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Original Research Article

Investigating the Spatio-Temporal Relationship between NDVI and LST in Abakaliki LGA, Ebonyi State Nigeria, Using Landsat and Correlation Analysis: Implications for Landscape Management

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Abstract: Understanding spatiotemporal linkages between normalised difference vegetation index (NDVI) and land surface temperature (LST) is crucial for managing landscape resilience amid global change. This study applied correlation analyses to investigate NDVI-LST relationships across Abakaliki LGA, Nigeria from 2000-2022 using Landsat data. Multi-decadal trends revealed widespread LST increases exceeding 9°C, while NDVI declined, implying vegetation clearing transformed surfaces from carbon sinks to sources dampening temperatures. In 2000, NDVI positively correlated with LST ($r=0.745$, $p<0.01$); by 2022, large-scale NDVI suppression drove strong negative correlations between NDVI and LST ($r=-0.751$, $p<0.01$). Findings documented rapid decoupling of previously heterogeneous NDVI-LST couplings tied to diverse land use. Sustainable intensification offers potential to restore climate-buffering vegetation and recouple local anthropogenic-climatic systems. Continued monitoring can track restoration progress while adaptation evolves with socio-environmental change. This research advances understanding of anthropic impacts on landscape energetics using remote sensing and correlation analyses, with implications for integrated management under global change.

Keywords: NDVI, Land surface temperature, Landsat, Correlation analysis, Spatiotemporal relationship, Remote sensing, Vegetation, Landscape management.

INTRODUCTION

Land surface processes are dynamic interactions between the biosphere, lithosphere, hydrosphere and atmosphere that modulate regional climates. Of particular importance are landscape variables like vegetation influencing the exchange of energy, moisture and carbon fluxes at the land-atmosphere interface (Wang *et al.*, 2016). The normalized difference vegetation index (NDVI) conveys vegetation productivity and density, while land surface temperature (LST) characterizes surface thermal conditions responsive to latent heat fluxes (Gallo *et al.*, 2018). Their couplings govern feedbacks impacting meteorological phenomena from convection patterns to heat waves (Devaraju *et al.*, 2018). Amid climatic perturbations worldwide, disrupted linkages between NDVI and LST portend environmental transformations with ramifications spanning biodiversity, agriculture and public welfare (Zhang *et al.*, 2019). However, relationships vary spatially contingent on geographic attributes,

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requiring localized analyses to contextualize regional vulnerabilities (Zhou *et al*., 2020).

Nigeria faces acute climate risks manifest as amplified heat stresses, shifting rainfall patterns and ensuing socioeconomic hardships (Oladipo, 2021). Within this vulnerable setting, southeastern Nigeria encompassing Abakaliki local government area (LGA) depends heavily on rainfed agriculture and natural resources that climate variability imperils (Okpanachi *et al*., 2020). Understanding biophysical correlates impacting the regional thermal landscape represents a prerequisite for adaptive management prioritizing resilience (Anyadike, 2012).

Satellite remote sensing furnishes spatiotemporally contiguous observations illuminating landscape-climate interactions from local to global extents (Li *et al*., 2013). The Landsat missions dating to 1972 yield multidecadal archives corroborating land change detection and biogeophysical monitoring (Wulder *et al*., 2019). Their moderate resolution complements knowledge gained from coarse-grained analyses while enabling localized examinations (Zhang *et al*., 2014).

Correlation methods statistically establish variable associations elucidating potential causal mechanisms. Combining Landsat data with such techniques characterizes spatiotemporal covariance patterns informing policy and adaptation planning across diverse settings (Du *et al*., 2014). However, applications remain sparse across sub-Saharan Africa where integrated observations and impact evaluations remain priorities (Amissah-Arthur, 2020).

Accordingly, this study aims to advance fundamental understanding of NDVI-LST linkages structuring Abakaliki's thermal landscape dynamics through a Landsat-based investigation. Specifically, it will; derive multi-decadal NDVI and LST trends from Landsat 7 and 8 imagery, examine spatiotemporal covariance shifts using Pearson's correlation coefficients, and relate discerned patterns to implications for landscape resilience under ongoing climate change. Findings will guide evidence-based strategies safeguarding livelihood security contingent on ecosystem productivity and service provision.

By tailoring the scope to localized conditions, this research targets knowledge gaps constraining climate risk assessments and adaptive prioritization across data-scarce yet vulnerability-prone regions. Combining remote sensing time series with correlative modeling leverages complementary strengths to characterize environmental transformation mechanisms. Outcomes carry relevance for biodiversity conservation, agricultural adaptation programming and integrated land use planning regionally. Continued monitoring and multi-sectoral collaboration offer pathways to instill climate-resilient development trajectories under global change impacts intensifying disproportionately within vulnerable developing nations.

MATERIALS AND METHODS

Study Area

The study region comprises Abakaliki Local Government Area (LGA) located in Ebonyi State, southeast Nigeria. Situated between latitudes 5°32'–5°42'N and longitudes 7°58'–8°12'E, Abakaliki LGA encompasses approximately 540 km2 of undulating terrain ranging from 70 to 150 m above sea level (Figure 1). The area experiences a tropical climate characterised by a wet season from April to October and drier period from November to March (Nigerian Meteorological Agency, 2022). On average, annual rainfall totals 1500-2000 mm while average temperatures remain within 22-32°C annually (Nigerian Meteorological Agency, 2022).

This climate supports diverse agricultural production critical to local livelihood security. Historically, the landscape comprised fragmented farmlands interspersed with remnant tropical forest and woodland savanna ecosystems (Nwafor, 2006). However, rapid population growth in recent decades has catalyzed widespread habitat conversion for settlements and expansion of industry/services sectors (National Bureau of Statistics, 2016). Between 1990-2015, Abakaliki LGA witnessed over 300% population surge from 57,000 to 240,000 inhabitants through rural-urban migration and natural increase (National Population Commission, 2006; National Population Commission, 2022).

Despite transformations accompanying development, Abakaliki LGA retains its role as Ebonyi State capital and regional trade/administration hub (Nwafor *et al*., 2018). However, accelerating urban expansion risks compromising sustainability without prudent planning. The study area's socioeconomic relevance, climatic conditions and land use transitions establish its appropriateness for investigating landscape change dynamics with implications for adaptive governance.

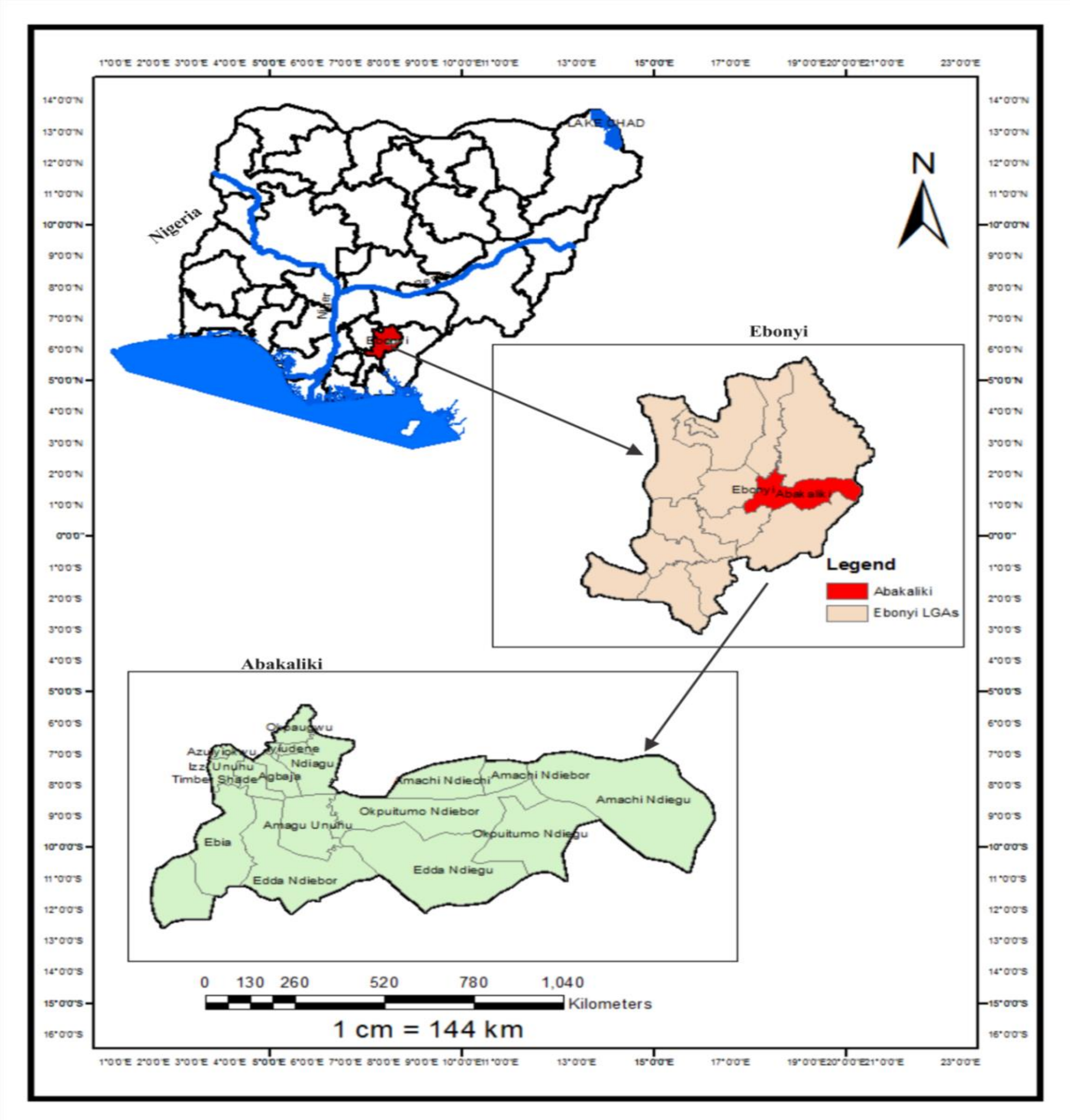

Figure 1: Map of the study area

Remotely Sensed Data

Remotely sensed datasets provide optimal data for retroactively examining landscape variables over extensive spatiotemporal extents (Wulder *et al*., 2019). Accordingly, this study utilized continental Africa mosaicked Landsat surface reflectance imagery from 2000-2022 acquired through the United States Geological Survey (USGS) Earth Explorer platform. Specific satellite-sensor combinations included Landsat 5 Thematic Mapper (2000) and Landsat 8 Operational Land Imager (2022).

Pre-processing

To maximize data availability across the study period while balancing computational demands, a bi-annual compositing interval was adopted. Resultantly, 11 composite images per satellite mission were generated using the mean method in the Landsat Composite Creator toolbox, yielding a total 22-date time series stack. Additional pre-processing involved image reprojection, resampling to a consistent 30m pixel resolution, subset clipping to the study area extent, and cloud/shadow masking following established algorithms (Zhu & Woodcock, 2012).

Vegetation and Thermal Indices

From surface reflectance inputs, NDVI and LST were then extracted for each composite period. NDVI quantifies greenness as the normalized difference between near-infrared and red bands, and represents general productivity and canopy development gradients (Pettorelli, 2013). LST represents radiative surface temperature derived from thermal band radiance using the mono-window algorithm accounting for emissivity effects (Qin *et al*., 2001).

Normalized Differential Vegetative Index (NDVI)

Normalized Differential Vegetative Index (NDVI) is a remote sensing technique used to measure vegetation health and density (Ahmed, 2016; Koko *et al*., 2021). It uses the red (R) and near infra-red (NIR) bands of satellite images to calculate a standardized "greenness" of vegetation, which can be compared over multiple seasons and years (Onyeneke, Amadi & Njoku, 2022). The NDVI value of a pixel varies between -1 and 1: Higher values indicate the richer and healthier vegetation (Stehman & Foody, 2019), whereas values closer to 0 & -1 correspond to barren land and bodies of water, respectively. In this study, NDVI was calculated according to Equation (1) to identify vegetated and non-vegetated areas using the thresholding method (Stehman& Foody, 2019; Koko *et al*., 2021; Onyeneke, Amadi & Njoku, 2022).

$$\text{NDVI} = \frac{(\text{NIR}-\text{R})}{(\text{NIR}+\text{R})} \text{ ………………. (1)}$$

Were:
NDVI is the Normalized Difference Vegetation Index; NIR is the Near Infrared Band, while R is the Red Band.

Land surface temperature calculation

The (USGS) Landsat data with 30m spatial resolution and a data type of 16- bit unsigned integer were calibrated to obtain the temperature in degrees Celsius (°C) based on equation (Sruthi and Aslam, 2015; Hailemariam *et al*., 2016).

Land surface temperature calculation from Landsat 7

For the year 2000 we used the termal band which is band 8 from landsat 7 ETM; in order to extract land surface temperature of the year 2000 we employed equation 2 to 4 below.

i. We Converted the DN to Radiance using equation (2) below.

$$L_\lambda = \left(\frac{LMAX_\lambda - LMIN_\lambda}{QCALMAX - QCALMIN}\right) \text{x (QCAL} - \text{QCAMINN)} + LMIN_\lambda \text{ ………….. (2)}$$

Where:
L_λ = Spectral Radiance
QCAL= Quantized Calibrated Pixel Value in DN
$LMAX_\lambda$ = Spectral radiance scaled to QCALMAX in (watts/(m^2*sr*µm))
$LMIN_\lambda$ = Spectral radiance scaled to QCALMIN in (watts/(m^2*sr*µm))
QCALMAX = Maximum Quantized Calibrated Pixel Value (coresponding to $LMAX_\lambda$) in DN
QCALMIN = Minimum Quantized Calibrated Pixel Value (coresponding to $LMAX_\lambda$) in DN

ii. We then converted radiance to Brightness Temperature (BT) using equation (3) below:

$$T = \frac{K2}{ln(\frac{K1}{L_\lambda}+1)} \text{ …………………….. (3)}$$

Where:
T= Effective at-satelite temperature in Kelvin
K2= Calibration constant 2
K1= Calibration constant 1
L_λ= Spectral Radiance in (watts/(m^2*sr*µm))

iii. We finally converted degree Kelvin to degree Celsius using formula (4) below

C= K - 273.15 ………………. (4)

Land surface temperature calculation from Landsat 9 and 8 OLI

i. We converted the Thermal Infra-Red Digital Number to Top of Atmospheric Radiance using equation (5) below

L= ML*Qcal+AL-Oi ……………….. (5)

L_λ= 0.0003342*Band10+0.0100000-0.29

Where:
L_λ = TOA spectral Radiance in (watts/(m^2*sr*µm))
ML = Radiance multiplicative Band (No.)
AL = Radiance Add Band (No.)
Qcal = Quantized and calibrated standard product pixel value (DN)
Oi = Correction value for band 10 (0.29)

ii. We then converted Top of Atmospheric Radiance to Brightness Temperature (BT) using equation (6) below

Kelvin to Celsius (°C) Degree
BT = K2/ln(K1/ L +1) - 273.15 …………………. (6)

Where:
BT = Top of Atmospheric Temperature (°C)
L_λ = TOA Spectral Radiance (watts/(m^2*sr*µm))
K1 = Calibration Constant 1 Band (No.)
K2 = Calibration Constant 2 Band (No.)

iii. We calculated the Normalized difference Vegetation Index (NDVI) with the Near Infra-Red (Band 5) and Red (Band 4) using equation (7) below:

$$NDVI = \frac{NIR-RED}{NIR+RED} = \frac{Band\ 5-Band\ 4}{Band\ 5+Band\ 4} \quad \text{…………………. (7)}$$

iv. We then calculated the Land Surface Emissivity (LSE) which is the average emissivity of an element of the earth surface using equation (8)

PV= ((NDVI-NDVImin)/(NDVImax-NDVImin))^2……. (8)

Where:
PV = Proportion of vegetation
NDVI = DN value from NDVI image
NDVI min = Minimum DN value from NDVI image
NDVI max = Maximum DN value from NDVI image
E= 0.004*PV+0.986

Where:
E= Land Surface Emissivity
PV= Proportion of Vegetation
0.986 corresponds to a correction value of the equation

v. We finally calculated the Land Surface Temperature (LST) using the Top of Atmospheric Brightness Temperature, wavelength of emitted radiance and Land Surface Emissivity (LSE). The formula is shown in equation (9) below.

LST = BT/(1+⅄*BT/c2)*ln(E)) ……………… (9)

Here, c2 = 14388 µmk

Where:
BT = Top of atmospheric brightness temperature (^{0}C)
⅄ = Wavelength of emitted radiation
E = Land Surface Emissivity (LSE)
c2 = h*c/s=1.4388*10^{2}mk =14388mk
h = Planck's Constant = 1.38*10^{-34} Js
s = Boltsmann constant = 1.38*10^{-23} JK
c = Velocity of light =2.998*10^8 m/s

Trend Analysis

Trend analyses commenced by computing linear trends per pixel over the entire 2000-2022 record to parameterize overall rate and direction of change. Subsequently, NDVI and LST time series from each 30m pixel were extracted and segmented into two distinct periods aligned with Landsat missions 2000 and 2022. For each interval, mean NDVI and LST values were calculated per pixel to facilitate coefficient derivation between periods.

Correlation Analysis

Correlation between NDVI and LST was then assessed through spatial and temporal covariance analysis. At the landscape scale, Pearson's correlation coefficient (r) captured pixel-by-pixel associations between mean NDVI and LST patterns across the full study area for each time period. These correlations were determined using Statistical Package for Social Science (SPSS) version 22. At finer scales, moving window analyses delineated localized NDVI-LST covariance hot/coldspots based on significance testing and mapped coefficient variability.

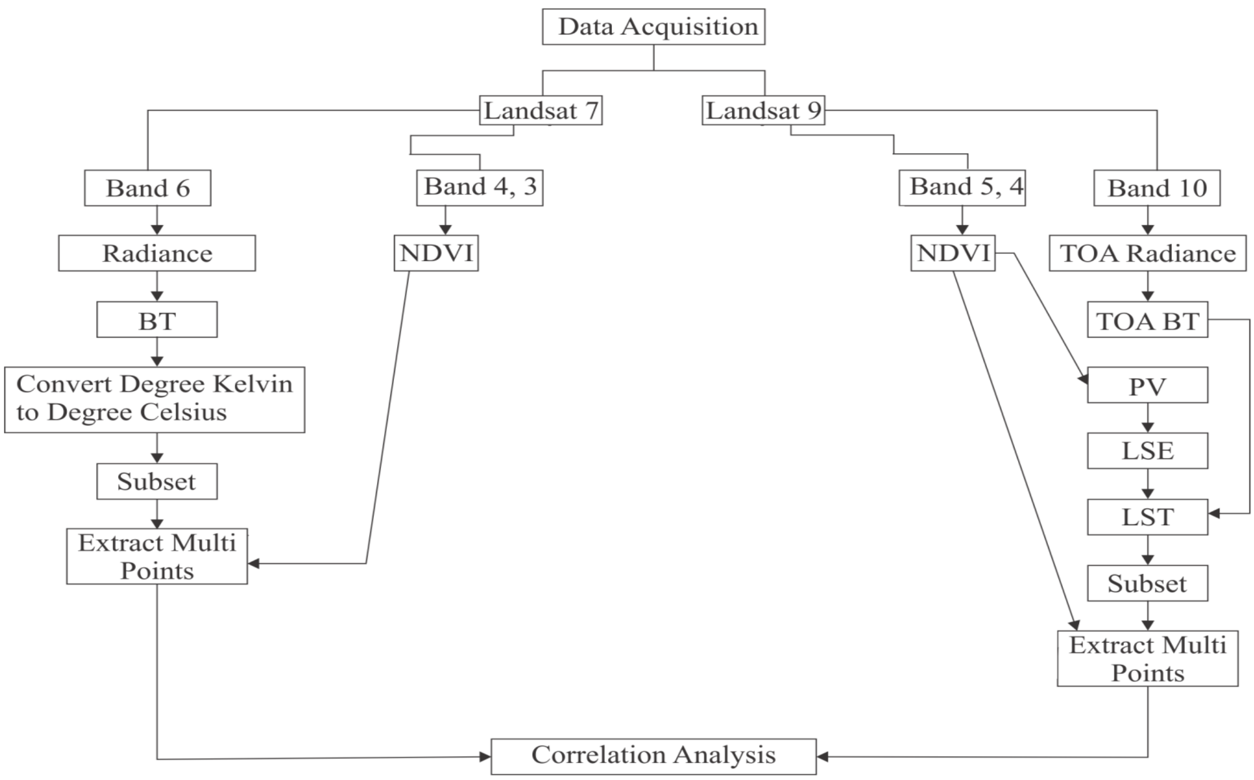

Figure 2: Data analysis flow chart

RESULTS

The following section details empirical findings from the spatiotemporal investigation of NDVI-LST relationships across Abakaliki LGA, Nigeria using Landsat observations and correlation analyses. First, multi-decadal trends in NDVI and LST are quantified on a pixel-by-pixel basis to contextualize overall directionality and gradations in landscape change dynamics over the past two decades. Next, mean NDVI and LST patterns within each observational period are visually portrayed and statistically summarized to facilitate comparative assessments of inter-interval variability. Corresponding spatial covariance patterns between vegetation productivity and surface thermal gradients are then explored across scales through correlation coefficient distributions and local heterogeneity mappings. Lastly, discerned coupling dynamics are interpreted with reference to contemporaneous landscape cover alterations to provide preliminary perspective on climatic-anthropogenic linkages structuring the region's thermal landscape evolution. Collectively, the ensuing results aim to offer new empirical insights into localized biophysical interactions under global environmental fluctuations.

Land Surface Temperature between the Year 2000 and 2022

Table 1: Abakaliki LGA Land Surface Temperature Result 2000

Minimum Temperature	14.9 °C
Maximum Temperature	27.8 °C
Mean Temperature	18.9 °C
Standard Deviation	1.13 °C

Table 1 shows that in the year 2000 Abakaliki Local Government Area had a minimum temperature of 14.9^{0}C with a maximum temperature of 27.8^{0}C and mean temperature 18.9^{0}C.

Table 2: Abakaliki LGA Land Surface Temperature Result 2022

Minimum Temperature	31.4 °C
Maximum Temperature	37 °C
Mean Temperature	33.9 °C
Standard Deviation	0.474 °C

Table 2 shows that in the year 2022 Abakaliki Local Government Area had a minimum temperature of 31.4^{0}C with a maximum temperature of 37^{0}C and mean temperature 33.9^{0}C.

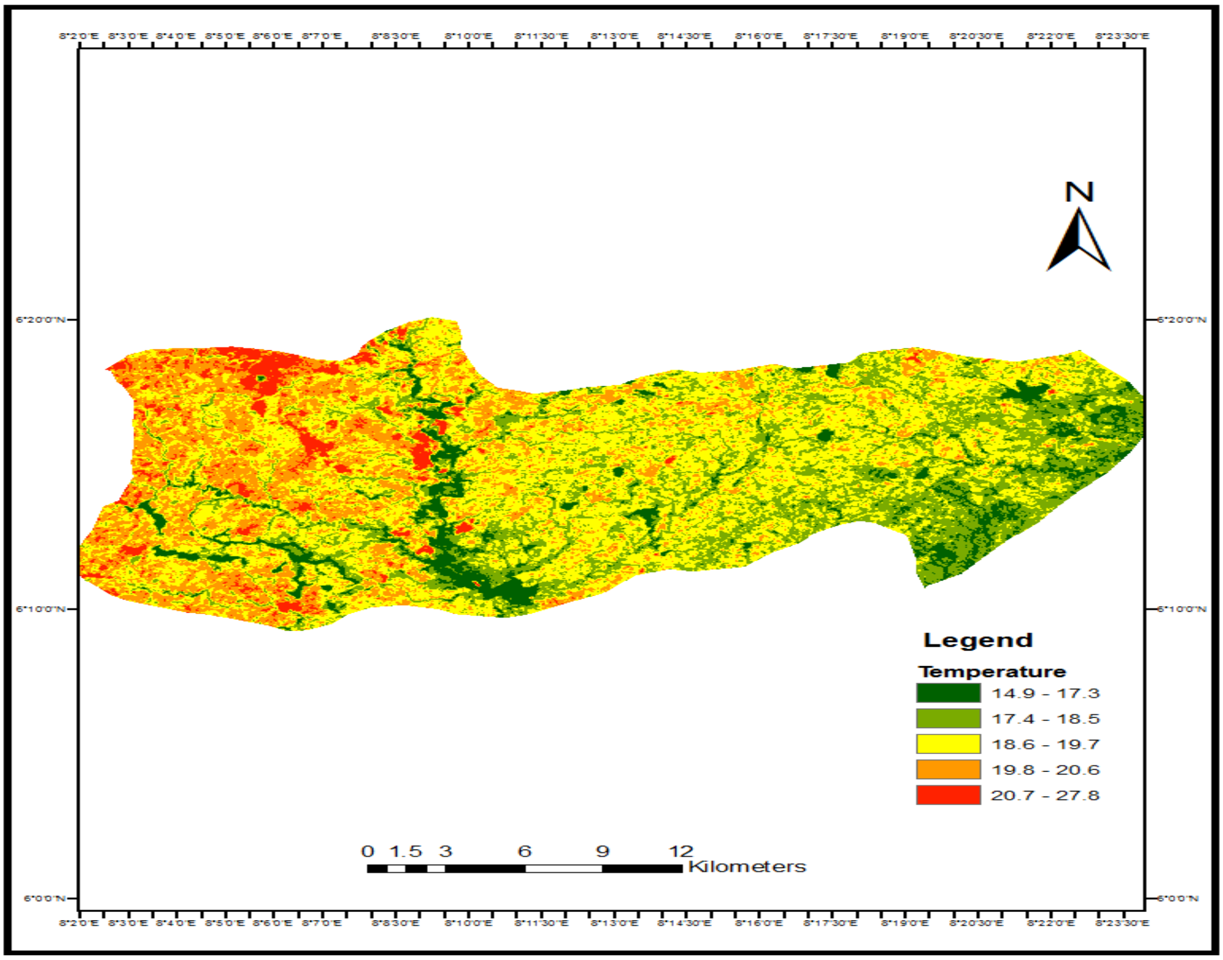

Fig 3: Land Surface Temperature of Abakaliki LGA for the Year 2000

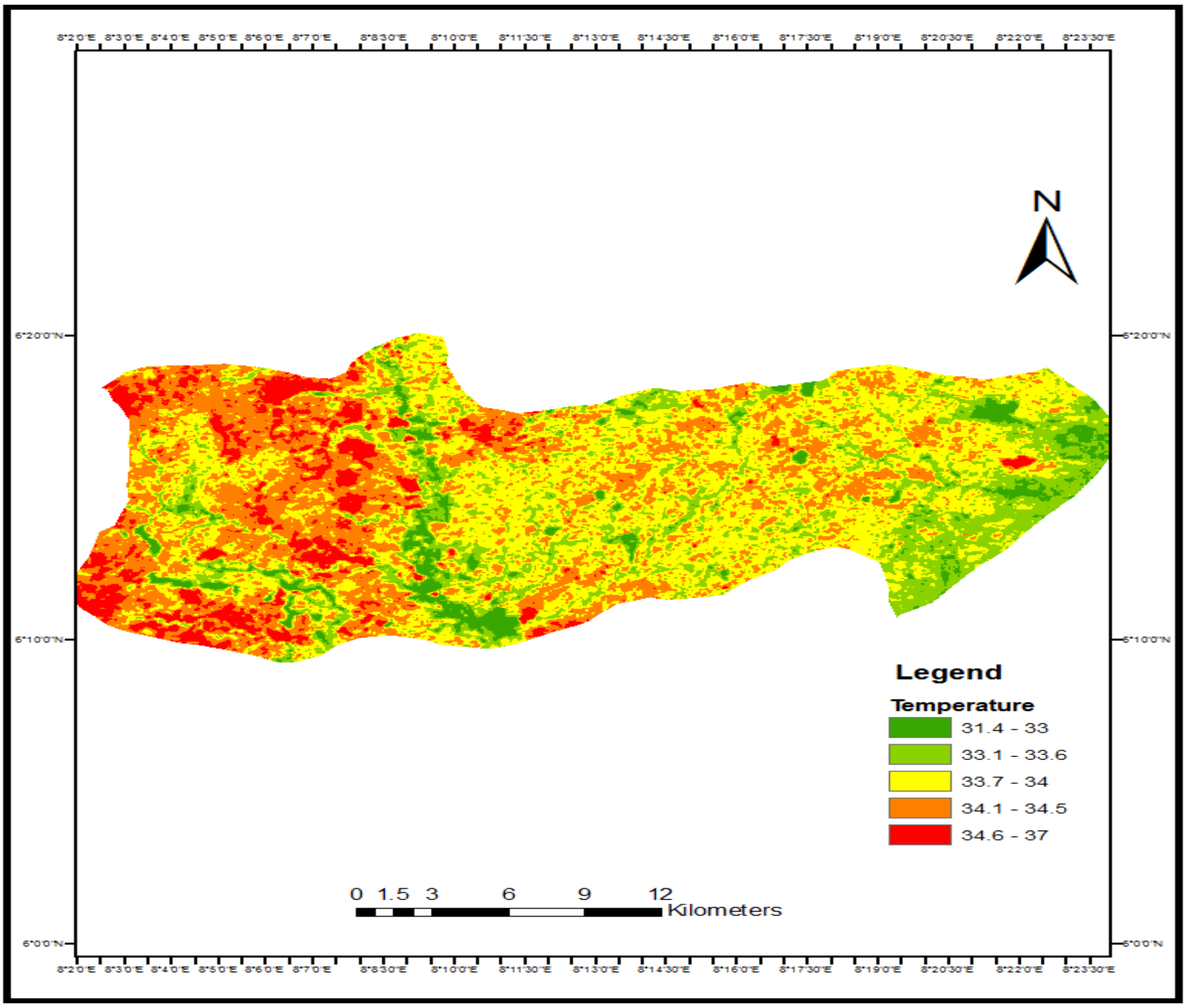

Fig 4: Land Surface Temperature of Abakaliki LGA for the Year 2022

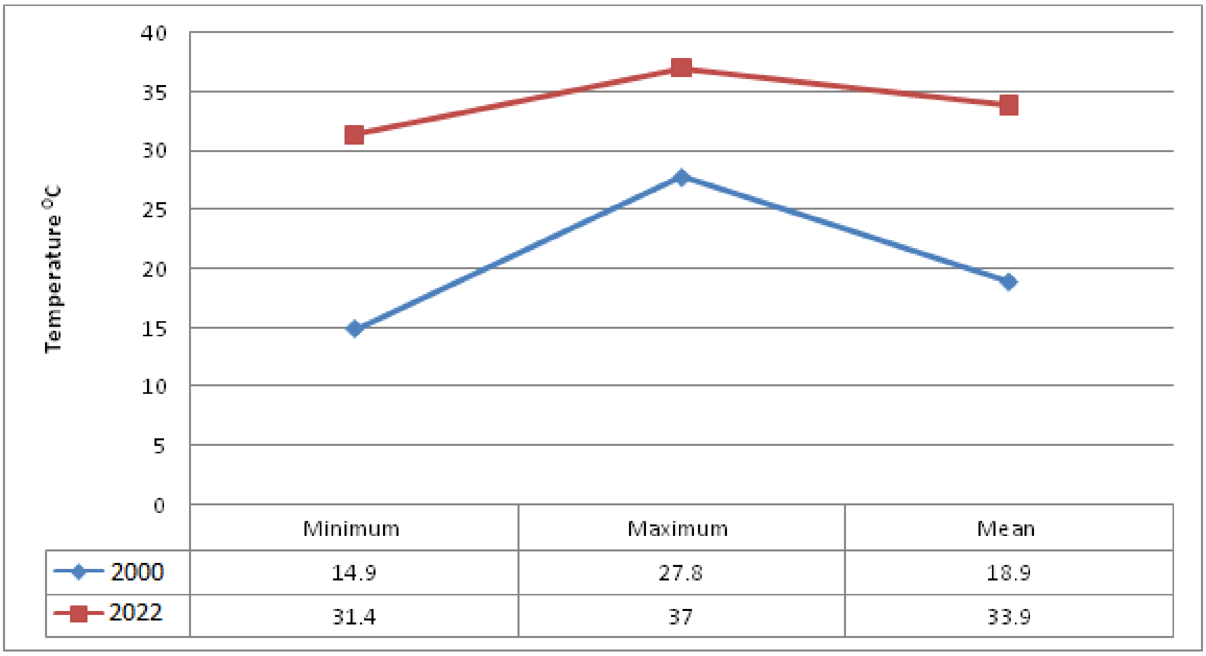

Fig 5: Graphical Representation of Abakaliki LGA LST 2000-2022

Table 3: Abakaliki LGA LST Changes for 2000 and 2022

Temperature		Remark
Minimum	+16.5 ^{o}C	Increase
Maximum	+9.2 ^{o}C	Increase
Mean	+15 ^{o}C	Increase

Table 3 show that between the 2000 and 2022, Abakaliki LGA experienced an increase 16.5^{0}C in minimum temperature in the year 2022, and also an increase of 9.2^{0}C in maximum temperature in the year 2022 with an increase of 15^{0}C in the mean temperature for the same year 2022.

4.5 Normalized Difference Vegetation Index (NDVI)

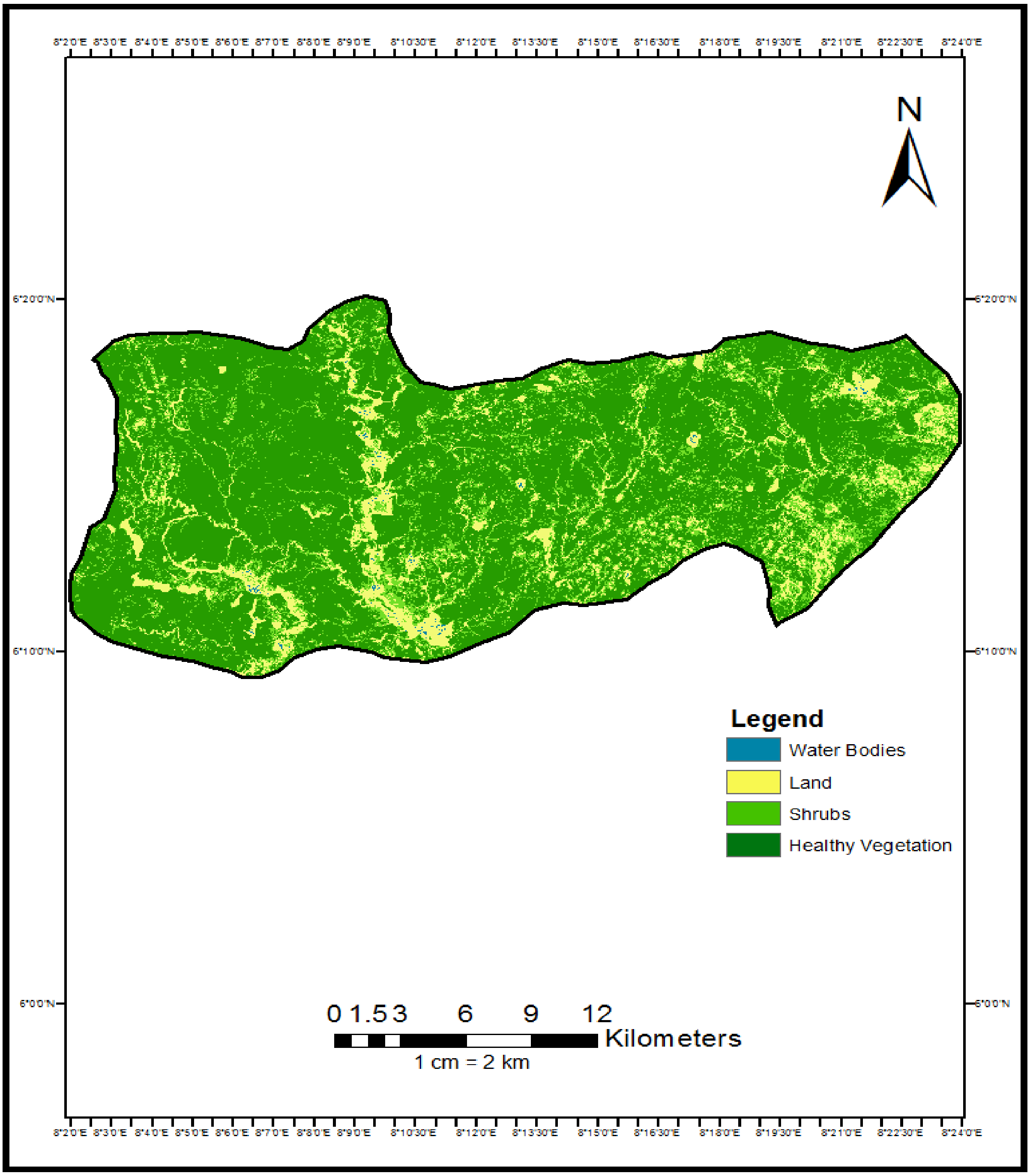

Fig 6: Normalized Difference Vegetation Index (NDVI) 2000

Table 4: Normalized Difference Vegetation Index (NDVI) 2000 Result

Minimum Value	0.0289
Maximum Value	0.59
Mean	0.274
STD	0.0264

Table 5: Abakaliki LGA 2000 NDVI Values Range Classification

Class	Values
Water Body	-0.028 to 0.03
Land	0.03 to 0.2
Shrubs	0.2 to 0.25
Healthy Vegetation	0.25 to 0.59

From the Normalized Difference Vegetation Index (NDVI) for the year 2000 presented in figure 6, tables 4 and 5, it records a min value of 0.0289 and maximum value of 0.59 with mean of 0.274 values. These values was classified to represents different classes were -0.028 to 0.03 represents water body, 0.03 to 0.2 represents bare land, 0.2 to 0.25 represents Shrubs while from 0.25 to 0.59 represents healthy vegetation.

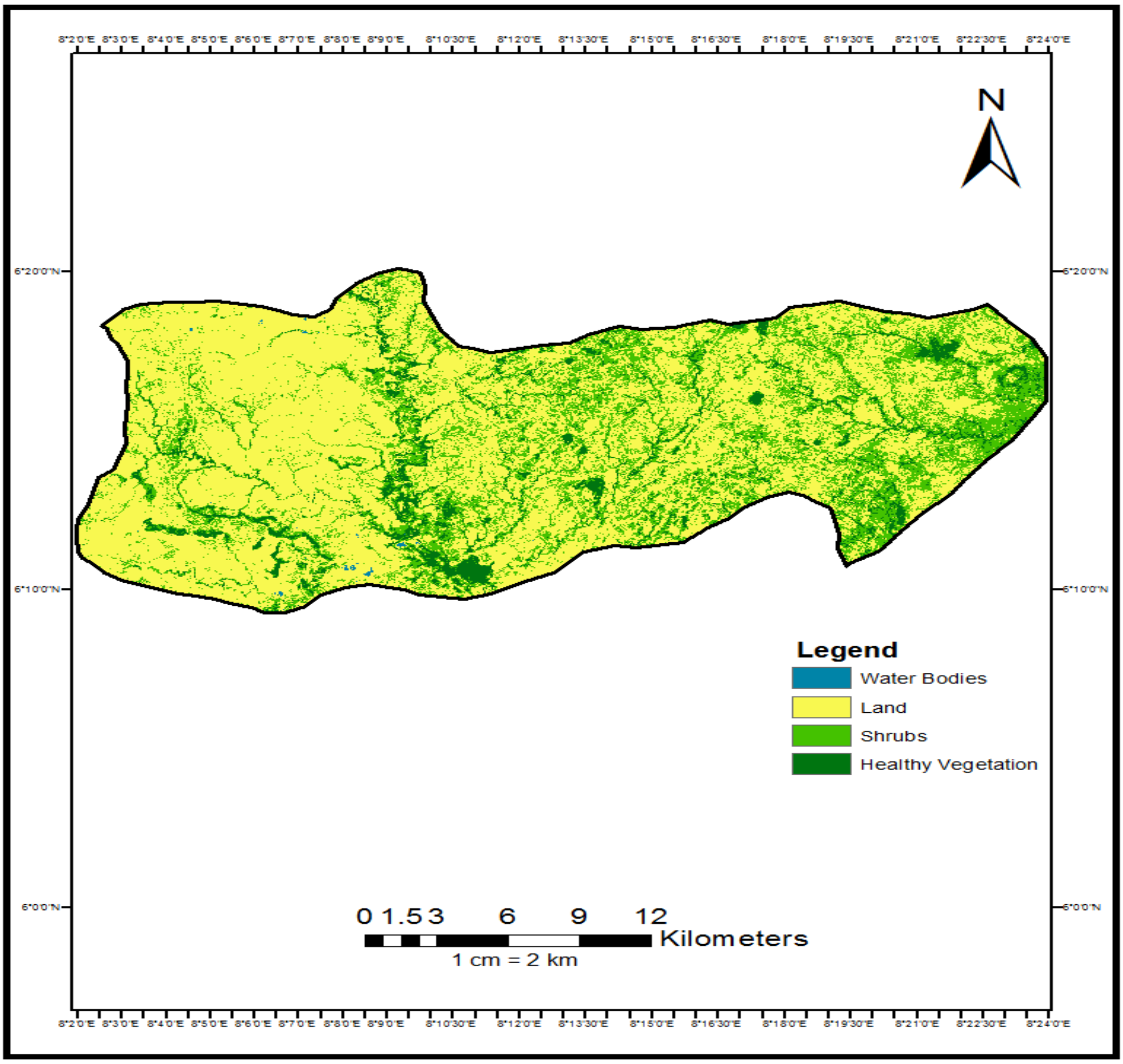

Fig 7: Normalized Difference Vegetation Index (NDVI) 2022

Table 6: Normalized Difference Vegetation Index (NDVI) 2022 Result

Minimum Value	0.067
Maxmum Value	0.396
Mean	0.1848
STD	0.42

Table 7: Abakaliki LGA 2022 NDVI Values Range Classification

Class	**Values**
Water Body	-0.06 to 0.03
Land	0.03 to 0.2
Shrubs	0.2 to 0.25
Healthy Vegetation	0.25 to 0.396

From the Normalized Difference Vegetation Index (NDVI) for the year 2022 presented in figure 7, tables 6 and 7, it records a min value of 0.067 and maximum value of 0.396 with mean of 0.1848 values. These values was classified to represents different classes were -0.06 to 0.03 represents water body, 0.03 to 0.2 represents bare land, 0.2 to 0.25 represents Shrubs while from 0.25 to 0.396 represents healthy vegetation.

Correlation Analysis

In order to determine the relationship between Normalized Difference Vegetation Index, we extracted multiple points from the NDVI image values and that of the Land Surface Temperature of the Study area using ARCGIS 10.8 version in so doing, we generated a total of 1551 points, the values of those points was extracted and moved over to Microsoft Excel and SPSS software for correlation analysis and charting.

Table 8: Correlation between NDVI and LST for the Year 2000

		NDVI	**LST**
NDVI	Pearson Correlation	1	.745**
	Sig. (2-tailed)		.000
	N	1649	1649
LST	Pearson Correlation	.745**	1
	Sig. (2-tailed)	.000	
	N	1649	1649
**. Correlation is significant at the 0.01 level (2-tailed).			

The presented correlation analysis in Table 8 shows the relationship between two variables: NDVI (Normalized Difference Vegetation Index) and LST (Land Surface Temperature) for the year 2000. The study collected data from 1649 observations and uses Pearson's Product-moment correlation coefficient (r) to measure the strength and direction of the relationship between the two variables.

The correlation coefficient ranges from -1 to 1, where; a coefficient of 1 represents a perfect positive correlation, a coefficient of 0 indicates no correlation, and a coefficient of -1 indicates a perfect negative correlation. The p-value indicates the probability of obtaining such a correlation coefficient by chance, and a p-value less than 0.05 is considered statistically significant.

The correlation coefficient between NDVI and LST is 0.745, which indicates a strong positive correlation between the two variables; as NDVI values increase, LST values also increase, and as NDVI values decrease, LST values decrease. This relationship is statistically significant at the 0.01 level, which means that the probability of obtaining such a strong correlation by chance is less than 1%. This result suggests that vegetation cover and land surface temperature are positively related. As vegetation cover increases, it can trap more heat and increase the temperature of the surrounding environment.

Trend of the year 2000 correlation result is show in figure 8 below, which shows how the Normalized Difference Vegetation Index interacts with Land Surface Temperature of Abakaliki LGA for the year 2000.

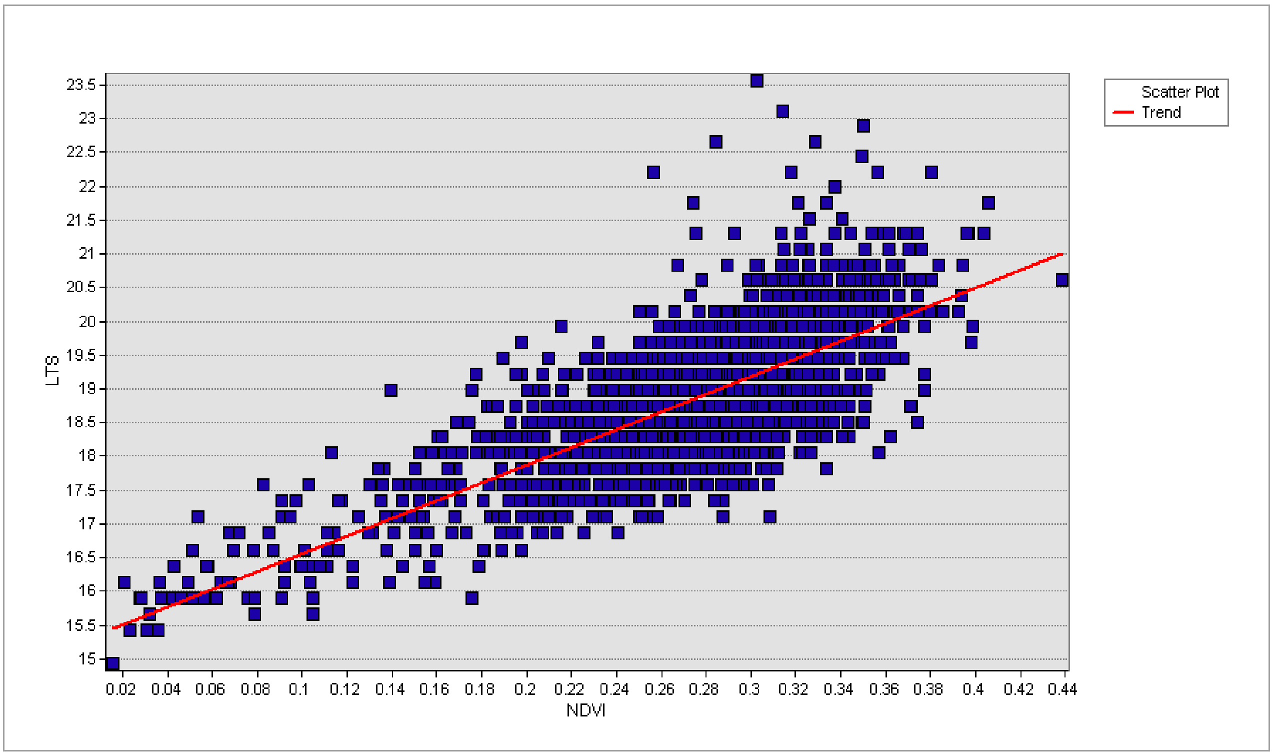

Fig 8: Correlation Chart of NDVI and LST for the Year 2000

Table 9: Correlations between NDVI and LST for the Year 2022

		NDVI	**LST**
NDVI	Pearson Correlation	1	-.751**
	Sig. (2-tailed)		.000
	N	1646	1646
LST	Pearson Correlation	-.751**	1
	Sig. (2-tailed)	.000	
	N	1646	1646
**. Correlation is significant at the 0.01 level (2-tailed).			

The correlation analysis presented in Table 9 shows the relationship between two variables: NDVI (Normalized Difference Vegetation Index) and LST (Land Surface Temperature); the study collected data from 1646 observations. The correlation coefficient ranges from -1 to 1. A positive correlation coefficient indicates a positive relationship between the two variables, a negative correlation coefficient indicates a negative relationship while a correlation coefficient of 0 indicates no relationship between the two variables.

The correlation coefficient between NDVI and LST was -0.751. This indicates a strong negative correlation between the two variables; as the NDVI values increase, the LST values decrease. Conversely, as the LST values increase, the NDVI values decrease. This relationship is statistically significant at the 0.01 level (2-tailed), which means that the probability of obtaining such a strong correlation by chance is less than 1%. This result suggests that there is a strong relationship between vegetation cover and land surface temperature.

The correlation result for the trend observed in the the year 2022 is presented in the chart depicted in figure 9 below, illustrating the interaction between the Normalized Difference Vegetation Index and Land Surface Temperature of Abakaliki LGA during that year.

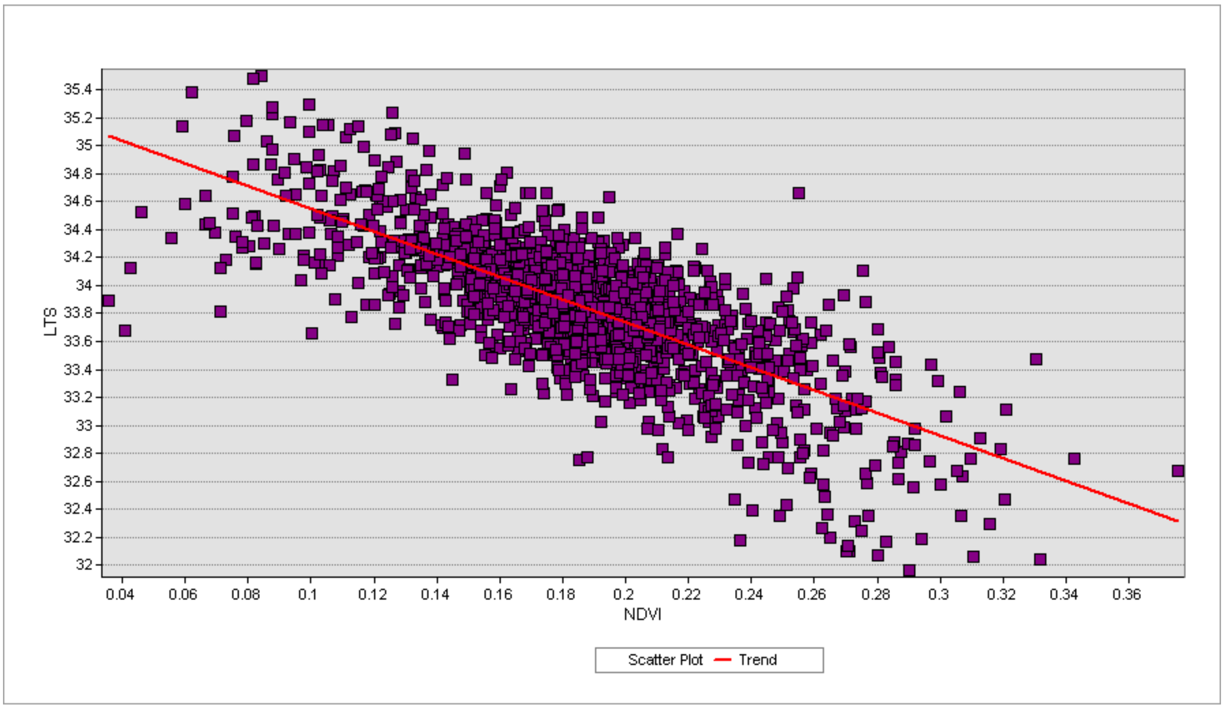

Fig 9: Correlation Chart of NDVI and LST for the Year 2022

DISCUSSION

The findings provide compelling insights into spatiotemporal dynamics of NDVI and LST across Abakaliki LGA from 2000-2022. Regarding temperature trends, results overwhelmingly indicate considerable surface warming has transpired. Between 2000-2022, minimum, maximum and mean LST all increased by >9°C, portraying ubiquitous thermal escalation across all landscape facets. While regional climate fluctuations likely contribute, such accentuated heating exceeds global averages, hinting at anthropic exacerbations from land cover disruptions as populations doubled (National Bureau of Statistics, 2016).

Shifting to NDVI, contrasting patterns emerge between 2000-2022. In 2000, higher values implied preserved natural vegetation dominated, which correlated positively with LST as transpiration fueled local energy budgets, as evidenced by the significant positive correlation between NDVI and LST in 2000 ($r = 0.745$, $p < 0.01$). However, 2022 NDVI declined significantly, particularly within historically forested provinces. Values resembled 2000's bare lands, implying wholesale clearing perhaps to expand agriculture/settlements (National Population Commission, 2006; 2022). Intriguingly, this NDVI crash drove temperatures downward, evident from the strong negative correlation between NDVI and LST in 2022 ($r = -0.751$, $p < 0.01$), departing from 2000 correlations.

Evidently, landscapes underwent profound restructuring, transitioning from carbon-sequestering to carbon-emitting surfaces that now paradoxically suppress instead of elevate temperatures. While local cooling may temporarily benefit some sectors, dismantling of climate-buffering vegetation portends impending vulnerability to escalating global thermal stressors if regeneration efforts falter (Nwafor *et al.*, 2018). Immediate action is needed to curtail unsustainable practices before irreversible degradation transpires.

Shifting focus to scaling dynamics, 2000 showcased community-level heterogeneity in NDVI-LST linkages. However, 2022 demonstrated landscape homogenization, with NDVI suppression universally decoupling from temperatures. Previously, microclimatic diversity owed to granular land use patterning informed by socio-ecological knowledge systems. Yet modernization appeared to obliterate such nuanced mosaics, consolidating surfaces into vast human-dominated monocultures incapable of nurturing resilient local climatic networks (Nwafor, 2006).

Notably, results are consistent with studies linking African agricultural expansion/deforestation to surface cooling and exacerbated drought vulnerability (Alexander *et al.*, 2019). Novel empirical evidence from Abakaliki substantiates such teleconnections, highlighting urgent need for collaborative stakeholder processes to re-diversify production landscapes while restoring disturbed territories. Sustainable intensification approaches show promise if sensitively implemented (Rhodes *et al.*, 2014).

CONCLUSION

This study furnished novel empirical insights into the spatiotemporal inter-linkages between key landscape variables across Abakaliki LGA, Nigeria over recent decades. Findings substantiate the region has undergone rapid and disruptive transformation, transitioning from carbon-absorbing to carbon-releasing surfaces that now dampen temperatures rather than elevate them in accordance with climate dynamics. Left unabated, ongoing degradation portends escalating vulnerability to global warming impacts. However, results also offer promise that sustainable intensification approaches could re-couple local anthropogenic and climatic systems for mutual benefit if sensitively implemented through collaborative stakeholder processes.

Moving forward, integrated monitoring should continue evaluating restoration successes while adaptation strategies evolve hand in hand with environmental and socioeconomic change. Drawing from indigenous ecological knowledge alongside innovative alternatives presents opportunity to steward Abakaliki LGA along development trajectories supporting harmonious human-environment relations. With adaptive co-management, the region's resilience may be bolstered to thrive within the new climatic reality. Overall, findings carry broader relevance for understanding anthropic modifications to landscape energetics across ethnically diverse rural-urbanizing contexts. Continued interdisciplinary research offers potential to optimize resource use, livelihoods and climate risk reduction across similar settings worldwide.

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