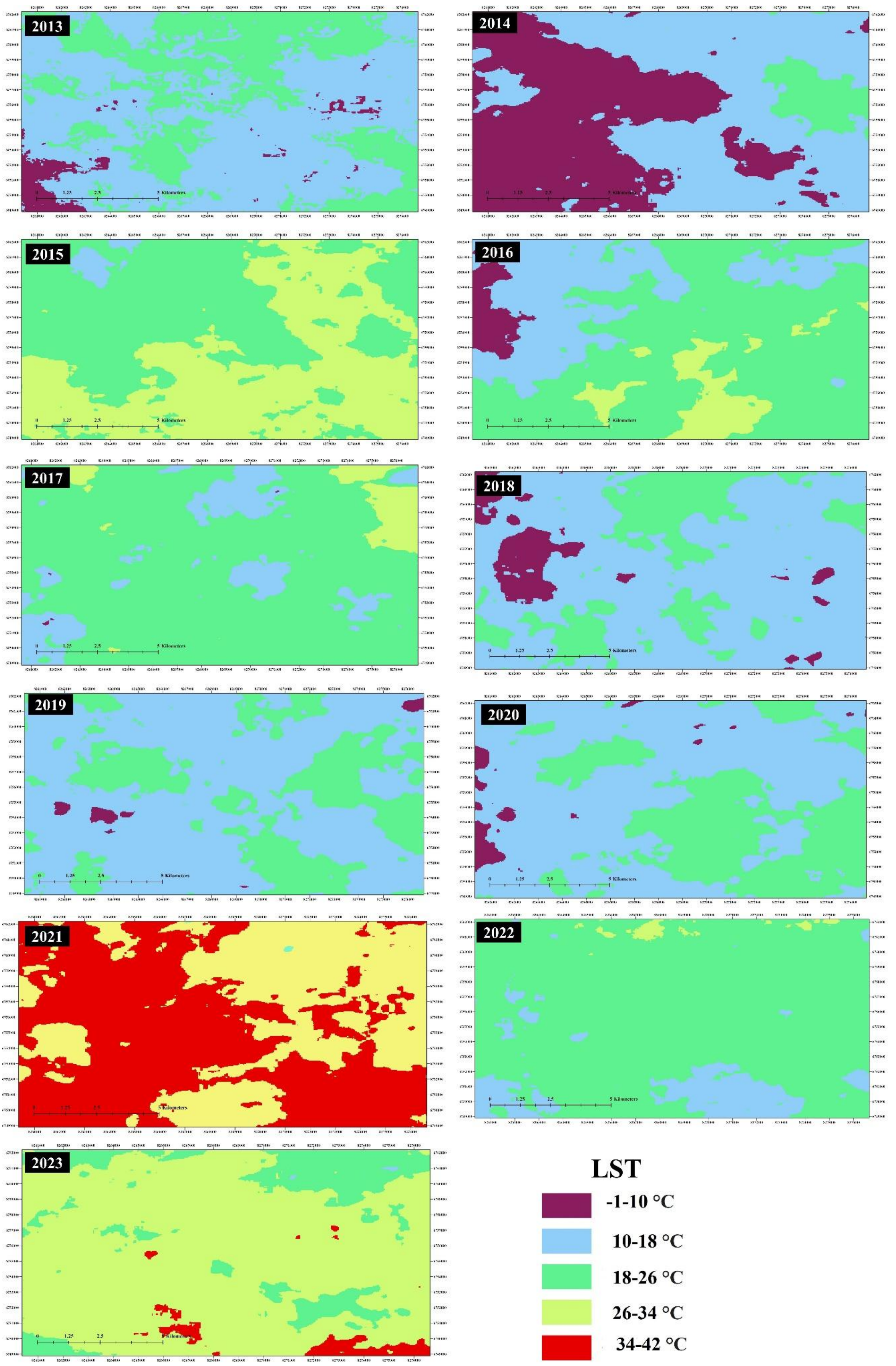

Figure 14. LST of the North Section for year 2013 to 2023 (Pixel graphs appendix B)

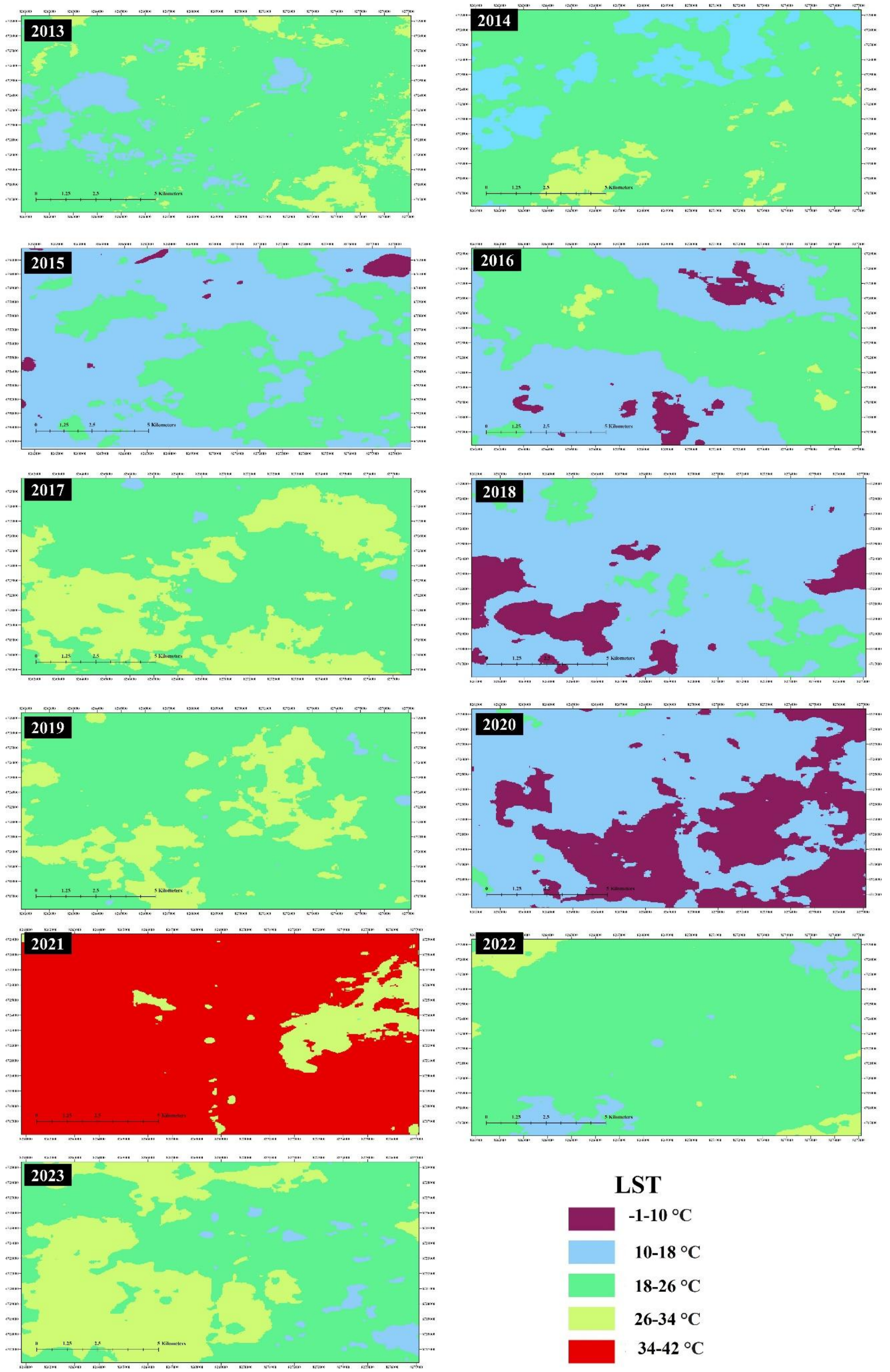

Figure 15. LST of South Section for Year 2013 to 2023 (Pixel graphs appendix B)

For spatiotemporal analysis, the percentage of area covered by these classes is calculated for each section of the study area. The goal is to detect and quantify changes before and after mining operations.

4.2 Mining Boundary and Land Cover Change Detection

To analyze the expansion of mining activities, the area of mine boundary, waste dump, and tailings is calculated for the years 2017, 2018, 2021, and 2023 (Figure 16). These years were selected based on the availability of high-resolution historical Landsat images. The changes in mining area are quantified using remote sensing classification techniques and GIS-based spatial analysis.

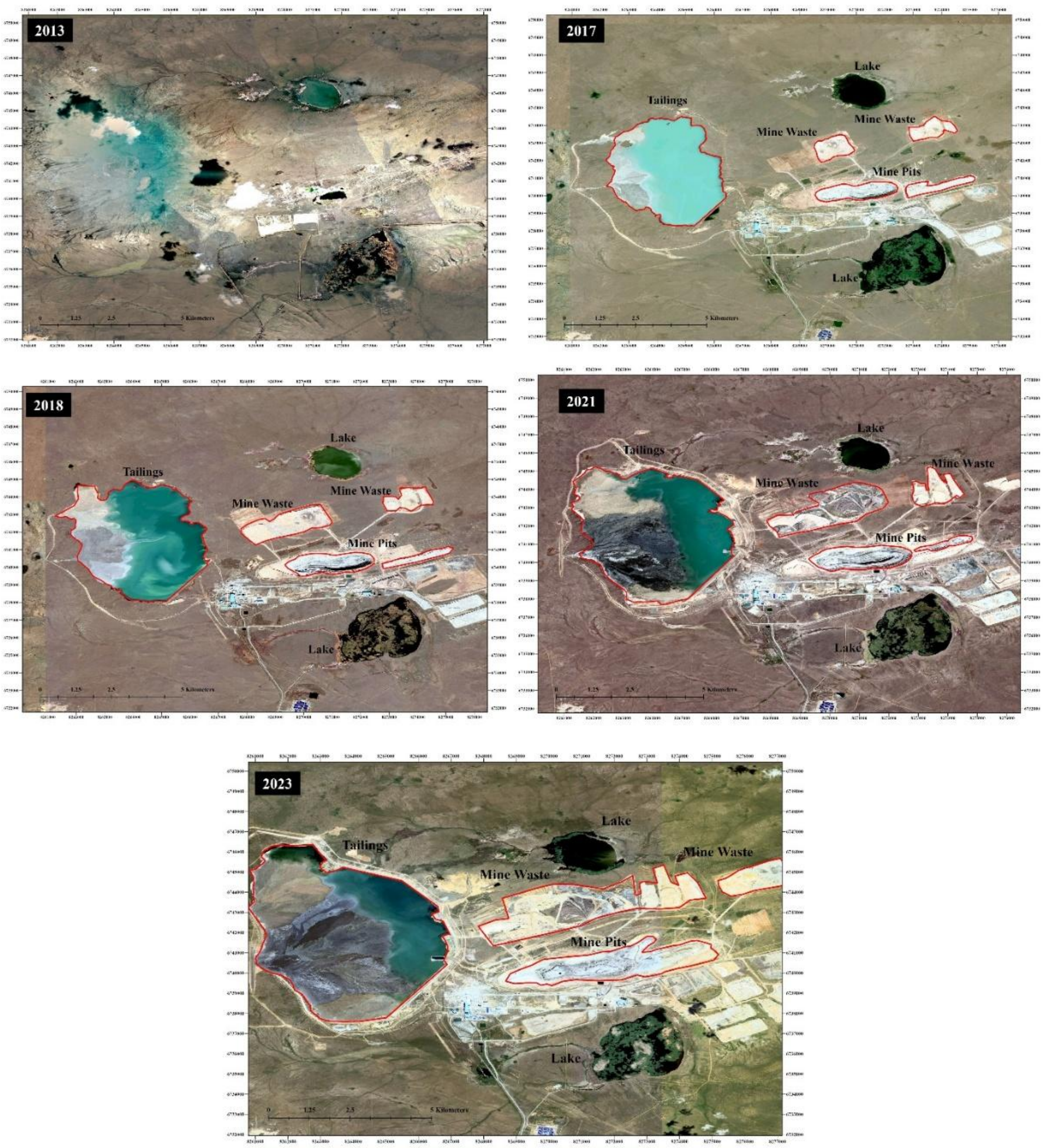

Figure 16. Assessment of Mine, Tailing and Waste Boundaries Change over time

4.3 Climatic Data Collection

The collection of meteorological data for air temperature, soil temperature, humidity, and precipitation are done by an open-access database of the National Meteorological Department from the nearest station to the Bozshakol mine (Figure 17). Trends and correlations with mining activities were identified by analyzing the data during the study period from 2013 to 2023.

Figure 17. Assessment of Mine, Tailing and Waste Boundaries Change over time (Data table appendix C)

4.4 Data Processing and Analysis

4.4.1 Remote Sensing Data Processing

- **Preprocessing:** The Google Earth Engine platform is utilized to apply atmospheric and radiometric corrections to Landsat images
- **NDVI and LST Extraction:** NDVI and LST values are extracted for each study.
- **Spatiotemporal Analysis:** To detect changes in vegetation and temperature over time, the area covered by every NDVI and LST class is measured annually.
- **Mining Boundary Detection:** The expansion of the mine area is tracked by analysing change detection.

4.4.2 Climatic Data Processing

- **Trend Analysis:** Change in values of climatic indicators are analyzed using statistical time series analysis.

- **Correlation Analysis:** The evaluation of climate factors on vegetation and temperature change is done by analyzing the relationships between NDVI, LST, and climatic variables.

This study investigates the trends of NDVI and LST for evaluating the impact of mining on the vegetation and surface temperature. It explores the relationship between NDVI and LST change, and climate trends in the region further. To determine impact of mining on land use, the study evaluates changes in mine boundaries, waste dumps, and tailings. This research provides detailed insights into environmental changes by dividing the study area into different sections, providing a comprehensive understanding of how mining activities have affected the surrounding landscape.

5 Results

This study investigates how the Bozshakol open pit mine located in the Northeastern part of Kazakhstan affects the environment specifically landcover change, using open access remote sensing and regional climate data. The analysis is mainly focused on how mining activities affect land cover and surface temperature over time as Mining activities progress. The main results obtained from spatiotemporal analysis are presented and shown in this section, examining variations in vegetation values and land surface temperature (LST) using remote sensing indices such as the Normalized Difference Vegetation Index (NDVI) and LST.

The use of NDVI and LST values allowed for assessing percentage increases or decreases in affected areas before and after mining operations started. The study examines patterns in vegetation loss, surface temperature, and other environmental changes by comparing pre-mining and post-mining conditions.

Additionally, Climate data including temperature, precipitation, and relative humidity, are included to determine whether observed changes in NDVI and LST are influenced by mining operations or general climate conditions. A more overall view of the environmental impact of the mine is analysed through this correlation, which differentiates between direct mining related activities and variation in natural climate.

5.1 Change in NDVI Mine Section

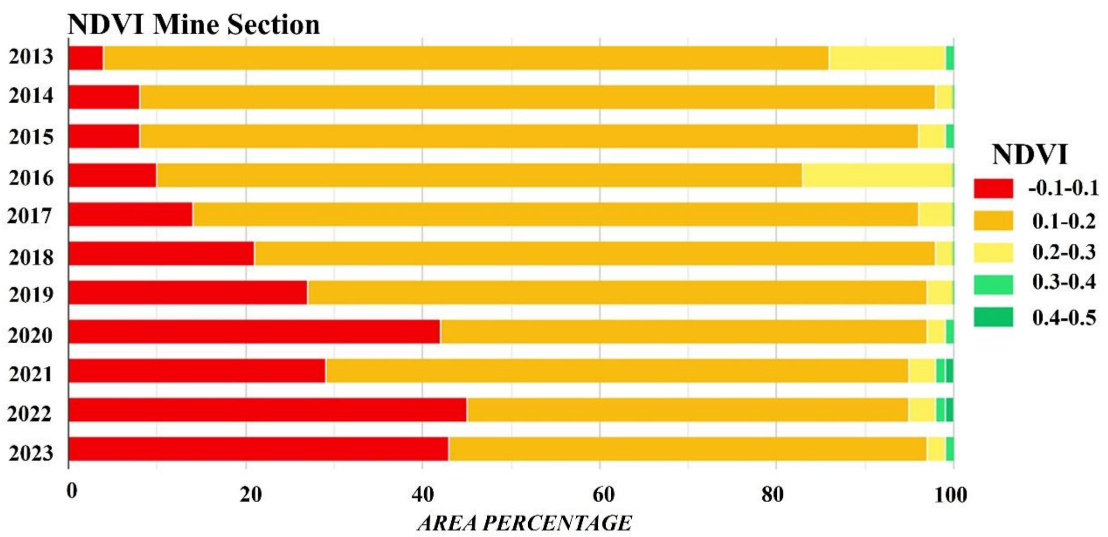

Figure18. Change in NDVI area of the Mine Section

As it is obvious from (Figure 18) that focuses on mine section, before mining (2013–2015), the area having a majority of moderate NDVI values (0.1–0.3), which indicated that there was stable vegetation cover with minimal barren land. However, since 2016, there has been a distinct increase in low NDVI values (-0.1 to 0.1) which shows gradual vegetation loss, in relation with the development of mining operations. By 2019-2023, negative NDVI values had been in placed in a large portion of the mine area, indicating widespread land degradation.

5.2 NDVI Change in North Section

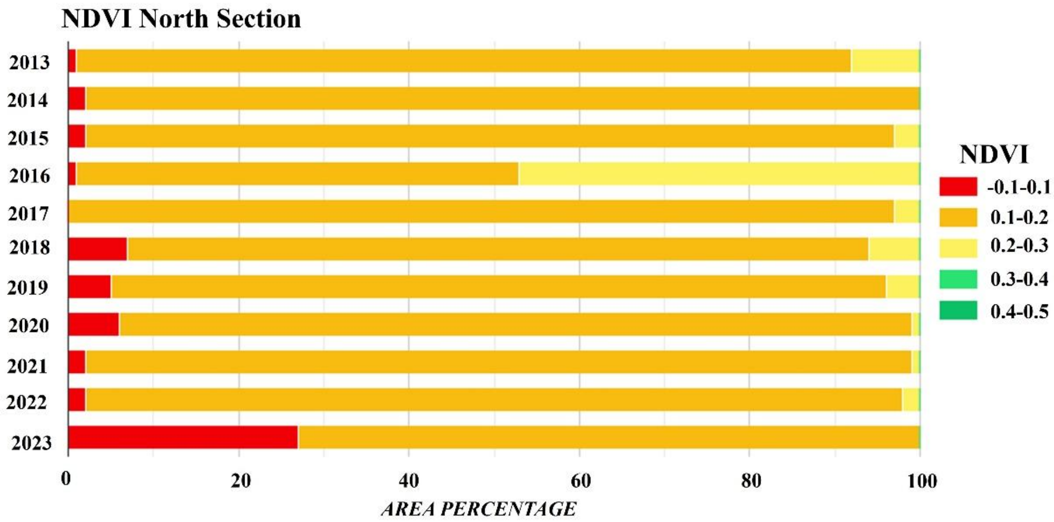

Figure19. Change in NDVI area of North Section

The North Section's NDVI analysis (Figure 19) shows a substantial reduction in vegetation, possibly caused by mining activities. Expansion of mining operations have caused soil disturbance or dust accumulation, as evidenced by the noticeable increase in low NDVI values (-0.1 to 0.1) since 2018. A short increase in 0.2–0.3 NDVI in 2016–2017 suggests temporary vegetation recovery, possibly due to reduced mining activity. However, the absence of NDVI values above 0.3 confirms a lack of healthy vegetation, indicating that there is a continuous impact on the environment. These patterns indicate that mining operations have had a significant impact on land cover, which has prevented significant ecological recovery in the North Section

5.3 NDVI South Section

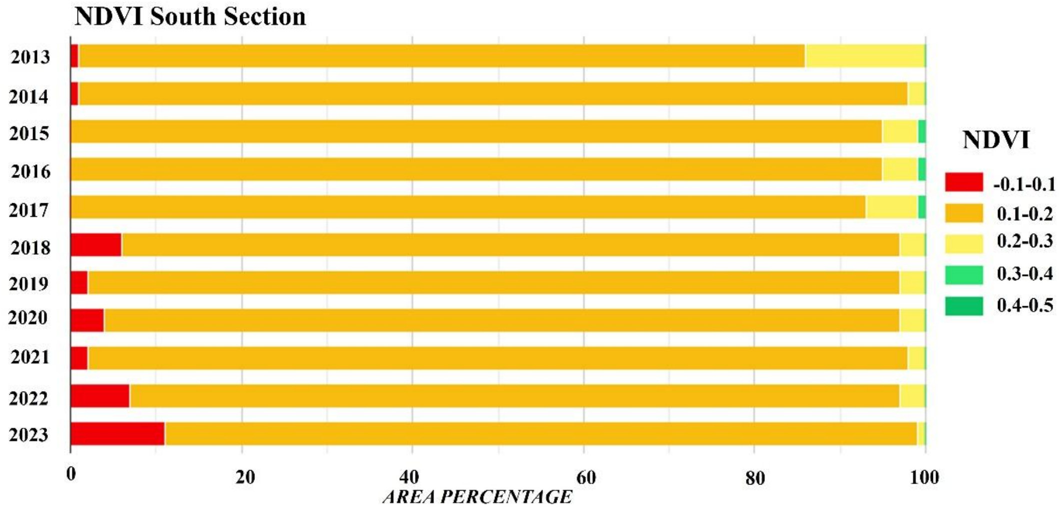

Figure 20. Change in NDVI area of the South Section

The NDVI analysis of the South Section (Figure 20) reveals that the degradation of vegetation is similar, but with a few significance differences from the North Section. The NDVI values that are dominant fall within the 0.1–0.2 range, which suggests persistent land disturbance, likely caused by mining activities. In earlier years (2013–2017), the South Section, compared to the North Section, have higher NDVI values (0.3–0.5), which suggests that vegetation was relatively present before mining expansion. However, the presence of low NDVI values (-0.1 to 0.1) increases from 2018 onwards, as a result of increased mining activity. The declining trend in 0.2–0.3 and 0.3–0.4 NDVI categories confirms that there is a gradual loss of vegetation cover. In contrast to the North Section, the South Section seems to have had a less rapid decline, with vegetation remnants persisting for longer periods of time.

5.4 LST Mine Section

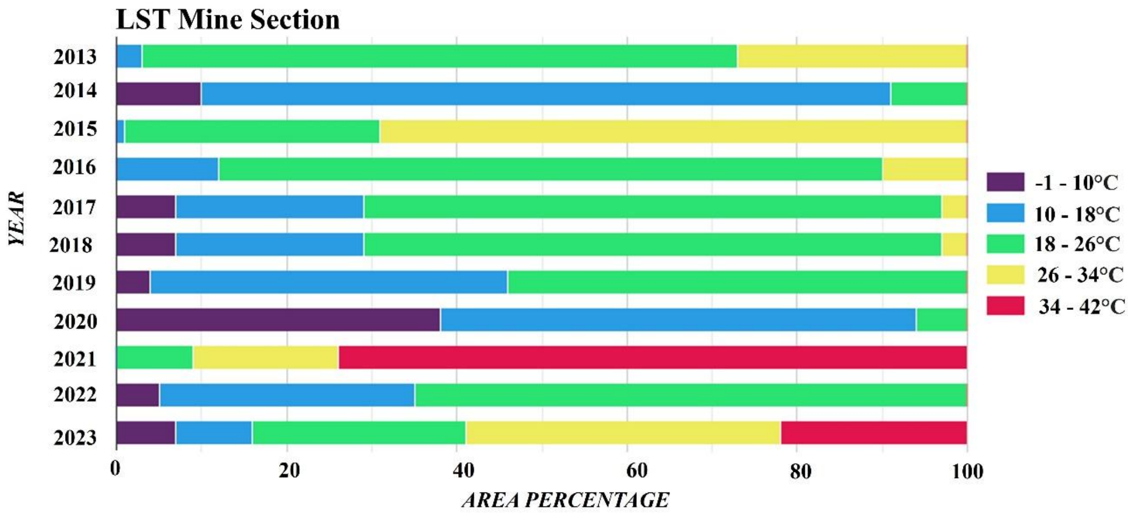

Figure 21. Change in LST area of the Mine Section

Moderate temperatures (10–26°C) were the dominant temperature in the LST trend in the Mine Section from 2013 to 2019, demonstrating a clear warming pattern over time, while colder temperatures (-1 to 10°C) gradually declined. A significant increase in temperature occurred in 2021, with a significant increase in the hottest range (34–42°C), likely due to increased mining activities and vegetation loss (Figure 21). Despite a slight reoccurrence of cooler temperatures in 2023, this warming continued in both 2022 and 2023. The general trend suggests that land degradation and decreased vegetation cover are causing an increase in surface temperatures, which could affect local ecosystems and microclimatic conditions.

5.5 LST North Section

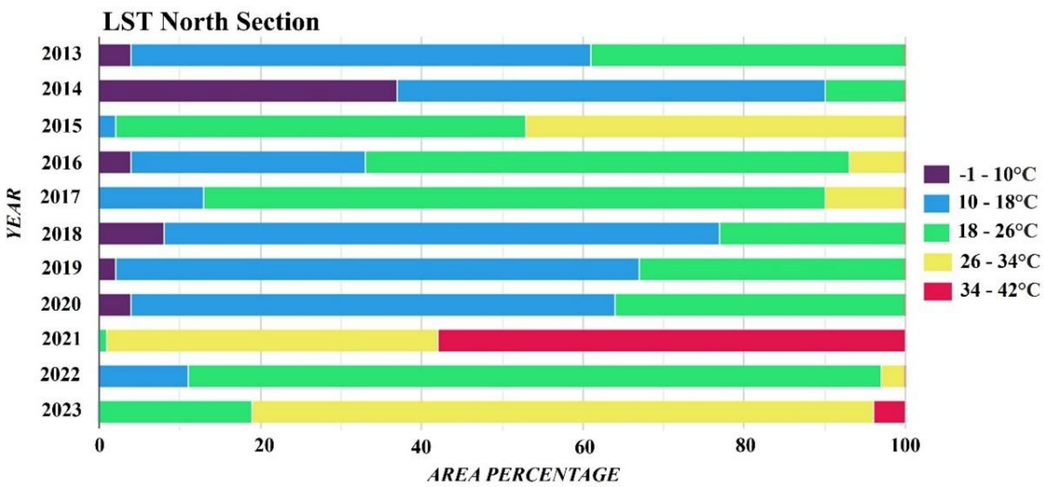

Figure 22. Change in the LST area of the North Section

A significant warming trend has been observed over the years in the LST analysis for the North Section. Temperatures within the 10–26°C range were experienced by a large portion of the area during 2013-2016, with some areas experiencing colder temperatures (0 to 10°C). However, from 2017 onwards, the colder temperature categories gradually decreased, while the warmer temperature ranges (26–34°C and 34–42°C) expanded (Figure 22). In 2021 and 2022, the highest temperature range (34–42°C) shows a significant high LST values, likely due to reduced vegetation cover, increased bare land, or mining activity. This pattern is in line with the decrease in NDVI seen in the North Section, suggesting that the mining area is experiencing high surface temperatures due to land degradation and vegetation loss.

5.6 South Section LST

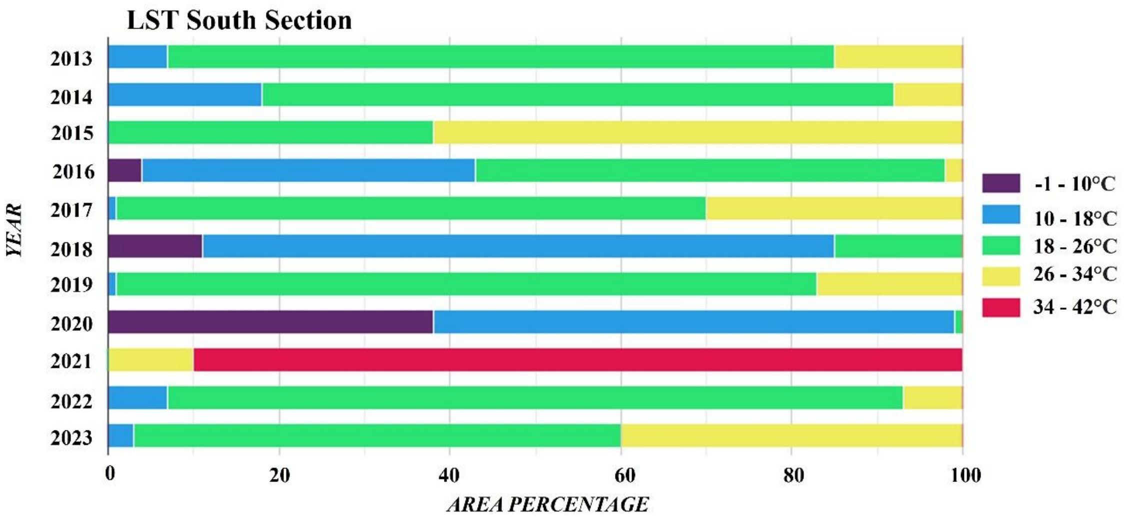

Figure 23. Change in LST area of the South Section

The South Section's LST trend is showing a gradual shift towards higher temperatures over time (Figure 23). Between 2013 and 2019, the average temperature range was between 10–26°C, with occasional colder temperatures (-1 to 10°C) occurring. However, the warming trend has increased significantly since 2020, with a sharp rise in the hottest temperature range (34–42°C) in 2021 replacing much of the previously dominant moderate temperatures. Although there was a slight resurgence of cooler temperatures, this trend was still present in 2022 and 2023. It appears from the overall pattern that the land surface is warming, and this is likely due to land cover changes, reduced vegetation, and increased mining activities.

5.7 Climatic Indicator

5.7.1 Precipitation VS NDVI

The correlation analysis between NDVI and precipitation over the years indicates that higher precipitation is associated with stable or improved vegetation cover, while lower precipitation corresponds to increased barren land. In 2016, there was a correlation between high precipitation and stable NDVI, while in 2017, NDVI experienced a slight decline due to the dry year. Moderate precipitation in 2018 resulted in a small improvement in the NDVI, but significant rainfall in 2019 resulted in a weak response, indicating other influencing factors such as soil degradation. Despite lower precipitation in 2020 and 2021, NDVI remained stable, suggesting that there could be moisture retention or human interventions like irrigation. However, Despite the relatively high rainfall in 2022, barren land increased, likely because of land degradation (Figure 24). The year 2023, with the lowest precipitation, exhibited the most significant NDVI decline, highlighting severe vegetation stress. According to these trends, while precipitation is a crucial factor in NDVI variation, other environmental and anthropogenic factors have a significant impact on vegetation dynamics.

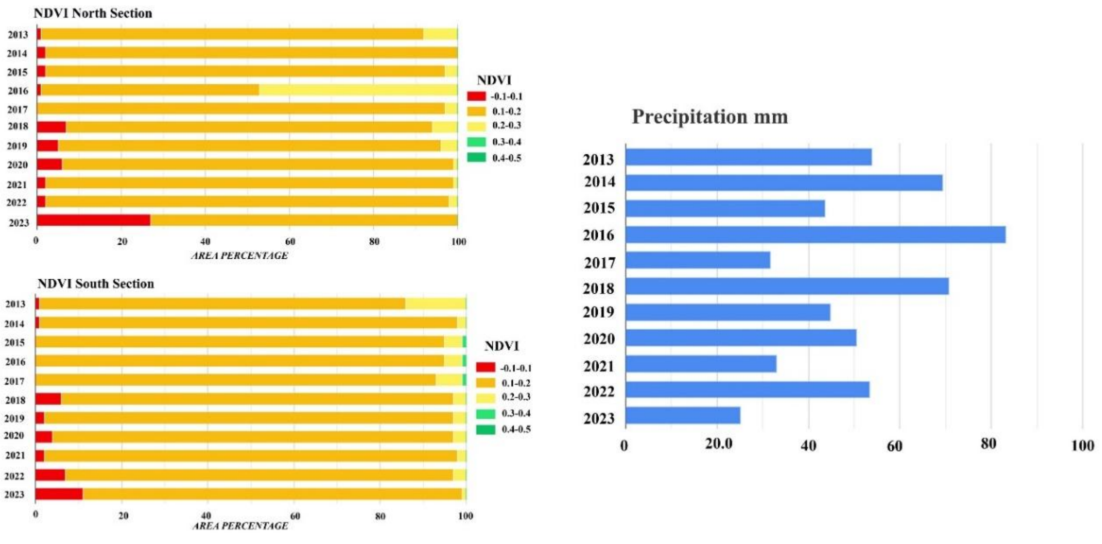

Figure 24. Comparison of NDVI and Precipitation of North and South Section

5.7.2 Precipitation VS LST

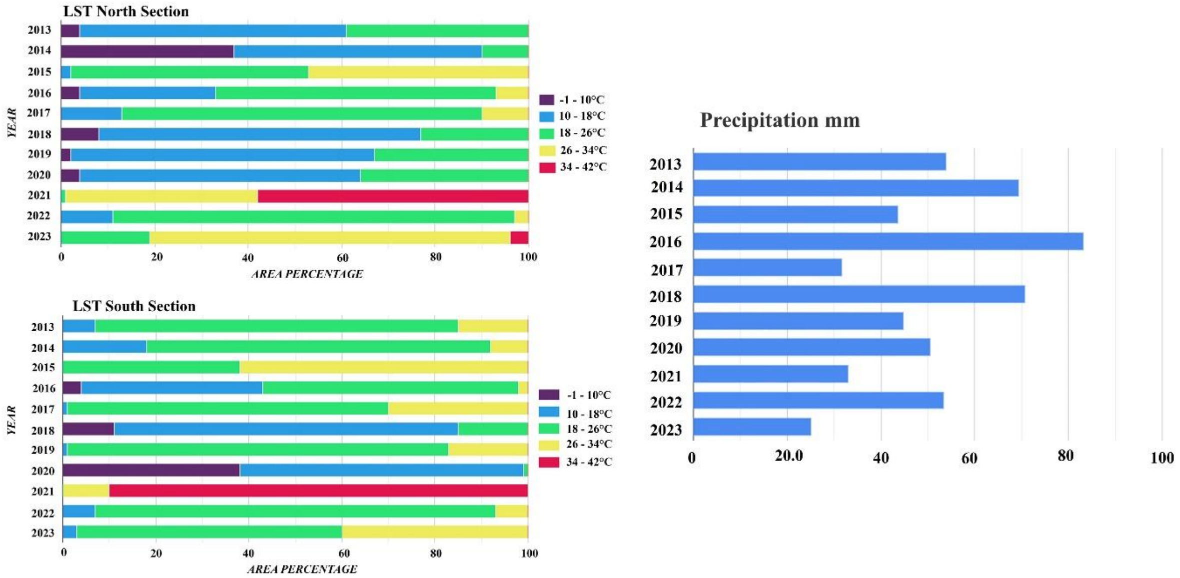

Figure 25. Comparison of LST and Precipitation of North and South Section

In term of LST the years with lower precipitation, such as 2017, 2021, and 2023, correspond to increased proportions of higher temperature zones (26–34°C and 34–42°C), particularly in 2021 and 2023, suggesting that reduced rainfall contributes to higher surface temperatures (Figure 25). Conversely, years with relatively higher precipitation, like 2016 and 2018, show a more balanced distribution of temperature zones, with a larger proportion of moderate temperatures (18–26°C). The trend highlights the significant influence of precipitation on surface temperature distribution, where lower rainfall leads to increased land heating, potentially exacerbating drought conditions and affecting vegetation and land cover stability.

5.7.3 Soil Temperature VS NDVI

The decline in vegetation cover (NDVI) and a rise in surface soil temperature from 2013 to 2023. The proportion of barren land (NDVI < 0.1) has increased, particularly in 2023, while healthier vegetation (NDVI > 0.3) has declined (Figure 26). Simultaneously, surface soil temperature has risen significantly, peaking at nearly 27°C in 2023. According to this trend, there is a strong link between vegetation loss and rising temperatures, which may be caused by climate change, land degradation, or reduced precipitation.

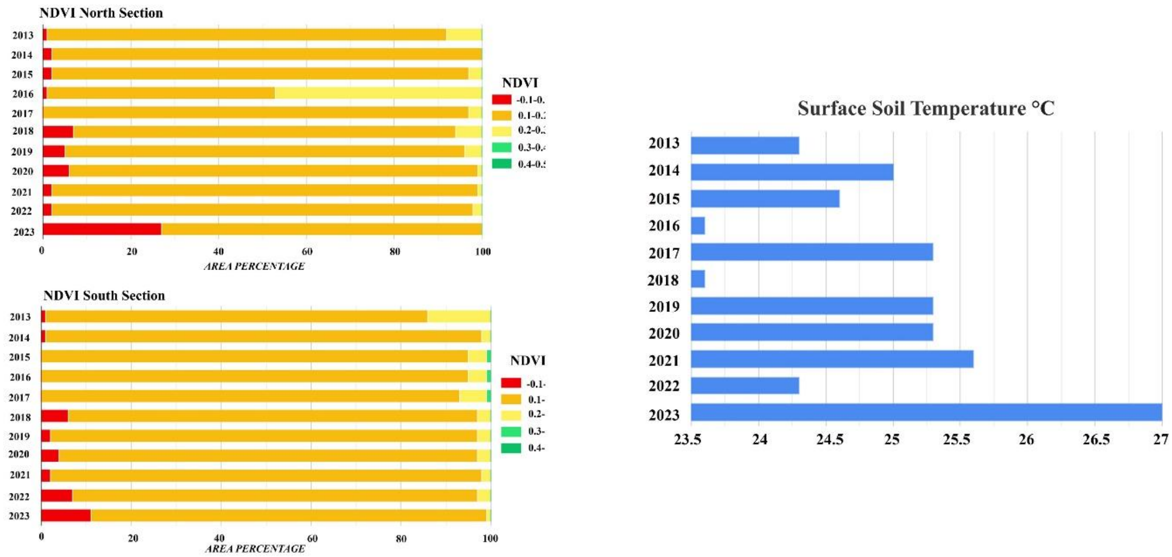

Figure 26. Comparison of NDVI and Soil Temperature of North and South Section

5.7.4 Soil Temperature VS LST

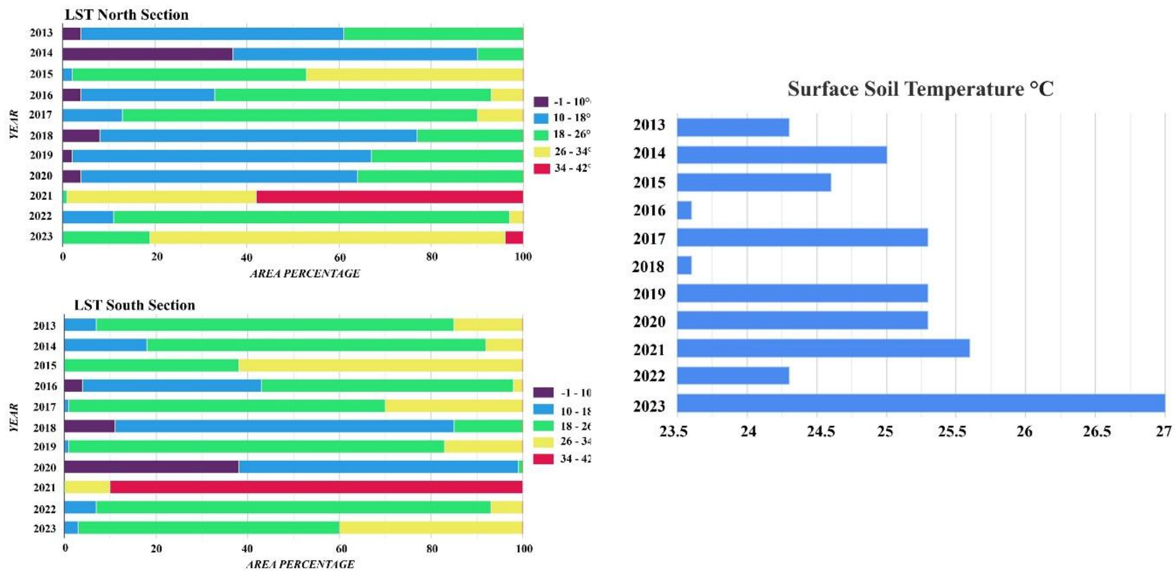

Figure 27. Comparison of LST and Soil Temperature of North and South Section

Land surface temperature (LST) and surface soil temperature data analysis suggest that there is an overall warming trend, with an increasing presence of higher temperature ranges (26–34°C and 34–42°C) in both the northern and southern sections. It can be seen that there has been a shift towards higher surface temperatures because the proportion of lower temperature ranges (-1–10°C and 10–18°C) has decreased over time. (Figure 27**)** shows surface soil temperature gradual increase, especially after 2020, and the highest temperature was recorded in 2023. There is positive correlation between LST and Surface Soil Temperature, indicating that rising LST is a significant contributor to soil warming, and this could have an effect on the vegetation, soil moisture, and overall land surface conditions.

5.7.5 Air Temperature VS NDVI

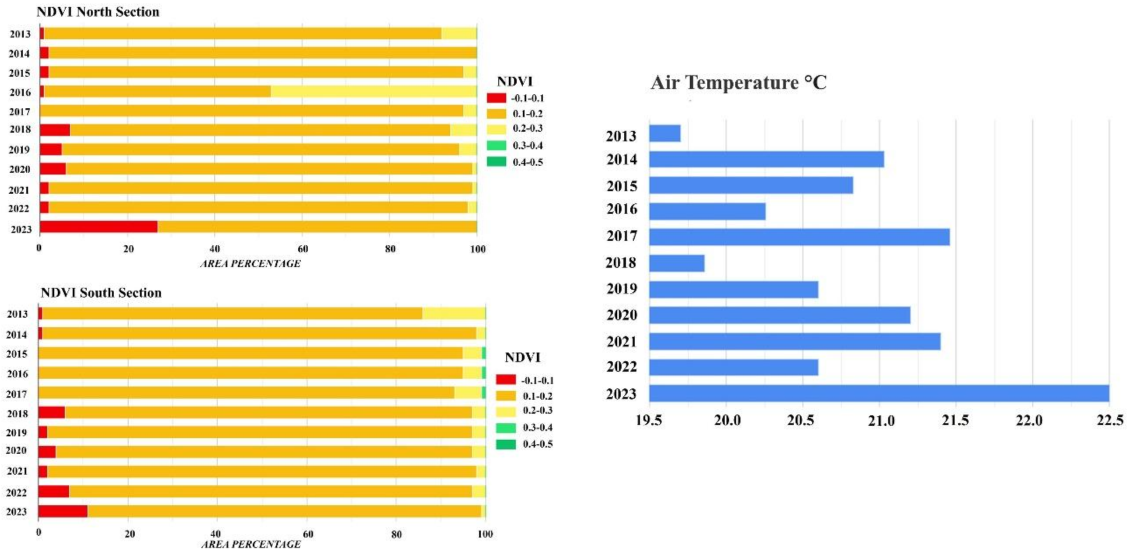

Figure 28. Comparison of the Air Temperature and NDVI of the North and South Section

Comparing Air temperature and NDVI it is obvious from the (Figure 28) that from 2013 to 2023, a negative correlation between air temperature and NDVI is observed, which means that rising temperatures are contributing to the decline of vegetation (Lower NDVI values). NDVI values in the North and South sections remained relatively stable until 2018, but then there was a gradual increase in low NDVI values (-0.1 to 0.1). The rise in air temperature, which reached its highest point in 2023 at over 22.5°C, coincides with this decline, which suggests that vegetation may be declined due to higher temperatures and accelerating land degradation. The relationship between vegetation and lower temperatures was strengthened in years with lower temperatures, such as 2016 and 2018.

5.7.6 Air Temperature VS LST

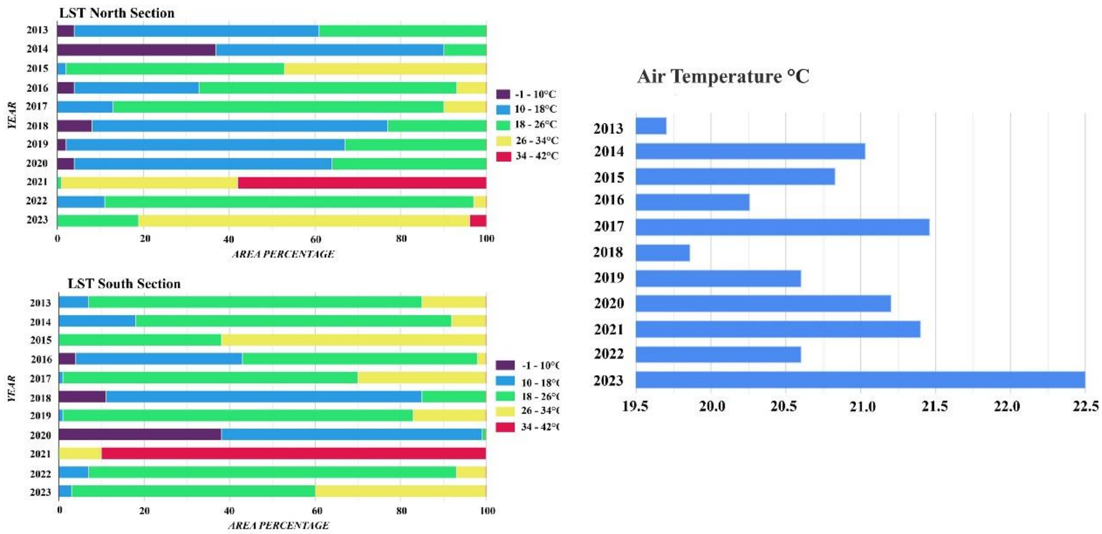

Figure 29. Comparison of Air Temperature and LST of North and South Section

The relationship between air temperature and LST shows that there is a positive correlation between the increase in air temperature and the increase in land surface temperature (LST) from 2013 to 2023, with a noticeable shift towards higher temperature ranges, especially after 2020 (Figure 29). The air temperature reached a peak of 22.5°C in 2023, with a decrease in LST in cooler zones (-1°C to 18°C) in both the North and South sections and an expansion of warmer zones (26°C - 42°C), particularly in 2021 and 2023. Regional factors such as land use changes may be causing the South Section to warm faster. These trends suggest that climate change or land degradation may have potential consequences, which highlights the need for sustainable adaptation strategies.

5.7.7 Relative Humidity VS NDVI

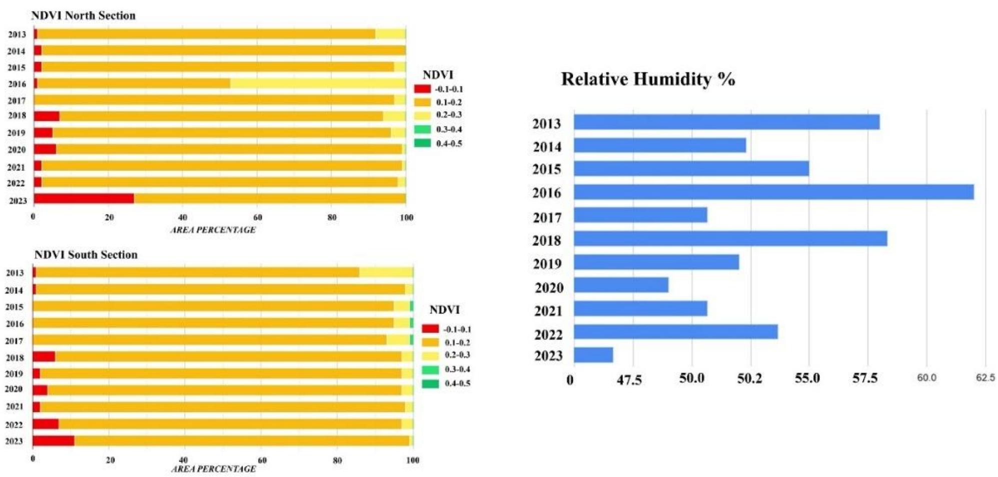

Figure 30. Comparison of the Relative Humidity and NDVI of North and South Section

According to the analysis of NDVI and relative humidity trends as shown in (Figure 30), from 2013 to 2023, vegetation values has declined, and humidity levels have decreased. Lower NDVI values are being observed for both the North and South Sections, with an increasing percentage of the area in the -0.1 to 0.1 range, especially in 2023. Simultaneously, the relative humidity data shows a downward trend, with a sharp decrease after 2018, indicating drier conditions that may contribute to reduced NDVI values

5.7.8 Relative Humidity VS LST

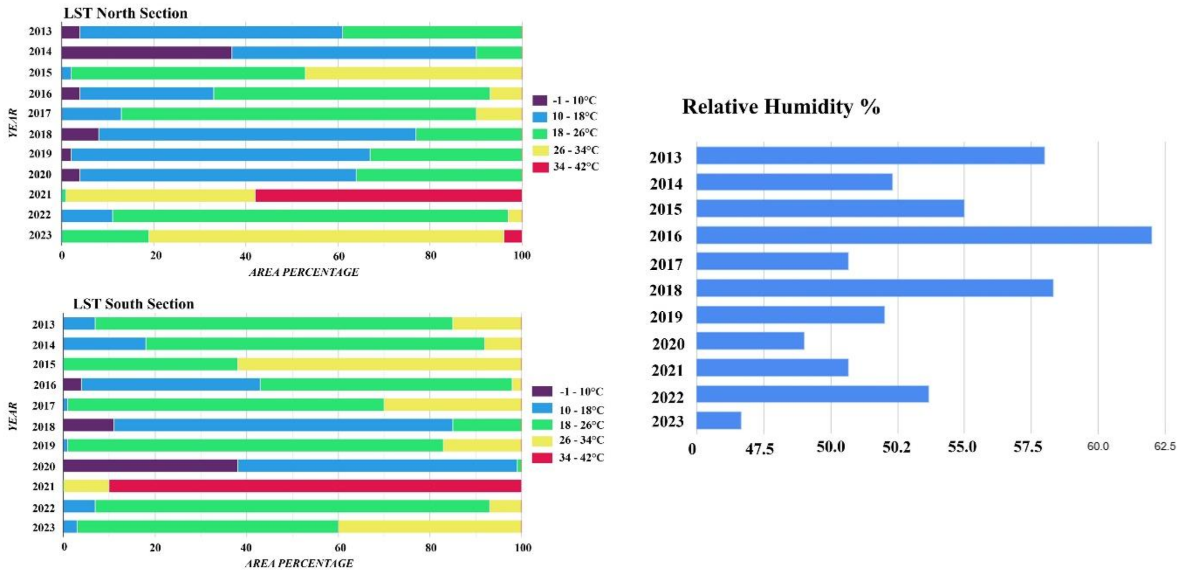

Figure 31. Comparison of relative humidity and LST of North and South Section

As shown in (Figure 31), from 2013 to 2023, the land surface temperature (LST) and relative humidity shows warming trend that is accompanied by a decrease in humidity levels. The LST value in both North and South and North Section increases over time, especially in the last few years (2021–2023). Simultaneously, relative humidity has decreased, with its lowest levels being recorded in 2022 and 2023.

5.8 NDVI VS LST

The mean values of LST and NDVI are inversely related from 2013 to 2023 with LST increasing and NDVI decreasing over the years**.** This happens because areas with high NDVI, which have more vegetation, tend to have lower temperatures, and vice versa. This trend is maintained across all three sections of the study (Figure 32).

The temporal pattern shows that if NDVI is variable such as in years between 2016 to 2018, decline in LST values appear or LST values are stable during those years. Because of mining activities, NDVI, and LST changes are more obvious in the mine section. In 2021 high LST is observed while NDVI has the lowest values in all three section of study area.

NDVI Values are higher in non-mined areas compared to mined sections. These areas have only indirect impact, resulting in moderate LST values. Like the North Section, the South Section varies in NDVI to a lesser extent. The opposite trend shows the juxtaposition, particularly around 2020–2021.

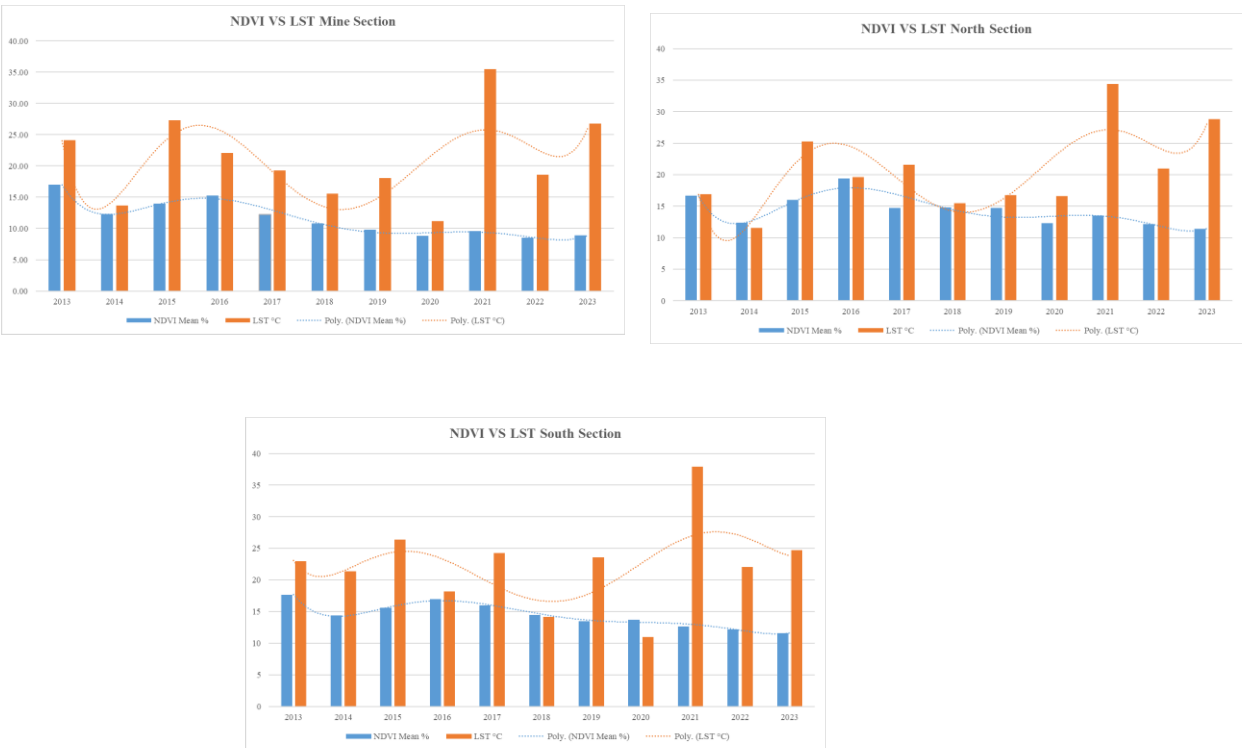

Figure 32. Relationship between NDVI and LST of all three sections of the study area

5.9 Mine Boundaries Changes

5.9.1 Mine Pit Boundaries Changes

Analysing Mine Pit Boundary changes over time, considering the area, it is shown that initial growth phase (2017–2018), a period of minor growth (2018–2021), and a significant increase from 2021 onward (Figure 33). The significant growth after 2021 may have environmental implications, including land degradation, and increased waste as evident in the NDVI and LST analysis

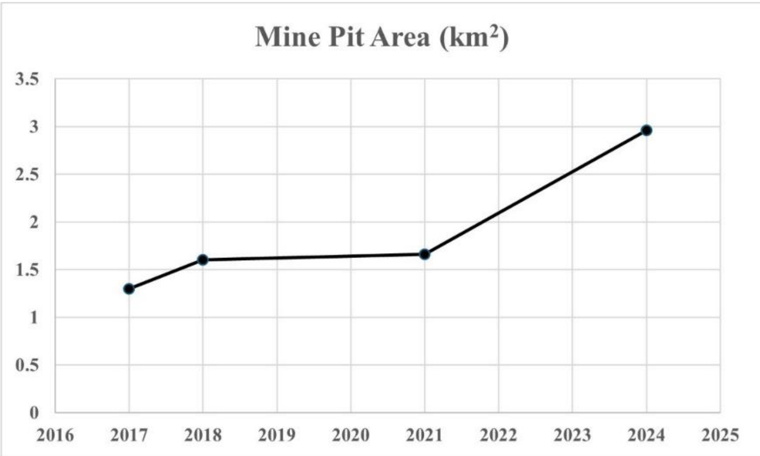

Figure 33. Mine Pit area Change over time

5.9.2 Mine Tailing Boundaries Changes

Expansion of the mine tailings area from 2017 to 2024, showing a progressive upward trend. In the beginning 2017 the tailing occupied an area of 7 km² which increased to 9.5 km² in 2018 (Figure 34). It reaches to12 km² by 2021 and exceeding 14 km² in 2024. The growth in tailings area aligns with mine pit expansion, indicating a proportional increase in waste generation.

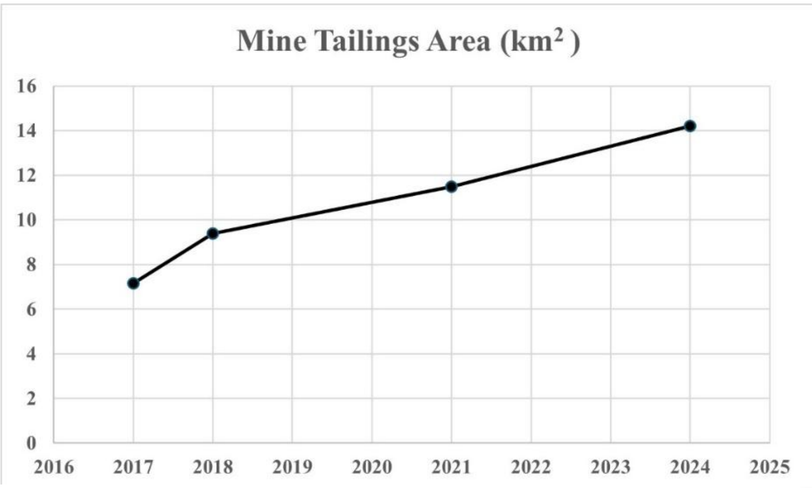

Figure 34. Mine Tailing area change over time

5.9.3 Mine Waste Dump Boundaries Changes

Mine waste dump area from 2017 to 2024, grew from around 1 km² in 2017 to 2 km² in 2018 Figure 18, reflecting an initial phase of increased excavation. The area increases to 3 km² by 2021 and approximately 4.5 km² by 2024 (Figure 35). The progressive expansion is due to ongoing mining activities and higher waste production.

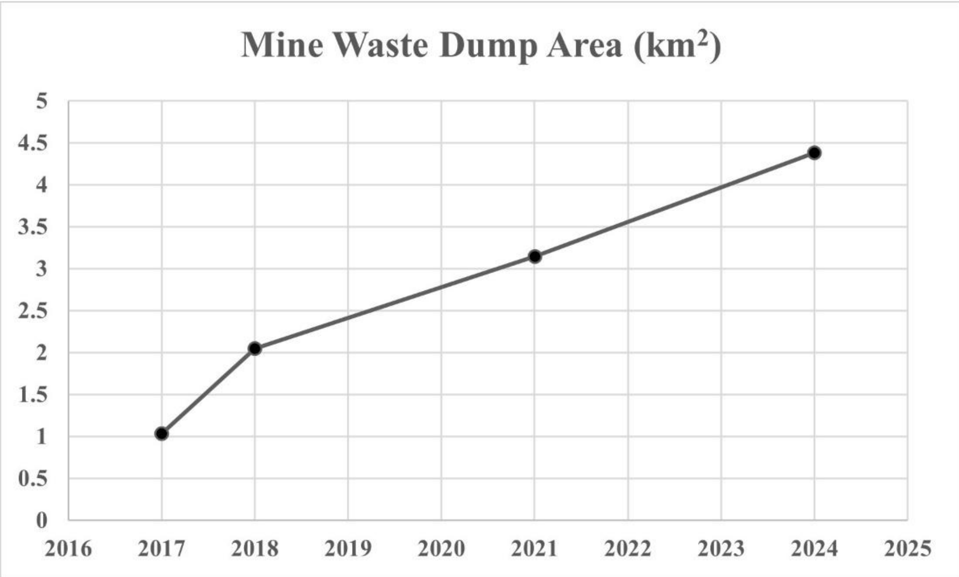

Figure 35. Mine Waste Dump area change over time

6 Discussion

Mining operations have considerable environmental consequences, especially open-pit operations cause large-scale land disturbances altering natural landscapes. Remote sensing techniques are used to investigate this relationship between mining and vegetation cover and land surface temperature (LST). The NDVI trends around the Bozshakol open pit mine Kazakhstan shows the difference before and after mining, which serves as a clear representation of environmental impact of mining activities. Before 2016, higher NDVI types (0.1–0.3) dominated in the area, characterizing stable vegetation and minimal barren land. Yet, from 2016 onwards, a notable drop in NDVI values, especially in the range -0.1 and 0.1, suggests a significant loss of vegetation because of mining operations. The spatio temporal distributions of NDVI showed that degradation was most severe in the North Section, perhaps as a result of increased excavation and their impact on surrounding areas.

The South Section experienced a similar phenomenon, but at a reduced rate of NDVI decline, indicating some residual vegetation remained longer (Figure 36). The difference in NDVI reduction between the two sections may be due to quality of soil and microclimatic conditions. The damage of vegetation due to the e expansion of the mine pit and the activity of constant excavation, lead to significant land cover change in the area. This pattern is similar with the result found in other mining sites, where a large amount of vegetation loss is caused by massive land-use changes (Sun et al., 2022; Nursaputra et al., 2021).

Moreover, the decrease in NDVI values is not only an indicator of vegetation loss but also show relation to broader environmental degradation. The removal of vegetation exposes the soil to erosion, reduces carbon sequestration capacity, and disrupts local ecosystems that depend on plant cover. Studies have shown that the loss of vegetation in mining areas significantly changes land use patterns and leads to further desertification in arid and semi-arid regions (Lei et al., 2016). Without proper reclamation efforts, the long-term consequences of vegetation degradation could extend beyond the immediate mining area, affecting adjacent ecosystems and agriculture land.

In addition to indicating the loss of vegetation, NDVI also serves as an indicator of ecosystem degradation. Vegetation removal leaves soils vulnerable to erosion, and decreases their capacity to sequester carbon, and harms local ecosystems dependent on vegetation cover. Studies indicate that the density and area of vegetation in mining areas have a large impact on land use change, which accelerates the desertification process in arid areas (Lei et al., 2016).

Without adequate reclamation efforts, such the long-term impacts on vegetation degradation might go beyond the mining areas affecting adjacent ecosystems and agricultural lands.

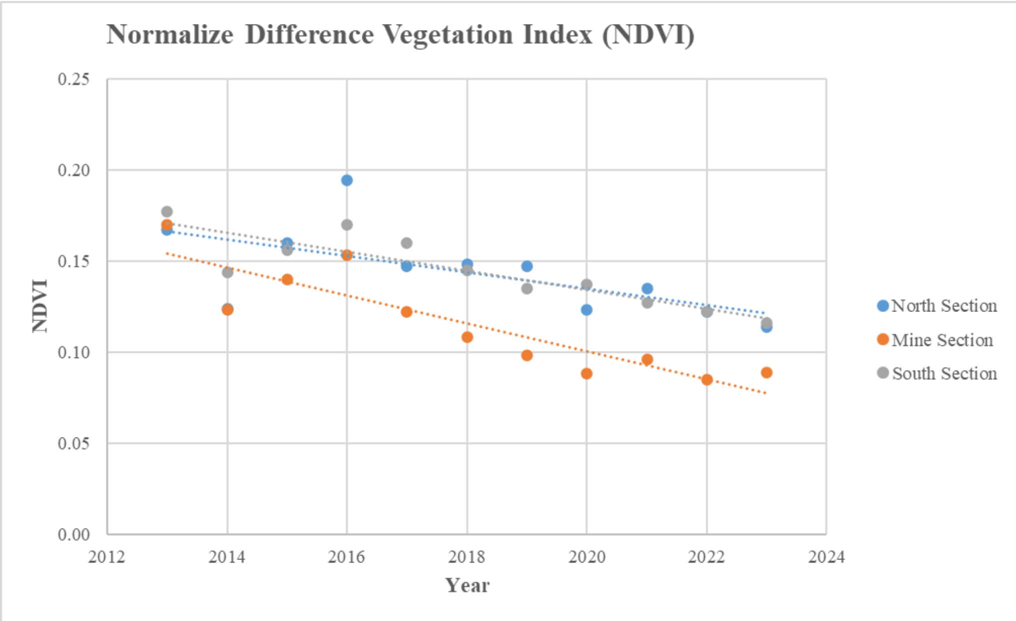

Figure36. Showing NDVI trend change over time for Mine, North and South Section

6.1 Land Surface Temperature (LST) Variability in Response to Mining

In the LST data, there was a considerable warming trend noted in all sections of the study area; this is consistent with vegetation loss and thus greater exposure of bare ground from mining. In the pre-production (2013–2015) period, moderate (10–26°C) surface temperatures were widespread and cold temperatures (-1 to 10°C) occupied a considerable area (Figure 37). Yet, starting from 2017 high LST values (26–42°C) began to significantly increase, with extreme values (34–42°C) enlarged significantly in 2021 and 2023.

Surface temperatures showed a hotter rate of rise in the North Section than in the South Section, indicating that disturbance of land and decreased vegetation cover contributed to an accelerated heating effect. The rise in LST is caused by vegetation lost as vegetation is important for controlling surface temperature. Because of land cover change, it increases the temperature and urban heat island effect in mining regions as vegetation removal increases the amount of solar radiation captured by the land surface. Additionally, the increase in LST has direct implications for soil quality and local climate. Higher surface temperature can evaporate moisture in the soil, leaving behind even drier soil conditions that can impede regrowth vegetation making it more challenging for ecosystems to recover. It has been shown in a number of studies that temperature increases due to mining can lead to changes in local climate, influencing precipitation patterns and further increasing drought in already vulnerable regions (Singh et al., 2018; Bhagat et al., 2024).

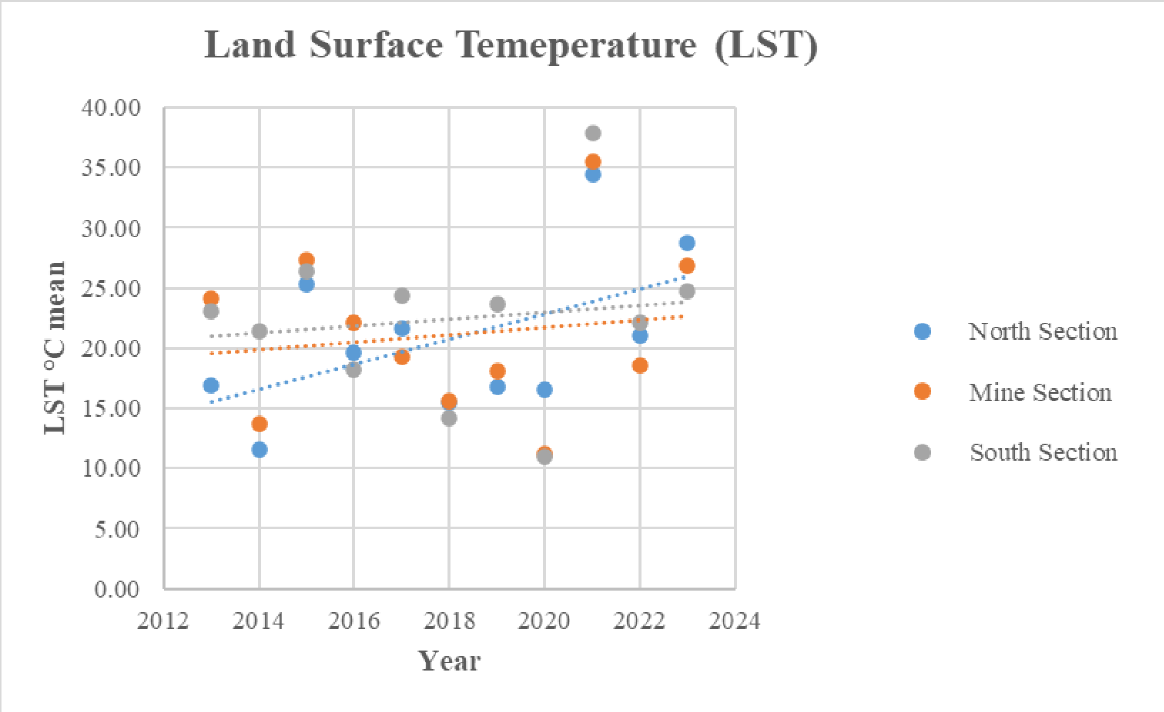

Figure 37. LST trend change over time for Mine, North and South Section

6.2 Climate Interactions: Precipitation, Temperature, and NDVI/LST

Though it seems vegetation is slightly affected when there is increased precipitation, mining activities exert more pressure than environmental factors on vegetation loss. NDVI values appeared to stabilize in years with higher precipitation (Figure 38), such as 2016 and 2018. However, after 2020, even during periods of increased or excess rainfall, NDVI continued to decline, implying the effects of land degradation were disproportionately greater than those observed in the case of precipitation. This is supported by previous research confirming that soil degradation and reduced water retention affected by mining impede vegetation regrowth despite adequate vegetation regrowth despite adequate rainfall (Lei et al., 2016).

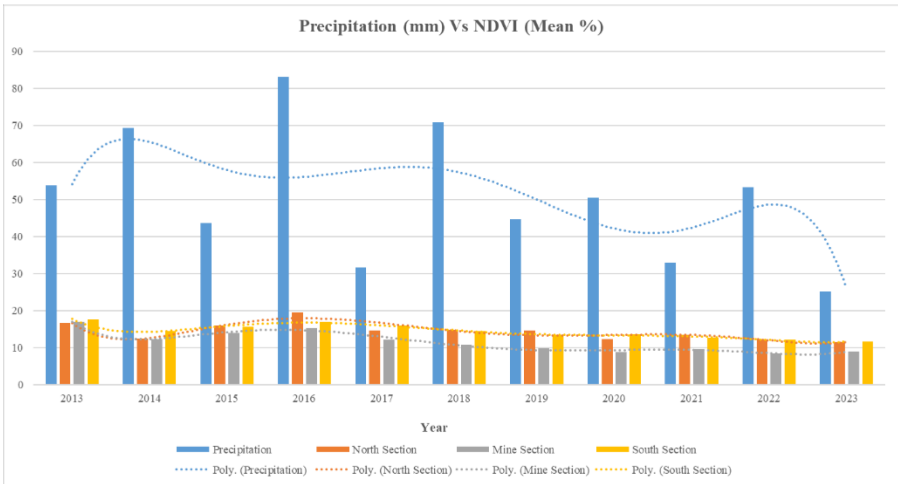

Figure 38. Precipitation and NDVI correlation over time for all three sections of the study area

Similarly, precipitation patterns influenced LST, where drier years such as 2017 and 2021 corresponded with increased high-temperature zones, reinforcing the role of precipitation in moderating surface temperatures. However, the general warming trend suggests that mining activities, through vegetation loss and exposure of bare soil, significantly contribute to rising LST, a trend observed in other mining-affected regions (Ogunro et al., 2023).

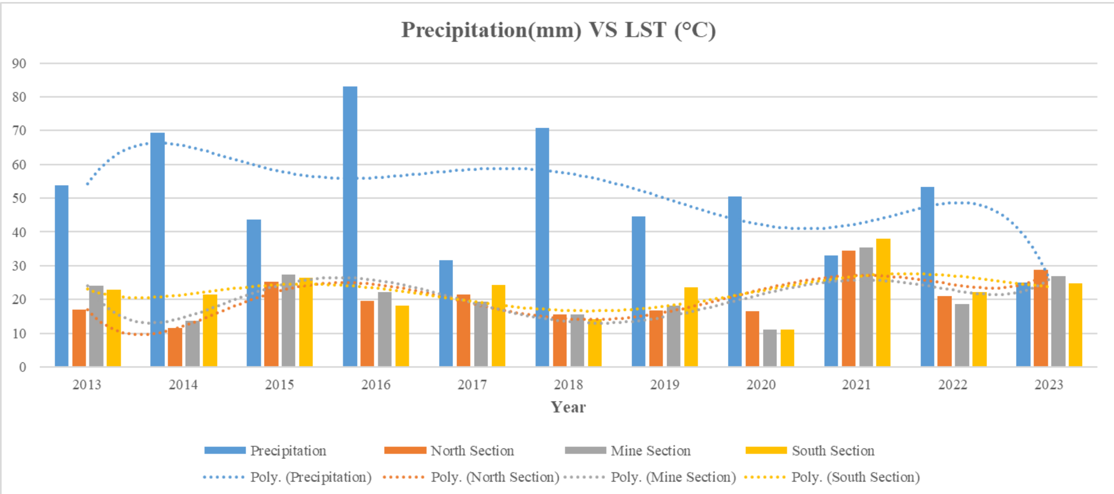

Figure 39. Correlation between LST and Precipitation for all three sections of study area

A more detailed analysis of temperature trends and humidity distribution shows an inverse relationship of air temperature and relative humidity in the studied area. Higher LST is associated with reduced relative humidity, a drying trend that further promotes land degradation (Figure 40); (Figure 41). This trend is consistent with global studies showing how deforestation and land-use change caused by mining have destabilized local microclimates, exposing it to desertification and drought conditions.

Figure 40. Correlation between NDVI and climatic indicators for all three sections of study area

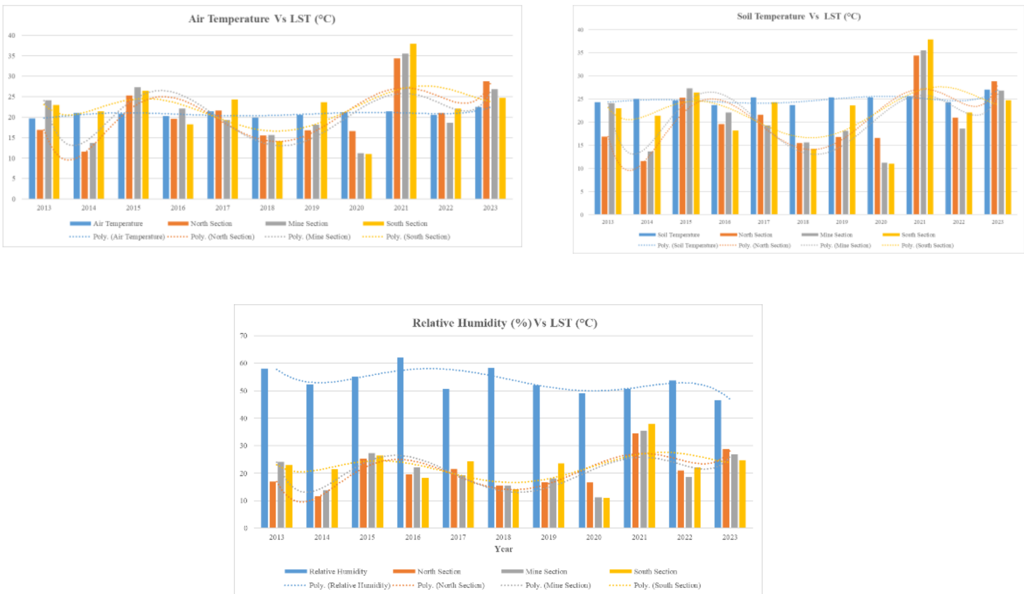

Figure 41. Correlation between LST and climatic indicators for all three sections of the study area

6.3 Mine Expansion and Environmental Implications

The progressive expansion of mine pit boundaries, tailings, and waste dumps over time mainly after 2016, further support the observed landcover changes and their relation to environmental indices. From 2017 to 2024, the tailings area increased from 7 km² to over 14 km², while the waste dump area increased from 1 km² to 4.5 km². The spatial analysis shows that areas with the high mining activities correlate with regions with the greatest decline in NDVI and highest LST values.

The expansion of mine pit boundaries and waste and tailing dump areas over time increases the observed environmental impacts. From 2017 to 2024, the tailings area increased from 7 km² to over 14 km², while the waste dump area grew from 1 km² to 4.5 km². Comparing the spatial distributions of NDVI and LST with the mining activity identified from the spatial analysis shows that areas of the high mining activity coincide with the areas of most decline in NDVI and highest values of LST.

The increase in mine waste and tailings make further environmental challenges, as these materials often contain harmful pollutants that can leach into surrounding ecosystems. The disposal of mine tailings without proper planning and monitoring can result in soil contamination, groundwater pollution, and the release of hazardous dust particles into the atmosphere. These environmental hazards emphasize the need for stricter regulations and better management practices in mining operations to minimize ecological damage (Dogan & Kahriman, 2008; Karan et al., 2016). More mine waste and tailings also mean more environmental consequences; these waste materials can include toxic pollutants that leach into the surrounding ecosystem. If mine tailings are not held within designated area, soil, groundwater may become polluted, and harmful dust particles may enter the atmosphere. Concerns over the significant impacts of these environmental hazards have emerged, and this necessitates stricter regulations and better management practices to mitigate the ecological damage associated with mining activities (Dogan & Kahriman, 2008; Karan et al., 2016).

6.4 Implications for Sustainable Mining and Climate Adaptation

The findings from this study emphasize the need for sustainable mining practices and monitoring framework that minimize environmental degradation. The observed correlation between NDVI decline and increasing LST highlights the long-term impact of land disturbances. This create a need for rehabilitation efforts to restore vegetation cover and increasing temperature. Moreover, integrating climate adaptation strategies, such as monitoring humidity and soil temperature fluctuations, can aid in designing effective land restoration programs.

It is obvious that if there are more mine waste and tailings, there will be more negative environmental consequences, as these waste materials can include toxic pollutants that leach into the surrounding ecosystem. If mine tailings are not held within designated area, soil, groundwater may become polluted, and harmful dust particles may enter the atmosphere. Concerns over the significant impacts of these environmental hazards have emerged, and this necessitates stricter regulations and better management practices to mitigate the ecological damage associated with mining activities (Dogan & Kahriman, 2008; Karan et al., 2016).

7 Conclusion

This study examined the environmental Impacts of the Bozshakol open pit mine in Northeastern Kazakhstan, considering monitoring spatiotemporal land cover changes and land surface temperature using remote sensing data. Data of Landsat 8/9 was used for NDVI and LST analysis of vegetation loss and temperature changes over the areas. The addition of climate data that include precipitation, air temperature, and relative humidity allowed to distinguish negative impacts caused by anthropogenic mining activities from natural climate variations. The study shows that mining activities have caused a major reduction in vegetation cover. The NDVI values prior to 2016 showed stable vegetation (moderate values, 0.1-0.3), whereas NDVI post-2016 that is time when active mining start at study area, showed a continuous decline, especially in the North and South section of the study area. The mine Section had the most vegetation loss, because of heavy excavation, while the South and North Section showed a slower rate of decline. The loss of vegetation is a strong indicator of environmental degradation, as it exposes soil to erosion, reduces carbon sequestration, and disrupts local ecosystems. However, field measurements (e.g., soil samples, local temperature logs) are needed to verify remote sensing results.

Land Surface Temperature (LST) Analyses showed that the constant upward trend of LST in the mining area, which is consistent with the growing vegetation loss. Pre-production (2013–2015) temperatures were moderate (10–26°C), while temperatures from 2017 onward strongly reflected the increasing higher temperature zones (26–42°C). In other words, the North Section was warming faster than the South Section, which indicates more intense land disturbances corresponded to higher warming in these areas. The rise in surface temperature is directly related to vegetation removal, which diminishes the land's capacity to moderate heat. Such a trend has serious implications for local climate conditions, soil moisture retention, and ecosystem resilience.

The interaction between climate variables and environmental changes further reinforces the role of mining activities in land degradation. In higher annual precipitation years (2016 and 2018), most of the land showed transient vegetation recovery; however, NDVI continued to increase from 2016 to 2018 and finally began to decline again post-2020 (even with an adequate amount of rainfall), demonstrating that the land degradation impacts from mining exceeded the benefits accrued from precipitation. Lower precipitation years also associated with higher LST, highlighting that less rainfall increases surface heating. Relative humidity trends also exhibited a decreasing pattern, lending further support to the drying process linked to reduced vegetation and land exposure.

Moreover, the spatial expansion of the mine pit, waste dumps, and tailings further confirms the environmental impact. The mine pit boundaries grew substantially after 2021, consistent with a corresponding drop in NDVI and increase in LST. The mine tailings increased from 7 km^2 (2017) to over 14 km^2 (2024) and waste dumps from 1 km^2 from 2017 to 4.5 km^2 in 2024. This increase shows not only more excavation but also more waste and the potential risk for contamination of soil and water may result if not handled correctly.

The study highlights the need for sustainable mining practices and monitoring framework to mitigate environmental degradation. The observed correlations between vegetation loss (NDVI), rising temperatures (LST), and mining expansion of the Bozshakol mine and surrounding area, underscore the importance of implementing land rehabilitation programs to restore vegetation cover. Additionally, there is a need for climate adaptation strategies, such as soil conservation, that could be integrated into mining operations to minimize long-term ecological damage. Stricter regulations on waste disposal and land reclamation are essential to prevent further degradation and ensure the sustainability of mining activities in the region.

In conclusion, the changes in ground cover significantly altered surface temperature and are expected to have long-term environmental consequences if not monitored and managed properly. A focus on sustainable mining practices, environmental monitoring, and proactive reclamation efforts will be necessary to address these issues and help balance benefits with costs in the future.

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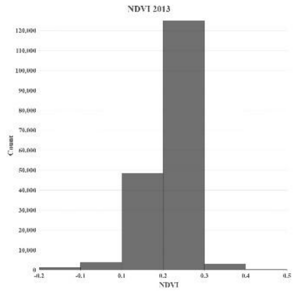
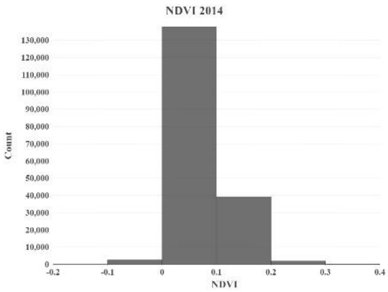
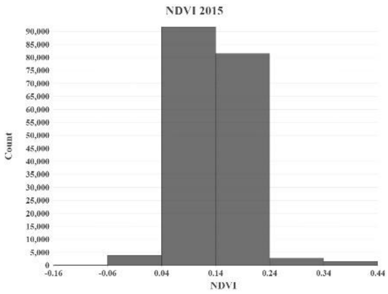
Appendix

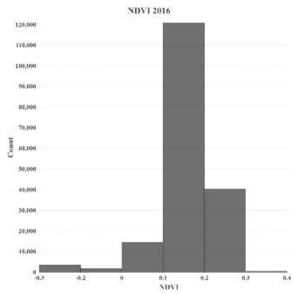
Appendix A

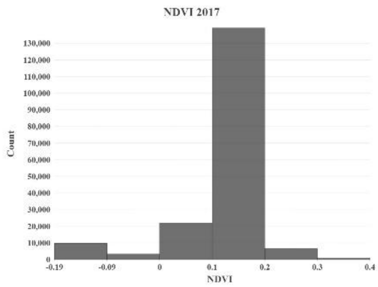
NDVI Mine Section pixel count graphs

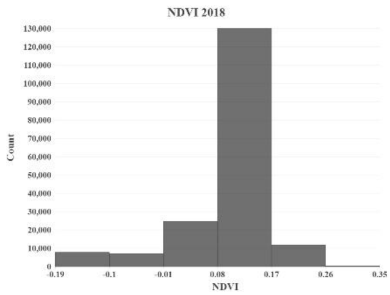


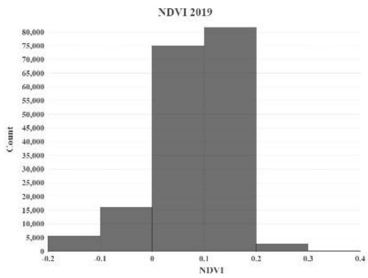


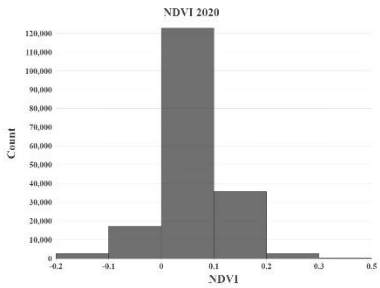


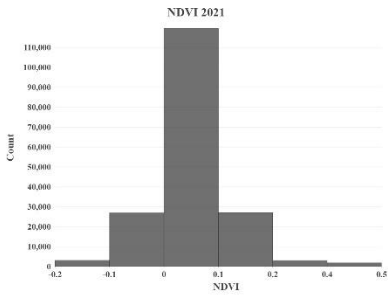


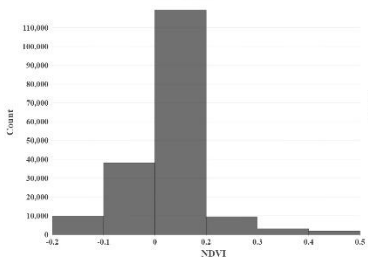


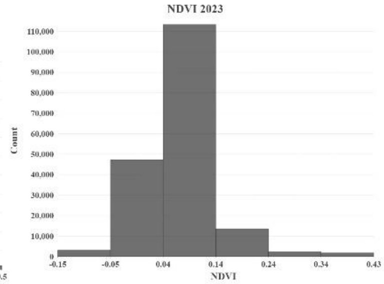




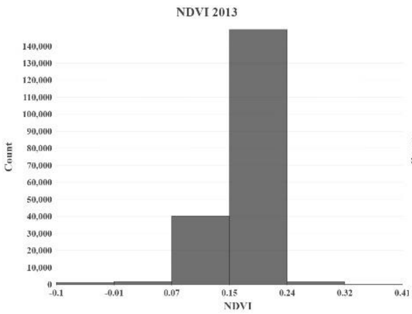


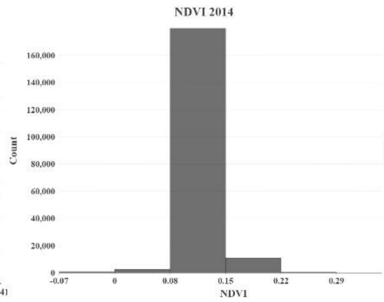


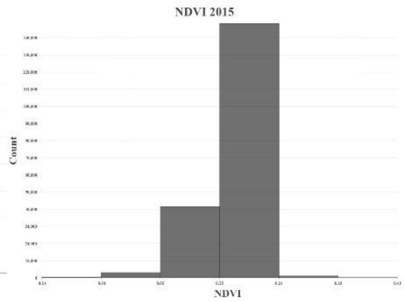


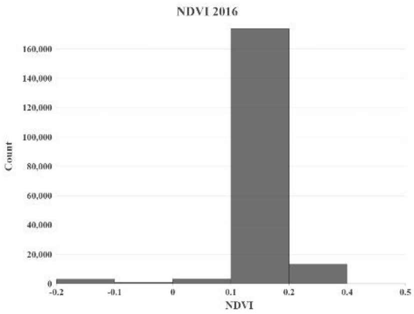


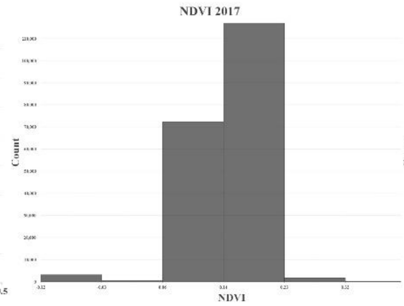
NDVI North Section pixel count graphs

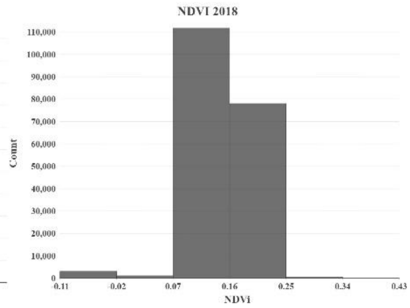


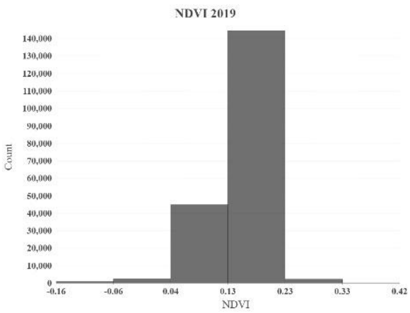


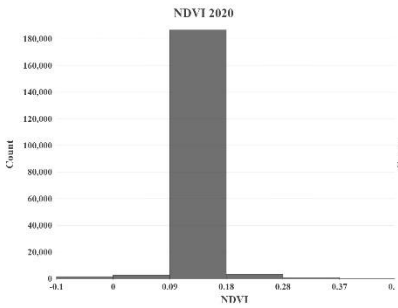


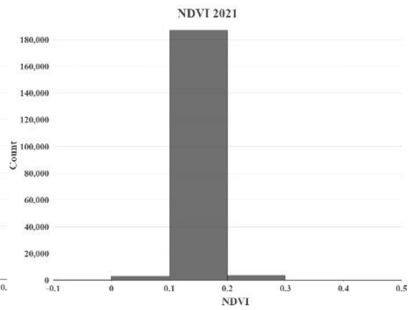


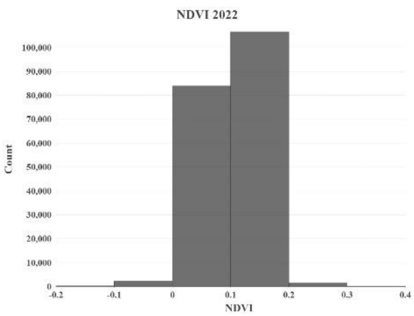


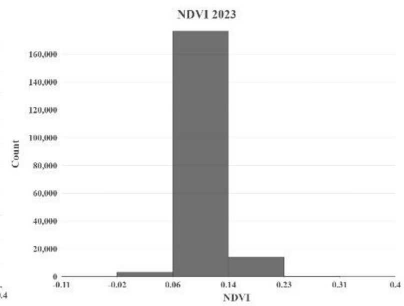




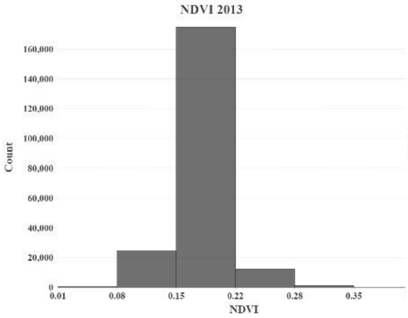


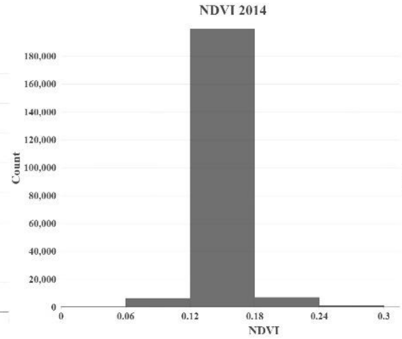


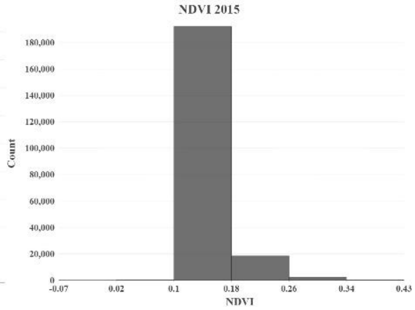


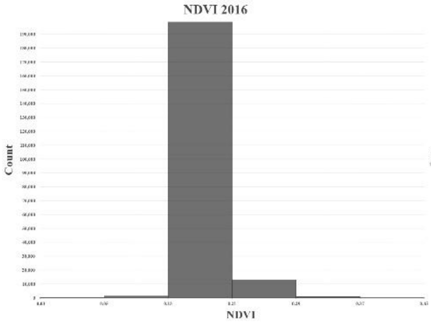


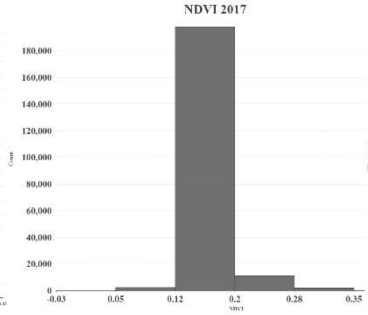
NDVI South Section pixel count graphs

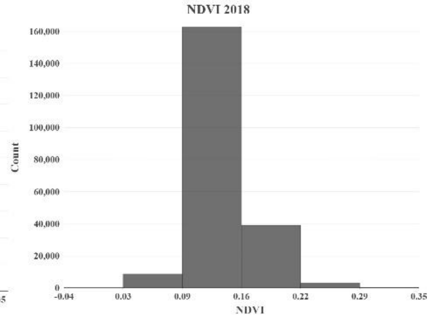


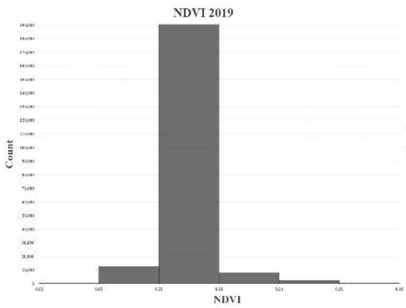


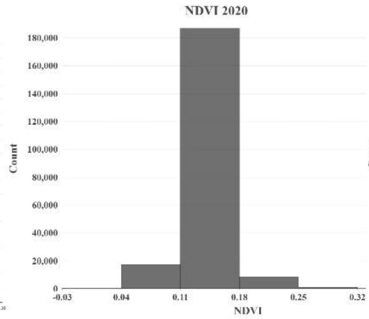


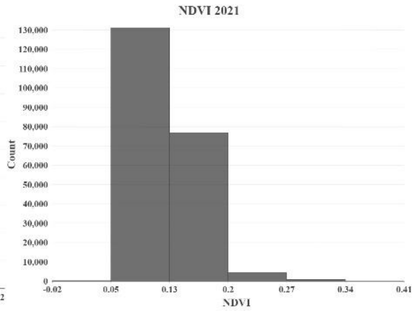


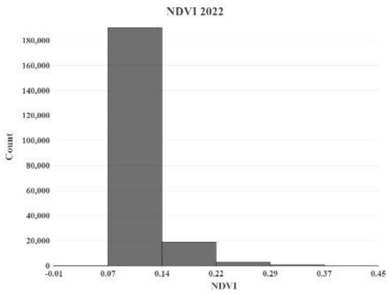


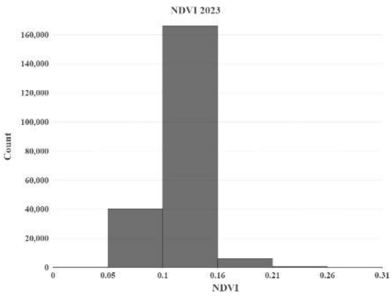






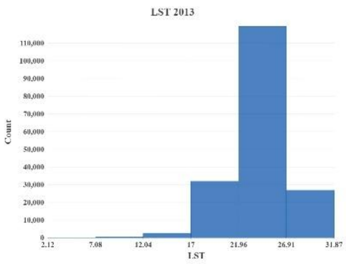


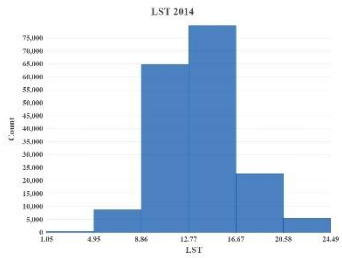


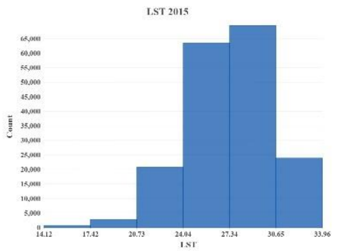


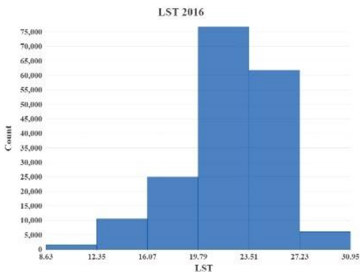
Appendix B

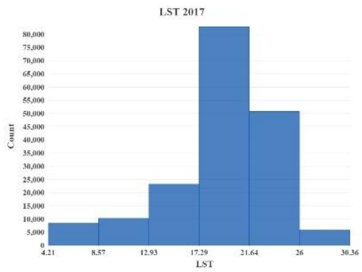
LST Mine Section Pixel count graphs

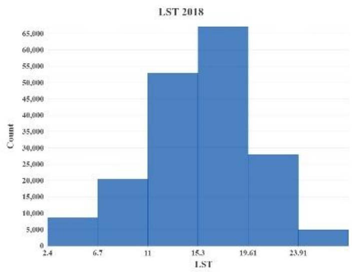


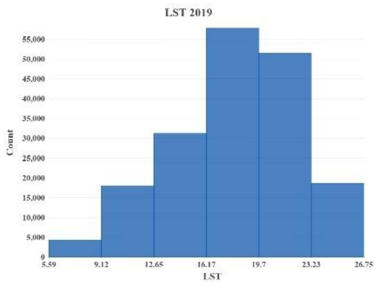


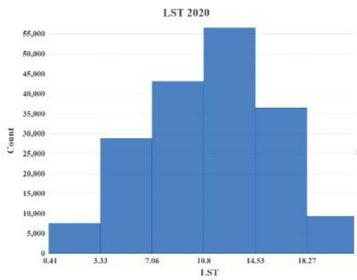


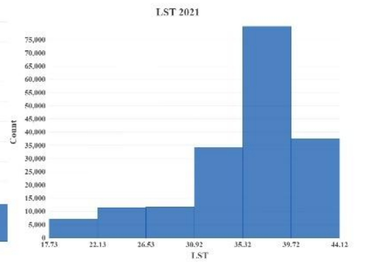


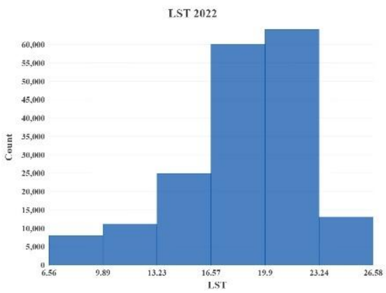


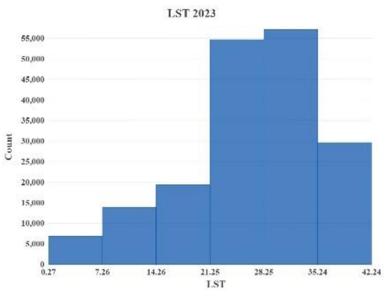












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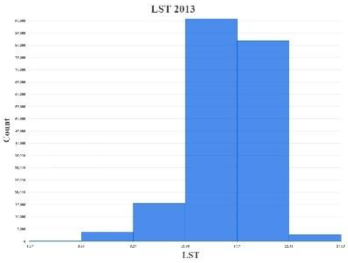
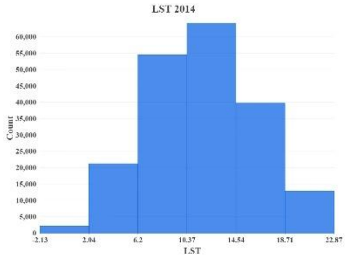
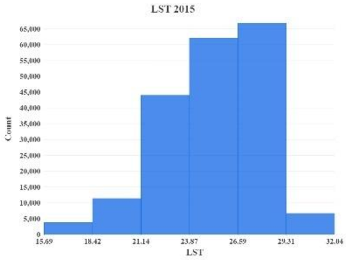
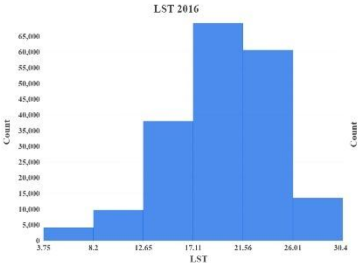
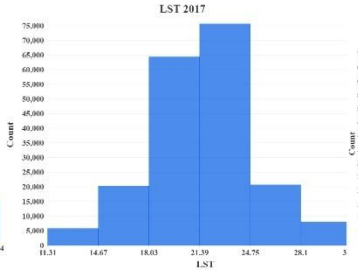
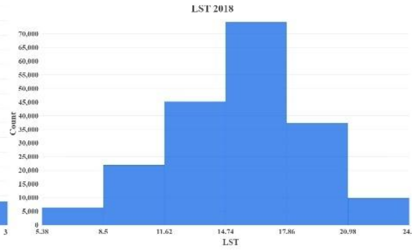


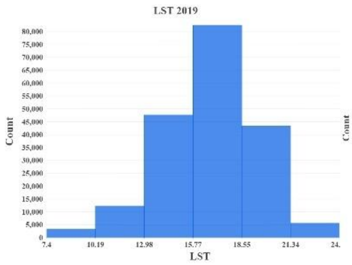


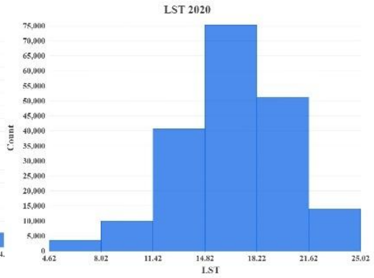


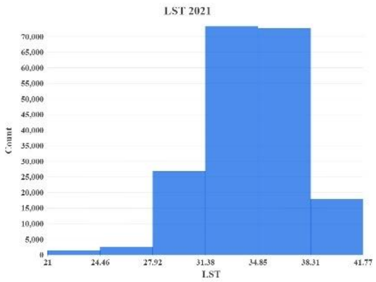


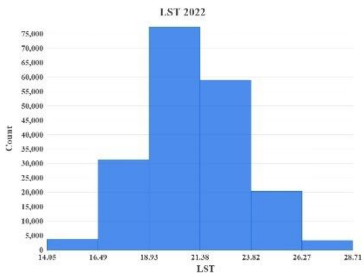


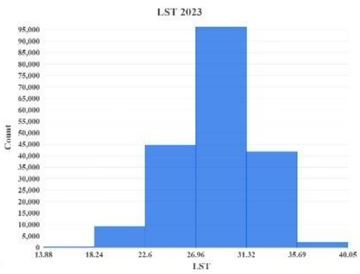




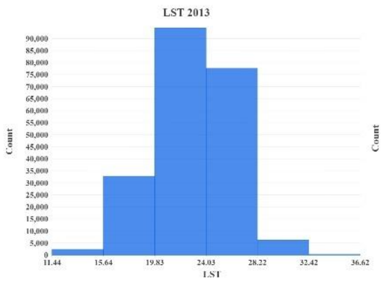


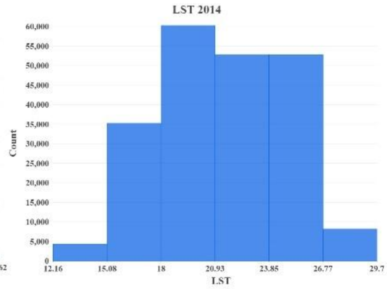


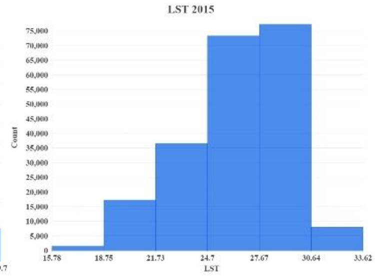


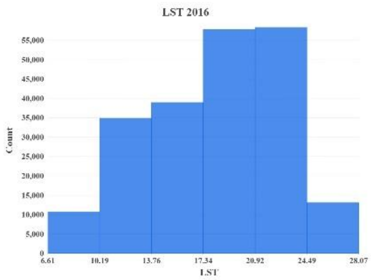


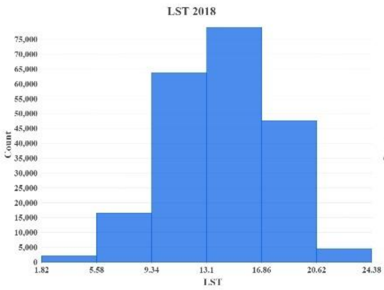
LST South Section pixel count graphs

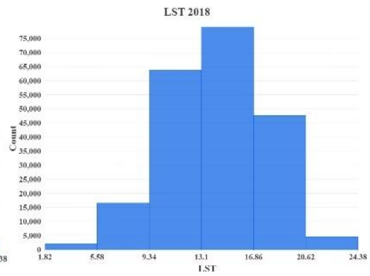


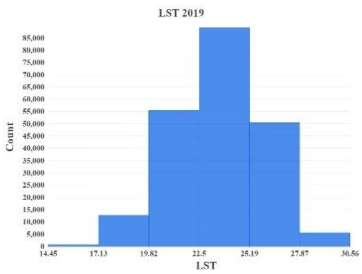


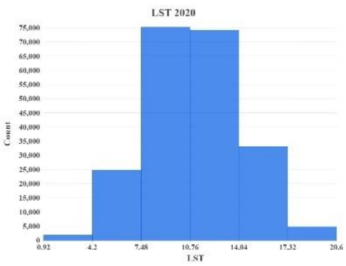


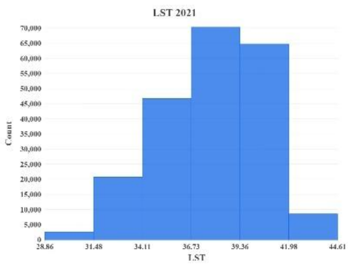


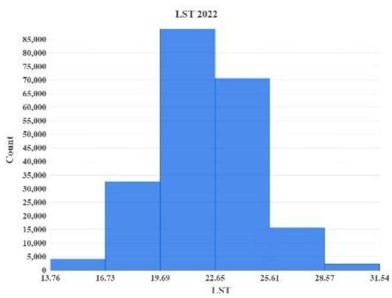


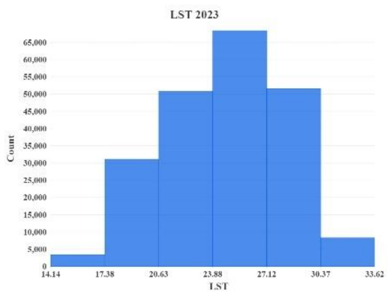












Appendix C

Climate Data from Nearest Station to the mine

Air Temperature	Month	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
	6	19.2	22	21.8	20	22.1	19.7	17.7	20.4	18.8	21.7	21.6
	7	20.5	20.1	21.7	20.8	21.4	21.2	22.8	22.4	22.6	22.5	25.2
	8	19.4	21	19	20	20.9	18.7	21.3	20.8	22.8	17.6	20.7
		19.7	**21.03333333**	**20.83333333**	**20.26666667**	**21.46666667**	**19.86666667**	**20.6**	**21.2**	**21.4**	**20.6**	**22.5**
Precipitation	**Month**											
	6	6.3	14	46	87.9	37.3	99.5	37.2	30	27.2	23.3	15.8
	7	80.1	106.2	61.4	144.6	50.8	65.2	66.1	96.5	14.8	77.5	13
	8	75	88	23.5	16.8	6.8	47.6	30.8	25	56.9	59.3	46.6
		53.8	**69.4**	**43.63333333**	**83.1**	**31.63333333**	**70.76666667**	**44.7**	**50.5**	**32.96666667**	**53.36666667**	**25.13333333**
Soil Temperature	**Month**											
	6	25	27	26	24	26	23	23	26	24	26	27
	7	26	24	25	23	25	26	28	26	28	26	30
	8	22	24	23	24	25	22	25	24	25	21	24
		24.33333333	**25**	**24.66666667**	**23.66666667**	**25.33333333**	**23.66666667**	**25.33333333**	**25.33333333**	**25.66666667**	**24.33333333**	**27**
Relative Humidity	**Month**											
	6	44	44	56	56	47	54	58	40	47	43	41
	7	65	59	55	73	57	58	51	55	47	53	43
	8	65	54	54	57	48	63	47	52	58	65	56
		58	**52.33333333**	**55**	**62**	**50.66666667**	**58.33333333**	**52**	**49**	**50.66666667**	**53.66666667**	**46.66666667**