SPATIAL ASSESSMENT OF TERMITES INTERACTION WITH GROUNDWATER POTENTIAL CONDITIONING PARAMETERS IN KEFFI, NIGERIA

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Abstract

Termite mounds are traditionally presumed to be good indicators of groundwater in places they inhabit but this hypothesis is yet to be scientifically substantiated. To confirm this assertion, it is expected that termite mounds would have strong correlations with groundwater conditioning parameters (GCPs). In this study, termite mounds distribution covering an area of about 156 km^2 were mapped and their structural characteristics documented with the aim of examining their relationships with twelve (12) chosen GCPs. Other specific objectives were to identify specific mound types with affinity to groundwater and to produce a groundwater potential map of the study area. To achieve this, 12 GCPs including geology, drainage density, lineament density, lineament intersection density, land use/land cover, topographic wetness index (TWI), normalized difference vegetation index (NDVI), slope, elevation, plan curvature, static water level and groundwater level fluctuation were extracted from relevant sources. Frequency ratio (FR) and Spearman's rank correlation were used to find relationships and direction of such relationships. The result revealed a consistent agreement between FR and Spearman's rank correlation that tall (≥1.8m) and Cathedral designed mounds are good indicators of groundwater. Further, the groundwater potential map produced from the Random Forest (RF) model via Correlation-based Feature Selection (CFS) using best-first algorithm depicted an erratic nature of groundwater distribution in the study area. This was then classified using natural break into very-high, high, moderate, low and very low potential classes and area under curve (AUC) of the receiver operating characteristics (ROC) showed an 86.5% validity of the model. About 75% of mapped termite mounds fell within the very-high to moderate potential classes thereby suggesting that although tall and cathedral mounds in particular showed good correlations with a number of GCPs, high mound density in a locality is also an indication of good groundwater potential.

Keywords: Termite mounds; groundwater; frequency ratio; GIS; spearman rank correlation; random forest.

1. Introduction

Termites are social insects of enormous ecological, economic and medicinal importance (Moe et al., 2009; Fufa et al., 2013; Figueiredo et al., 2015). They are found mainly in the tropical and temperate regions of the world, but the highest diversity is recorded in Africa with more than 1000 species of the about 3000 species worldwide (Huis, 2017). The nest of termites more referred to as 'termite mounds' are long lasting structures that can remain for centuries (Davies et al., 2014) and are traditionally presumed to be good indicators of groundwater in many rural settings of Africa (Ahmed-II and Pradhan, 2018). However, studies to scientifically prove this hypothesis are lacking. During a 2015 groundwater investigation exercise in a rural community in Nigeria, notoriously known for the difficulty in locating good spots for groundwater drilling owing to the complex geology, senior citizens of the community advised the investigation team to survey a point around a termite mound. That point turned out to be the best from the electrical resistivity measurements and was thus, recommended for drilling with expected moderate to high yield (author pers. obs.).

One of the most important ecosystem functions of termites is bioturbation (Levelle et al. 1997), where a large amount of subsurface soil is burrowed to the surface (probably after breaking down softer rocky materials in some cases) in mound building process. This form of biological weathering modifies the soil structure and alters the physical and mineralogical properties of the soils around termite mounds (Jouquet et al., 2016; Jouquet et al., 2011; Bottinelli et al., 2015). Hence, because of the increased weathering process around mounds, many studies have revealed increased soil porosity and water infiltration (e.g. Ackerman et al., 2007; Eldridge 1994; Léonard and Rajot, 2001; Mando etal., 1996; Moura et al., 2014) which could likely have a positive effect on groundwater storage. In another scenario, the burrowed paths could serve as pathways to groundwater reserves or water table for the termites' water requirements which include maintaining their body metabolism, making mud for protective tunnels, surface foraging and keeping the mound interior warm and humid (West, 1970).

It will be safe to assume a relationship between termite mounds and important factors controlling groundwater occurrence and movement such as lithology, geological structures, fracture density, slope, drainage pattern and groundwater table. Mège and Rango (2010) observed a correlation between termite mounds and fractured dykes in the Ethio-Sudanese plains of Ethiopia. These dykes have similar mineralogical composition but differ significantly in the degree of jointing from the surrounding lava flows thereby suggesting them to be conduits for runoff collection and providing wetter subterranean conditions that nourish dense vegetation along the strike of the dykes. Interestingly, the authors recorded 20 dome-shaped mounds with heights ranging between 1.5 – 2m preferentially occupying a dyke that spans for about 2km (visible on remotely sensed imagery), with remarkable equal spacing between them. Although the termite species were not identified from the Ethio-Sudanese plains, *Macrotermes natalensis* (West, 1965) and *Odontotermes latericius* (Watson, 1972) were identified in the Bulawayo goldmines of Zimbabwe as locating and borrowing through fissures in basement rocks that lead to the groundwater table.

Prospective sites of groundwater reserves can be identified and delineated on a regional to semi-regional scale using morphological, topographical, climatological and land use data obtainable from remote sensing imageries and other ancillary data (e.g. Ahmed-II and Mansor, 2018; Das and Pardeshi, 2018; Golkarian et al., 2018; Nampak et al., 2014; Rajaveni et al., 2015). This approach saves time and cost compared to the traditional approach through drilling, hydro-geological, and geophysical explorations (Jha et al., 2010; Jha et al., 2007; Sander et al., 2006). The occurrence of groundwater in a given area is controlled by a number of surface indicator factors such as lithology, low elevation, low slopes, flat to concave landforms, fracture density, low drainage density, high vegetation density, groundwater table distribution, rainfall intensity etc. Information about these surface factors can be extracted from the integration of remote sensing, field and ancillary data sources and Geographic Information System (GIS) techniques for spatial analysis, visual interpretation and validation (e.g. Fenta et al., 2014; Jasrotia et al., 2013; Kordestani et al., 2018; Mahato and Pal, 2018; Sameen et al., 2018).

The integration of remote sensing and GIS data to delineate potential zones of groundwater was first achieved by the National Remote Sensing Agency of India in 1987 (Yeh et al., 2009) and since then, many studies have utilised this technology to investigate groundwater potential with recorded successes (Edet et al., 1998; Rose and Krishnan, 2009; Solomon and Quiel, 2006). Combination of statistical and probabilistic models with remote sensing and GIS data have now become popular in groundwater potential prediction. These models which could either be knowledge-driven or data-driven include the multi-criteria decision analysis (MCDA) (Akinlalu et al., 2017; Razandi et al., 2015), frequency ratio (Guru et al., 2017; Oh et al., 2011), weight of evidence (Lee et al. 2012), Evidential belief function (Mogaji et al., 2016; Nampak et al., 2014), logistic regression (Ozdemir 2011; Pourtaghi and Pourghasemi, 2014) etc. However, in recent times, data mining Machine Learning Algorithms (MLAs) have become more useful due to their ability to handle data from various sources and in different scales thereby improving the predictive accuracy of models. Many researchers have utilized a number of these algorithms with impressive results. Some of these include the Random Forest (Golkarian et al., 2018; Naghibi et al., 2017; Rahmati et al., 2016), K-nearest neighbour (KNN) (Naghibi and Dashtpagerdi 2017), Naïve Bayse (Chen et al., 2019c), Support Vector Machine (Naghibi et al. 2017; Chen et al. 2019c), and several hybrid ensemble methods such as the bagging-based Fisher's Linear Discriminant Function (Chen et al., 2019a) and Adaptive Neuro-fuzzy Inference System (ANFIS) ensemble with Teaching-learning based optimization and biogeography-based optimization (Chen et al., 2019b).

Unlike surface groundwater conditioning factors that can easily be identified from remote sensing data, large termite mounds are discernible only on high resolution imageries such as Light Detection and Ranging (LiDAR) (e.g. Davies et al., 2016; Levick et al., 2010) as they are mostly mapped by ground surveys. If at all, termite mounds can be used to indicate the presence of groundwater in a locality, the use of remote sensing; GIS and statistical analysis can be useful in analysing the existence of relationships between the termite mounds and groundwater controlling factors. Such investigation will go a long way in determining the mound type in terms of the size, design, activity status and species occupying them that are instructive to the local occurrence of groundwater. Given that no study has been done on this, putting groundwater structures haphazardly around just any type of termite mounds as currently done in many rural settings might be counterproductive. The present study however, provides baseline information as to the type of mounds important in indicating the occurrence of groundwater which would be especially useful for the rural communities in improving their precision at hitting groundwater.

The principal aim of this study therefore, is to examine the relationships between termite mounds and twelve (12) chosen important groundwater conditioning parameters using various statistical tools. Other specific objectives are to identify specific mound types with affinity to groundwater and to produce the groundwater potential map of the study area.

2. Materials and Methods

2.1 Study area description

Keffi town geographically lies between latitude N8^0 46' 40" - N8^0 53' 30" and longitude E7^0 46' 03" – E7^0 55' 30", covering an area of about 156km^2 (Fig. 1). It is characterized by tropical climatic condition with rainy season spanning from late April to October and dry periods experienced between November to March of each year (Mahmud and Achide, 2012). The annual rainfall range between 850mm - 1800mm while temperature range between 22^0C – 34^0C. An undulating topography characterizes the area with elevation ranging from 271 m to 388 m above mean sea level. The drainage pattern is dendritic with north-south orientation of the major river systems of Uke and Antau whose flow directions are concordant with the structural trend of the underlying crystalline basement rocks (Anudu et al., 2014).

The vegetation has largely been altered by anthropogenic activities (Lyam, 2000) but typifies that of Guinea Savannah belt that extends from western Senegal to eastern Nigeria. Geologically, the study area is situated within the basement complex of central Nigeria with three (3) major distinguishable lithological units namely; the Precambrian migmatitic gneisses, Upper Proterozoic schist and Lower Paleozoic older granites (Obaje, 2009; Obaje et al., 2005) with sporadic occurrences of pegmatites and quartz dykes. As with many basement complex environments, groundwater occurrence is highly variable and occurs only in the weathered and fractured bedrock aquifers (Adeyemo et al., 2017; Bayewu et al., 2017). Aquifers in this region are recharged by direct rainfall infiltration and infiltration through stream and lateral subsurface flows (Edet and Okereke, 2002). Groundwater is a major source of water in the study area since the piped water supply had become grossly inadequate. Unfortunately, the growing reliance on groundwater is not followed with strict regulations on its development, making room for many ill-experienced operators in the drilling sector to operate freely. Consequently, many boreholes have been drilled without proper completion which include testing of the boreholes performances resulting in chronic lack of borehole data for adequate planning and management of the groundwater resources (Ahmed-II and Mansor, 2018).

Figure 1**:**

2.2 Data collection

An intensive field survey was conducted to identify and map out termite mounds in the study area. This survey was carried out along road banks of 68 major and minor road networks as well as footpaths. Recordings of the coordinate position of each termite mound along with its structural features such as height, basal diameter, activity status and mound architectural design were recorded using Survey 123 mobile application tool (ESRI, Redlands, CA, USA). Height and diameter measurements were achieved using a measuring tape. Activity status was checked by either observing evidence of new building on any part of a mound (fresh wet clay soil) or breaking a part of the mound in the early hours of the morning to sample termite species if available using a metallic forceps. The sampled termite species were preserved in a solution of 70% alcohol (e.g. Choosai et al., 2009; Sarcinelli et al., 2009) and later identified at the Zoology laboratory of Nasarawa State University, Keffi.

Borehole yield inventory of 56 locations within the study area were jointly obtained from the Office of the Senior Special Assistant on Sustainable Development Goals (SDGs) Lafia, Nasarawa State and Earth-tech Nigeria Limited, Keffi. The borehole yield data were classified into high yielding (>1.5 L/s) and low yielding (≤1.5 L/s). Static water level and groundwater level fluctuation data was acquired from recording the water table of 43 wells at the peaks of wet and dry seasons.

Landsat 8 imagery of 30m spatial resolution on path 188 and row 54 and Advanced Space-borne Thermal Emission and Reflection Radiometer-Digital Elevation Model (ASTER DEM) equally of same path, row and resolution were downloaded from USGS's data distribution website (www.https://earthexplorer.usgs.gov) and used to prepare various thematic layers necessary for this study. Hard copy Geology map was obtained from existing source on a scale of 1:100,000 from where it was digitized.

2.3 Methodology

This study consists of four main steps that include: (1) development of a spatial database containing the conditioning parameters related to groundwater potential as well as termite mounds coordinate locations, (2) data standardization and analysis of relationships between termite mounds and groundwater conditioning parameters, (3) modelling the groundwater potential condition, and (4) model interpretation and validation.

Figure 2:

2.3.1 Database development and preparation of thematic layers

Selection of conditioning parameters is a pre-requisite for groundwater potential prediction. For this study, the parameters were selected based on literature review and data availability (Adji and Sejati, 2014; Yeh et al., 2009; Zabihi et al., 2016). These include: geology, lineament density, lineament intersection density, drainage density, land use/land cover, Topographic Wetness Index (TWI), Normalized Difference Vegetation Index (NDVI), slope degree, elevation, plan curvature, static water level (SWL) and groundwater-level fluctuation (GWLF). Discussion on how the layers were prepared is given below.

Termite mounds layer (TM)

The use of Survey123 for ArcGIS software application in the mapping of termite mounds and recording of their structural features made it feasible to straightforwardly download the field data in a spreadsheet format, which was then converted to CSV format. From the CSV format, the data was displayed in ArcMap 10.5 using the display XY command and subsequently converted to a shape-file. From the attribute table, all the recorded field data could be viewed, analysed, queried and manipulated.

Geology

Geology is germane in controlling the recharge of aquifers (e.g. Fashae et al., 2013; Manjare, 2014; Pinto et al., 2015) as it is the main initiator of hydrological processes (Miller et al., 1990). This layer was digitized from the geological map of Keffi and environs originally prepared by Arikawe (2016) at 1:100,000 scale. The lithology is composed of Achaean-Proterozoic crystalline Basement Complex rocks. Massive biotite-hornblende gneiss (ca. 2500Ma) occupies high-hill ranges and other isolated hills prominent amongst them are the Maloney hill. This rock type is mostly exposed to the surface and is in many cases un-fractured making groundwater exploration a difficult task. Granites, on the other hand occupy the southwestern edge of the studied area and occur as intrusives with porphyritic texture and composition ranging from granodioritic to granitic. Rocks of schistose lithology overlie the central and northeastern fringe. They generally occupy low relief areas such as riverbeds and control the stream flow directions. Their strike direction is generally north-south and are highly foliated, weathered, jointed, fractured and faulted. Obviously, this weathered and fractured rock type holds more promise for groundwater storage.

Lineament

Lineament is about the most important parameter in groundwater potential mapping from remote satellite images (Ahmed-II and Mansor, 2018). They are simple linear to curvilinear features that may be related to geological structures (faults, joints and other lines of weaknesses), geomorphological features (linear valleys, cliffs and terraces) and tonal contrast due to rock composition, soil moisture and vegetation. They are important in enhancing secondary porosity in rocks thus influencing weathering, soil erosion and groundwater movements (Edet et al., 1998). Lineaments were extracted from a cloud-free Landsat 8 OLI/TIRS image. Initial pre-processing steps employed include image calibration to reflectance, re-sampling, pan-sharpening and principal component analysis (PCA) using ENVI

5.3 software environment. This was followed by automatic lineament extraction in the line extraction module of PCI Geomatica software via edge detection, thresholding and curve extraction procedures. The interpreted lineaments were further loaded into ArcGIS 10.5 environment to obtain statistics on the length, density and intersection. Automatic lineament extraction algorithm has the advantage of being reproducible and elimination of interpreter bias (Meijerink, 1996; Raghavan et al., 1995; Ramli et al., 2010) but operates only on linearity contrast in an image thereby incorporating other linear features that are not significant to groundwater occurrence. To filter out these lineaments, only extensional fractures (formed because of tectonic movements) striking between N60^{0}W and N60^{0}E directions were considered (Caponera, 1989; Travaglia 1989). The lineaments strike directions were analysed using a rose diagram in Rockwork v-17 software. Parameters evaluated from the interpreted lineament distribution include lineament density and lineament intersection density. These parameters are defined in the equations below:

$$Ld = \sum_{i=1}^{i=n} \frac{\mathrm{Li}}{\mathrm{A}} (km^{-1}) \qquad (1)$$

where *Ld* is Lineament density, ΣLi is the total length of lineaments and A is the area of grid under consideration in square kilometre.

$$Lid = \sum_{i=1}^{i=n} \frac{\mathrm{LPI}}{\mathrm{A}} (km^{-1}) \qquad (2)$$

where *Lid* is the lineament intersection density, ΣLPI is the total points of lineaments intersection and A is the area of the grid.

Drainage density

Drainage is another important parameter of hydrogeological control and is determined majorly by the nature and structure of the bedrock, vegetation type, infiltration rate of the soils and slope gradient (Manap et al., 2013). Drainage network was extracted from the ASTER- DEM using the Hydrology tools in ArcMap, Spatial Analysts Toolbox. To avoid misleading result, sinks in the DEM were filled before it was used to produce flow direction and subsequently flow accumulation. Further, the density was calculated using the focal statistics in the neighbourhood statistics package of the ArcMap Spatial Analysts Toolbox. The mathematical expression is given in the equation below;

$$Dd = \sum_{i=1}^{i=n} \frac{\mathrm{Di}}{\mathrm{A}} (km^{-1}) \qquad (3)$$

where *Dd* is drainage density and Di is total length of drainage lines.

Land use/land cover

Land use/land cover pattern was derived from a combination of field data and Landsat 8 imageries. Land use is a significant factor that controls infiltration and runoff of surface water (Kumar et al., 2010; Shaban et al., 2006). A false colour composite (FCC) was generated using bands 5, 4 and 3 which was useful in highlighting and identifying land use classes such as water bodies and vegetated areas. Next, training sites were selected for supervised classification using the maximum likelihood algorithm in ENVI 5.3. Six classes of land use/ land cover were delineated which include built-up areas, cultivated lands, degraded forests, sparse vegetation, floodplains and swamps.

Elevation

Elevation parameter was prepared from ASTER DEM and it describes the general configuration of the topography showing a series of rise and fall of height values (undulation). Areas of low elevation collect surface runoff from high-elevated areas which increase the residence time of water on the surface, thereby allowing more time for surface water infiltration and recharging of groundwater (Manap et al., 2014).

Slope

Slope angle is yet another critical parameter in hydrogeological investigation. Gently sloping to flat areas generally promotes infiltration and recharge of groundwater (Nag and Saha, 2014) and are expected to hold more promise for groundwater accumulation (e.g. Dadgar et. al., 2017; Fenta et al., 2014; Jasrotia et al., 2013; Jha et al., 2007). As slope gradient increases, so does runoff (Israil et al., 2006) and these encourages little or no infiltration (Jaiswal et al., 2003). The slope map was prepared from ASTER DEM using the slope script in Spatial Analyst tools of ArcGIS 10.5 software and it ranges between 0^0 - 30^0.

Topographic Wetness Index (TWI)

TWI is a measure of subsurface lateral transmissivity (Nampak et al., 2014), influencing the movement and accumulation of runoff over the surface. A high value of TWI represents a lower slope area and consequently, a higher potential for groundwater accumulation (Naghibi and Dashtpagerdi, 2017). TWI is unit-less and mathematically expressed as (Beven and Kirby, 1979):

$$TWI = ln \left[\frac{\alpha}{tan\,\beta}\right] \qquad (4)$$

where α is the local upslope area draining through a certain point per unit contour length and $tan\,\beta$ is the local slope in radians. The TWI map was prepared from ASTER DEM in QGIS 3.4.1 software.

Normalized Difference Vegetation Index (NDVI)

NDVI is a measure of vegetation density and health (Kinyanjui, 2011). It quantifies vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red band (which vegetation absorbs). For this study, a dry season Landsat 8 imagery was used to assess the vegetation density where high values of the NDVI would indicate the presence of lush vegetation in the drought period that is nourished by groundwater. The NDVI map was prepared in ENVI 5.3 using the equation;

$$\text{NDVI} = \frac{(NIR-Red)}{(NIR+Red)} \qquad (5)$$

Plan Curvature (P-curve)

Plan curvature has to do with the convergence and divergence of flow perpendicular to the direction of maximum slope (Naghibi and Dashtpagerdi, 2017). Plan curvature values highlights the existence of ridges and valleys on the topography with positive values indicating upwardly convex, negative values indicating upwardly concave and zero values indicating flat surfaces. An upwardly concave slope accumulates more water and retains it for a longer period (Arabameri et al., 2019; Falah et al., 2016; Pothiraj and Rajagopalan, 2013).

Static water level (SWL)

The normal resting levels of water in 43 wells were measured using a Seba Water Level Contact Dip-meter KLL. This measurement was carried out in the early hours of the day, prior to the commencement of pumping/fetching episode. The static water level is an indication of the hydraulic gradient of any point and hence useful in quantifying groundwater potential (Madrucci et al., 2008). There is less likelihood for an aquifer to be productive when the static water level is deep compared with when the water level is shallow (Abiye et al., 2018).

Groundwater level fluctuation (GWLF)

Fluctuation in groundwater level is related to the aquifer type, recharge, abstraction and regional circulation of groundwater in an area (Abiye et al., 2018). Water level rises and falls primarily in response to recharge availability (rainfall, which is seasonal) and abstraction rate (Varni et al. ,2013). To measure this parameter, water level was measured in the peak of rainy (August) and dry (March) seasons. The change (fluctuation) is the difference between the depth of water level in the dry season and the depth in the wet season and is given by equation 6.

$$hd - hw = \Delta h \qquad (6)$$

where hd is water level during the dry season, hw is water level during wet season and Δh is the difference in water level depth (fluctuation).

The greater the change in water level (fluctuation) the less the groundwater potential and vice-versa.

With the exception of geology, plan curvature and NDVI which were classified into 3 classes each, the remaining parameters were classified into 5 classes according to natural breaks classification that assemble groupings that best group similar values and maximize the differences between classes.

Figure 3:

2.3.2 Data standardization

Standardization of individual conditioning parameters was carried out because of the large variation in the values of the processed datasets. In the standardization procedure, each conditioning parameter pixel value was normalized to have a value range between 0 and 1 for the purpose of unification and reducing high dimensionality for the modelling task (Elkadiri et al., 2014). This approach stabilizes variance, removes nonlinearity, neutralizes non-normality and improves model response. The standardization was achieved using equation 7.

$$Z_{i,n} = \frac{Z_i - \left(\frac{Z_{max}}{2} + \frac{Z_{min}}{2}\right)}{\frac{Z_{max} - Z_{min}}{2}} \quad (7)$$

where $Z_{i,n}$ is the standardized value of Z_i and signifies separate data point while $Z_{min} and\ Z_{max}$ are the minimum and maximum in the dataset.

2.3.3 Cell values extraction

Termite mounds point layer was superimposed on the twelve (12) groundwater conditioning parameters from where the multi-values to point tool in ArcGIS 10.5 software environment was used to extract the cell values of all the conditioning parameters that coincide with each of the termite mounds point locations. The cell values data were automatically drawn to the attribute table of the termite mounds layer for further analysis.

2.3.4 Relationships

To analyse the spatial relationship that exists between termite mounds and the chosen groundwater conditioning parameters, two statistical methods were employed; Frequency Ratio (FR) and Non-parametric Spearman correlation. To employ these methods, termite mounds data was set as the dependent variable and the groundwater conditioning parameters as independent variables. Following this, correlation analyses were run between the entire termite mounds data and the conditioning factors. Furthermore, splitting of the dataset according to activity status, height, diameter, architecture, species occupying the mounds and whether a mound is under tree canopy or not, was effected and their relationships with the conditioning parameters analysed.

Frequency Ratio

Frequency ratio model is a bivariate statistical method that analyses the spatial relationship between dependent variable and independent variables (Oh et al., 2011; Razandi et al., 2015). In the case of this study, the FR was used as a probability measure of the occurrence of termite mounds across reclassified conditioning parameters of groundwater occurrence. The FR value for each class of the conditioning parameters is expressed in equation 8.

$$\mathrm{FR} = \frac{w/x}{y/z} \qquad (8)$$

where, w is the number of pixels with termite mounds in each class of a conditioning parameter; x is the total pixels of termite mounds in the study area; y is the total number of pixels in each class of a conditioning parameter and z is the total number of pixels in the study area.

The value of 1 and larger indicates an average spatial correlation between termite mounds locations and a conditioning parameter class while a value lower than 1 indicates a low correlation (Lee and Pradhan, 2006).

Spearman's rank correlation

The Spearman's rank-order correlation (ρ) is a non-parametric statistics that measures the strength and direction of monotonic association between two variables (Bolboaca and Jäntschi, 2006). It assesses how satisfactory the relationship between two variables can be described using a monotonic function. The Spearman correlation coefficient is the Pearson correlation coefficient between ranked variables and is given as equation 9.

$$\rho = \frac{\Sigma(xi-\bar{x})(yi-\bar{y})}{(N-1)\sigma_x\sigma_y} \qquad (9)$$

where ρ denotes Pearson correlation coefficient applied to ranked variables, $xi - \bar{x}$ and $yi - \bar{y}$ are covariances of the ranked variables, N is the sample size and $\sigma_x\sigma_y$ are the standard deviation of the ranked variables.

To use the Spearman's rank correlation, the termite mound data was converted to a point density function then the correlation was run only between measurable conditioning parameters i.e. categorical parameters (geology and land use/land cover) were excluded. The correlation is to detect how increase/decrease in the density of the independent variables affects the density of the dependent variable.

2.3.5 Parameter selection

Not all parameters can be effective in a modelling process. In fact, large number of input parameters does not guarantee the quality of a model's output rather, it adds to cost of data collection and model processing time which might lead to misleading result (Chen, et al., 2018). It is therefore essential to test the credibility of the selected conditioning parameters in order to achieve optimum output. To achieve this, 70% of borehole yield data were treated as decisions A (high yield >1.5 L/s) and B (low yield ≤1.5 L/s). The Correlation-based Feature Selection (CFS) based on the best-first search algorithm was utilised. The CFS is a multivariate feature selection filter that identifies optimal features in a given dataset having a strong relationship with the training data of interest but uncorrelated with one another (Jain et al., 2018). The advantage of this method is that it identifies the most important and non-redundant subset of the groundwater conditioning parameters by assessing the worthiness of each of the parameters in predicting the decisions A and B. The best-first search algorithm takes advantage of the domain information to select locally best options on a forward selection at each point and the resulting parameters identified as the bests are based in terms of lowest error term and highest performance accuracy (R^2). The parameter selection was achieved in Waikato Environment Knowledge Analysis (WEKA 3.9.2) open source software. Thereafter, the insignificant parameters in the prediction were excluded out of the modelling process.

2.3.6 Random Forest Model

The Random Forest (RF) model is a machine learning technique that is powerful but flexible in handling data from various measurable scales without statistical assumptions (Rahmati et al., 2016). This ensemble classification model first developed by Breiman (2001) creates a combination of many classification trees with each generated by bootstrap samples (training dataset) while leaving behind about one-third of the overall samples for validation using the out-of-bag (OOB) prediction error (Oliveira et al., 2012; Rahmati et al., 2016). The RF model appraises the importance of a parameter by viewing at how much the prediction error rises when the OOB dataset for that parameter is permuted while others are left unchanged (Catani et al., 2013; Naghibi et al., 2017). To effectively run the RF model, there is need to define two parameters which include; the number of trees to be built in the forest (ntree) and the number of variables (mtry) to be used in each tree stochastically chosen from the available dataset.

RF model has many advantages over other machine learning techniques such as Artificial Neural Network (ANN) and Support Vector Machine (SVM) some of which include; non over-fitting, low bias and low variance due to averaging over a large number of trees. Others are low correlation of individual trees since the diversity of the forest is increased through the usage of a limited number of variables, robust error estimates using the OOB data, and higher prediction performance (Prasad et al., 2006; Wiesmeier et al., 2011; Sameen et al., 2018).

In this study, the RF was employed to establish a suitable model to use in analysing the relationship between dependent variables (39 groundwater yield data) and independent variables (GCPs) thereby, determining the weight value for each independent variable. Unlike previous studies (e.g. Golkarian et al., 2018; Naghibi et al., 2017; Rahmati et al., 2016; Zabihi et al., 2016), that selected only high yielding boreholes or springs for model training and validation or simply presence (1) and non-presence (0) of springs, this particular study embraced a different approach where high (>1.5 L/s) and low (≤1.5 L/s) yielding borehole inventory data was used in both prediction and validation. The high yielding boreholes were categorized as "1" while the low yielding ones were categorized as "0". Following this, WEKA 3.9.2 was used for the RF modelling, after which the final map was produced in ArcGIS 10.5.

2.3.7 Model validation

Validation is a very important step in assessing a model's accuracy without which a model is scientifically worthless (Chung and Fabbri, 2003). The accuracy of the produced groundwater potential model was evaluated by calculating the receiver operating characteristics (ROC) (e.g. Kalantar et al., 2018; Naghibi et al., 2017; Tahmassebipoor et al., 2016). The ROC is a graphical representation of the trade-off between the false-positive (X-axis) and true-positive (Y-axis) rates for every possible cut-off value (e.g. Chen et al., 2018a; Naghibi et al., 2018). The area under the ROC curve (AUC) represents the prediction value of a model characterized by its ability to estimate the true positive and true negative events. The relationship between

AUC and prediction accuracy of a model can be classified into the following categories: 0.5–0.6 (poor), 0.6–0.7 (average), 0.7–0.8 (good), 0.8–0.9 (very good), and 0.9–1 (excellent) (Chen et al., 2018b).

3. Results

3.1 Termite mounds characteristics

The total number of termite mounds mapped in the studied area is 361. Out of this, 66% were active and 34% were non-active. In addition, 78.7% of the mounds were situated under tree canopies while 21.3% were without canopy cover. Height of the mounds ranged between 0.23m to a maximum of 3.10m while the diameter is in the range of 0.30m to 6.15m. Four (4) designs of mounds were encountered, these include; conical design (28.6%), dome design (59.0%), lenticular design (10.7%) and cathedral design (1.7%). In terms of termite species, four (4) genus were encountered in 95 mounds. These include; *Macrotermes* (68.4%), *Nasutitermes* (13.7%), *Coptotermes* (7.4%) and *Trinervitermes* (10.5%). No mound was found to be inhibited by more than one species. Figure (4) presents the subdivision of termite mounds data according to the characteristics described above.

Figure 4:

Figure 5:

3.2 Frequency Ratio Relationships

3.2.1 All termite mounds

Result of the spatial relationship between all the mapped termite mounds and groundwater conditioning parameters using the FR model is summarized in table 1. The analysis showed that the flat and convex class of plan curvature have good correlations with termite mounds distribution with FR values of 1.01 and 1.05 respectively while there was no correlation with the concave class. As for the drainage density parameter, the 7.7-11 density class had the highest FR value of 1.10. The 4.7-7.6 and < 2.0 density classes with 1.03 and 1.0 FR values respectively follow this. About 60% of the termite mounds belong to the < 2 density class. The lowest elevation class (250-288m) together with the 321-339m class are the only classes with good correlation with termite mounds having FR values of 1.09. These classes contain only about 33% of the termite mounds. The result regarding geology showed that only the areas covered by gneissic rock have a correlation with the termite mounds having FR value of 1.01 with about 70% of mounds within the class. In the case of land use/ land cover, two (2) classes; sparse vegetation and cultivated areas revealed a correlation with the termite mounds. More than 85% of termite mounds fall within these classes of very-high to high groundwater potential classes of land use/land cover. The highest (1.9-3.6) and middle (0.7-1.2) classes of lineament density showed no correlation with termite mounds distribution. However, the 1.3-1.8 class together with the 0.26-0.69 and the <0.25 classes showed correlations with FR values of 1.02, 1.02 and 1.04 respectively. The lineament intersection density parameter on the other hand, showed no correlation with the highest and lowest classes but good correlations with middle classes with FR values of 1.04, 1.00 and 1.03 respectively. These three classes account for only about 46%. As for the NDVI parameter, the highest correlation of 1.09 falls in the 0.024 – 0.11 class (no vegetation class) and followed by the 0.16 – 0.28 class (highest vegetation class) with no correlation with the 0.12 – 0.15 class. The slope parameter showed a correlation in two classes, the lowest slope class (< 2.7) and the middle class (4.8 – 7.1) with FR values of 1.06 and 1.01 respectively. Regarding TWI, the highest correlation is with the highest class (8.9 – 12) with FR value of 1.10. Two other classes (5.4-6.2 and 6.3-7.1) also showed a good correlation with termite mounds distribution with FR values of 1.05 and 1.09 respectively.

Table 1:

From table 1 above, it is clear that termite mounds did not show particular relationships or correlations with suitable classes (high to very high groundwater potential classes) of the GCPs except with static water level. For example, NDVI parameter showed correlations in both the low and very high classes likewise the drainage density class, which showed correlations in the very high, moderate and low classes. For this reason, the termite mounds data was segmented according to the descriptions in figure 4 to find specific and/or strongest correlations with only the suitable classes of groundwater conditioning parameters.

3.2.2 Subdivisions of termite mounds

Plan curvature

Concave and flat areas have respectively very good and moderate potential for groundwater (Falah et al. 2016). These two classes of plan curvature showed correlation with all the subdivisions of termite mounds except with short mounds (0.5 – 1m height), while dome shaped mounds show correlation with both concave and convex classes. The strongest correlation however, is with Cathedral shaped mounds with FR value of 2.67 followed by *Coptotermes* species with FR value of 2.29.

Drainage density

The <2.1 and 2.2 – 4.6 classes of drainage density are considered to be of very-high to high potential classes for groundwater. Active mounds, *Macrotermes* mounds, dome and Cathedral shaped mounds show correlations with only the <2.1 density class while *Nasutitermes* and *Coptotermes* mounds have correlations with only the 2.2 – 4.6 density class. *Trinervitermes* mounds on the other have correlations with both classes while non-active mounds show correlations with all drainage density classes except with the <2.1 class. This might be a reason why some mounds become inactive as surface water inundation exterminate termite colonies

(Choosai et al., 2009; Davies et al., 2016; Levick et al., 2010), hence their avoidance of high drainage density areas. The non-active mounds correlation pattern is similar to that of conical shaped mounds where correlation strength increases with an increase in drainage density.

Elevation

Elevation classes of 250 – 288m and 288 – 305m have greater potential for groundwater storage owing to the low elevation that collect surface runoff. Conical mounds showed correlation only with both classes of elevation while *Coptotermes* mounds displayed the only correlation with the 288 – 305m elevation class. Mound heights showed a trend in correlations where shorter mounds correlated with lower elevation classes and taller mounds correlated with higher elevation classes. Other sub-divisions of the mounds did not show any particular trend of correlations, for example, lenticular shaped mounds showed correlations with lowest and highest elevation classes.

Geology

Groundwater borehole drillers' experiences have attested that of the three (3) major rock types in the study area, the Schist has greater potential for groundwater storage owing to its degree of fracture and weathering. The Gneissic rocks follow this because, there has not been many drilling experiences in the Granodiorite covered areas. The Frequency Ratio showed that mounds of *Macrotermes* and *Coptotermes*, dome-shaped mounds, short (0.5-1m) and medium height (1-2m) mounds have correlations only with the Schist rock covered areas while the non-active mounds, mounds under trees, *Nasutitermes* and *Trinervitermes* mounds, conical and lenticular-shaped mounds, as well as very short (<0.5m), small diameter (≤1m) and large diameter mound (>3m) correlate with only the Gneissic rocks. Other subdivisions showed correlations with two (2) classes of the rock types, for example, tall mounds showed a very strong correlation with Granodiorite and another with Gneiss rocks.

Land use/ land cover

The built-up and swamp classes of the land use/ land cover parameter are considered the most unsuitable in-terms of groundwater potential. This is because, built-up areas encourage runoff but not recharge due to man-made constructions that seals the ground surface (Fashae et al., 2013; Sikakwe et al., 2015) while swampy areas are highly porous but not permeable due to the high clay content of the soil, hence do not easily allow water infiltration. Other classes are considered as very high to moderate potential classes. While active mounds showed correlation with only the sparse vegetation class, non-active mounds correlated with floodplain, sparse vegetation and cultivated areas. There are quite a number of similarities in the correlation pattern among the different subdivisions of termite mounds. For instance, cathedral and tall (>2m) mounds displayed the same pattern, with correlations in the degraded forest and sparse vegetation class while *Macrotermes* mounds and large diameter mounds showed correlations in the floodplain and sparse vegetation classes. Another pattern similarity is between very short mounds and small diameter mounds with correlations in all classes except in degraded forest and built-up areas.

Lineament density

Lineament is a very important parameter in groundwater potential modelling. Places with high lineament density are known to have influence in enhancing secondary porosity for the conduit movement and storage of groundwater (Al Saud, 2010; Nejad et al., 2017). The 1.3-1.8km/km^2 and 1.9-3.6km/km^2 density classes are considered as the most suitable in terms of groundwater potential. Lenticular-shaped mounds and small diameter mounds are the only subdivisions that show correlations with only these classes of lineament densities. Other mounds such as non-active mounds, *Coptotermes* mounds, Cathedral mounds, very short mounds and large diameter mounds have their strongest correlations with either of the density classes while others such as mounds with tree canopy cover, *Trinervitermes* and *Nasutitermes* mounds as well as tall and medium diameter mounds showed no correlations with these density classes.

Lineament intersection density

There is not a single subdivision that showed correlations with only the best classes of lineament intersection density parameter (i.e. 5.8 -14km/km^2 and 15-20km/km^2 classes). However, cathedral mounds, tall mounds, lenticular mounds as well as *Nasutitermes* and *Macrotermes* mounds showed stronger correlations with the 15-20km/km^2 class. On the other hand, *Trinervitermes* mounds, dome shaped mounds, and medium height mounds did not show any correlation with either of the classes of lineament intersection density.

NDVI

The study area is generally poorly vegetated due to human activities that ranged from lumbering, cultivation and urbanisation. From the little vegetation available, it was seen that non-active mounds, mounds under trees, *Trinervitermes* mounds, very short and tall mounds and small diameter mounds have correlations with only the vegetated class while active mounds, mounds not under tree canopy, dome-shaped mounds and large diameter mounds correlate with only non-vegetated class.

Slope degree

Tall mounds is the only category that showed correlations with the lowest classes of slope (<2.7m and 2.8-4.7m) while lenticular mounds showed correlation with only 2.8-4.7m class. Few other categories have their strongest correlations in either of the two classes and these include mounds under trees, conical shaped mounds and large diameter mounds. Mounds not under trees and dome shaped mounds are the only category that showed no correlation with any of the two classes of the slope.

TWI

No single correlations with only the high TWI classes except that many categories indicated their strongest correlations with the high TWI classes (7.2-8.8 and 8.9-12). Strongest correlations were found among the categories that include active mounds, mounds under trees, *Macrotermes* mounds, *Coptotermes* mounds, conical mounds, medium height, medium diameter and large diameter mounds. Many other categories did not show correlations with the high TWI classes.

SWL

Places with shallow water table are indicative of a good groundwater potential condition and provides easiness of groundwater abstraction (Adji and Sejati, 2014; Mahato and Pal, 2018). The shallow classes of the water table appear to have a major control on mounds distribution as all the mound subdivisions showed correlation with shallow water levels classes (<2.5m and 2.6-3.7m depth). Only the tall and cathedral shaped mounds showed correlation with the deepest water table class (6.1 – 11m depth).

GWL fluctuation

Termite mounds correlation pattern with groundwater level fluctuation parameter is the complete opposite of that with static water level. Places with shallow water level in this study area were seen to have higher fluctuation in groundwater level. Consequently, all the mound subdivisions that show correlation with only shallow classes of static water level now show correlation with higher groundwater fluctuation classes (3.8-5.2m and 5.3-8.1 m). Again, tall mounds and cathedral shaped mounds have correlations with only the low fluctuation class (≤1.9m). However, conical shape mounds and mounds without tree cover also showed correlations (although not their strongest correlation) with the low fluctuation class.

Table 2:

3.3 Spearman's rank correlation

Result of the spatial relationship between all the mapped termite mounds and groundwater conditioning parameters using the Spearman's rank correlation is summarized in table 3. The analysis revealed that all mapped termite mounds together did not show any meaningful correlation with the GCPs except with lineament intersection density ($\rho = .304$, $p <.001$) and static water level ($\rho = -.321$, $p <.001$) where a significant moderate correlation was found. Further splitting of the termite mounds into categories as described in figure 4 revealed a completely different correlation pattern with that of the frequency ratio. It revealed that lineament and lineament intersection densities are the major GCPs whose increase/decrease affects the increase/decrease in density of most of the categories of termite mounds. It also revealed that NDVI is the only parameter that has no positive relationship what so ever with termite mounds, in-fact density of most categorisation of the termite mounds increase in the direction of decreasing vegetation. Spearman's correlation is instructive in showing the direction of relationships. For example, mounds of *Coptotermes* were found to have good correlations with suitable classes of the GCPs in frequency ratio but the correlations were actually in the wrong direction where the density of the mounds increase with decreasing lineament density, lineament intersection density and NDVI. The same pattern of even stronger correlation coefficients was found with mounds of *Nasutitermes*.

There is agreement between frequency ratio and spearman's rank correlation that tall and cathedral shaped mounds have about the highest correlations with GCPs. Cathedral mounds displayed strong correlations with lineament density ($\rho = .840$, $p = .036$), lineament intersection density ($\rho = .880$, $p = .021$), plan curvature ($\rho = .828$, $p = .042$) and groundwater level fluctuation ($\rho = -.828$, $p = .042$) and moderate correlations with slope ($\rho = -.414$, $p = .414$) and TWI ($\rho = .414$, $p = .414$). On the other hand, tall mounds (>2m in height) displayed moderate correlations with lineament density ($\rho = .518$, $p = .084$), lineament intersection density ($\rho =$

.664, $p = .019$), plan curvature ($\rho = .587$, $p = .045$), slope ($\rho = -.489$, $p = .211$) and groundwater level fluctuation ($\rho = -0.583$, $p = .047$).

Table 3:

3.4 Parameter selection

Twelve (12) conditioning parameters were selected for Random Forest groundwater prediction in the study area. However, as noted in sub-section 2.3.5, not all parameters can be especially useful for any prediction model. Hence, CFS attribute selection using the best-first algorithm selected seven (7) parameters as the best in predicting groundwater potential in the study area. The importance of each of these parameters is indicated as a percentage score and is shown in figure 6.

Figure 6:

3.5 Groundwater potential map

As noted earlier in subsection 2.3.6, the aim of RF model is to determine the appropriate weight value for each independent variable in the modelling process. Therefore, from the chosen best seven (7) GCPs, the percentage order of influence on groundwater occurrence (fig. 7) is geology, lineament intersection density, elevation, lineament density, static water level, groundwater level fluctuation and finally, slope. These GCPs were all converted to raster with cell values of 30 from where the weighted linear combination (WLC) method was adopted for their integration in raster calculator. The obtained cell values were then classified using the natural break classification scheme (e.g. Kordestani et al., 2018; Naghibi et al., 2018; Díaz-

Alcaide et al., 2017) into very high, high, moderate, low and very low potential classes. Further, the derived groundwater potential map (fig. 8) visually depicted the erratic nature of groundwater in the study area just as it has been described for crystalline basement rocks environment (Ejepu et al., 2017; Fashae et al., 2013). The highest groundwater potentiality of Keffi town is located in the eastern part in communities such as BCG, GRA, Keffi hotel, Gwaza area, Pyanku and El-Kabir estate. Lowest potentials are on the western part where communities such as CRDP, Angwan Tanko, Kaduna road, NYSC camp area, Sabon gari and Angwan Zakara are located.

The very-high potential class occurs as isolated patches and predominates in the eastern part of the study area although few patches are also found in the south, south-western and north-western parts. This class has area coverage of about 13.1sqkm representing only about 8.43% of the study area. The high potential class follow a similar pattern with the very high potential and covers an area of about 25.68sqkm representing 16.53% of the study area. The moderate potential class also predominate in the eastern part and has an area coverage of about 47.1sqkm representing 27.43% of the study area. The low and very low potential classes put together dominate the western part of the study area with area coverage of about 73.93sqkm representing about 47.61% of the study area.

Figure 7:

Figure 8:

3.6 Model validation

As stated earlier, a ratio of 70/30 of groundwater yield data was used for model training and validation respectively. Therefore, the yield data of 17 boreholes not applied to training the RF model were used to assess the model performance instead. The model performance assessed using the ROC curve is shown in figure 9. The curve represents the high yielding boreholes (>1.5 L/s) treated as true positives on the Y-axis and the low yielding boreholes (≤1.5 L/s) treated as false positives on the X-axis. True positives were assigned a value of 1 while the false positives were assigned a value of 0. The area under curve (AUC) was calculated to give an accuracy measure of 0.864. This explains how well the model and parameters utilized can make a good prediction (Ozdemir, 2015; Rahmati et al., 2014). Given the calculated AUC value, the produced RF groundwater model is very much acceptable for successful groundwater exploration (Oh et al., 2011).

Figure 9:

3.7 Discussion

It is obvious that not all termite mounds have a relationship with the GCPs hence, not every termite mound can be indicative of good groundwater potential location. Of the twelve (12) groundwater-conditioning parameters analysed using the FR, the strongest relationship with termite mounds is with the shallow water level. All the mounds subdivisions showed correlations with shallow water level and this has earlier been examined to exert a great control on the distribution of termite mounds (Ahmed-II et al., 2019). Further, the Spearman's rank correlation also indicated more relationships between termite mounds density and static water level than with any of the parameters analysed. Moderate negative correlations exist between static water level and mounds without tree canopy, *Nasutitermes* and *Trinervitermes* mounds, dome-shaped mounds, short and very short mounds. This relationship is such that as the static water level becomes shallower, the density of all the correlated subdivisions increases. On the other hand, tall and cathedral shaped mounds indicated strong and moderate positive correlations respectively, which mean that, as static water level becomes deeper, the densities of tall and cathedral mounds increases. Therefore, the taller the termite mound, the deeper is the water table.

From both FR and Spearman's rank correlation, it is apparent that groundwater level fluctuation is a good determinant of mound height and to some extent, mound design. While shorter mounds (≤2m) can tolerate longer periods of desiccation due to lowering of water level, tall mounds (>2m) require almost steady water level probably owing to the large size of colony inhibiting such mound types. Conversely, cathedral mounds are localized within low fluctuation zones while dome and lenticular mounds are of the medium fluctuation zones. Conical mounds however, have traits of both medium to low fluctuation zones (fig. 10).

Lineament density and lineament intersection density are other GCPs that both FR and Spearman's rank correlation agree to have moderate to strong correlations with various subdivisions of termite mounds. Most prominent among the subdivisions are tall and cathedral mounds. The density of these two (2) mound types increases with increase in hydro-lineament density. Thus, lineament as a GCP is influential in the distribution of these mound types. Again, both lineament density and lineament intersection density are additional determinants of mound heights. Spearman's rank correlation showed a nearly linear relationship between lineament intersection density and mound heights as shown in figure 10.

Figure 10:

In this study area, both the tall and cathedral mounds are built and inhabited by *Macrotermes* termite species. This species is the largest in terms of body and colony size (Turner, 2000) and are renowned in building high-rise mounds, some reaching heights of up to about 8m (e.g. Grohmann et al., 2010; Mujinya et al., 2013; Yamashina, 2010). For the area under study, termite mounds of 1.8m height and above can be instructive to indicating promising groundwater zones owing to their good correlations with GCPs such as lineament density (ρ = .513, p = .073), lineament intersection density (ρ = .607, p = .028), static water level (ρ = .513, p = .073), and groundwater level fluctuation (ρ = -.570, p = .042). Furthermore, from the prepared groundwater potential map, 270 (74.8%) of the mapped termite mounds fall between very high to moderate potential classes. Amongst them are 75% of mounds ≥1.8m and 67% of cathedral mounds.

3.8 Conclusion

In conclusion, there appears to be a semblance in the groundwater potential map produced in this study with a termite mound distribution suitability map produced by Ahmed-II et al., (2019). In preparing the said suitability map, the authors used information regarding the mound density distribution, mortality rate of mounds, height and diameter distribution as well as termite species diversity to model the suitable sites for termite nesting using five (5) environmental factors. Although our findings showed correlations between a number of GCPs with tall (≥1.8m) and cathedral mounds, the high density of mounds in a particular locality can also be an indication of good groundwater potential. The correlation between GCPs and termite mounds was underpinned by regional scale groundwater control variables and so does not effectively take into account the local scale drivers of groundwater distribution such as aquifer unit thickness and resistivity. Further field surveys aimed at locally investigating the aquifer potentials of some of these mounds are being considered in the future to refine the interpretations presented here.

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Declaration of interest

None

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