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Geospatial Assessment of Land Use/Land Cover Changes from Feldspar Exploitation in Zango-Daji, Nigeria

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ABSTRACT
This study investigates the extent to which feldspar mining has altered land use/land cover (LULC) changes in Zango Daji, a topic underexplored in existing literature. These changes are linked to reduced agricultural productivity and increased conflicts over land rights. The Landsat imageries were used to assess the LULC changes as a result of artisanal mining of feldspar in the study area from 2002 to 2022. Online imageries obtained from archive of Global Land Cover Facility (GLCF) under the United States Geological Survey (USGS) were analyzed using Enhanced Thematic Mapper Plus (ETM+) of 2002, 2007 and 2012, and the Operational Land Imager (OLI) of 2017 and 2022. ArcMap 10.8 was used for the pre-processing and clipping of the area of interest, using both the administrative and local government maps. It was later used for visualization, calculation, processing and analysis of all the digital imageries. Four geospatial index maps of normalized difference vegetation index (NDVI), modified normalized difference water index (MNDWI), normalized difference built-up index (NDBI), and dry bare soil index (DBSI) were generated between 2002 and 2022 at an interval of five years. The accuracy was enhanced using Google Earth imagery for validation. The results revealed that vegetation improved marginally after mining began, compared to the pre-mining era. Meanwhile, a year (2012) after artisanal mining began in 2011, water witnessed its peak stress. Dry bare soil and built-up have increased considerably since feldspar mining began in the area. The findings inform sustainable land management and conflict mitigation strategies in mining regions.

Keywords:
Artisanal mining,
Feldspar mining,
Geospatial index,
Land use/land cover,
Zango-Daji.

INTRODUCTION

The practice of man to extract mineral wealth from the earth in order to meet its sustenance of life, technological development, and modernization has led to continuous degradation of the mining environment (Ogbamikhumi & Eguagie, 2023; Molua, 2024). This practice usually involves excavation of land on which host populations depend for their livelihood (Alaba et al., 2023). Land serves as a critical interface where both human and environmental systems engage with one another, leading to land use/cover (LULC) changes, which encompass various efforts that modify the land to meet human and developmental requirements (Khawaldah et al., 2020). Land cover change (LCC) refers to alterations in the persistent properties of land, encompassing various vegetation categories and soil characteristics, among others (Patel et al., 2019). In contrast, land use change (LUC) represents a complex process through which human actions modify the natural environment (Ado et al., 2022). LULC is a frequent, worldwide occurrence that involves both natural and human-induced systems that affect soil, water, and air. Studies show that mining-induced LULC changes might result in soil erosion, habitat loss, and modified hydrological patterns (Afolabi et al., 2021; Pande et al., 2021; Ogunro & Owolabi, 2022). There are currently conflicting interests between the host communities and the mine operators across the globe as a result of the LULC changes that were caused by the mining operations. Suh et al. (2017) attribute this to a number of problems stemming from lack of sustainability management due to either failure to plan or inappropriate execution of the mineral exploitation designs. Scholars from other nations and regions have investigated the dynamics of LULC using different techniques. In Ghana, Kumi et al. (2024) employed remote sensing along with bird population sampling techniques to analyze the impact of LULC changes due to mining on bird communities within the mining area. Blanche et al. (2024) investigated the deterioration of land cover resulting from mining operations in Cameroon's Adamawa area by using remote sensing and digital photogrammetry. Lameck et al. (2025) combined remote sensing with social survey methodologies to explore LULC transformations caused by gold mining in the Singida area of central Tanzania. Nigeria, including the study area, has benefited greatly from the mining of feldspar mineral resources in terms of socioeconomic growth and foreign exchange earnings (Ogbamikhumi & Eguagie, 2023; Isah & Aliyu, 2024; Omoijuanfo et al., 2024a). However, the exploitation of this mineral comes with the risks of LULC changes, as many land areas that previously supported farming, woodland pasture use, gardens, natural medicinal plants, and various other functions have been depleted (Ogunro & Owolabi, 2022; Yakubu et al., 2024). The circumstances are quite dire because mining is prevalent without any consideration for mining legislation and regulations (Omoijuanfo et al., 2024b). Several articles have been published regarding the impact of mining on LULC changes in various states of Nigeria using remote sensing and GIS (Owolabi, 2020; Ado et al., 2022; Alaba et al., 2023). However, the consequences of feldspar mining on LULC changes have been predominantly overlooked in Zango-Danji.Since previous studies have failed to investigate the LULC changes in Dango Daji, this study aims to investigates the extent and nature of LULC changes associated with feldspar mining from 2002–2022 using geospatial indices such as NDVI (Normalized Difference Vegetation Index), MNDWI (Modified Normalized Difference Water Index), NDBI (Normalized Difference Built-up Index), and DBSI (Difference Built-up and Soil Index). The application of NDVI, MNDWI, NDBI, and DBSI is important for the examination of LULC changes in mining contexts. This is because NDVI will be used to obtain data on the vegetative quality and volume that revealing ecological changes in the area as a result of mining activities. The MNDWI will be used to evaluate water bodies and their modifications, especially in areas impacted by mining activities. The NDBI will be used to determine the urban growth and infrastructure expansion associated with feldspar mining, while DBSI will be used to distinguish between developed areas and soil in order to provide status of changes in land use. The adoption of these indices would provide a comprehensive structure for monitoring and assessing the ecological effects of mining, leading to improved management as well as mitigation techniques.

MATERIALS AND METHODS

Description of the Study Area

The study area is a significant site for feldspar deposits, situated in Zango-Dagi village within the Adavi Local Government Area. It is located in the central senatorial district of Kogi State, Nigeria, and is bordered by latitudes 6° 36' 2.99"N to 6° 36' 3.11"N and longitudes 7° 44' 3.15" to 7° 45' 4.31" as shown in Figure 1. It shares its southern border with Edo State and its northern edge with the state capital, Lokoja. Zango village is around a twenty-minute drive from Lokoja and covers an estimated land area of 718 km² with a population of 202,194 (Isah & Aliyu, 2024). The majority of the population of Adavi Local Government, which has its headquarters in Ogaminana, is Ebiran, and their primary religion is Islam. However, as natives and settlers, members of other tribes and religions also live in the region and work in a variety of occupations (Isah & Aliyu, 2024). According to geology, the area is a part of the Precambrian basement rocks and is situated in the north-central section of Nigeria (Christopher et al., 2022). These rocks are intruded by the Mesozoic ring formations of the Jos plateau, and the Cretaceous to Quaternary sediments of the five sedimentary basins mostly cover the area in an unconformable manner. In Zango-Daji, it is hot all year round, with a heavy and generally cloudy wet season and a partially cloudy dry season. The study area experiences 1,100 to 1,300 mm of yearly rainfall during the wet season, from April to October, while the dry period spans between November and March. Rarely does the average yearly temperature fall below 12.2°C or rise above 41.7°C; it often ranges between 15°C and 39.4°C (Zango-Daji, 2024).

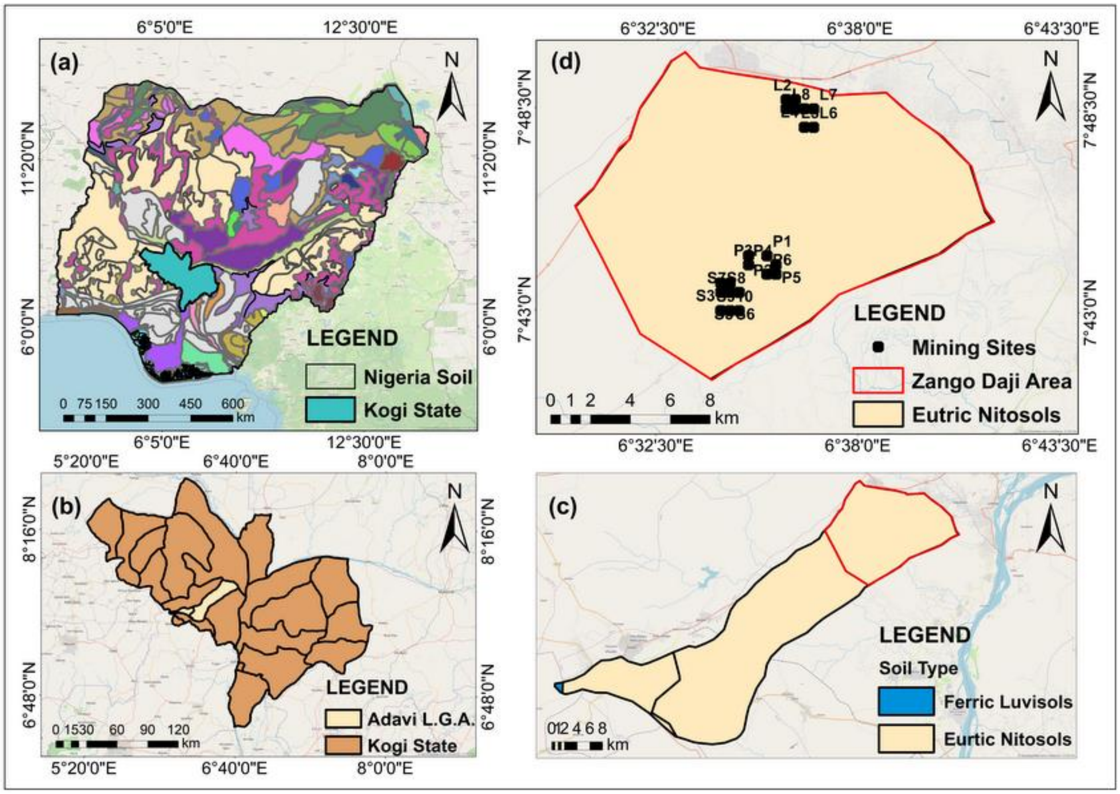


Figure 1: Map of Nigeria and Kogi State Showing the Study Area

Data Collection

Table 1 presents data from the Landsat-7 Enhanced Thematic Mapper (TM/ETM+) and Landsat-8 Operational Land Imager/Thermal Infra-Red Sensor (OLI/TIRS) captured with a 30 m resolution over five years, specifically in 2002, 2007, 2012, 2017, and 2022. These datasets were utilized to assess the changes in LULC within the research region. The images were sourced from the United States Geological Survey (USGS) website and featured no cloud interference.The images were mapped to the Universal Transverse Mercator (UTM) of WGS84, whilethe acquired satellite data was analyzed utilizing ArcGIS 10.8. However, radiometric validation and atmospheric adjustment were used to eliminate haze, background shadows, and correct for topographical variations to produce images with real reflectance.The unprocessed quantized calibration of pixel data for both the multispectral and thermal bands was transformed into Top of Atmosphere (TOA) reflectance using a conventional approach (USGS, 2017). Four geospatial indices (NDVI, MNDWI, NDBI, DBSI) were computed from the integration of red, green, near infrared (NIR), and short wave infrared (SWIR) bands, as shown in Table 2. The training data for each land use and land cover category was defined through visual analysis, followed by the use of ground truth data for validation. The training data, along with a signature file, served as the basis for performing Maximum Likelihood Classification (MLC) on each of the satellite images. The method of utilizing geospatial indices was selected because the process of categorizing images and assigning values to each category typically does not adequately represent the differences in coverage levels within the pixels of one land cover class.

Table 1. Details of the acquired five landsat imagesused for the study

Satellite	Sensor	Resolution	Path/Row	Acquisition Date	Spectral Band
Landsat 7	TM/ETM+	30 m	189/55	30 December, 2002	1-7
Landsat 7	TM/ETM+	30 m	189/55	28 December, 2007	1-7
Landsat 7	TM/ETM+	30 m	189/55	25 December, 2012`	1-7
Landsat 8	OLI/TIRS	30 m	189/55	31 December, 2017	1-7
Landsat 8	OLI/TIRS	30 m	189/55	29 December, 2022	1-7

Table 2. Geospatial Indices used for the Study

S/N	Description	Formula	References
1	Normalized Differential Vegetation Index (NDVI)	$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED}$	Rouse et al., 1973
2	Modified Normalized Difference Water Index (MNDWI)	$MNDWI = \frac{\rho GREEN - \rho SWIR}{\rho GREEN + \rho SWIR}$	Xu, 2006
3	Normalized Difference Built-up Index (NDBI)	$NDBI = \frac{\rho SWIR - \rho NIR}{\rho SWIR + \rho NIR}$	Zha et al., 2003
4	Dry Bare Soil Index (DBSI)	$DBSI = \frac{\rho SWIR - \rho GREEN}{\rho SWIR + \rho GREEN} - NDVI$	Rasul et al., 2018

[1]In Landsat 7 ETM+, band 4's surface reflectance is (near infrared), while band 3's surface reflectance is ; in Landsat 8 OLI, band 5's surface reflectance is along with band 4's surface reflectance. The values range from -1 to +1; non-vegetated surface characteristics are indicated by negative values, while vegetated areas are indicated by positive values.
[2]The surface reflectance of band 2 and (short wave infrared) is the surface reflectance of band 5 in Landsat 7 ETM+. In Landsat 8 OLI, is the surface reflectance of band 3 while is the surface reflectance of band 6.
[3]The surface reflectance of band 5 while (near infrared) is the surface reflectance of band 4 in Landsat 5 TM and Landsat 7 ETM+. In Landsat 8 OLI, is the surface reflectance of band 6 and is the surface reflectance of band 5.
[4]The surface reflectance of band 2 and is the surface reflectance of band 5 in Landsat 5 TM and Landsat 7 ETM+. In Landsat 8 OLI, is the surface reflectance of band 3 while is the surface reflectance of band 6.Tables may have a footer.

RESULTS AND DISCUSSION

Impact of Feldspar Mining on Spatial Distribution of Normalized Differential Vegetation Index (NDVI)

The analysis of NDVI vegetation's spectral reflectance shows the presence of vegetation and its general health. The values of NDVI vary between -1 and +1, with negative values, or values below 0.1, indicate a lack of vegetation and it can be bare land, build up area and others. Meanwhile, a value of zero signifies bodies of water, while positive values denote various kinds of vegetation growth rates. The positive NDVI values in the range of 0.2 to 0.5 denote dormant crops or sparse vegetation, including grasslands and bushes whereas dense vegetation, like that seen in temperate and tropical forests, is indicated by high NDVI values (0.6 to 0.9) (Bid, 2016; Kurtis, 2021). Figure 2 displays the spatial patterns of the vegetation distribution of NDVI from 2002 to 2022, indicating the existence of both green vegetated and non-vegetated areas within the study area. According to the NDVI results, there was a slight decline in vegetation from 2002 to 2007. Also, an increasing in vegetation was recorded from 2007 to 2012, whilea significant decline occurred from 2012 to 2017, with a slight decline from 2017 to 2022.

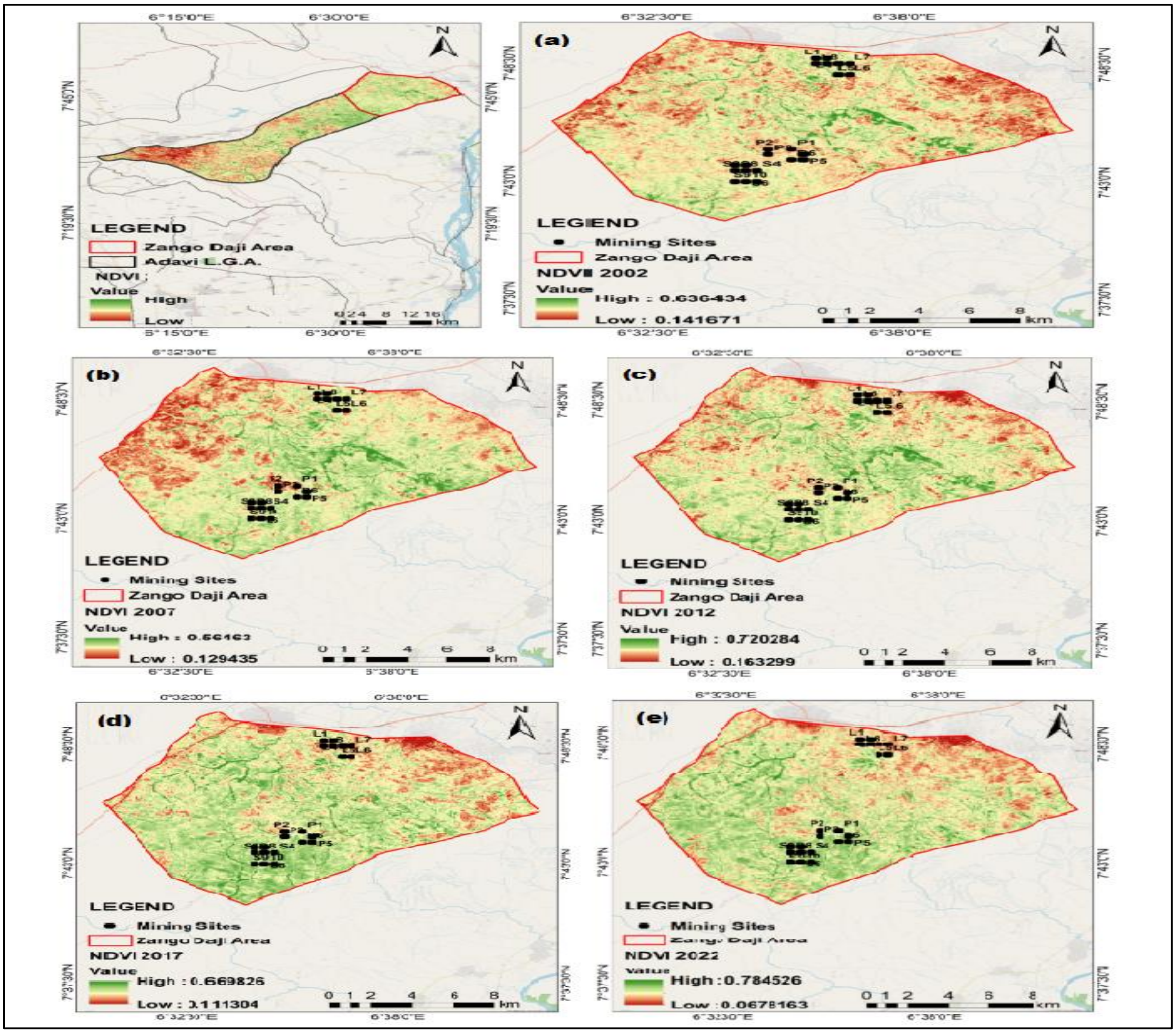


Figure 2. Spatial Vegetation Distribution Patterns of NDVI

The calculated mean values of the NDVI are presented in Table 3, which show an increase in vegetation from 0.373±0.052 in 2002 to 0.457±0.060 in 2012, a year after the commencement of feldspar mining operations. Meanwhile, anoticeable decline was observed between 2012 (0.457±0.060) to 2022 (0.420±0.068) after the commencement of mining operation. This implies that vegetation had improved before the artisanal mining of feldspar and other human-induced operations commenced in Dango-Daji. This finding aligns with the insights of Gbedzi et al. (2022) in the Asutifi region of northern Ghana, where it was reported that the land use during the baseline year was primarily characterized by vegetation. Based on this, the NDVI results from 2002 to 2022 showed that, both before and after mining commenced, the study area was characterized by sparse vegetation, such as bushes and grasslands, or dormant crops, as the values fell between 0.2 and 0.5 (Kurtis, 2021). This suggests that the feldspar mining in the study areas has not significantly affected the vegetation over the last 20 years (2002–2022). However, the results show that during the 11 years (2011–2022) of operations, feldspar mining involved clearing of vegetation with a negligible contribution to vegetation loss. Therefore, the loss of forest and canopy trees in the study area may be attributed to intense agriculture, firewood collection and charcoal production other than mining activities (Bhatt, 2023). Consequently, drought, seasonal variation, uneven rainfall patterns, and strong evaporation may also be responsible for the uneven spatial distribution of vegetation in the area (Zhang et al., 2024).

Table 3. Descriptive Statistics of NDVI (2002-2022) for Zango Daji

Year	Minimum	Maximum	Mean
2002	0.142	0.636	0.373±0.052
2007	0.129	0.565	0.340±0.049
2012	0.163	0.720	0.457±0.060
2017	0.111	0.670	0.399±0.052
2022	0.068	0.785	0.420±0.068

Impact of Feldspar Mining on Spatial Distribution of Modified Normalized Difference Water Index (MNDWI)

Figure 3 presents MNDWI spatial and temporal water variations in Zango Daji with blue colors indicating high water bodies while the light green color indicates low water bodies. The MNDWI values varied from -0.734 to -0.214 in 2002, -0.611 to -0.193 in 2007, -0.656 to -0.295 in 2012, -0.638 to -0.260 in 2017, and -0.611 to -0.193 in 2022 respectively. The negative values indicate the absence of water bodies across the study area (McFeeters, 1996) as the satellite was unable to detect any water bodies in the study area. This consistent with the NDVI values reported by Bid (2016), where negative values associated with water bodies were not detected during the five-year research conducted at the Panchet Hill Dam in India. However, the inability to detect water bodies does not depict an absolute absence of water bodies in the study area. It simply shows that it could be present in amounts below the detection of the Landsat satellite sensors.The mean values of MNDWI revealed that within the span of 9 years (2002-2011) before the mining of Feldspar began in the study area (Table 4), water body availability had its highest peak of -0.422±0.040 in 2007 and lowest peak of -0.550±0.032 in 2012, which is one year after mining began. The resultpresents surface water as most pressured natural resource in the study area. This is inline with Samal & Gedam's (2021) findings, which revealed that the overall impact of LULC changes on the hydrological properties of India's water bodies has led to the depletion of the water bodies. According to this study, water scarcity would persist in the study area unless water collection technologies are developed.

Table 4. Descriptive Statistics of MNDWI (2002-2022) for Zango Daji

Year	**Minimum**	**Maximum**	**Mean**
2002	-0.744	-0.145	-0.497±0.043
2007	-0.611	-0.193	-0.422±0.040
2012	-0.656	-0.295	-0.550±0.032
2017	-0.638	-0.260	-0.496±0.031
2022	-0.734	-0.214	-0.540±0.029

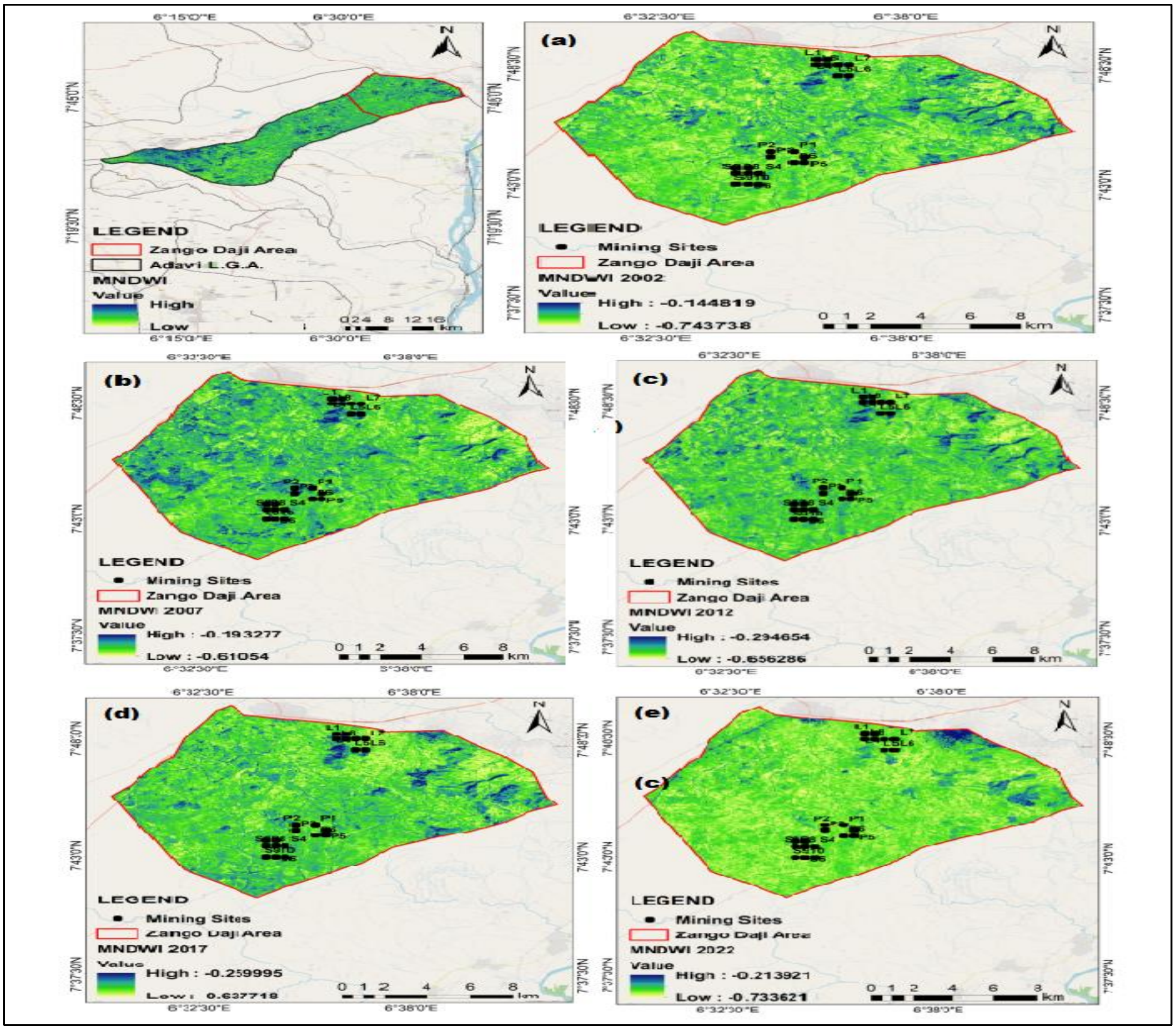


Figure 3. Spatial Water Distribution Patterns of MNDWI

Impact of Feldspar Mining on Spatial Distribution ofNormalized Difference Built-up Index (NDBI)

Figure 4 shows NDBI spatial and temporal built-up variations in Zango Daji, with the blue color indicating low-built-up areas while the brown color indicates high-built-up areas. The NDBI values varied from -0.299 to 0.481, -0.233 to 0.345 in 2007, -0.329 to 0.292 in 2012, -0.311 to 0.303 in 2017, and -0.343 to 0.469 in 2022, respectively. According to the NDBI maps from 2002 to 2022, it showed that low built-up areas are indicated by areas with blue color and negative values, which varied from -0.299 to -0.34253. Conversely, the brown-colored regions with positive values, whose values varied from 0.292 to 0.481, indicate growing amounts in built-up areas (Sresto et al., 2022).The computed mean values of the NDBI are presented in Table5, which show a decrease in built-up areas from 0.089±0.063 in 2002 to 0.047±0.067 in 2012 before mining operations. On the other hand, the built-up areas showed an increase from 0.047±0.067 in 2012 to 0.061±0.059 in 2022 after the commencement of mining operations. This study supports that of Jothimani et al. (2021) from Ethiopia's Rift Valley, which found that the NDBI value increased significantly between 2013 and 2020. The finding suggests that feldspar mining is responsible for the study area's rapid urbanization and population expansion, as evidenced by the progressive increase in built-up areas in 2012, one year after feldspar mining commenced.

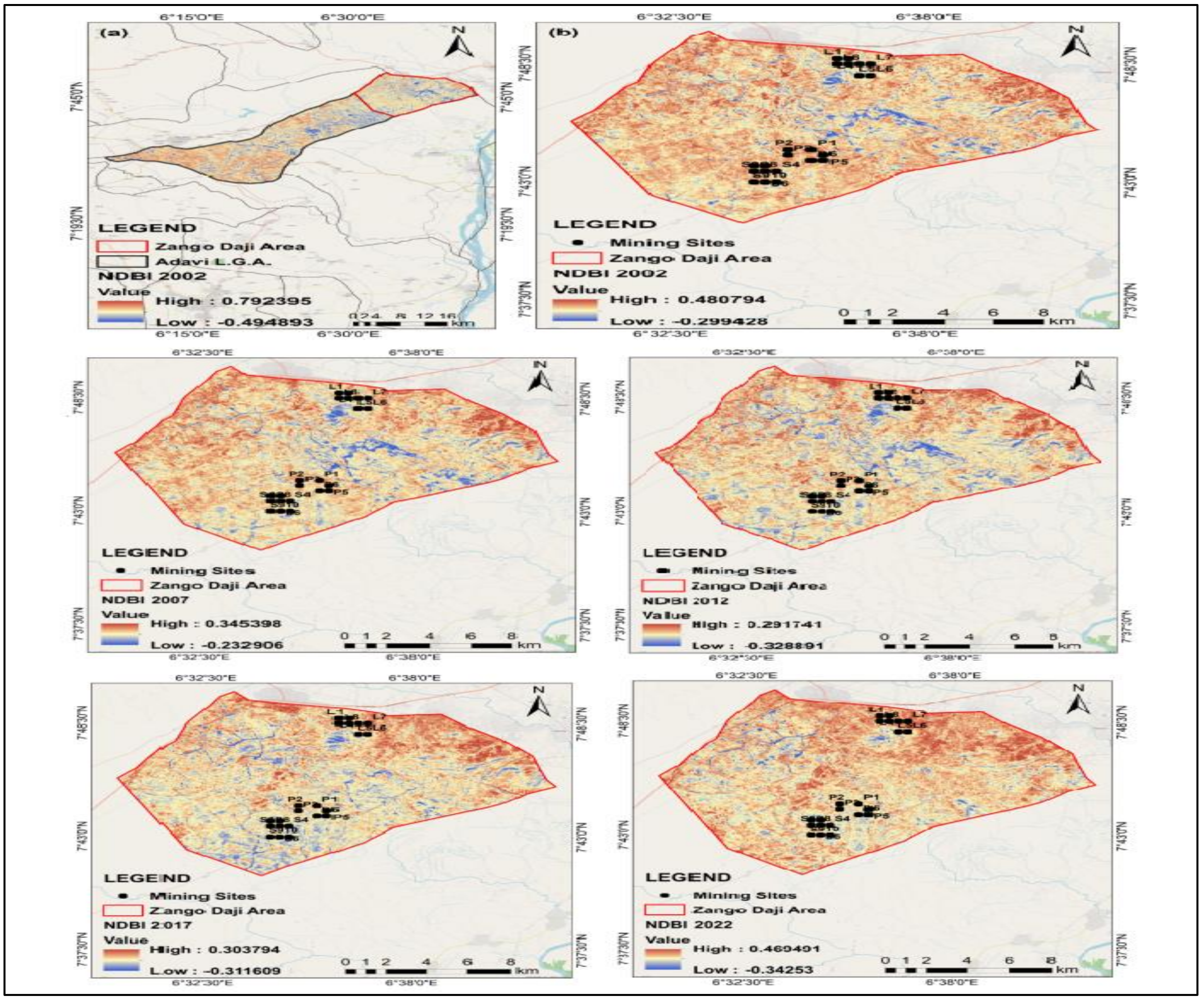


Figure 4. Spatial Built-up Distribution Patterns of NDBI

Table 5. Descriptive Statistics of NDBI (2002-2022) for Zango Daji

Year	Minimum	Maximum	Mean
2002	-0.299	0.481	0.089±0.063
2007	-0.233	0.345	0.053±0.052
2012	-0.329	0.292	0.047±0.067
2017	-0.312	0.304	0.052±0.058
2022	-0.343	0.469	0.061±0.059

Impact of Feldspar Mining on Spatial Distribution of Dry Bare Soil Index (DBSI)

Figure 5 illustrates the range of NDSI values, which were -0.292 to 0.414 in 2002, -0.236 to 0.363 in 2007, -0.288 to 0.383 in 2012, 0.064 to 0.383 in 2017, and 0.061 to 0.455 in 2022. The results revealed that between 2002 and 2022, the blue color indicated low or no presence of dry bare soil in the study area, as their values were negative and close to zero. Meanwhile, the brown color indicates high dry bare soil areas, with the highest value of 0.455 recorded in 2022 and the lowest value of 0.364 recorded in 2007, respectively. The NDSI mean value, as shown in Table 6, decreased from 0.124 in 2002 to 0.082 in 2007 but increased from 0.082 in 2007 to 0.226 in 2022. The results showed that, over a twenty-year period, the average values of 0.124 in 2002 and 0.082 in 2007 (before mining operations) illustrated that there were relatively few bare land areas, as opposed to 0.235 in 2017 and 0.226 in 2022. This indicates that the region's consistently rising land surface temperature is a result of the expansion of bare lands spurred by feldspar mining and other human activities. This was consistent with a study by Sayão et al. (2020), which found that the LST of bare soil areas in São Paulo, southeast of Brazil, rose by an average of 0.13°C per year, indicating a warming trend. This has led to the buildup of various gases in the atmosphere of the study area due to the radiation of sunlight, resulting in a rise in the Earth's temperature or making it exceedingly hot. Even worse, excessive erosion was observed as people altered the landscape without regard to the degradation of the exposed soil surface due to rain runoff. This result is in line with that of Fabolude and Aighewi, (2022), who noted the detrimental effects of barren land in Benin City as a result of the sharp decline in surface water area from 1987 to 2019. Moreover, Lenhardt et al. (2014) in Burkina Faso investigated the relationship between the variation in rainfall and barren land area, noting that as rainfall increases, the barren land area reduces and vice versa. This established that rainfall is a crucial factor determining changes in the extent of bare land area.

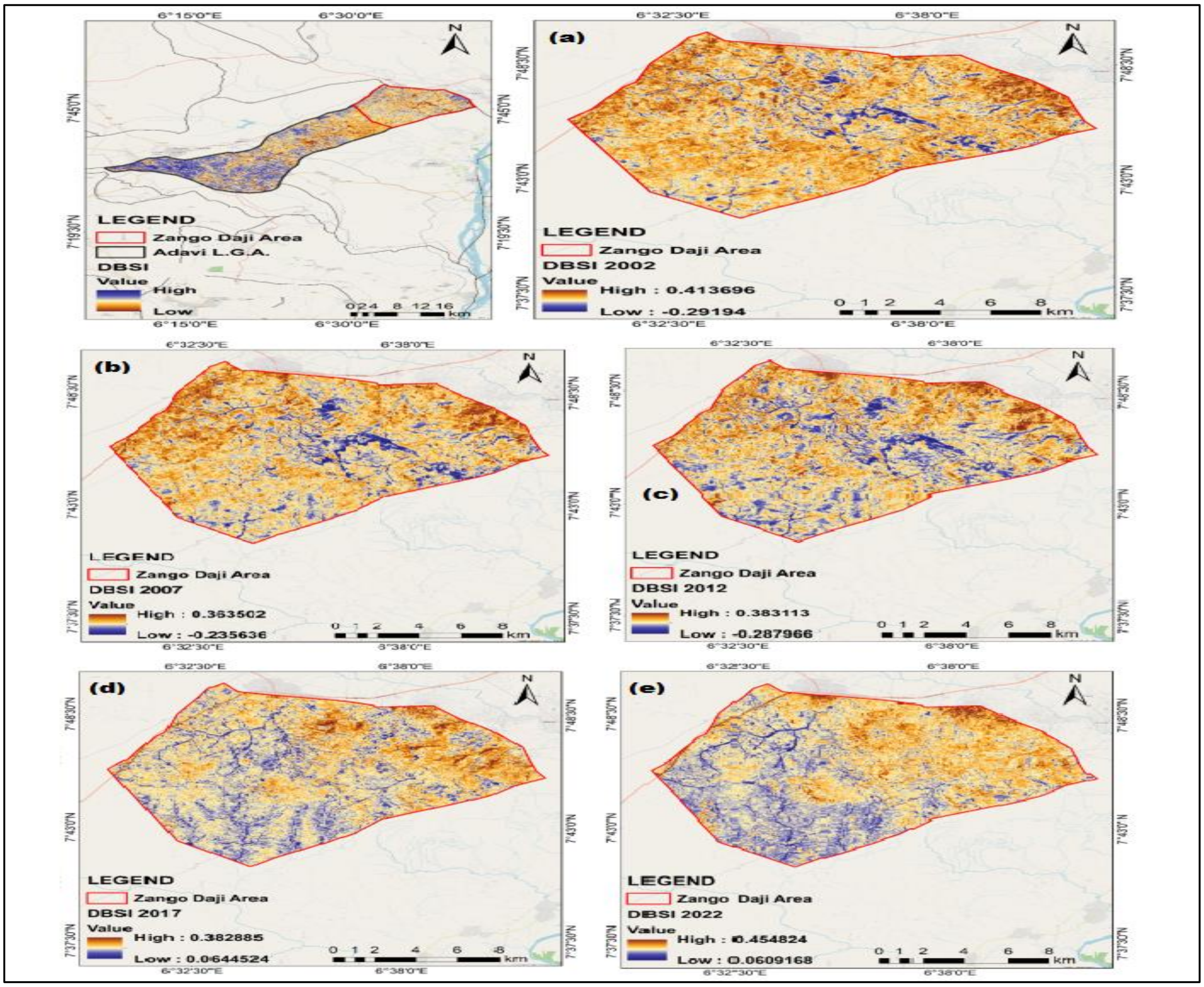


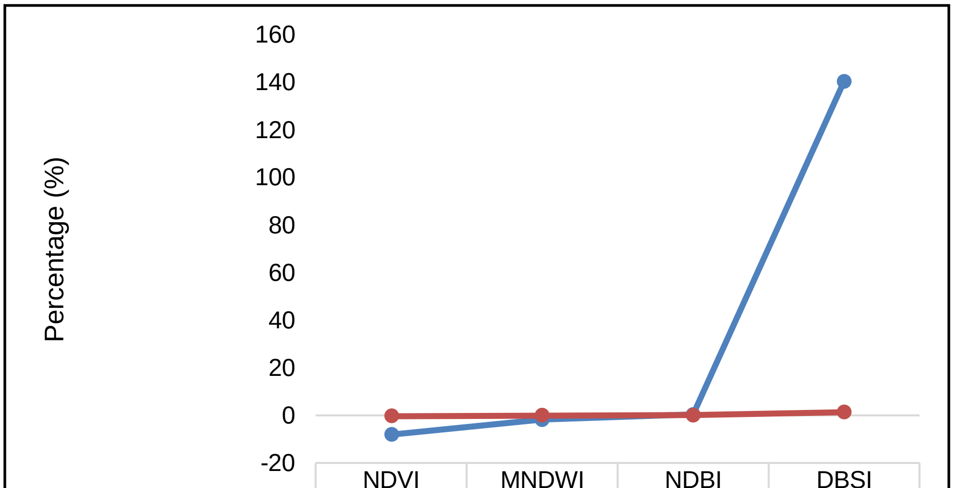
Figure 5. Spatial Built-up Distribution Patterns of DBSI

Table 6: Descriptive Statistics of DBSI (2002-2022) for Zango Daji

Year	Minimum	Maximum	Mean
2002	-0.292	0.414	0.124±0.073
2007	-0.236	0.364	0.082±0.063
2012	-0.288	0.383	0.094±0.076
2017	0.064	0.383	0.235±0.020
2022	0.061	0.455	0.226±0.027

Changes in Spatial Distribution of LULC

The percentage change (PC) and annual percentage change (APC) values for LULC spatial distribution from the year 2012 (a year after the feldspar mining operation) to 2022 are presented in Figure 6. The findings indicated that from 2012 to 2022, NDVI recorded a decline with a PC of -8.09% and an APC of -0.37%, whereas MNDWI recorded a PC of -1.82% and an APC of -0.10%. Conversely, NDBI experienced an increase with a PC of 0.30% and an APC of 0.14%, while DBSI attained a PC of 140.0% and an APC of 1.32%. The significant rise in DBSI has been linked to the excavation of feldspar mineral deposits, the construction of vehicle access roads, and other operations. Meanwhile, the prevalence of NDBI in comparison to NDVI found in this study is consistent with the findings documented in previous studies regarding LULC in Nigeria's mining regions (Owolabi, 2020; Ado et al., 2022; Alaba et al., 2023). Other countries that have reported similar scenarios in their mining environments are Ghana (Gbedzi et al., 2022), the USA (Gyawali et al., 2022), and India (Samal and Gedam, 2021). These reports found that LULC changes in the mining environment primarily occur in the form of NDBI expansion at the expense of other land use types. The results indicate a high degree of conversion of NDVI to other land use types, with NBSI and NDBI accounting for the largest vegetation loss. This is because of a significant increase in the population of the study area due to infrastructure development, migration of people from neighboring towns, and employment opportunities arising from feldspar mines. These observed reasons agreed with the previous studies conducted on LULC in the other regions (Afolabi et al, 2021; Ado et al., 2022). Therefore, feldspar mining in the study area is a key indicator of land use change, leading to large-scale negative effects on biodiversity and the human environment.



	NDVI	MNDWI	NDBI	DBSI
% Change	-8.09	-1.82	0.3	140.4
Annual % Change	-0.37	-0.1	0.14	1.32

Figure 6. Changes in Spatial Distribution of LULC

CONCLUSION

The study employed geospatial indices' analysis to study land use/land cover change from feldspar exploitation in Zango Daji, Nigeria. The average values of NDVI revealed a decline in vegetation from 0.373 in 2002 to 0.340 in 2007, whereas vegetation increased from 0.340 in 2007 to 0.457 in 2012. This demonstrated that vegetation had improved marginally prior to the advent of feldspar mining and other human-induced activities. Also, the NDVI results from 2002 to 2022 showed that, both before and after mining commenced, the study area was characterized by sparse vegetation, such as bushes and grasslands, or dormant crops, as the values fell between 0.2 and 0.5. The negative average values of MNDWI indicate the absence of water bodies in the study area, with values of -0.497 in 2002, -0.422 in 2007, -0.550 in 2012, -0.496 in 2017, and -0.540 in 2022. This results in surface water being the most pressured natural resource in the study area. The average NDBI values elevated from 0.052 in 2017 to 0.061 in 2022 but declined from 0.089 in 2002 to 0.047 in 2012. The steady increase in built-up areas from 2017 to 2022 after mining operations implies that feldspar mining contributed to the study area's population growth and urbanization. Based on the above, the study suggested stricter mining regulation, community reforestation programs, and water management initiatives for sustainable mining activities in the study area.

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

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