



Structural and geophysical constraint mapping for hydrocarbon resources within parts of the Bida Basin, Central Nigeria

Serah Japhet Habu¹ · Olabisi Adeleye Adekeye¹ · Andongma Wanduku Tende²

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Abstract

Remote sensing (RS) and geographic information systems (GIS) play an important role in the exploration of geological resources and are most effective when used during reconnaissance scale surveys. In Nigerian frontier basins, the use of GIS-based spatial predictive mapping and regional scale evaluation of geological structures is regarded as the best tools for downscaling exploration targets. The Fry analysis and distance correlation analysis were used to infer structural control over hydrocarbon resources, whereas the prediction area plot analysis assessed the spatial relationship between the evidential and target data. A hydrocarbon prospectivity map for the Bida Basin was generated using a multi-criteria weighted sum model, and the hydrocarbon predictive model was discretized and classified using a multi-fractal analytical approach. ROC/AUC analysis was used to evaluate and assess the reliability of the hydrocarbon predictive model. According to evidence from Fry and distance correlation analysis, hydrocarbon manifestations is primarily controlled by the WNW-ESE tectonic trend. Based on the prediction area plot analysis, there is a significant correlation between hydrocarbon occurrences and spatial data on magnetic (0.67), gravity (0.68), and distances to the WNW-ESE lineaments (0.81). The weighted sum model was used to integrate spatial data, which revealed significant potential for hydrocarbon resources in the study location's south-central and north-eastern regions. The hydrocarbon predictive model was discretized into four classes (very low, low, high and very high) using multi-fractal analysis, with percentile extents of 25.88%, 42.43%, 21.46%, and 10.23%, respectively. The ROC/AUC revealed an accuracy level of more than 80%. The reliable identification of exploration targets, demonstrated by a high level of accuracy, suggests that this approach could be ideal for supplementing exploration expeditions in the Bida basins and other sedimentary basins throughout Nigeria.

Keywords Bida Basin · Hydrocarbons · Multi-criteria · Fry analysis · Spatial prediction

Introduction

Geological exploration of hydrocarbon resources is regarded as an efficient but highly complex process that includes everything from identifying an exploration site to discovering it, as well as reserve estimation and production plant construction (McLay et al. 2003). The primary goals of designing exploratory surveys are to successfully discover economic deposits of hydrocarbon

occurrences using the most efficient but cost-effective approach. These methods are used systematically to reveal the most fundamental information about the surface and subsurface geological conditions (Wei and Qinyan 2010). To be completed successfully, this task necessitates the use of petrophysical, structural, geophysical, geochemical, and GIS techniques. The combination of these techniques is thought to be invaluable in identifying the best signatures indicating the locations of source, reservoir, and cap rocks (oil traps). Implementing these techniques could aid in identifying prospective zones and accelerate the discovery of potential hydrocarbon occurrences. On a regional scale, the use of RS and GIS provides a sustainable approach to fine-mapping hydrocarbon resources (Amiri et al. 2014; Amiri et al. 2015; Garain et al. 2021). Over the years, RS and GIS techniques have been successfully applied to the mapping of numerous mineral resources, groundwater occurrences, and geothermal energy resources (Atmaja

Responsible Editor: Biswajeet Pradhan

✉ Andongma Wanduku Tende
andongmatende@gmail.com

¹ Department of Geology and Mineral Sciences, University of Ilorin, Ilorin, Nigeria

² Department of Geology, Kano University of Science and Technology, Wudil, Nigeria

et al. 2019; González and Rodríguez-Gonzálvez 2019). For example, orogenic gold mineralization has been investigated in northern Nigeria using both spatial predictive mapping and satellite image processing (Andongma et al. 2020; Tende et al. 2021a), while GIS structural analysis has been used to explore groundwater in parts of southern Nigeria (Akinwumiju et al. 2016). Furthermore, bivariate statistical analysis has been used successfully to map geothermal energy resources within parts of the middle Benue Trough (Tende et al. 2021b). RS and GIS technologies are regarded to be the most fundamental tools for rapid decisions on hydrocarbon resource prospecting (Liu et al. 2001). Most studies on RS applications in hydrocarbon mapping are based on the intrinsic processing of multispectral and hyperspectral images to identify hydrocarbon micro-seepages, their structural features, and the overlying stratigraphic formations (Garain et al. 2021; Sabins 1998; Segal 1989). The execution of GIS technology has facilitated the development of hydrocarbon prediction maps through the spatial integration of diverse data, combined using knowledge-driven or data-driven approaches. The data-driven technology in hydrocarbon prospectivity mapping is based on the availability of evidential data such as oil seeps or known occurrences of oil wells (Amiri et al. 2014; Amiri et al. 2015; Ouko et al. 2018), while the knowledge-driven approaches are largely subjective but highly applicable in scenarios with little or no evidential information on hydrocarbon resource occurrences (Hamzeh and Karimipour 2020; Sheng et al. 2020).

Despite their potential benefits in the geological exploration of natural resources, RS and GIS technology applied to hydrocarbon investigations are widely underutilized in most developing countries, including Nigeria. Existing research on regional exploration within Nigeria's frontier and oil-producing basins has relied on datasets from aeromagnetic, radiometric, and gravity sensors (Akinsete et al. 2020; Kamureyina 2019; Mbah et al. 2017). Emujakporue et al. (2018) for example, used aeromagnetic data to investigate the tectonic attributes and their relationship to hydrocarbon occurrences within the Sokoto Basin, whereas Aderoju et al. (2016) applied a magnetic exploratory analysis for hydrocarbon exploration over the Chad basin. However, satellite image processing for hydrocarbon exploration has relied on a thorough examination of surface temperature patterns, lineaments, and tectonic characteristics (Adejato et al. 2018; Emetere 2017).

The declining oil reserves in the Niger Delta basin have resulted in a significant shift in exploration expeditions to other sedimentary basins as a means of sustaining the future economy. In recent years, various exploration activities have been launched in most frontier basins, including the Bida Basin, Sokoto Basin, Borno Basin, and Benue Trough.

Exploration in these basins has been generally ineffective, with no documented reports on the economic occurrence of hydrocarbon targets. In some of these sedimentary basins, test wells that were blindly drilled have been ineffective and have produced no evidence of economically viable hydrocarbon deposits. Furthermore, problems arising from insecurity, cost, and time constraints have hampered the mesoscale implementation of these exploration techniques, and despite massive investment, a successful economic discovery of hydrocarbon resources remains uncertain. Unlike most Nigerian sedimentary basins, the Bida Basin is widely regarded as the least explored, despite numerous occurrences of hydrocarbon seepages that can serve as indirect evidence for economic-bearing hydrocarbon deposits within the subsurface. Numerous stakeholders and government agencies have expressed renewed interest in exploring the Bida Basin for potential hydrocarbon resources in recent years. Despite renewed interest in Bida Basin exploration, there is growing uncertainty about how to best implement the exploration process. Recent prospectivity studies in the Bida Basin have relied heavily on geophysical, geochemical, stratigraphic, and paleogeographic studies, and in rare cases, exploratory wells have been drilled blindly to gain access to subsurface information (Aigbadon et al. 2022; Ajama et al. 2017; Obaje et al. 2011). Nonetheless, these studies have been slow and generally imprecise in defining the best zones for future exploration expeditions.

The application of GIS-based spatial data integration techniques and tectonic analysis of geological lineaments presents a formidable front in defining the most feasible location for exploratory drilling of hydrocarbon targets. Previous GIS studies on hydrocarbon prospecting have revealed a high degree of reliability, with accuracy levels exceeding 70% (Amiri et al. 2014; Amiri et al. 2015). The primary goal of the study is to present a regional GIS framework illustrating the hydrocarbon potential across the Bida Basin. A systematic application of the weighted sum multi-criteria predictive model, on the other hand, is regarded as a novel approach for hydrocarbon exploratory studies in the Bida Basin and other sedimentary basins throughout Nigeria. Unlike most hydrocarbon exploration techniques, the use of RS and GIS may provide an invaluable template for reconnaissance-scale exploration expeditions. RS and GIS tools are frequently used in conjunction with ground-based exploration approaches to achieve the best results. We attempted to regionally explore hydrocarbon deposits within the Bida Basin using cutting-edge technology based on spatial data integration and structural interpretations of geological lineaments in this study. The findings of this study have the potential to transform future hydrocarbon exploration programs in Nigeria's frontier basins.

Regional geology

The study region comprises the middle and southern parts of Nigeria's Bida Basin, which has a linear NW-SE structure with a length of 35 km and a breadth of 35–150 km. As illustrated in Fig. 1, it occurs perpendicular to the Nigerian Benue Trough (Zaborski 1996). A small section of basement rocks that are present in the vicinity of Shegwa in the Kainji Dam area separates the Bida Basin from the Sokoto Basin in the north. Sedimentary blocks from the Anambra Basin border the southern portion, of the Bida Basin (Fig. 1). The absence of volcanic, carbonate rocks, and Tertiary-age sediments makes the basin unique among all other Nigerian sedimentary basins (Rahaman et al. 2019).

The Bida Basin is thought to be a gently down-warped trough whose origins are linked to Santonian orogenic movements in southeastern Nigeria and the Benue valley. Furthermore, the Bida Basin runs perpendicular to the main axis of Nigeria's Benue Trough and Niger Delta Basin (Obaje et al.

2013). It is thought to be the northwest extension of the Anambra Basin and served as a significant depocenter for the third major transgressive cycle in the Late Cretaceous (Fig. 2).

Structures (tectonic setting/origin) of the Bida Basin

According to Nwajide (1990), the tectonic evolution of the Bida Basin is generally obscured and undefined. He also stated that the basin's large width, approximately 160km, is extensive when compared to the typical rift of 50 ± 13 km. Furthermore, the absence of igneous and volcanic rocks, as well as no major fault or intermittent uplift within the Bida Basin, contradicts the conventional rift theory for the basin's origin. He also asserted that the rifting theory cannot be completely ruled out because the gravity effect on the shallow structural features may have been destroyed. He did, however, note that the Bida Basin only contained folded

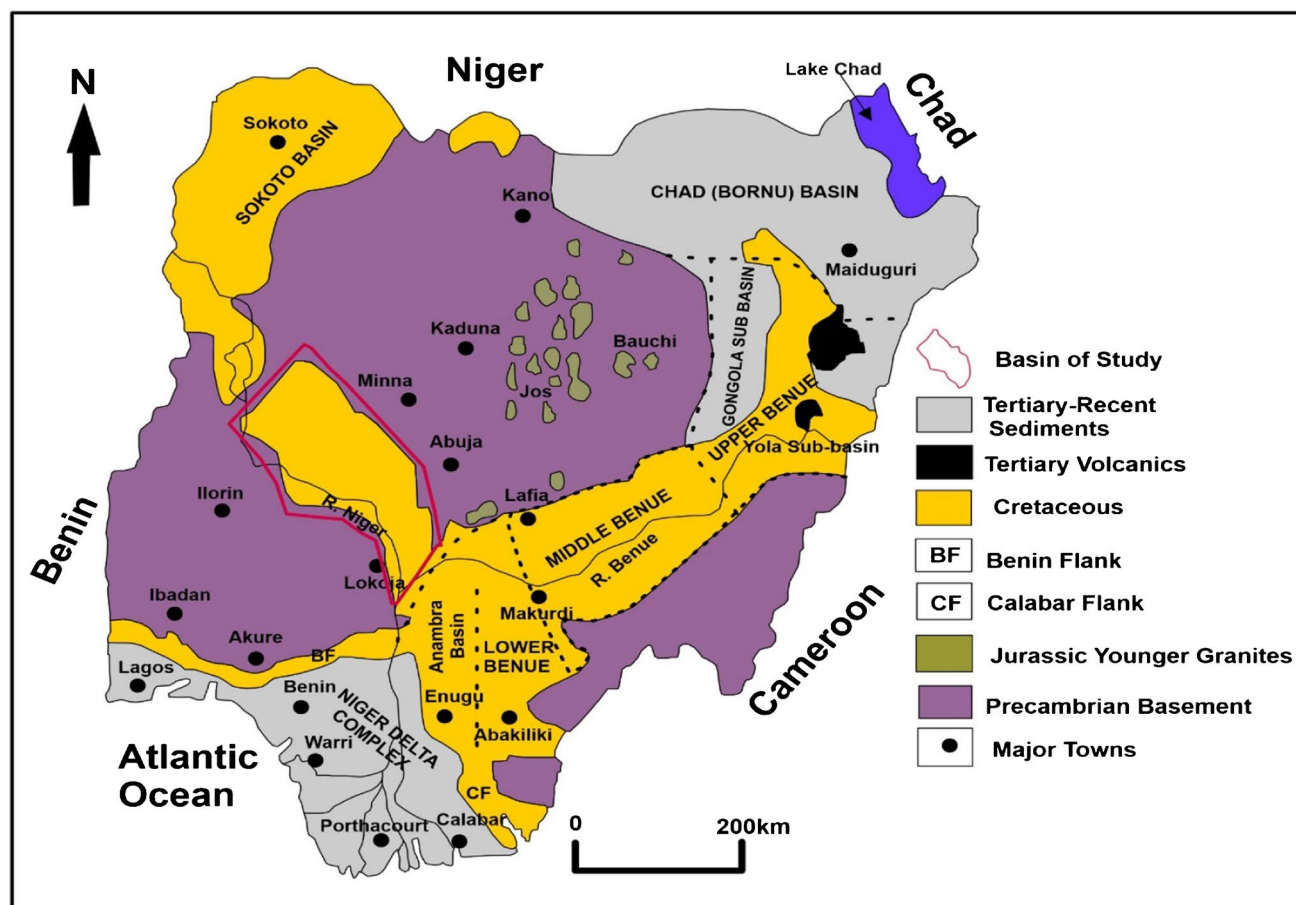


Fig. 1. Geological map of Nigeria showing the bounded Bida Basin with Sokoto Basin, Anambra Basin, and Benue Trough. Modified after Obaje et al. (2004)

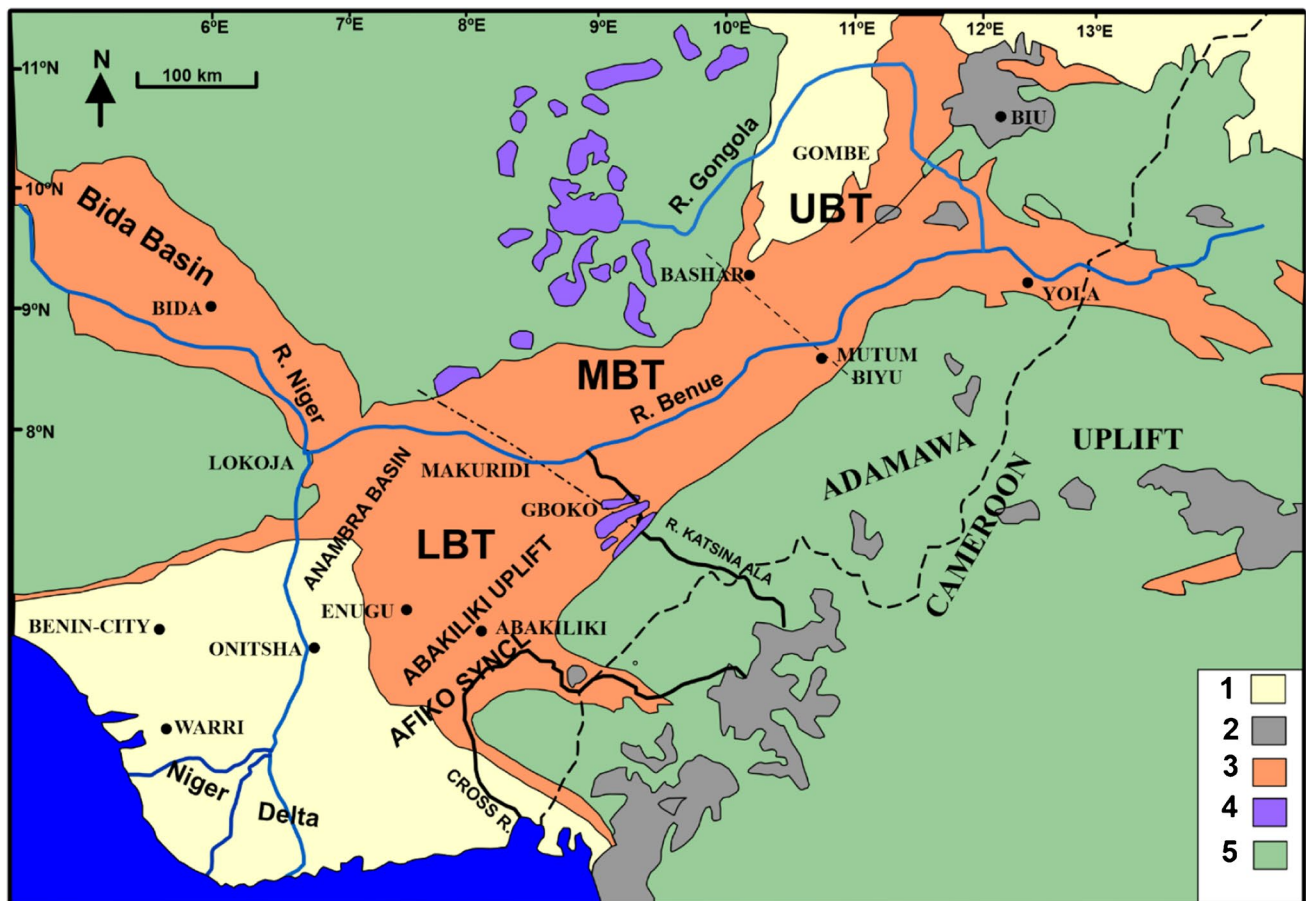


Fig. 2. Outline of the geological map for the Bida Basin bound to the adjacent Anambra Basin extending to the Bida Basin, 1. Tertiary to recent sediments, 2. Tertiary volcanic rocks, 3. Cretaceous Sedi-

ments, 4. Jurassic Younger granites, 5. Precambrian basement Complex. Modified after Zaborski et al. (1998)

Upper Cretaceous strata. Rahaman et al. (2019) reported that the tectonic setting of the Bida Basin has been a subject of discussion over the years and to date, there is no satisfactory explanation for the origin of the basin yet to be accepted by geoscientists. Regional structural studies by Kogbe (1983) using Landsat imageries suggest the Bida Basin is structurally controlled by faults that trend in the NW-SE direction around basement rocks. Conclusively, he attributed the origin of the Bida Basin, to the rift tectonic mechanism. These findings were in coherence with the work of Ojo (1990), who described the basin as an elongated east-west negative aeromagnetic anomaly flanked to the south by a positive anomaly. He ascribed the positive anomalies to the presence of basic rocks at depths between 4 and 6km. He also resolved that a deep-seated rift may probably exist in the crust under the basin. Ojo and Akande (2012) reported that the basin could be considered a graben developed at an angle to the strike-slip principal fault movement along the Benue Trough.

Stratigraphy of the Bida Basin

The stratigraphy and sedimentary successions of upper cretaceous sediments within the Bida Basin have been well documented by numerous researchers. Based on geographical settings, the Bida Basin can be subdivided into the northern and southern Bida basins as shown in Fig. 3. In the northern section of the Bida Basin, lithostratigraphic sections include the Bida Formation (conglomerate, sandstone). These formations could further be subdivided into the Doko Member and the Jima Member, the Sakpe Ironstone, the Enagi Formation (siltstone, claystone, and sandstone), and the Batati Formation (pisolitic ironstone in clayey groundmass) (Rahaman et al. 2019). The Southern Bida Basin comprises three lithostratigraphic units, namely, Lokoja Formation (mainly conglomerate and sandstone); Patti Formation (shale, claystone, and sandstone), and Agbaja Formation (Ironstone) (Jones 1958; Obaje et al. 2013). The lithostratigraphic units of the Northern and Southern Bida Basin are shown in Fig. 4.

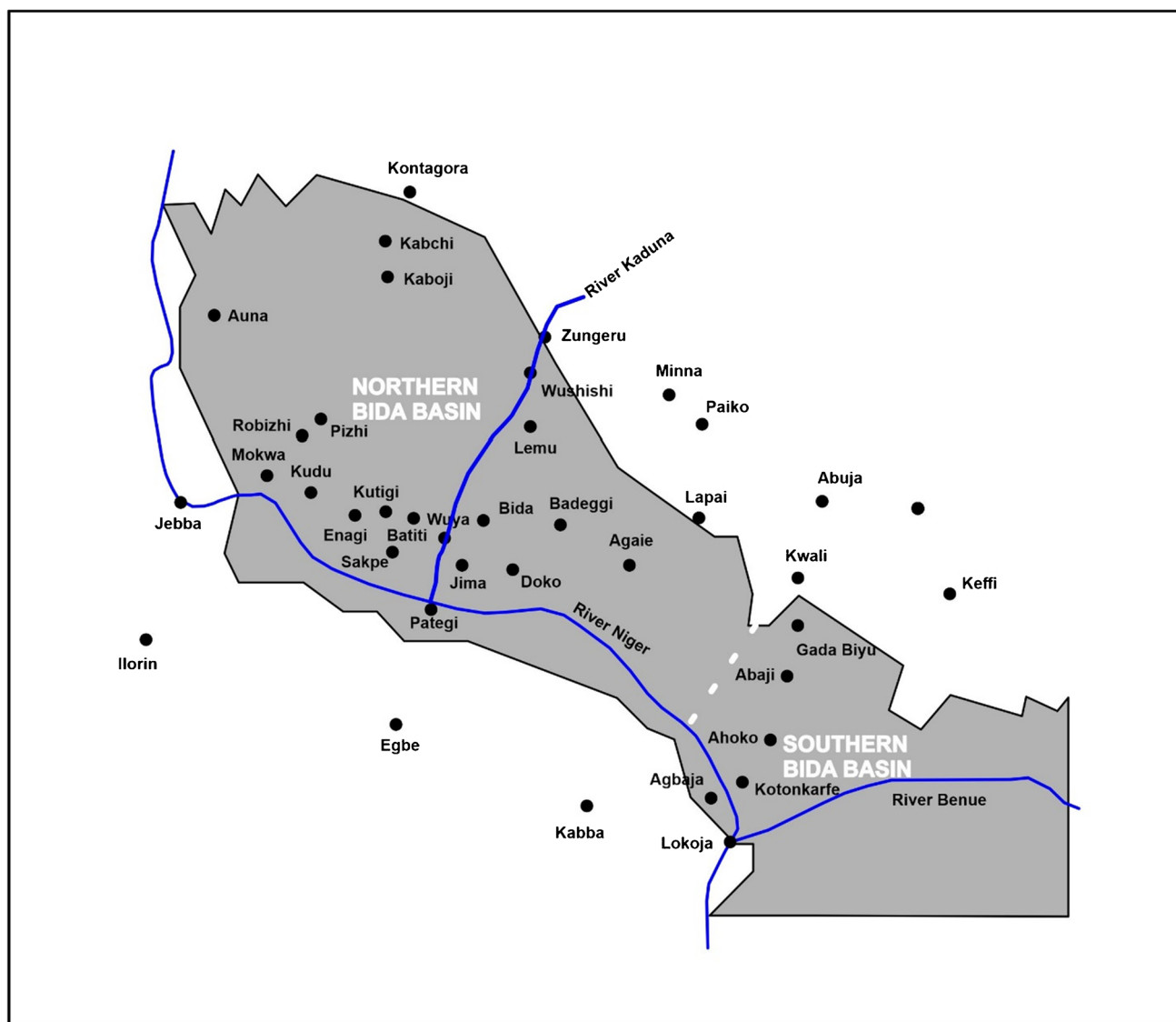


Fig. 3. Outline of Bida Basin indicating the inferred boundary between the northern and southern Bida Basin, Modified after Obaje et al. (2013)

Materials

Target data

Oil seeps, natural gas seeps, and pockmarks (underwater craters generated by escaping gas) are visible surface characteristics that provide basic evidence of hydrocarbon exploration (Segal 1989). Within the Bida Basin, known occurrences of hydrocarbon seeps were used as target data for prospectivity mapping (Fig. 5). Table 1 characterizes target data used in prospectivity mapping. Preliminary information on these seepages was gleaned from existing literature, for example, Obaje et al. (2020). A field survey was then undertaken, during which information on the geographic coordinates of different seepage locations was recorded. The recorded

coordinates were then transferred to an Excel file and loaded into ArcMap 10.3 software after fieldwork. For further investigation, the coordinate positions were transformed into point data and used in validating the prospectivity map.

Spatial data

A hydrocarbon predictive map for the Bida Basin was generated using structural and geophysical data (gravity and magnetic). Table 1 depicts the basic characteristics of spatial data used in hydrocarbon predictive mapping in the Bida Basin. Regional geological structure information within the study area was manually digitized using a high-resolution digital elevation model (DEM) downloaded from www.earthexplorer.usgs.gov. The DEM-derived

Fig. 4. Lithostratigraphical subdivisions of the northern and southern Bida Basin. Modified after Adeleye (1974)

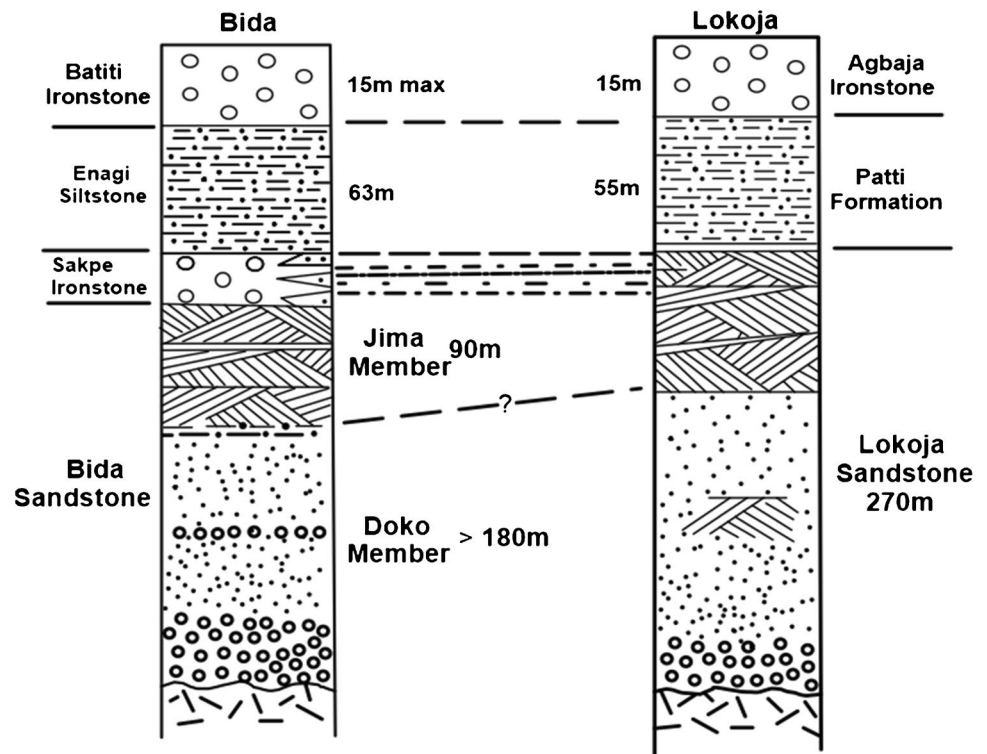


Fig. 5. Occurrence of oil seepages around river Madeko in the Dab-ban community

lineaments were digitized using the Global Mapper 16 software. Extracted lineaments were then imported into the ArcGIS 10.3 software, where spatial analyses such as lineament density and intersection density were performed (Hung et al. 2005). Figure 11a and b show the lineament density and intersection density data for the research site. Furthermore, the lineaments were separated spatially based on their orientation. The separated WNW-ESE lineaments were then buffered at different distances, yielding spatial data on the proximal distance to favorable geological structures (Fig. 11c). The magnetic data used in this study were obtained as an Earth Magnetic Anomaly Grid (EMAG), from <https://www.ngdc.noaa.gov/>. The EMAG is a regional scale magnetic data with a resolution of 2 arc-minutes generated from magnetic data obtained from ships, satellites, and airborne surveys. The tilt derivative algorithm was used to generate spatial data on magnetic intensity for prospectivity mapping (Miller and Singh 1994). The tilt derivative data were utilized to enhance shallow geological structures that might serve as migrational routes for oil seepage. Figure 11d depicts the filtered magnetic data for the study site. The satellite gravity for the study location was obtained as Bouguer corrected gravity (BCGD) data from <https://bgi.obs-mip.fr/>. The BCGD data is essentially a high-resolution gravity dataset with a $1' \times 1'$ grid resolution that depicts the entirety of the Earth's gravity anomaly. The analytical signal algorithm was used to filter gravity data for the

Table 1 Characterization of spatial data for prospectivity mapping

Sn	Primary data	Data source	Target/evidential data	Data class	Recognition criteria
1		Field survey	Hydrocarbon seepages (target data)	Hydrocarbon seepages	
2	Digital elevation model	www.earthexplorer.usgs.gov	Distance to geological structures (evidential data)	Structural	Proximal distances to geological structures
3			Lineament density (evidential data)	Structural	Zones of high lineament intensities
4			Lineament intersection density (evidential data)	Structural	Zones of high intersection intensities
5	Earth magnetic grid (EMAG)	http://www.ngdc.noaa.gov/	Tilt derivative (evidential data)	Geophysical (magnetic)	Zones of high magnetic anomalies
6	Bouguer corrected gravity data (BCGD)	http://bgi.obs-mip.fr/	Analytical signal (evidential data)	Geophysical (gravity)	Zones of low gravity anomalies

study location (Nabighian 1972). In order to ascertain the relative depth to basement lithologies, analytical signal data was utilized. Figure 12 shows the filtered gravity data.

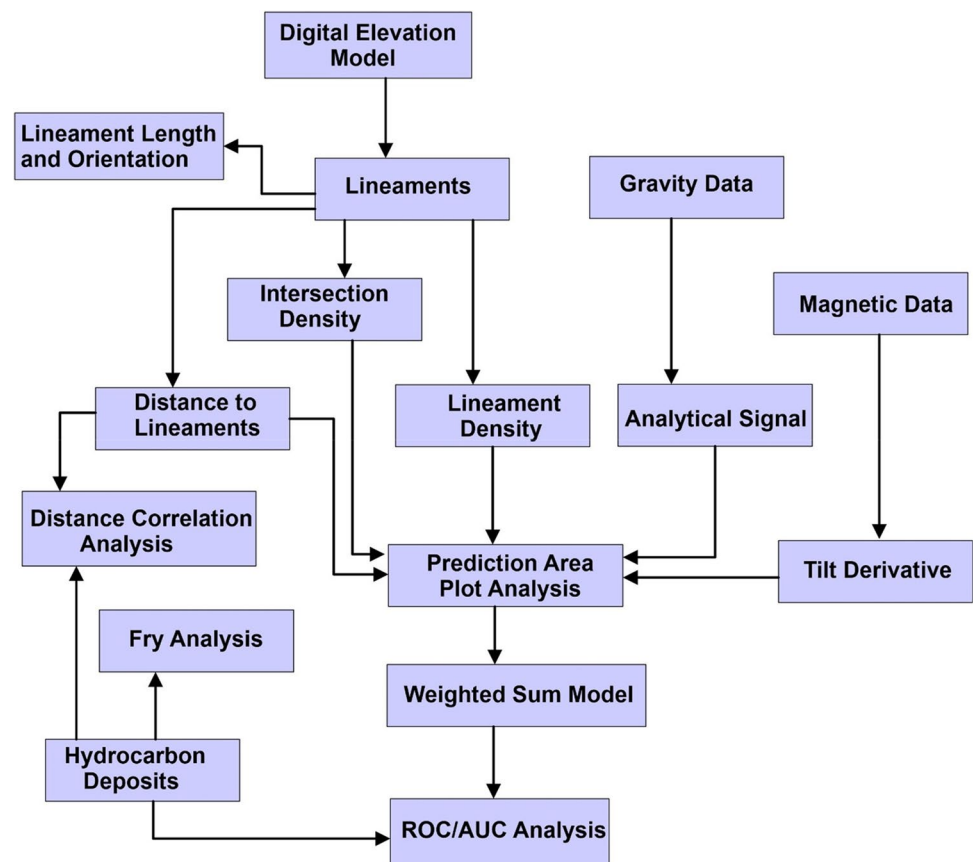
Methods

Figure 6 depicts a systematic approach to the study's methods.

Lineament extraction and analysis

Manual digitization from a high-resolution digital elevation model was used to extract lineaments. Lineaments were manually digitized using Global Mapper 16 software. Lineaments were extracted and then imported into the ArcMap 10.3 software for processing and analysis. To assess the dominant trends for lineaments, orientation analysis was used to create a rose plot. Lineaments were also measured to

Fig. 6. Flowchart illustrating methodology used in the study



determine their length. The length parameters of lineaments were evaluated using basic univariant statistical analytical tools. Lineament density and intersection density for lineaments were then generated using Eqs. 1 and 2 as prescribed by Hung et al. (2005).

$$L_d = \frac{Ln}{a} \quad (1)$$

$$L_{id} = \frac{Ni}{a} \quad (2)$$

where

L_d and L_{id} represent the lineament density and intersection density

Ln is the number of lineaments

Ni is the number of intersections

a is the area under consideration

Fry analysis

The Fry analysis is a simple technique for determining the directional affinities of point features that have been frequently used to illustrate the structural control of mineral resources (Vearncombe and Vearncombe 1999; Wormald et al. 2003) or assessing the general tectonic strains in rocks using fossils or mineral grains as markers (Genier and Eparé 2007). Successful implementation of the Fry technique can be accomplished manually or automatically with specialized software (Carranza 2009). However, manually implementing the Fry method is performed by placing a sheet of tracing paper on a map constraining a data point and parallel lines pointing northward. The data points and lines are recorded on this tracing paper. A second tracing paper with a central point and parallel lines is then placed on one data point while ensuring the lines on both papers are parallel to each other. Data points on the first tracing paper are then recorded except for the central point. The central point is then moved to every point while the digitization procedures of the points are repeated. According to Vearncombe and Vearncombe (1999), a given “n” number of data points will result in $n^2 - n$ translational points. The resultant output from the Fry analysis is displayed using rose plots and can be implemented for diverse distances.

Distance correlation analysis (DCA)

The statistical relationship between point and linear features can be effectively summarized using the distance correlation analysis. In applicability, the DCA compares the relative cumulative frequency of objects of a certain type to every location and the cumulative relative frequencies of distances from the object to a specific geological event. Previously, the DCA has succeeded in evaluating the relationship between

geological features and mineral deposits, geothermal indicators, and landslides (Carranza 2009; Carranza et al. 2008; Gosh and Carranza 2010). The DCA can be implemented by plotting and comparing the relative distances from a set of geological structures to a set of geological events using a binary curve.

Prediction area curve analysis

Spatial predictions of geological events are dependent on the reliability and quality of the spatial data used. Very accurate predictions are often derived from spatial data with a substantial level of reliability. The predictive area curve analysis (PAC) validates the reliability of the spatial data as an integral part of the predictive model. It computes the probable certainty of every spatial data in predicting a given geological event (Yousefi and Carranza 2015). The prediction area curve is implemented by plotting the curve of the prediction rate of a known geological event corresponding to different classes of the weighted evidential map with the curve of the percentage of occupied areas corresponding to the classes of the weighted evidential map (Yousefi and Carranza 2017).

Weighted sum modeling

Multi-criteria decision analysis is defined by a subjective attribute being influenced by the experience level of the analysts. In statistical prediction, the weighted sum model establishes a systematic computation of weighted values representing the proportionate importance of various aggregated factors (El Amine et al. 2014), displaying a linear transformation of standardized scores and maintaining an equal order of magnitude (Afshari et al. 2010). According to Annette et al. (2016), the weighted sum model calculates an assessment score for each option by multiplying the relative weights by a normalized score of criteria for each option supplied by the analyst. By adding the product for all criteria, the overall score for each characteristic is calculated (Afshari et al. 2017; Putra and Pungara 2018). The weighted sum model can be statistically implemented using the equations provided below.

$$s_i = \sum_j (w_j * r_{ij}) \quad (3)$$

where s_i is the resultant weight of the data used, r_{ij} denotes the normalized rating

“ i ” represents the i^{th} alternative

“ j ” indicates the j^{th} criterion.

w_j represents the j^{th} criterion weighting.

Normalization of rating of r_{ij} for the benefits and non-benefit criteria can be implemented using Eqs. 4 and 5.

$$r_{ij} = \frac{x_{ij}}{\max_i(x_{ij})} \quad (4)$$

$$r_{ij} = \frac{1/x_{ij}}{\max_i(1/x_{ij})} \quad (5)$$

Multi-fractal analysis

The separation of anomalous values from background composition can be effectively implemented using the multi-fractal approach previously employed in segregating anomalous values for a diverse dataset including geochemical, geophysical, and remote sensing (Aramesh et al. 2014; Asadi et al. 2014; Wang et al. 2013). The C-A multi-fractal approach, first proposed by Cheng et al. (1994), is considered the most popular fractal tool for anomaly delineation. The C-A fractal method can be implemented using Eq. 6.

$$A(p \leq v) \propto p^{-a1}; A(p \geq v) \propto p^{-a2} \quad (6)$$

where $A(p)$ represents a defined area with a defined value above the contour value p

v is the threshold

$a1$ and $a2$ represent the exponential components.

The breakage point of a log-log plot for $A(p)$ against p signifies the threshold values of a given data.

Receiver operating curve/area under curve analysis

The ROC and AUC analysis are generally considered complementary tools for testing the prediction accuracy of GIS models. Their implementation is principled by a model's ability to separate the positive from negative cases by summarizing the classifier performance over a range of tradeoffs between true-positive and false-positive rates. The ROC can be statistically realized by plotting the sensitivity (the ability of a model to predict an event correctly) versus 1-specificity for all possible cutoff classification probability values. Statistically, the sensitivity and 1-specificity can be computed using Eqs. 7 and 8.

$$FPR = \frac{FP}{(FP + TN)} \quad (7)$$

$$TPR = \frac{TP}{(TP + FN)} \quad (8)$$

where :

FP represents the false-positive or incorrect prediction of positive classes

TN denotes the true-negative or correct prediction of negative classes.

TP illustrates the true-positive or correct prediction of positive classes.

FN represents the false-negative or incorrect prediction of negative classes.

The AUC illustrates a systematic approach for summarizing the diagnostic accuracy of predictions and ranges from 0 to 1. AUC values of 0 represent perfectly inaccurate test, while values of 1 represent a perfect accuracy test (Mandrekhar 2010). The AUC value of 0.5 corresponds to the random chance of the prediction model (Zou et al. 2007).

Results

Analysis of lineament patterns

A total of 85 lineaments were extracted using the manual digitization technique, and visual analysis of lineaments suggests lineament patterns trending to the ENE-WSW, NW-SE, NNW-SSE, and WNW-ESE (Fig. 7a). A rose plot for lineaments suggests a dominant NW-SE lineament trend accompanied by a less dominant NE-SW (Fig. 7b). Analysis of lineament length suggests variations from 9.50 to 73.90km with a mean length of 34.40km and a standard deviation of 15.36km. A histogram plot for the length of the lineaments is characterized by a negative skew pattern (Fig. 7c). A maximum frequency of 20 is observed for lineaments lengths between 22.4 and 29.9km. Analysis of lineament density suggests density variations from 0.01 to 0.26 with a mean and standard deviation of 0.14 and 0.05. Generally, zones of high lineament density were common in the southern, central, and northern parts of the study location (Fig. 11a). The intersection density varies from 0 to 0.02, with a mean density of 0.01 and a standard deviation of 0.00. Zones of high intersection density were observed in the northwestern, central, and southeastern parts of the study (Fig. 11b).

Structural control on hydrocarbon occurrence

Figures 8 and 9 depict structural characteristics of hydrocarbon occurrences in the Bida Basin. The evidence from the Fry analysis suggests that hydrocarbon occurrences in the Bida Basin are strongly associated with the WNW-ESE tectonic trend, both on a regional and a more localized scale of less than 500km. Furthermore, evidence from the distance correlation analysis shown in Figure 8 suggests that known occurrences of hydrocarbon imprints across the study area had a strong relationship with both the WNW-ESE and NNW-SSE lineaments. Hydrocarbon occurrences showed a positive spatial association with the WNW-ESE lineaments, with a maximum association at a distance equivalence of 4km. Within this distance, there is a 0.57% greater chance than expected of discovering HC deposits at the study site.

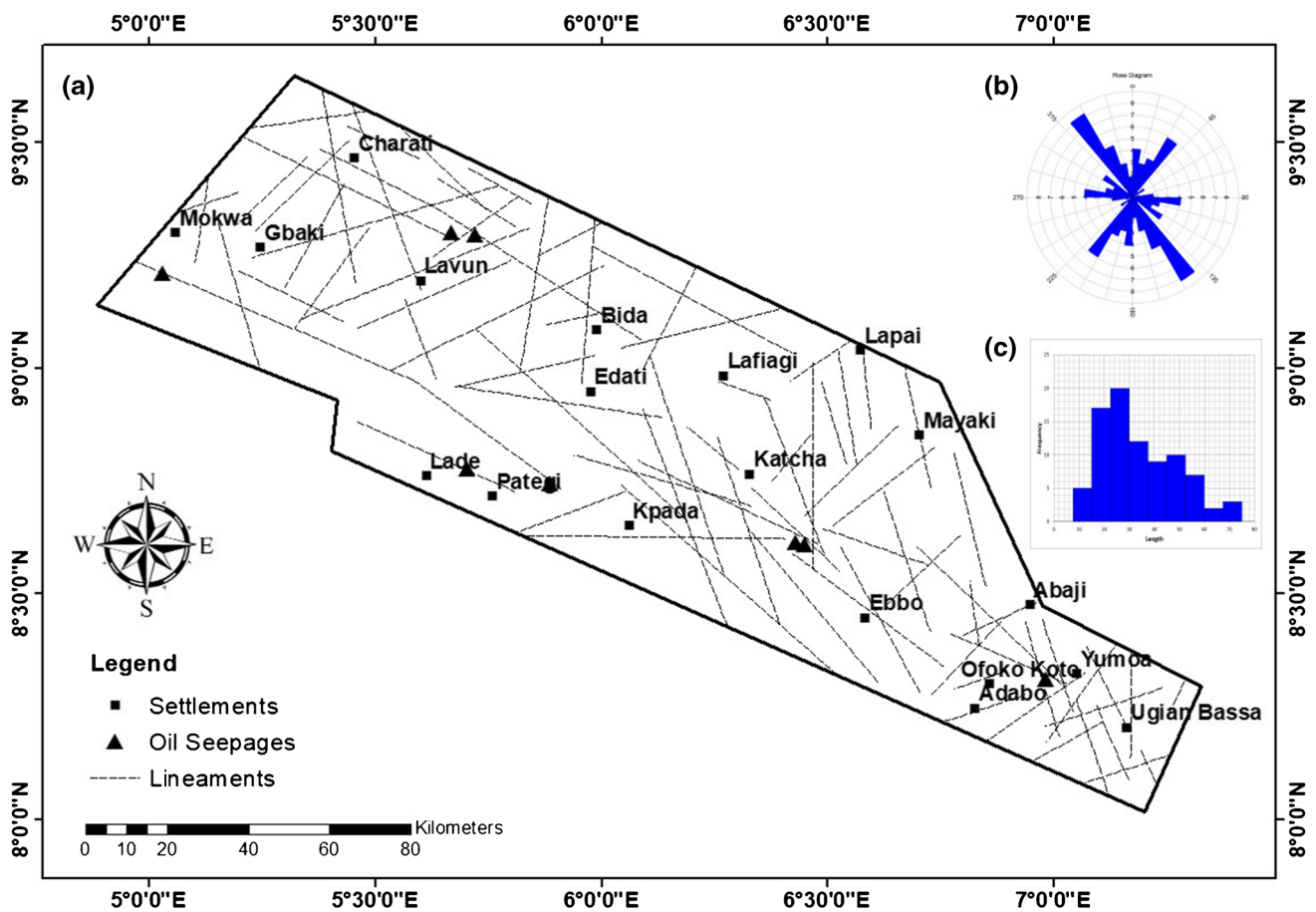


Fig. 7. Tectonic analysis of lineaments. (a) Occurrence of lineaments within the study location. (b) Rose plot for lineaments. (c) Histogram plot for lineaments within the study

Positive spatial association with the NNW-SSE tectonic trend is characterized by a maximum spatial association at a distance equivalence of 26km. Within this distance, there is a 0.16% chance that this is higher than normal to find HC deposits. Analysis of the distance correlation plots suggests no spatial association within the ENE-WSW, E-W, NW-SE, and NE-SW tectonic trends.

Evaluation of variable correlation

Figure 10 illustrates a prediction area plot that exemplifies the predictive strength and the statistical relationship between hydrocarbon occurrences and the spatial data used in the predictive mapping. Evidence from this analysis suggests that known hydrocarbon occurrences analysis displayed an augmented relationship with predictive datasets. However, spatial predictive data on distances to the WNW-ESE, analytical signal gravity, and tilt derivative displayed the most significant relationship with known hydrocarbon occurrences. This association was characterized by a spatial correlation of 0.80, 0.68, and 0.67, respectively. The least

correlation was observed for spatial data on lineament density and lineament intersection density with a spatial association of 0.61 (Table 1).

Application of weighted sum modeling

The application of weighted sum modeling for spatial weighting of evidential data is presented in Table 2. For the lineament density attribute, a minimum weight of 4.27 was assigned to density classes below 0.08, while a maximum weight of 20.47 was assigned to density classes above 0.21 (Fig. 11a). The weighting of the intersection density parameter was characterized by a minimum weighting of 4.88 for intersection classes below 0.00, while a maximum weighting of 20.74 was assigned to intersection classes above 0.02 (Fig. 11b). The spatial weighting of distances to favorable geological structures (WNW-ESE lineaments) was characterized by a maximum weight of 29.60 for distances less than 4.5km, while a minimum weight of 4.80 was assigned to distance classes beyond 23.90km (Fig. 11c). The weighting of tilt derivative (magnetic) data was defined by a minimum weight value of

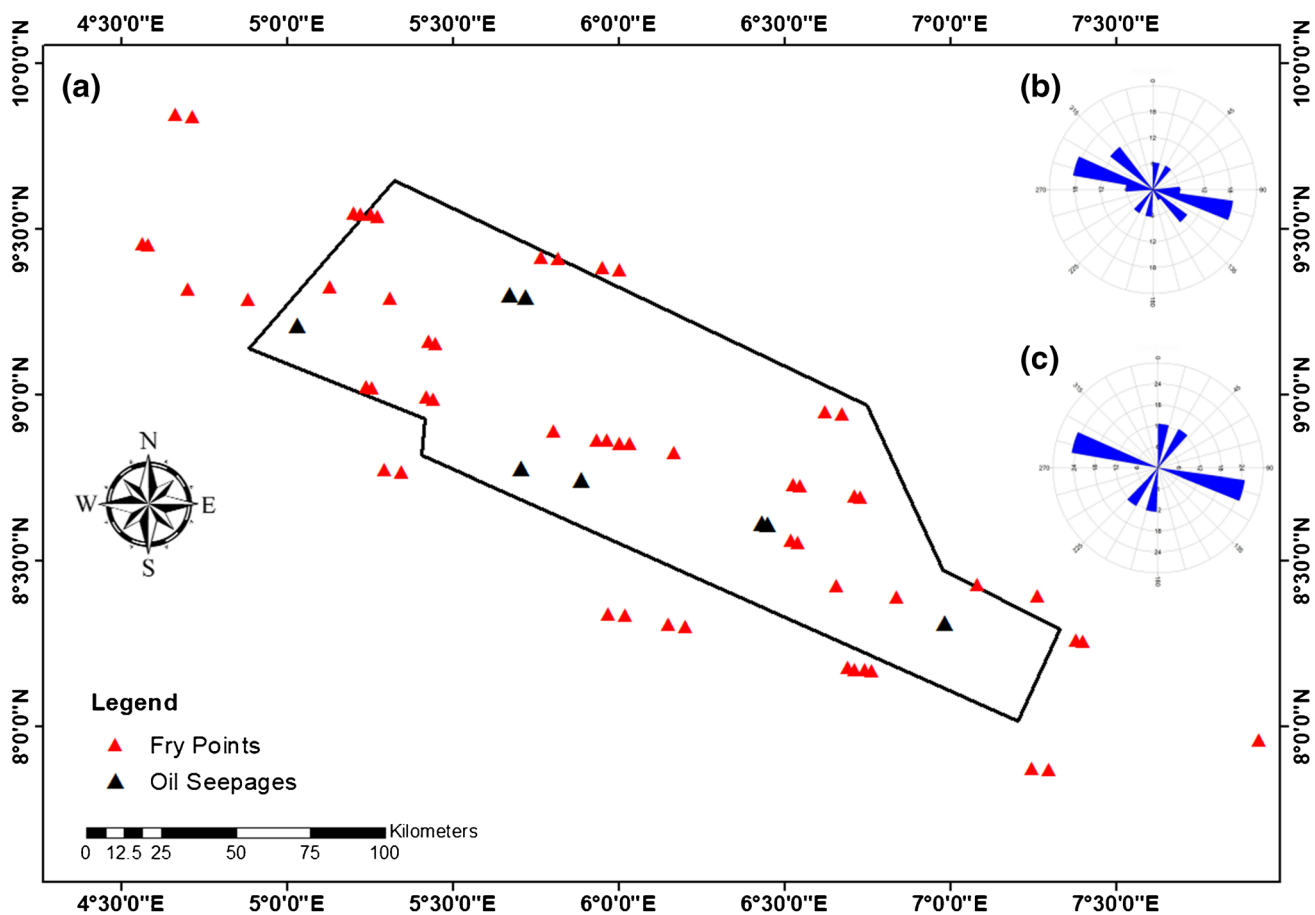


Fig. 8. Analysis of hydrocarbon structural control using Fry analysis. (a) Fry plots of hydrocarbon seepages. (b) Rose diagram for all pairs of fry points. (c) Rose diagram for pairs of fry points within 500 Km

5.36 for parameter classes below -0.87 . However, a maximum weighted value of 21.44 was assigned to magnetic intensity classes above 0.83 (Fig. 11d). The weighting of analytical signal (gravity) data was defined by a minimum weight of 4.08 and a maximum weight of 25.84 for parameter classes above 0.0032 and below 0.0009, respectively (Fig. 12).

Hydrocarbon predictive mapping and multi-fractal analysis

A predictive map for hydrocarbon productivity across the Bida Basin is presented in Fig. 13. Statistically, prospectivity levels ranged from 30.80 to 118.38, with a mean and standard deviation of 73.03 and 18.18 (Fig. 13). Visually, zones of high prospectivity levels appear within the south-central and north-eastern parts of the study location. However, low prospectivity zones were more common within the peripheries of the study site. The application of multi-fractal analysis (Fig. 14) revealed threshold values of 60, 80, and 100 discretized the hydrocarbon prospectivity map into 4 classes (Fig. 15). The very high prospectivity classes

were defined by an area extent of 1836.56 km² occupying approximately 10.23% of the total study location (Table 3). The high prospectivity class is characterized by a total area of 3852.37 km² which occupies approximately 21.46% of the study site. The low prospectivity class accounts for 42.43%, which contributes to a total area of 7616.41 km². The very low prospectivity class covers an area extent of 4644.66 km², accounting for 25.87% of the study location (Table 2).

Validation of a predictive model

Visual observation of the hydrocarbon predictive model suggests a high correlation between known hydrocarbon occurrences and the most probable predictive classes. A total of 62.5% of all known hydrocarbon occurrences are within the very high prospectivity class, while 25% fall within the high predictive class. However, 12.5% of all known hydrocarbon occurrences fall within the low predictive class, while 0% lie within the very low predictive class. A statistical validation using the ROC/AUC suggests a high prediction accuracy of 80.9 % is envisaged for the predictive model (Fig. 16).

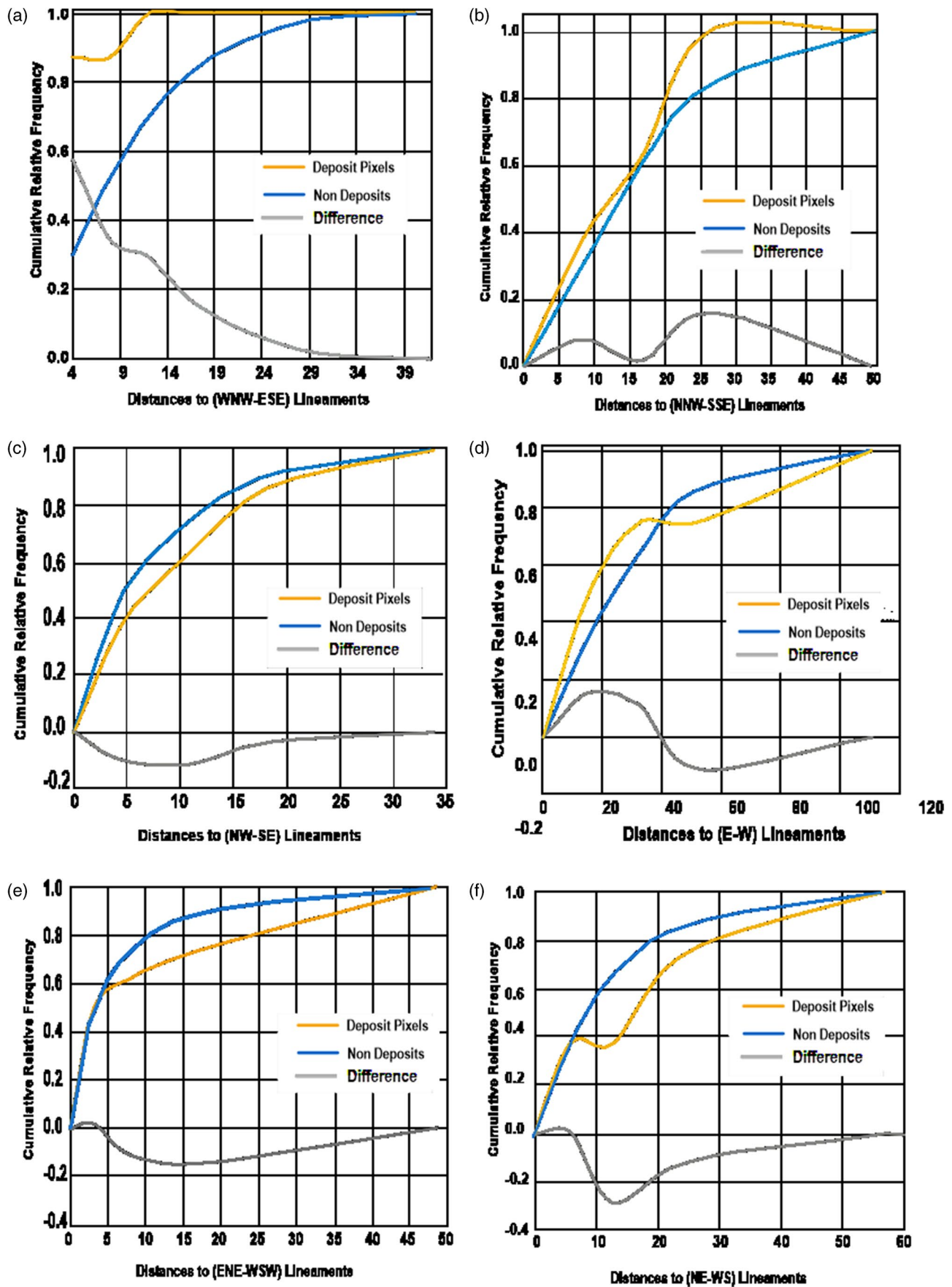


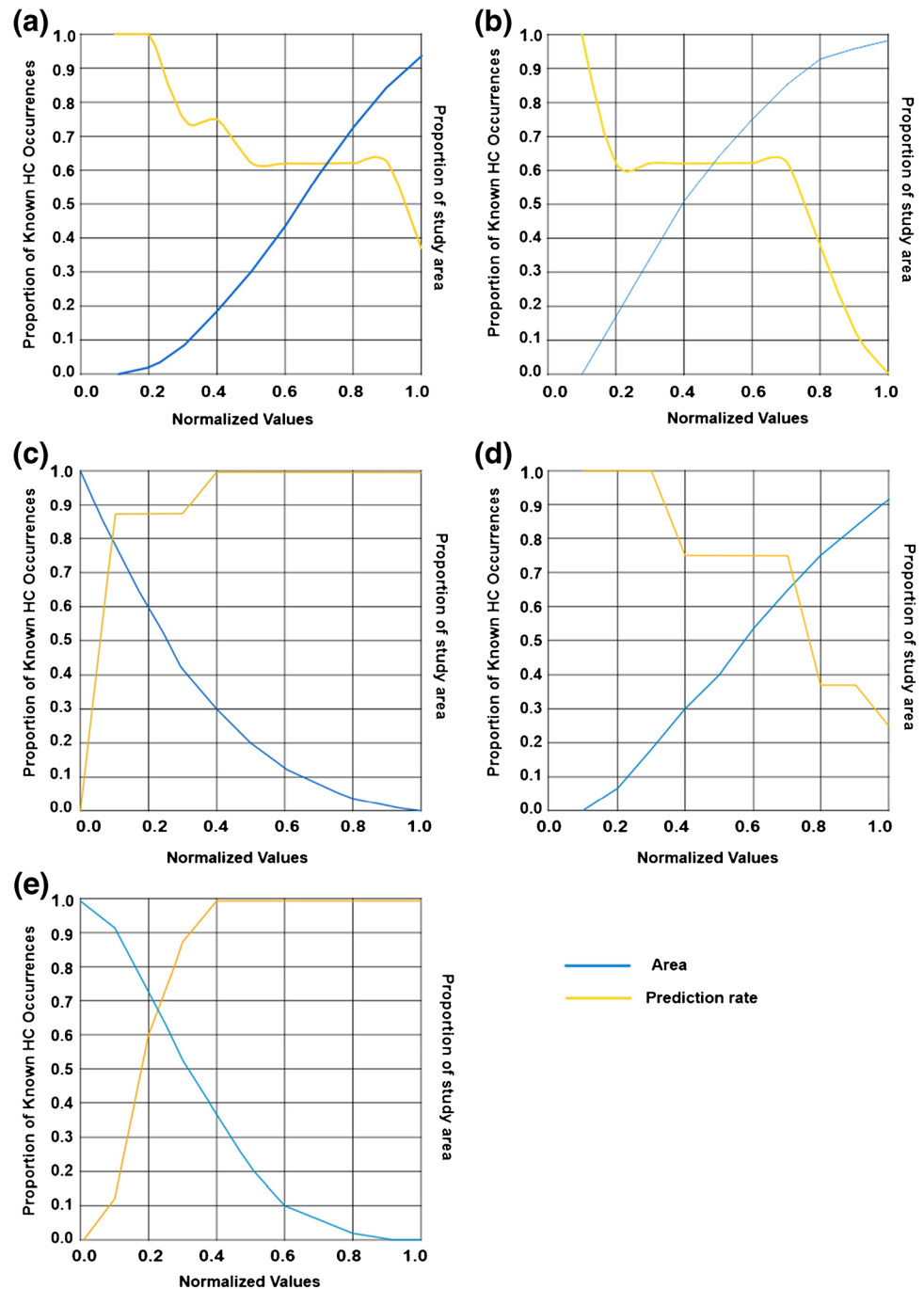
Fig. 9. Distance correlation plots for hydrocarbon occurrences and **a** WNW-ESE lineaments, **b** NNW-SSE lineaments, **c** NW-SE lineaments, **d** E-W lineaments, **e** distances to the ENE-WSW lineament, **f** distances to NE-SW lineaments

Discussion

Regional structural studies for the Bida Basin have been based on gravity and magnetic data analysis and interpretation (Auduson and Onuoha 2020; Awoyemi et al. 2017a;

Awoyemi et al. 2017b; Likkason 1993). Despite this, a high-resolution digital elevation model (DEM) was used to generate tectonic features across the study area. Based on existing studies, for example, Tende et al. (2022), DEMs are regarded as a reliable tool for structural mapping because they represent a true representation of topographic variations and are free of anthropogenic defects such as roads and railway lines that may be imprinted on spatial data as lineaments. Lineaments generated and analyzed from digital elevation models reveal that the NW-SE tectonic trend dominates

Fig. 10. Prediction area plots for hydrocarbon occurrence and **a** lineament density, **b** intersection density, **c** distances to ENE-WSW, **d** tilt derivative (magnetic), **e** analytical signal (gravity)



the structural framework for the study location, with a less dominant but equally prominent NE-SW trend and a subtle E-W trend. The structural features generated for the location of the study area are consistent with previous Bida Basin studies (Auduson and Onuoha 2020). The dominant NW-SW trend, on the other hand, is interpreted as a tectonic deformation episode caused by the ubiquitous Santonian movement, which affected a large portion of Southeastern Nigeria (Likkason 1993). Within the Nigerian Basement Complex, structural trends in the NE-SW directions are thought to be one of the main tectonic trends (Awoyemi et al. 2017a). Ike (1988) asserts that the NE-SW trend, along with the NW-SE trend, is conjugate fault systems of dextral and sinistral characteristics. The predominance of these trends (NW-SE and NE-SW) in the study area suggests a significant basement control on the structural characteristics of the Bida Basin. Ojo (1990) considered sub-basement intrusions to be associated with subtle E-W trending lineaments. Based on Fry and distance correlation analysis, known hydrocarbon occurrences are strongly associated with the WNW-ESE tectonic trend. The findings of these analyses contradict the work of Braide (1990) who proposed the Bida Basin's NW-SE tectonic trend as a potential trap for hydrocarbon accumulation. Although Fry and distance correlation analysis has

been used to evaluate the structural affinity for hydrocarbon resources in the Bida Basin, this method has also been used successfully to determine mineral deposit control in the Malumfashi Schist Belt in North Western Nigeria (Tende et al. 2021a). As a result, their application to hydrocarbon research is relatively new, and they continue to be an intrinsic parameter for defining geological control over hydrocarbon resources, which may be invaluable for the exploration process. The majority of structural investigations for hydrocarbon prospecting are mesostructure, as defined by field analysis or seismic geophysical surveys. Existing GIS-based structural studies on hydrocarbon resources have been steadfast in quantifying the regional scale tectonic control for HC deposits. However, only a few studies, for example, Prabakaran et al. (2013), have superimposed geologically extracted lineaments on existing hydrocarbon manifestations to define the basic structural control

GIS-based techniques in prospectivity mapping enable the reliable integration of spatial data based on an understanding of the prevailing geological conditions associated with the event under consideration (Aziz and Saibi 2014). It is essential to note that the predictive data used to generate a hydrocarbon predictive model must be reliable and accurate. The prediction area curve analysis was used to assess

Table 2 Spatial weighting of evidence data used in predictive mapping of hydrocarbons

Spatial data	Class	Rating	Weights	Total weights
Distances to WNW-ESE lineaments	0–4,497.36	37	0.80	29.60
	4497.37–9770.12	30		24.00
	9770.13–16,128.46	17		13.60
	16,128.47–23,882.52	10		8.00
	23,882.53–39,545.74	6		4.80
Lineament density	0.01–0.08	7	0.61	4.27
	0.09–0.12	14		8.54
	0.13–0.16	19		11.59
	0.17–0.2	26		15.86
	0.21–0.26	34		20.74
Intersection density	0–0.003	8	0.61	4.88
	0.004–0.006	12		7.32
	0.007–0.01	18		10.98
	0.011–0.014	28		17.08
	0.015–0.021	34		20.74
Tilt derivative (magnetics)	–1.544 to –0.873	8	0.67	5.36
	–0.872 to –0.35	13		8.71
	–0.349–0.223	19		12.73
	0.224–0.832	28		18.76
	0.833–1.564	32		21.44
Analytical signal (gravity)	0.0001–0.0009	38	0.68	25.84
	0.001–0.0015	29		19.72
	0.0016–0.0022	17		11.56
	0.0023–0.0031	11		7.48
	0.0032–0.0056	6		4.08

the validity of spatial data to be integrated for hydrocarbon prospectivity mapping. Although it had not previously been applied to hydrocarbon occurrences, the predictive area curve has been used successfully with mineral exploration surveys (Bahrami et al. 2022; Yousefi and Carranza 2015). The prediction area curve analysis, according to Yousefi and Carranza (2015) and Yousefi and Carranza (2016), is best interpreted by estimating the degree of intersection between the proportion of the mineral deposit curve and the proportion of the area curve. Higher values indicate that there is a significant correlation between known hydrocarbon occurrences and the evidence under consideration. The prediction area curve analysis reveals that the most correlating attributes were spatial data on distances to geological lineaments, analytical signal (gravity), and tilt derivatives (magnetics). However, the correlation tendencies of the lineament density and intersection density were slightly lower but more significant. The statistical association between hydrocarbon occurrences and distances to geological lineaments, analytical signal, and tilt derivatives was defined as 0.80, 0.68, and 0.67,

respectively. In most geological settings, tectonic attributes are known to play a significant role in the formation of hydrocarbon resources. Hydrocarbons can migrate through geological structures for potential subsurface accumulation (Prabaharan et al. 2013). This information validates and explains the possible reasons for the proximal association of geological structures with specific types of lineaments and their occurrence within intense fracture zones (high lineament density and intersection density). Also, it is important to note that the Bida Basin is characterized by the presence of rift structures (Ojo 1984; Ojo and Ajakaiye 1989), a common tectonic feature in most oil-producing basins around the world (Obaje et al. 2020). In gravity data, known hydrocarbon seepages are observed to have a close association with low-gravity zones. Although sedimentary rocks are characterized by low gravity signatures, the proximities of hydrocarbon seeps in zones of low gravity suggest a depocenter characterized by thick sedimentary sequences, considered to be more favorable for hydrocarbon formation (Garain et al. 2021). Gravity studies for hydrocarbon prospectivity have

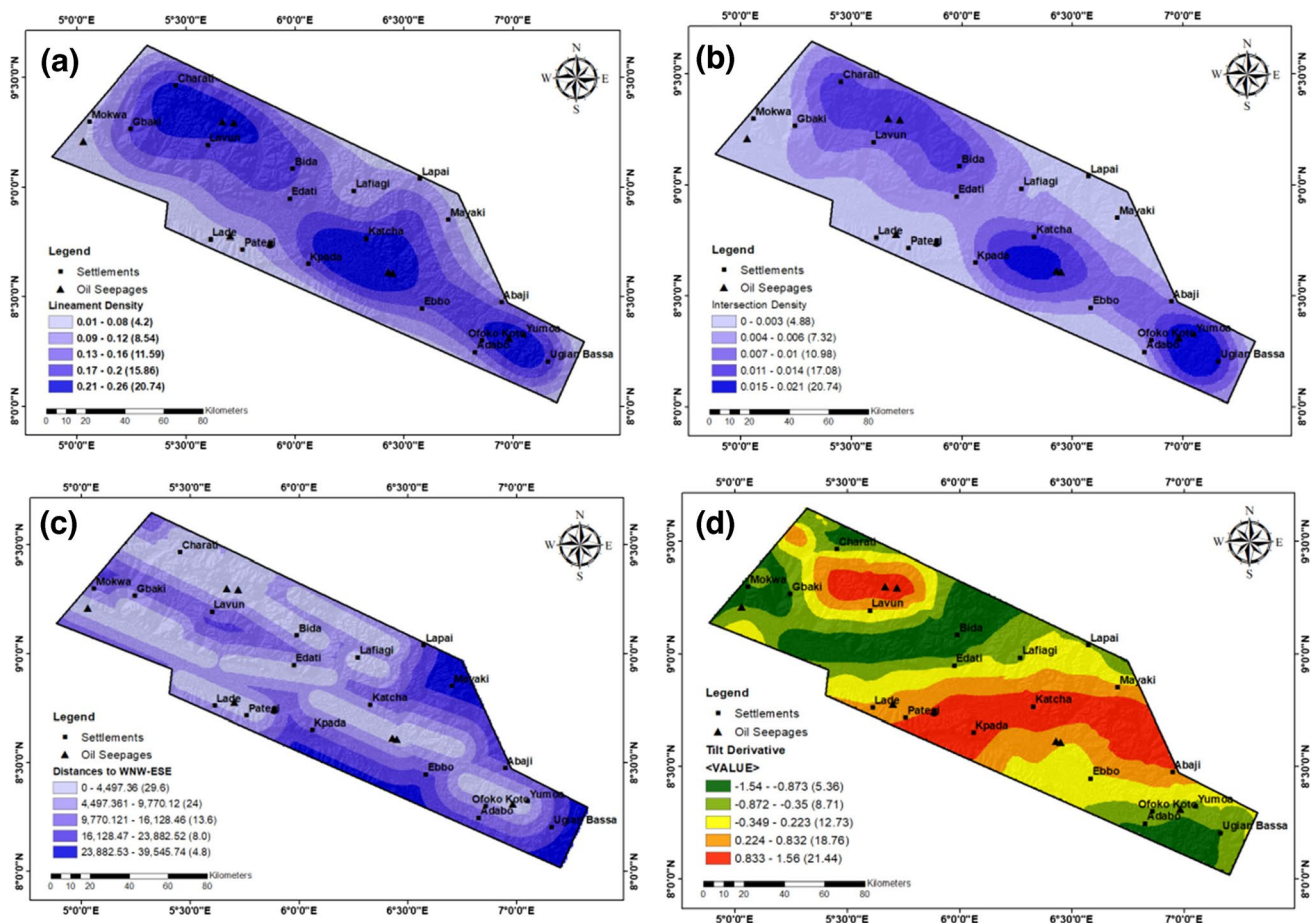


Fig. 11. Spatial predictive data used for hydrocarbon prospecting. **a** Lineament density, **b** intersection density, **c** proximal distance to the WNW-ESE lineaments, **d** tilt derivative (magnetic data)

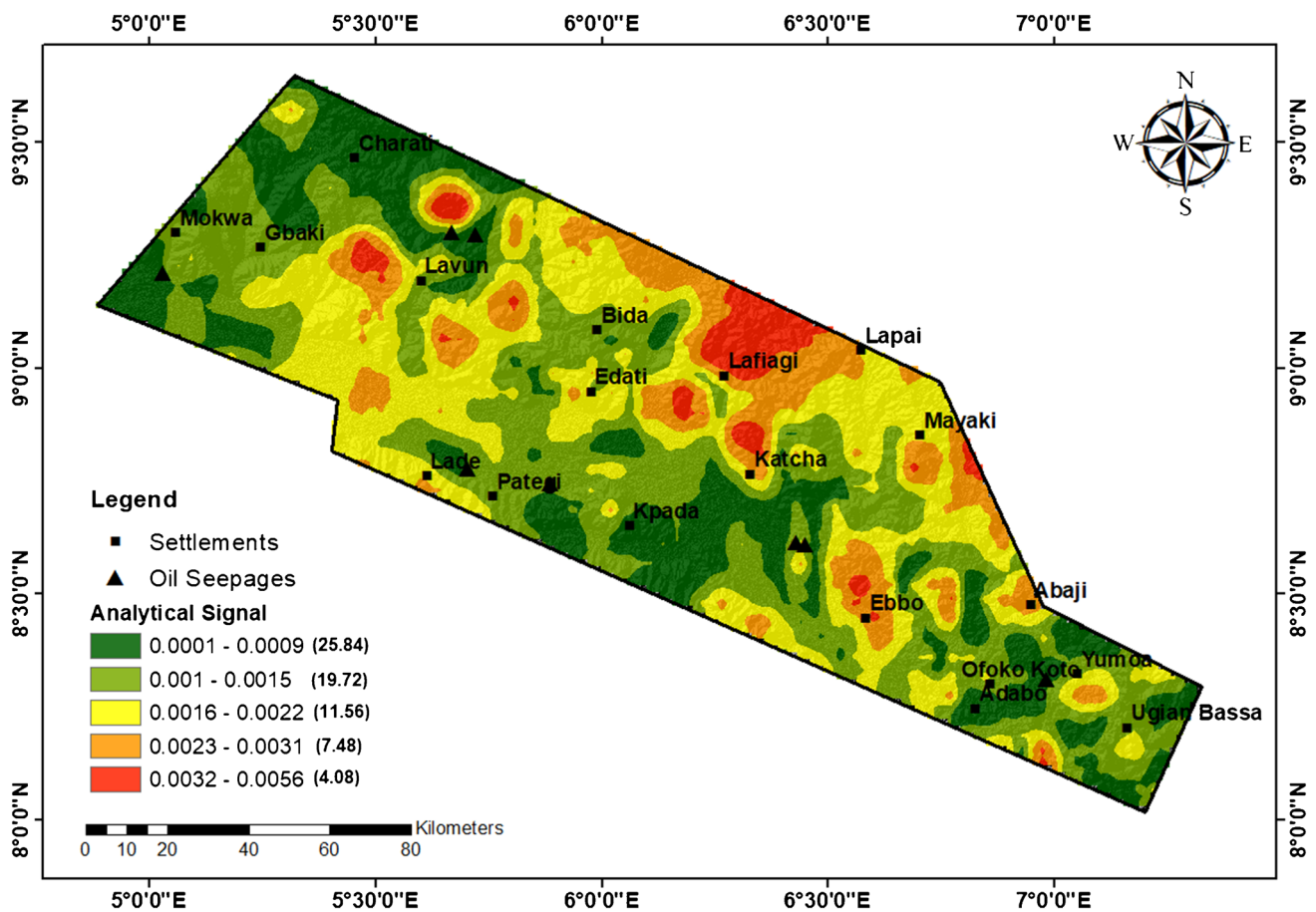


Fig. 12. Gravity data for predictive mapping of hydrocarbons

been previously applied to the Nigerian sedimentary basins where it has been used to characterize geological structures and estimate the depth of basement lithologies (Bassey et al. 2017). However, the interpretation of gravity data within these basins suggests the presence of horst and graben, a very common tectonic feature observed in the Bida Basin (Obaje et al. 2015). The high correlation of hydrocarbon seepages to zones of intense magnetic anomalies may be related to the presence of magnetic minerals within zones of hydrocarbon seepages (Liu et al. 2004). Two theories have been proposed to explain the possible occurrence of magnetic minerals within hydrocarbon-bearing zones. According to Burton et al. (1993) magnetic response to magnetic minerals could be regulated depending on the local chemical environment, for example, sulfur rich or not and the proximity to hydrocarbon plumes. Aldana et al. (2003) proposed an abiotic formation mechanism for the magnetic mineral formation and have suggested a microbial action may significantly form magnetic minerals in the presence of crude oils. Existing magnetic interpretations for hydrocarbon favorability within the Bida Basin are based on the dominance of magnetic minerals, within lithological units (Obaje et al.

2015). A high magnetic anomaly suggests the dominance of magnetic minerals which are usually abundant in basement rocks and limited within the sedimentary sequences.

Knowledge-driven multi-criteria decision models are well-known prediction tools for the exploration of hydrocarbon resources (Bingham et al. 2012; Hamzeh and Karimipour 2020), and their application to the Bida Basin is characterized by a significant range in prospectivity values. The concentration area (C-A) fractal model further segregated the prospectivity levels into 4 classes with the most prospective zone existing within the south-central and northeastern part of the study location. Fractal studies in predictive studies are not relatively new and have been applied in the discretization of anomalies within mineral potential maps (Zhang et al. 2017). In hydrocarbon studies, the C-A fractal analysis has been used in the statistical modeling of hydrocarbon reservoirs (Shafieyan and Abdideh 2019). The delineated prospective zones within the study location are in agreement with existing studies on hydrocarbon exploration across the Bida Basin (Kolo et al. 2015). The occurrence of favorable hydrocarbon potentials within these zones can be attributed to the recurrence of the most auspicious recognition criteria within every evidential dataset.

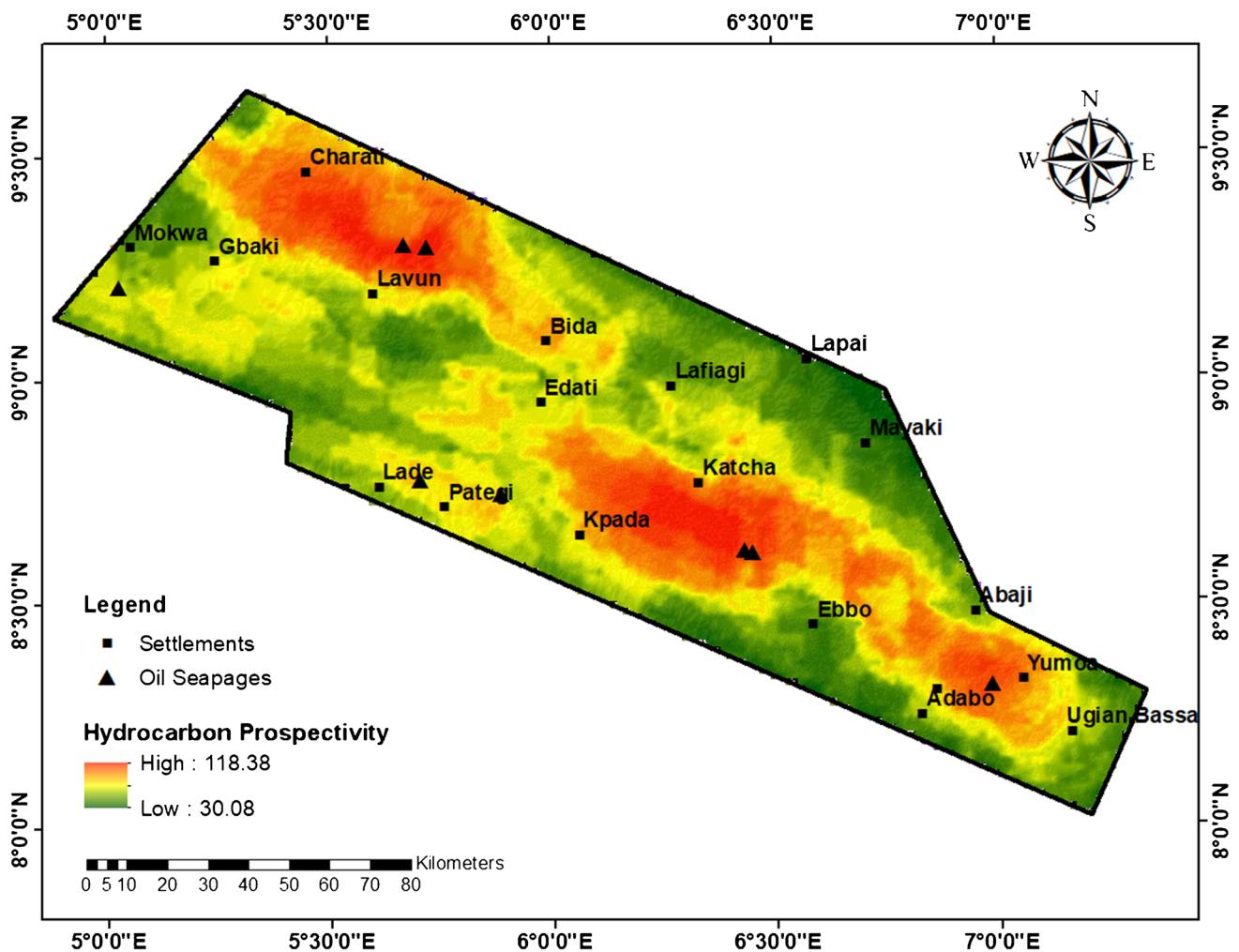


Fig. 13. Regional hydrocarbon prospectivity map for the Bida Basin

Statistical validation of the hydrocarbon-weighted sum model reveals a high degree of accuracy of approximately 80.9%. Comparatively, the accuracy levels of 80.9% deduced from the weighted sum (WS) model appears to be more reliable compared to the application of evidential belief function (EBF) in petroleum prospectivity mapping within the Ahvaz/Khuzestan province of the southwestern part of Iran (Amiri et al. 2014). However, this model was observed to be generally inferior to the frequency ratio model but almost superior to the EBF model applied to petroleum exploration within the southeastern part of Saskatchewan, Canada. Also, accuracy levels for the WS models were considered significantly inferior in comparison to the application of the artificial neural network model to hydrocarbon prospecting within Turkana County, north-west of the Kenyan republic. Although the multi-criteria weighted sum model has not been previously applied to hydrocarbon prediction, its application in the prediction of other geological phenomena is characterized by a high prediction accuracy (Tende et al. 2021a). However, prediction levels above 80%

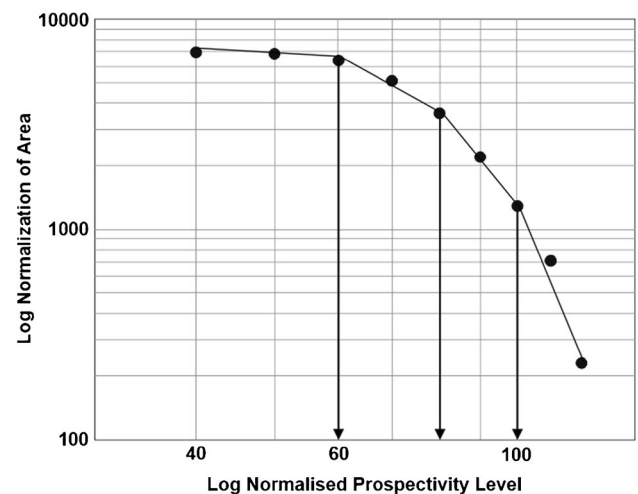


Fig. 14. Fractal plot for segregating hydrocarbon prediction levels

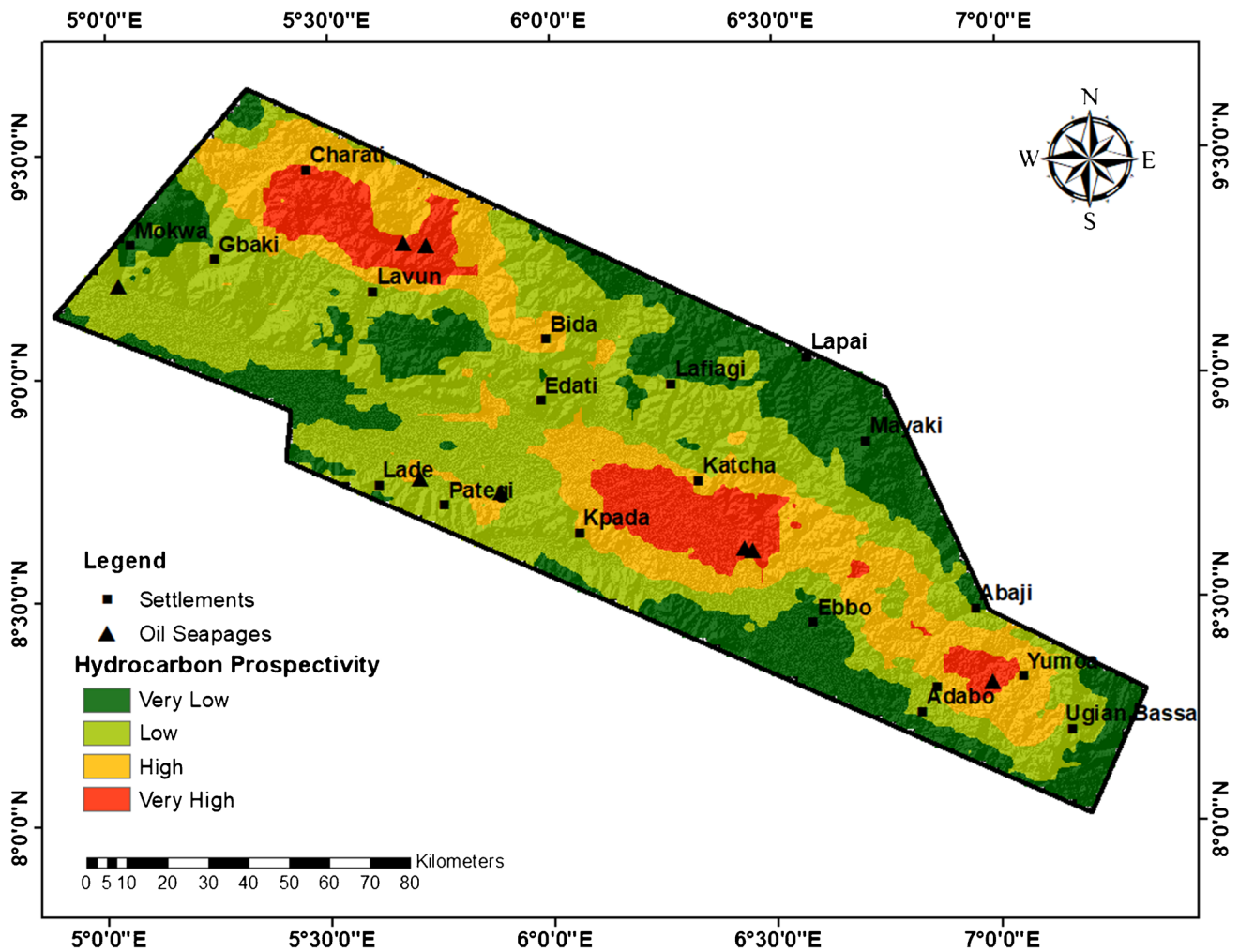


Fig. 15. Discretized hydrocarbon prospectivity map for the Bida Basin

are generally considered excellent discrimination of predictive analysis (Hosmer et al. 2013).

Conclusion

This study provides a complementary method for exploring hydrocarbon resources in the Bida Basin and involves the evaluation of various exploratory data. According to the study's findings, hydrocarbon occurrences in the Bida Basin

Table 3 Statistical analysis of prospectivity levels for the study area

S/n	Prospectivity Level	Percentage (%)	Area (Km ²)
1	Very low	25.88	4644.66
2	Low	42.43	7616.41
3	High	21.46	3852.37
4	Very high	10.23	1836.56

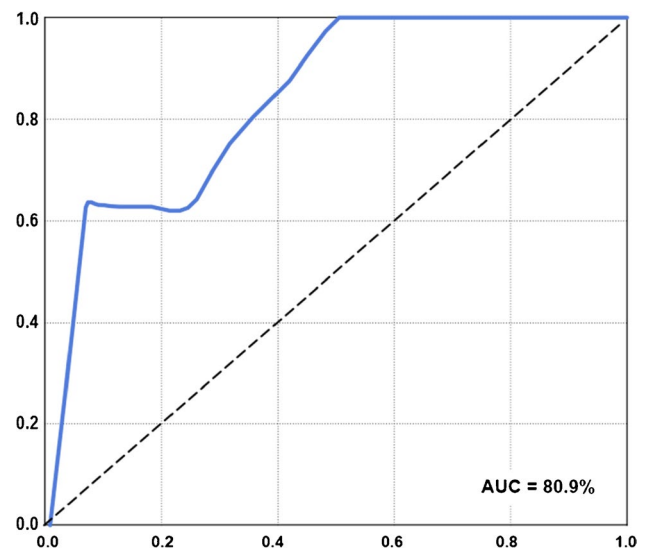


Fig. 16. Validation of the hydrocarbon prospectivity map for the Bida Basin

are structurally controlled primarily by WNW-ESE tectonic trends. Spatial data integration suggests that the best zones for discrete scale exploration are in the study area's south-central and northeastern corners. The weighted sum model's excellent reliability is a positive predictor that can be used in future exploration surveys of Nigerian frontier basins.

Declarations

Conflict of interest The authors declare no competing interests.

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