FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 9 No. 9, September, 2025, pp 257 – 266
DOI: https://doi.org/10.33003/fjs-2025-0909-4035

MULTI-CRITERIA EVALUATION FOR OPTIMAL ROUTE DETERMINATION BETWEEN BOSSO AND GIDAN KWANO CAMPUSES OF THE FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGER STATE NIGERIA

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ABSTRACT

Sustainable transport planning requires optimized road networks that minimize travel distance, reduce construction costs, and mitigate environmental degradation. Route selection, however, is inherently complex due to the heterogeneous interaction of biophysical, socio-economic, and infrastructural variables. This study employed an integrated geospatial approach, combining Remote Sensing, Geographic Information Systems (GIS), and Least Cost Path Analysis (LCPA), to delineate the optimal route between Bosso and Gidan Kwano campuses of the Federal University of Technology, Minna, Niger State, Nigeria. The Analytical Hierarchy Process (AHP) was implemented to derive criterion weights for multi-criteria decision-making, incorporating land use/land cover, slope gradient, settlement distribution, and hydrological constraints. The resultant least-cost model identified an alternative route that reduced travel distance from 15 km to approximately 13 km, translating into an estimated travel time saving of 12 minutes. Additionally, the optimized alignment circumvented built-up areas, water bodies, and rugged terrain, thereby lowering potential construction and long-term maintenance expenditures. These findings demonstrate the efficacy of coupling AHP with LCPA in optimizing linear infrastructure planning, particularly in data-scarce environments. The study contributes to sustainable transport discourse by evidencing how geospatial decision-support tools enhance route optimization, support cost-effective infrastructure development, and minimize ecological footprints. This methodological framework offers replicability for road network planning in comparable contexts, reinforcing its utility for advancing sustainable mobility and resilient infrastructure systems.

Keywords: GIS, Least Cost Path Analysis (LCPA), Multi-criteria Analysis (MCA), Route, Travel Time

INTRODUCTION

Transportation systems are fundamental to socio-economic development because they provide the framework for the mobility of people, goods, and services across space (Kara and Usul, 2012). Efficient road transportation is central to urban and regional development, as it influences accessibility, land use, and the integration of economic activities. Road networks, in particular, serve as the most widely used mode of transportation in developing countries, linking rural and urban centers, facilitating trade, and improving access to social services such as education and healthcare (Olubajo, 2025). As urbanization and population density increase, the demand for efficient transport corridors also rises, making the determination of optimal routes a vital concern for planners, policymakers, and researchers. In transportation planning, the concept of route optimization involves the selection of the most efficient, reliable, and sustainable path that minimizes cost, travel time, and environmental impact (Delavar and Naghibi, 2003). Several methods have been employed in this regard, but multi-criteria evaluation (MCE) approaches have gained prominence because they integrate multiple spatial, social, environmental, and economic factors into decision-making (Heydari, *et al.,* 2025). Among these approaches, the Analytical Hierarchy Process (AHP) and Least Cost Path Analysis (LCPA) are widely recognized. AHP provides a flexible decision-support framework that assigns weights to decision criteria based on their relative importance, thereby enabling a structured prioritization of factors such as slope, land use, road condition, and traffic density (Kara and Usul, 2012). LCPA, on the other hand, is a GIS-based tool that calculates the least costly or most efficient path across a spatial surface by integrating weighted factors into a cost raster (Effat and Hassan, 2013). These methods, when combined, enable researchers to evaluate alternative routes holistically and identify the most optimal corridor for transportation development.

The integration of Geographic Information Systems (GIS) and remote sensing (RS) has revolutionized transportation planning by providing accurate and up-to-date geospatial data for route analysis (Dai *et al.*, 2019). GIS facilitates the integration of multiple datasets such as elevation models, land cover maps, road networks, and demographic distributions into a single analytical environment where spatial interactions can be modelled and optimized. Remote sensing complements this process by supplying high-resolution imagery that supports land use classification and environmental monitoring. Together, these technologies enhance decision-making in route determination by enabling objective and data-driven analyses. Beyond cost and efficiency, modern transportation planning also emphasizes environmental and risk considerations (Sobczuk *et al*., 2024). Road transport projects are often associated with ecological disruption, land degradation, and social displacement; hence, environmental considerations must be integrated into route selection models (Effat and Hassan, 2013; Nguyen *et al.,* 2024). Additionally, the increasing frequency of climate-related hazards highlights the need for resilience-based planning. The incorporating risk assessment and probabilistic modelling, transportation planners can ensure that selected routes remain robust and adaptable under uncertain future conditions (Zheng et al., 2021; Welle *et al*., 2020). This aligns with global best practices in sustainable infrastructure development, where efficiency is balanced with resilience and environmental stewardship.

In Nigeria, road transportation remains the most dominant mode of mobility, accounting for over 80% of goods and passenger traffic (Federal Ministry of Works and Housing, 2020). However, road networks in many parts of the country are faced with challenges such as poor maintenance, traffic congestion, seasonal flooding, and limited alternative routes. These problems are particularly acute in urbanizing areas and institutional corridors where mobility demand is high. The Federal University of Technology, Minna (FUT Minna), which operates two campuses Bosso and Gidan Kwano relies heavily on the road linking these sites for academic, administrative, and social activities. The Bosso campus, located within Minna metropolis, hosts a significant student population, while the Gidan Kwano campus, situated along the Minna Bida Road, serves as the main campus of the university.

The road linking these two campuses is not only critical for daily commuting of students and staff but also for the movement of goods and services essential for the smooth running of the university. However, the corridor is frequently characterized by traffic congestion, poor pavement conditions, long travel time, and increased vehicular accidents, especially during peak hours. These issues negatively affect mobility, increase transportation costs, and reduce the overall efficiency of the university's operations. Seasonal weather variations further exacerbate these problems, as heavy rainfall often leads to road deterioration and safety risks (Touloumidis *et al.,* 2025). Despite these challenges, limited research has applied GIS-based multi-criteria evaluation methods to propose and analyze alternative routes between the two campuses. Applying MCE through AHP and LCPA in a GIS framework presents an opportunity to address these gaps. Such an approach would enable a holistic evaluation of multiple criteria including slope, land use, road condition, traffic density, and environmental constraints to determine the most suitable and sustainable route between Bosso and Gidan Kwano. Furthermore, the use of spatial analysis allows for the comparison between the existing road and proposed alternatives, thereby providing evidence-based recommendations for infrastructural planning. By leveraging these methods, FUT Minna can improve campus connectivity, reduce travel inefficiencies, and enhance safety and environmental sustainability.

Therefore, the background of this study underscores the importance of adopting multi-criteria geospatial evaluation for route optimization. With the increasing demand for sustainable transport planning in Nigeria, this study not only addresses a local infrastructural challenge but also contributes to the broader discourse on applying GIS and remote sensing in solving transportation problems in developing countries.

Study Area

The study area is Bosso Town-Minna in Bosso Local Government Area of Niger State, Nigeria. Bosso town is where the Federal University of Technology, Minna Bosso campus is situated. The cultural diversity in Niger State is evident, with Gbagyi and Nupe being the major dominant groups in Bosso-Minna. Positioned at Latitude 6° 30'E and Longitude 9° 40'N. The temperature in Bosso-Minna seldom drops below 22°C, reaching peaks of 40°C in February/March and 30°C in November/December. The average temperature during the wet season is approximately 29°C (Musa *et al.,* 2011; Mohammed and Chukwuma, 2011).

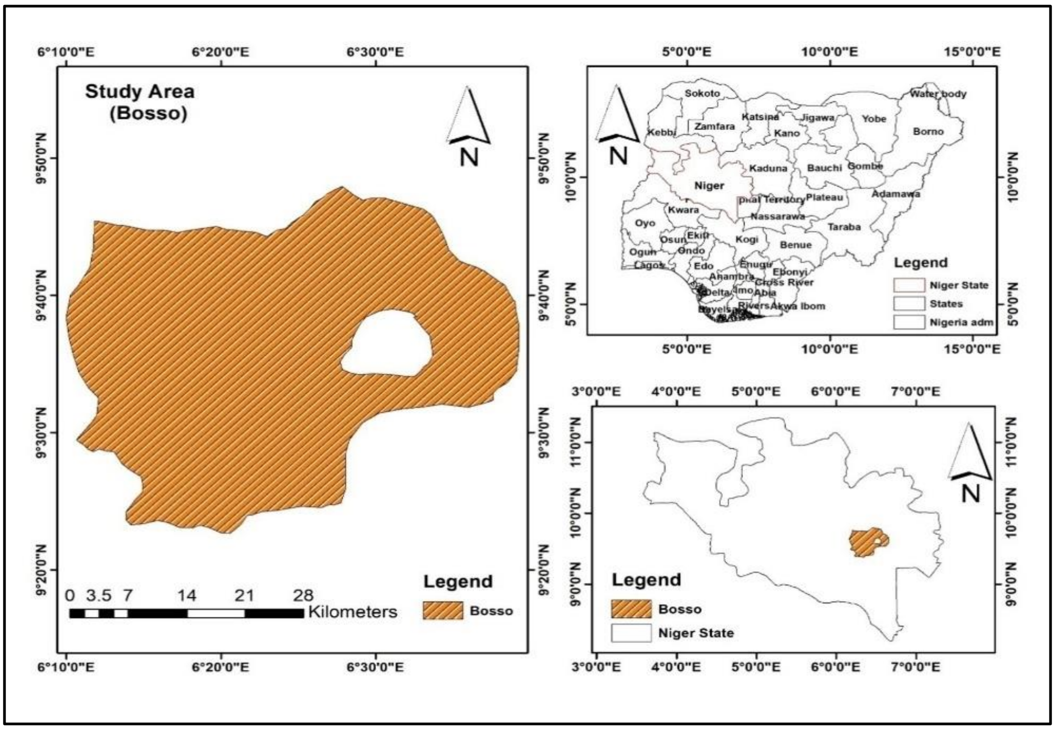


Figure 1: Study Area Map, Sourced from Google and Developed in the Lab

MATERIALS AND METHODS

Methodology

This study adopted Remote sensing and Geographic Information Systems- GIS to find the optimum route between Bosso and Gidan Kwano campus in Minna, Niger State, Nigeria. The decision to use these tools is because they are useful decision-making tools for solving problems related to geographic and environmental planning. The process of finding the optimal route is presented in a flow chart in figure 1 indicating the steps followed to obtain the least-cost path based on spatial analysis functions of Arc GIS 8.0.

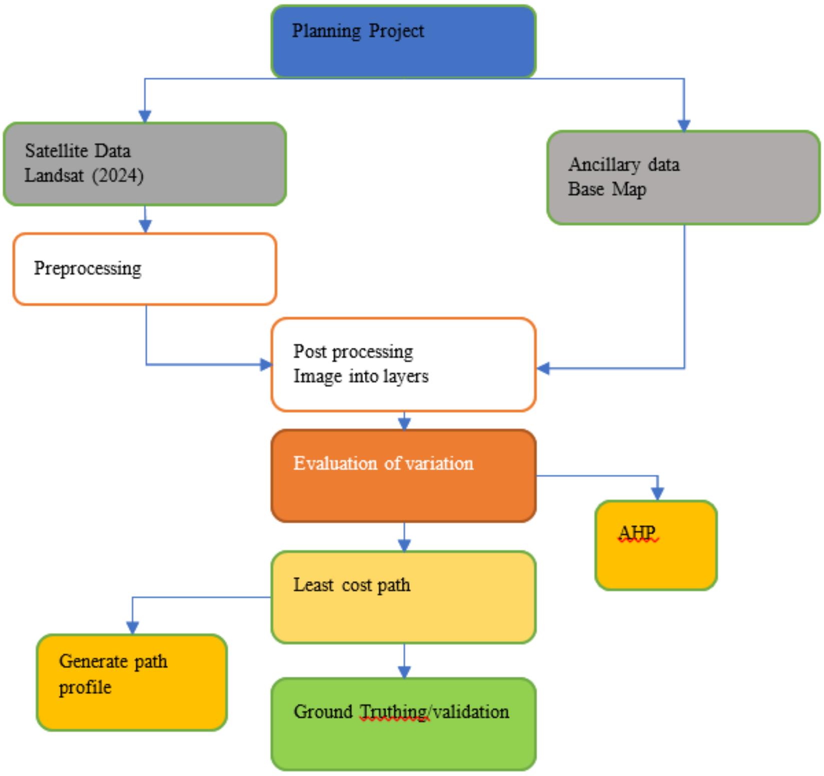


Figure 2: Conceptual design

Data collection and Sources

A satellite multispectral image data was downloaded from the United State geological survey. The spatial resolution of the image is 30m. Table 1. summarized the datasets and their characteristics used for the research.

Table 1: Data and Data Source

S/N	Data	Resolution	Year	Source	Relevance
1	Administrative boundary Shape file	1:1,300.000		OSGOF	For spatial boundary
2	TAN DEM X	12m x 12m	2024	Earth explorer USGS	Terrain analysis, drainage density and for overlay analysis
3	Land sat 8 OLI	30m x 30m	2024	Earth explorer USGS	For Land use land cover
4	Road Network			Open street map	For Euclidean distance

The satellite image data underwent atmospheric and geometric correction aimed at improving the clarity of the image data and to remove the effects of terrain displacement. Geometric correction was carried on the image to restore displacement while atmospheric correction was aimed at correcting the image distortion due to cloud cover and other form of noise. The elevation map of the study area would be raster clip from digital elevation model (DEM) with spatial resolution of 12m x 12m using Tan DEM X and the surface analysis were carried out on the DEM to generate the slope in ArcGIS environment. The Drainage Density was measurement by summing the total channel length per unit area. It is generally expressed in term of kilometer of channel per km^2, it is calculated using the equation 1 below.

$$Dd = {\sum li}/{A} \qquad (1)$$

Whereas; Dd = Drainage density, $\sum li$ = Sum of stream length and A= Total area

The process involves pre-processing of the DEM using hydrology algorithms i.e. fill, flow direction, flow accumulation to extract the stream network from the pixels and raster to feature function were used to convert the raster to polyline. However, grid index feature on cartographic tool were used to create map units on the spatial boundary, and the gridded boundary were intersected with the stream network and dissolve by "Page Number" to enable the calculation of equation (1). Line density was also utilized to estimate the density surface of the area and was classified into five classes using natural break method. The Euclidean Distance was modelled by importing the road network in the Arcgis environment then the Selected Euclidean distance module on the spatial analyst tool Selected the road network as input layer and the 500m maximum distance was inputted and Planar was selected as the distance method. Finally, the environment was set to produce the output within the defined boundary

Land Use Land Cover

The digital or satellite image pre-processing is the process of rectifying distortion in the satellite imagery caused by sensor, noise, sun angle and atmosphere. The essence of these pre-processing is to correct errors in the pixels (Revanna *et al.*, 2017). The images were processed both, radio-metrically, spatial filtered to suppress the errors arising from either the sensor, anomalies, sun angle and atmosphere effect. The pre-processing process is aimed at reducing the visual complexity of the images and also to improve the visual quality and recognition of features for the purpose of easy image interpretation (Wang *et al*., 2023). The Image classification is the overall objective where the image features are automatically categorizing all pixels in an image into land cover classes or themes. It is the process of grouping or categorizing different image classes relatively to their pixel characteristics. The categorized data are then used to produce the thematic map present in the scene. supervised classification approach was employed using an interactive maximum likelihood algorithm as the classifier. Considering the visual and digital interpretation of satellite images, about four (4) different land use/land cover types were classified. The land cover and land use classes were categorized into agricultural land, bare soil, urban slum and vegetation, then vectorization was done to convert raster to polygon for geometry calculation.

Accuracy Assessment

Accuracy assessment is performed by comparing the classification results by remote sensing analysis to a reference map based on a different information source (Sophia and Ndambuki, 2017). The user's accuracy is computed using the number of correctly classified pixels to the total number of pixels assigned to a category. It takes errors of the commission into account by telling the user that, for all areas identified as group X, a certain percentage are correct. The *producer's accuracy* informs the image analyst of the number of pixels correctly classified in a category as a percentage of the total number of pixels belonging to that category in the image. Producer's accuracy measures errors of omission. After that, the confusion matrix was created, and overall accuracy and Kappa values were evaluated. Below given is the formula to calculate Kappa coefficient (K; Equation 2),

$$K = \frac{[N \sum_{i=1}^{r} X_{ij} - \sum_{i=1}^{r}(X_i * X_j)]}{N^2 - \sum_{i=1}^{r}(X_i * X_j)} \quad (2)$$

Where N is the total number of same point and X is the element in row i and column j.

Criteria Weights

One of the semi-quantitative methods that is used to determine least cost path is named Analytical Hierarchical Process (AHP). AHP may be a structured tool that helps to process difficult decisions supported by mathematics and psychology (Cho *et al*. 2015; Nguyen *et al*. 2015; Saaty 2000). In this study, a pairwise comparison matrix was conducted using excel to supply weights for every parameter or criteria considering Saaty's ranking scale (Luu *et al*. 2018; Saaty 2008). Before a pairwise comparison matrix is performed, scale is extremely important. For this, Saaty (2008) developed a scale, which ranges from 1 to 9. One indicates equal importance of parameters whereas nine indicates extreme importance of the factor or the parameters (Malczewski 1999; Saaty 1980). In this study, a 6×6-comparison matrix was performed by assigning a value from the range of 1-9 by comparing the parameter within the row to the parameter within the column (Table 2).

Table 2: Scale for Pairwise Comparison

Scale	Degree of preference
1	Equal importance
3	Moderate importance of one factor over another
5	Strong or essential importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Values for inverse comparison

Source: Saaty, 2008

After completed comparison among all possible criteria or parameters, normalization was performed by dividing the cell by the column total (Saaty, 1980). Normalization of the matrix is extremely important to work out the standards weight. The weight of every criterion or parameter is extremely important to measure the importance of every parameter for vulnerability analysis or evaluation. This was calculated using AHP calculators during a pairwise comparison matrix (Saaty 2000). Principal Component Analysis (PCA) method was introduced to construct weighting factors for individual criterion by applying a ranking scale, which was estimated and assessed by a random consistency index (Singha *et al*., 2016). The average RI varied as per number of factors or for different matrix orders. The Consistency Ratio (CR) was defined for validation (Equation (1), which was defined as the ratio of the Consistency Index (CI) and the RI (Equations (3) and (4) Luu, C, *et al*, 2013).

$$CR = \frac{CI}{RI} \quad (3)$$

$$CL = (\lambda_{max} - n)^{n-1} \quad (4)$$

Where:

CR: Consistency ratio, CI: Consistency index, λ: Average value of consistency vector n: Number of criteria, RI: Random CI randomly generated PCM, which was accessed from the table of random inconsistency indices (Drobne *et al*., 2009). To validate the criteria weights, the final CR value should be below (0.10) value indicates inconsistent judgments, requiring re-estimation of the weights

$$S = \sum_i W_i X_j C_j \quad (5)$$

Where: S: Suitability composite score. W_i: Weight given to the factor I, X_j : estimated score of the factor I, C_j: Constraint j score (0 to1).

Four (4) criteria would be considered to be suitable for least cost path. The primary criteria would be slope, road network, drainage density and land use land cover. All criteria were well defined and digitally processed in the form of raster datasets with same pixel size. Their weights were estimated using Analytical Hierarchical Process (AHP). All the criteria influencing the least cost path suitability in study area were evaluated and their ranking and rating criteria as shown in Table 3 below while Table 4 shows the weights of the criteria that influence Least Cost Path Suitability

Table 3: Ranking and Rating of the Criterion

S/N	Factor	Classification scheme	Units	Vulnerability Class	Rank & Number rating
				Very Low	1
				Low	2
1	Road Network	Vector	M	Moderate	3
				High	4
				Very High	5
				Very High	5
				High	4
2	Slope	Raster	Degree	Moderate	3
				Low	2
				Very Low	1
				Very Low	1
				Low	2
3	Drainage density	Vector	Km/km^2	Moderate	3
				High	4
				Very High	5
4	Land use land cover	Raster	Class	Very Low	1

Table 4: Weight of the Criteria that Influence Least Cost Path Suitability

Criterion	Slope	Distance to road	Drainage density	LULC	Weight age (%)
Slope	1	0.33	0.11	0.11	52.05
Distance to road	3	1	0.2	0.25	33.04
Drainage density	9	5	1	0.33	10.67
LULC	9	9	3	1	4.22
Total					**100**

Weight Sum Overlay

The weight sum overlay is the total sum of multi raster by their assigned weight generated from pair wise comparison matrix to produce a single raster layer. The process was done using weighted sum analysis function in the spatial analyst tool. However, all the raster layer was imported, and weight were assigned to the layers respectively. The generation of the optimal route from Gidan Kwano to Bosso using least cost path analysis was achieved by Importing the origin point as the source layer and the suitability as the cost distance. Also imported the origin point as source layer and cost distance as the cost raster to define the backlink raster. Thirdly, the destination data, cost distance and backlink were inputted to define the least cost path. Furthermore, the path was converted to polyline to determine the distance and stack profile was used to estimate the path profile.

Finally, tessellation module was used to define the cost path in 500m chainage for ground truthing. Table 5 depicts the weight consistent matrix of the factors considers

Table 5: Weight Consistent Pairwise Matrix $\left(aij = {}^{w_i}/_{w_j}\right)$

Criteria	Slope	D_R	Dd	LULC
Slope	1.0000	1.5747	4.8774	12.3291
D_R	0.6349	1.0000	3.0966	7.8286
Dd	0.2049	0.3228	1.0000	2.5258
LULC	0.0811	0.1277	0.3960	1.0000

Where: D_R is distance to road, Dd; distance density, LULCC; land used land cover change

The Slope factor dominates, having a relative weight of 52%, contributing more than half the decision power. Its pairwise ratios show it strongly outweighs all other factors, especially LULC (12× more important). Distance to Road is second: At 33%, it is the next strongest factor, more than 3× stronger than drainage density and nearly 8× stronger than LULC. Drainage Density is moderate: At 10.7%, it is weaker than slope and distance, but still more than twice as important as LULC. LULC is least important: At only 4.2%, it is consistently the lowest priority in comparisons.

RESULTS AND DISCUSSION

Creation of Criteria Layers

Slope

As presented in Figure 3A, the slope gradient was symbolized into five colour classes depicting dark green and light green which varies from ($0 – 6.19^{O}$) are categorized as the flat ground, whereas the yellow colour which varies from ($6.19^{O} – 9.44^{O}$) is considered as slight slope. The orange and red colour which denotes ($9.45^{O} – 39.5^{O}$) is grouped as the incline and steep slope. However, the reclassified slope as shown in Figure 3B demonstrates the class of the suitability probability as seen in Table 3. The area with low slope gradient occurs to be suitable for the least cost path analysis.

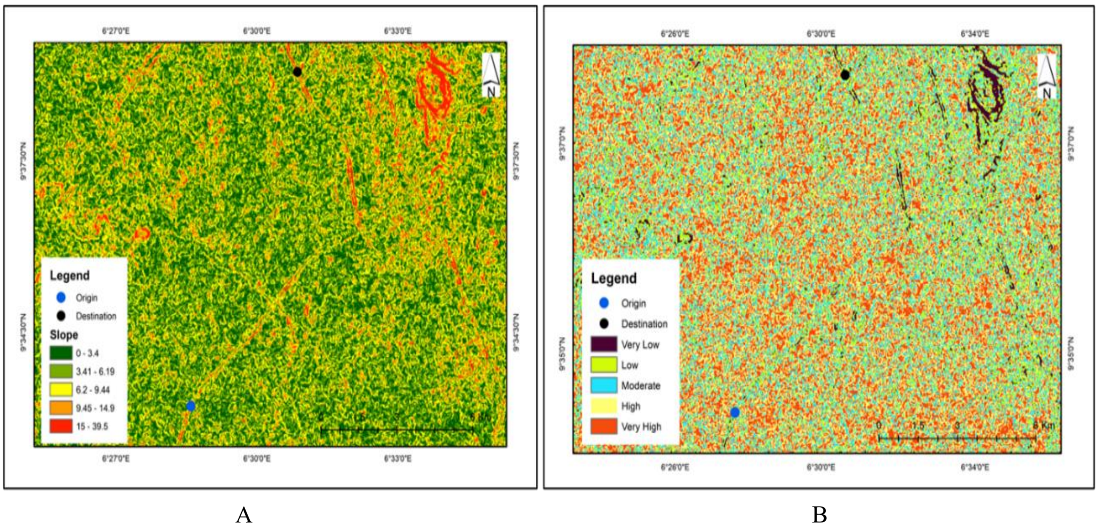


Figure 3(A, B): Depicts the Slope and the Reclassified Slope of the Study Area

Distance to Road Network

As shown in Figure 4A, the distance to road ranges from 0 to 6050m, which is categorized into five colours, the electron gold colour ranges from 0 to 1210m, orange colour varies from 1220m to 2420m, dark pink also ranges from 2348 – 3630m, ginger pink denotes 3640 – 4840m and blue colour depict the value of 4850m – 6050m. However, the reclassified layer as shown in Figure 4B was also categorized according to the suitability probability as seen in Table 3. It is concluded that the closer the existing, the less the cost of operation.

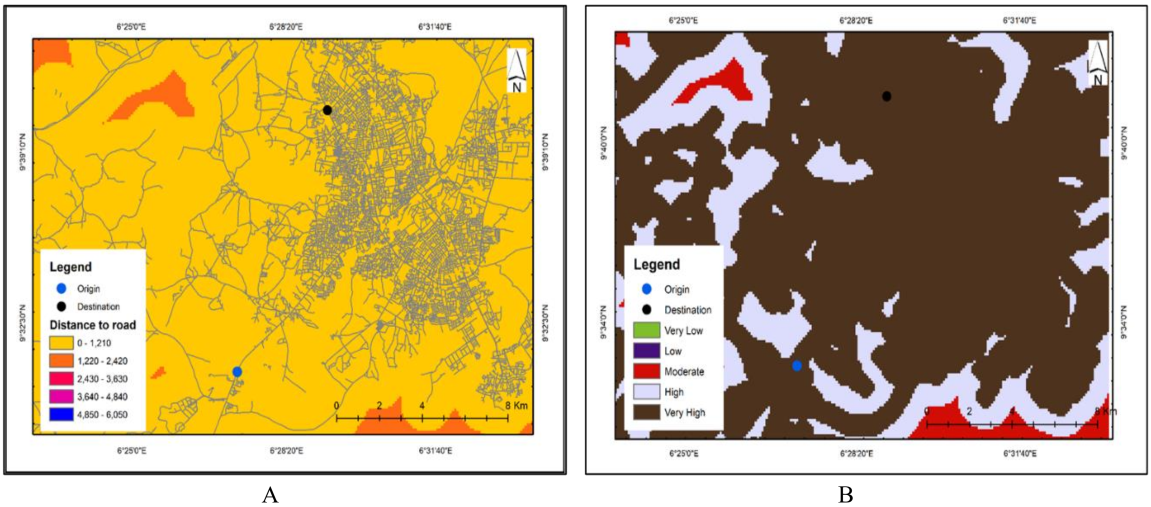
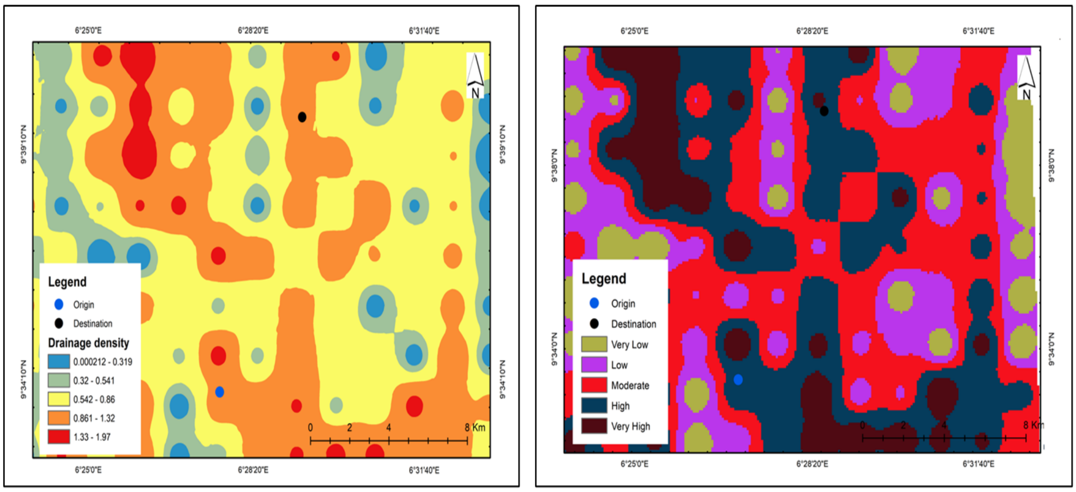


Figure 4(A, B): Depicts Distance to Road Network and Reclassified Distance to Road Network across the Study Area

Drainage Density

As provided in Figure 5A, it is evident that the drainage density with high value denotes 0.861 to 1.62, 1.33 to 1.97km/km^2 consecutively, this implies that the areas experience high water infiltration which could be suitability for the least cost path, where the 0.000319 to 0.86km/km^2 are categorized as areas with low infiltration region which could increase the construction cost operation such constructing bridges, culvert and drainage systems.



A B

Figure 5(A, B): Depicts Drainage Density and the Reclassified Drainage Density of the Bosso LGA

Land Use Land Cover

Land use land cover is an essential factor to consider during least cost path analysis, the result shows that blue colour depict water bodies which is the Talba Dam situated at Chanchaga Local Government, the red colour denotes the urban area (Minna metropolis), Light brown represents the bare surface, light green demonstrates the agricultural land and the dark green denote the natural vegetation as seen in Figure 6A. However, the reclassified layer was assigned according to the suitability factor, the bare surface occurs to the best factor, followed by agricultural and vegetation due to their low-cost operation and the built-up area and water are considered as low suitable factors because of environment impact, cost of compensation and constructing overhead bridges.

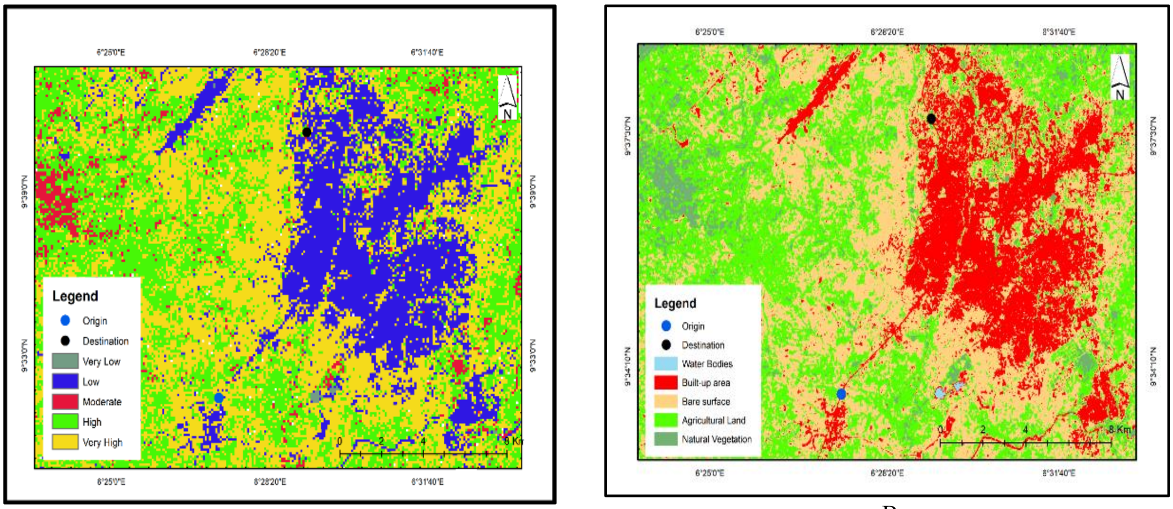


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Figure 6(A, B): Land Used Land Cover Map and Reclassified Land Use Land Cover Map of Bosso LGA

Discussion

Generation of the Suitability Layer Using Weighted Overlay Analysis

The least cost path suitability map was derived by the weighted overlay of the suitability factors (thematic layers) in ArcGIS 8.0 environment using the weighted overlay in the spatial analyst tool. The final land suitability map was produced by the AHP reclassification technique from four (4) criteria weightage, the result shows that highly suitable and suitable zones occupy the area with 92.65km^2, 55.22km^2, marginally suitable with 77.00km^2, whereas currently not suitable and permanently not suitable zone covers with 59.91km^2 and 28.35km^2 of the total area of the study area.

Table 5: Suitability Class

S/N	Suitability class	Area (km^2)	%
1	Not suitable	28.358	9.056
2	Low	59.907	19.13
3	Marginally	77.009	24.592
4	Suitable	92.652	29.588
5	Highly suitable	55.222	17.634

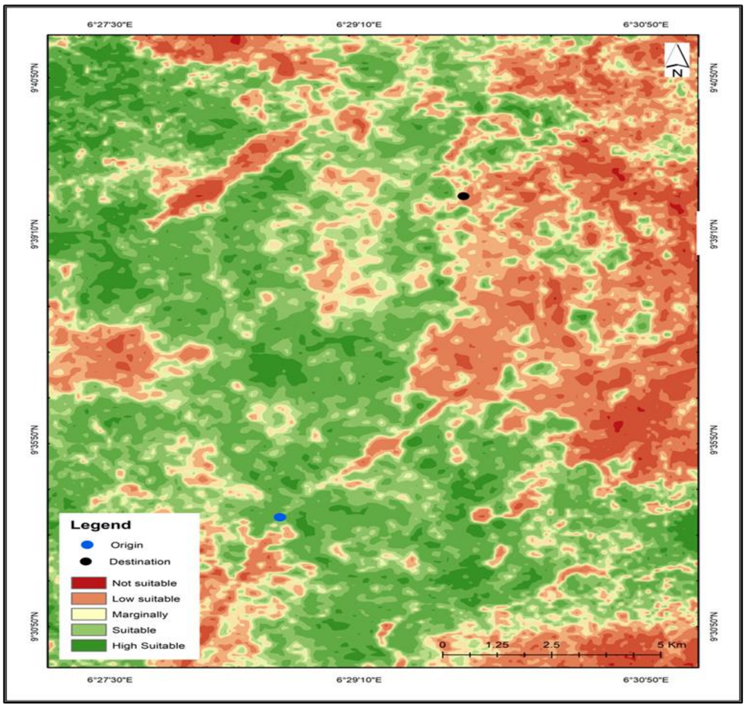

Figure 7: Land Suitability for Least Cost Path

Generation of the Optimal Route from Gidan Kwano to Bosso Using Least Cost Path Analysis

Figure 8 shows the suitable optimal route from the origin to the destination from the weighted overlay map that resulted. It could be designed to select the best highway route by carefully designing the route to travel through the colored areas marked by a high suitable while avoiding the less suitable.

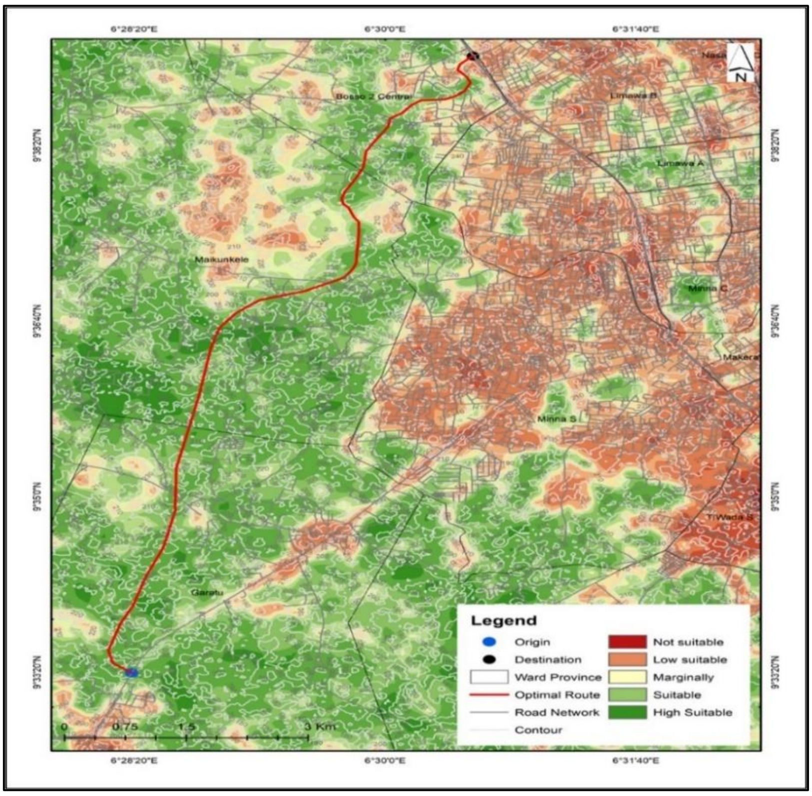

Figure 8: Optimal Route from Gidan Kwano to Bosso Community

Findings between Existing Road and Optimal Route

After determining the alternative routes, the best highway route can be chosen by considering a set of new multiple criteria, as the multicriteria decision helps in the selection of an alternative from a set of options identified by criteria values. Considering corridors such as, time of travel, rivers and stream crossing route direction among other factors, a comparison is drawn in Table 6 below

Table 6: Comparison of Existing Road and Optimal Route

Factors	Existing road	Optimal route
Travel time	38 minutes	26 minutes
Length of route	15km	13km
Highway crossing	2	1
Rail line crossing	1	1
River and stream crossing	3	1
Route direction	East-ward direction	West-ward direction
Number of bridges/ culverts	4	2

From the comparison shown in Table 6, it could be concluded that the optimal route offers several advantages over the existing route. For instance, since the optimal route is 2km shorter than the existing route and the travel time is reduced by 12 minutes, it is safe to say road user can save money on fuel and operating cost. Also, the west-ward direction of the optimal route avoids the built-up areas and therefore tackles the challenge of the complexity of the pattern of settlements and terrain associated with route selection.

Summary

The Analytical Hierarchy Process (AHP) forced pairwise comparison matrix derived from the documented weights indicates that slope (52.05%) is the most influential factor in least-cost path determination between the Bosso and Gidan Kwano campuses of FUT Minna. The forced matrix ensures perfect consistency by setting each entry as the ratio of criterion weights, eliminating inconsistencies found in the original pairwise judgments. This results in slope being approximately 1.6 times more important than distance to road, nearly 5 times more important than drainage density, and about 12 times more important than land use/land cover (LULC). These ratios highlight slope's critical role in route optimization, consistent with studies emphasizing terrain's impact on accessibility and transportation planning (Saaty, 1980; Malczewski, 1999). The second most significant factor is distance to road (33.04%), which is about 3 times more important than drainage density and nearly 8 times more important than LULC. This reflects the necessity of minimizing travel costs and maximizing accessibility in route selection. Accessibility analysis frequently prioritizes road networks because they directly influence connectivity, travel efficiency, and cost of transport (Drobne and Lisec, 2009). Thus, its relatively high weight aligns with the principle that route determination is not only a matter of terrain feasibility but also of proximity to established infrastructure.

Drainage density (10.67%) and LULC (4.22%) received relatively lower weights, indicating their secondary influence in decision-making. Drainage density is still about 2.5 times more important than LULC, confirming its role in evaluating flood-prone or erosion-sensitive areas (Ouma & Tateishi, 2014). On the other hand, the very low weight of LULC suggests that, in this case study, land cover classes exert minimal constraints on route selection compared to physical terrain and road accessibility. The forced AHP matrix, therefore, not only validates the documented weights but also quantifies the comparative strength of each factor, producing a perfectly consistent structure for decision support in multi-criteria spatial analysis.

CONCLUSION

This study analyzed routes between two locations and utilized remote sensing, Geographic Information System (GIS) and Least Cost Path Analysis (LCPA) to determine the optimal route between Bosso and Gidan Kwano campuses of the Federal University of Technology Minna, Niger State, Nigeria. The least-cost path analysis function is a useful approach in finding the best route (path) for new hillside development, as it provides rapid and important applications in finding all kinds of linear features for the planning of water supply lines, sewer pipes, gas pipes and electrical cables. It is a powerful GIS tools to integrate user information and replaces the conventional method of path planning. It can minimize costs (Delavar and Naghibi, 2003) and project time (Iqbal *et al*., 2006). Environmental constraints are involved in hillside development such as forest clearing, landscape and natural water bodies. This requires a sustainable approach to find a route in the development of the hillside. The method which is based on LCPA has been applied in considering the environmental and economic aspects of the road with integration of GIS and MCDA approach. In fact, LCPA is successfully implemented from sources of a predetermined point and the end goal. It could be concluded that LCPA is a cost-effective application of GIS-based intelligent approach in planning for the route that leads to a method, sustainable planning faster and cheaper (Iqbal *et al*., 2006).

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