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Using artificial neural network to predict dry density of soil from thermal conductivity

Uporaba umetnega nevronskega omrežja za napovedovanje suhe gostote tal iz toplotne prevodnosti

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Abstract

Artificial neural network (ANN) was used to predict the dry density of soil from its thermal conductivity. The study area is a farmland located in Abeokuta, Ogun State, Southwestern Nigeria. Thirty points were sampled in a grid pattern, and the thermal conductivities were measured using KD-2 Pro thermal analyser. Samples were collected from 20 sample points to determine the dry density in the laboratory. MATLAB was used to perform the ANN analysis in order to predict the dry density of soil. The ANN was able to predict dry density with a root–mean-square error (RMSE) of 0.50 and a correlation coefficient (R^2) of 0.80. The validation of our model between the actual and predicted dry densities shows R^2 to be 0.99. This fit shows that the model can be applied to predict the dry density of soil in study areas where the thermal conductivities are known.

Key words: thermal conductivity, ANN, MATLAB, prediction, model

Povzetek

Umetno nevronsko omrežje je bilo uporabljeno za napovedovanje suhe gostote tal iz podatkov o njihovi toplotni prevodnosti. Metodo so preskusili na kmetijski površini v kraju Abeokuta, država Ogun v jugozahodni Nigeriji. V mrežnem razporedu so vzorčili tla v tridesetih (30) točkah in jim izmerili toplotno prevodnost s toplotnim analizatorjem KD-2 Pro. Vzorce tal so vzeli v dvajsetih točkah in jim določili v laboratoriju gostoto v suhem stanju. Nevronsko omrežno analizo za napovedovanje gostote tal v suhem stanju so izvedli s programskim paketom MATLAB. Z opravljeno nevronsko metodo je bilo mogoče napovedati gostoto tal s povprečno srednjo kvadratno napako 0.50 in kvadratom korelacijskega koeficinta (R^2) 0.80. Preskus modela s primerjavo ocenjene suhe gostote z dejansko izmerjeno je izkazal R^2 0.99. Ta odlični rezultat priča o uporabnosti metode za napovedovanje gostote v suhem stanju iz podatkov o toplotni prevodnosti tal.

Ključne besede: toplotna prevodnost, umetno nevronsko omrežje, MATLAB, napovedovanje, model

Introduction

The movement of heat in soil and rocks is a very important concept in many areas of science and engineering [1]. This movement of heat in media is dependent on the thermal properties of such media, such as thermal conductivity, thermal diffusivity and volumetric specific heat capacity. These properties serve as the transmission and storage properties of the material, which show the rate at which temperature changes within the media.

Knowledge of these thermal properties is important for the safe execution of various engineering projects (design and laying of high-voltage buried power cables, oil and gas pipelines as well as ground modification techniques using heating and freezing) and environment-sensitive projects, such as disposal of high-level radioactive waste in deep underground disposal sites or repositories [2, 3]. The understanding of thermal properties of soil is also essential for proper management of soil and water for irrigated agriculture, as well as determination of the energy balance at the soil surface, soil water retention and unsaturated hydraulic conductivity [4]. Heat is transmitted into/from the soil by either conduction or convection as a result of the thermal gradients within the soil mass. The main thermal characteristics of soil are the thermal conductivity and the thermal capacity. Soil thermal conductivity measurements describe the soil properties that govern the flow of heat through the soil. The thermal conductivity is defined as the quantity of heat that flows through a unit area in a unit time under a unit temperature gradient, as seen in Equation 1.

$$q = -\lambda grad\ T \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where q = heat flux (watts per square metre, W/m^2; λ = thermal conductivity (watts per metre Kelvin, W/m·K); grad T = temperature gradient (Kelvin per metre, K/m).

The soil thermal conductivity is significantly influenced by its dry density [5–8]. Dry density refers to the mass of soil particles per unit volume. An increase in dry density of a soil results in an increase in its thermal conductivity [6, 9, 10]. Other factors that have a secondary effect upon soil thermal conductivity include mineral composition, temperature, texture and time. The dry density plays a significant role in soil thermal conductivity but it is difficult to manage. Therefore, there is need to estimate the dry density in the laboratory. Therefore, in order to simplify the prediction of dry density of soil in the study area, the relationship between thermal conductivity and dry density was determined. This was achieved by carrying out artificial neural network (ANN) analysis. Thus, this study aims at the prediction of dry density from the thermal conductivity of soil obtained in the study area.

Description and geology of the study area

The study area is part of Southwest Nigeria (Figure 1), having mean annual rainfall of about 1500 mm. The rainfall pattern is marked by a double maxima regime. The dry season lasts up to 4 months [11]. Temperatures are constantly high, with a maximum of 32°C and minimum of ~22 °C. Relative humidity is constantly high, with a maximum of ~95% and minimum of ~70%. Most of the area is covered by rainforest and secondary forest.

The study area falls within the Abeokuta Formation (Figure 2), comprising mainly sand with sandstone, siltstone, silt, clay, mudstone and shale interbeds. It usually has a basal conglomerate, which may measure ~1 m in thickness and generally consists of poorly rounded quartz pebbles with a silicified and ferruginous sandstone matrix or a soft gritty white clay matrix [12].

Methodology

Thermal conductivity was measured on the field using a thermal analyser called KD-2 Pro (Figure 3). The KD-2 Pro is a fully portable field and laboratory thermal properties analyser. This probe uses the transient line heat source technique to determine the thermal properties of materials. A small dual-needle sensor called SH-1 (Figure 4) was used for the measurements. The sensor measured the thermal conductivity, thermal diffusivity, volumetric specific heat and

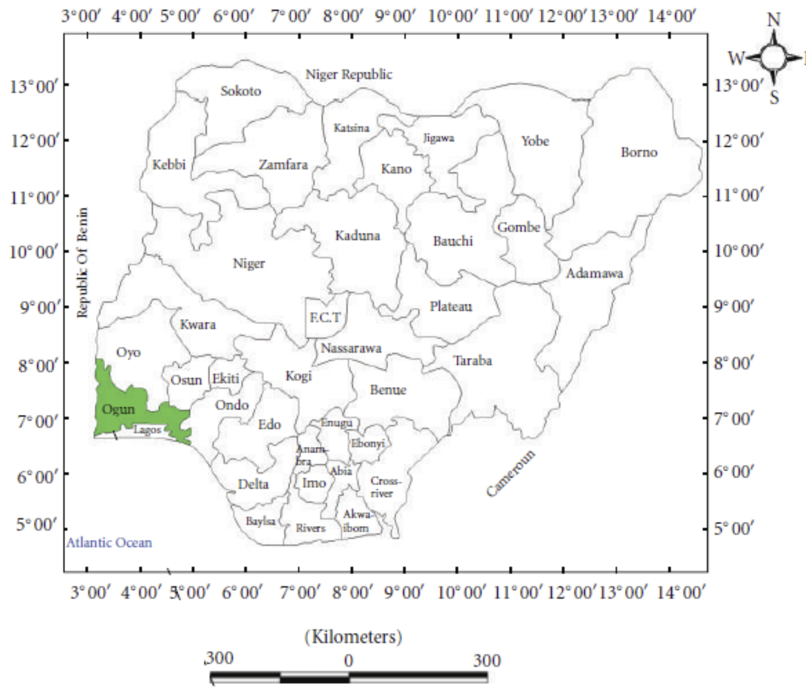


Figure 1: *Map of the study area.*

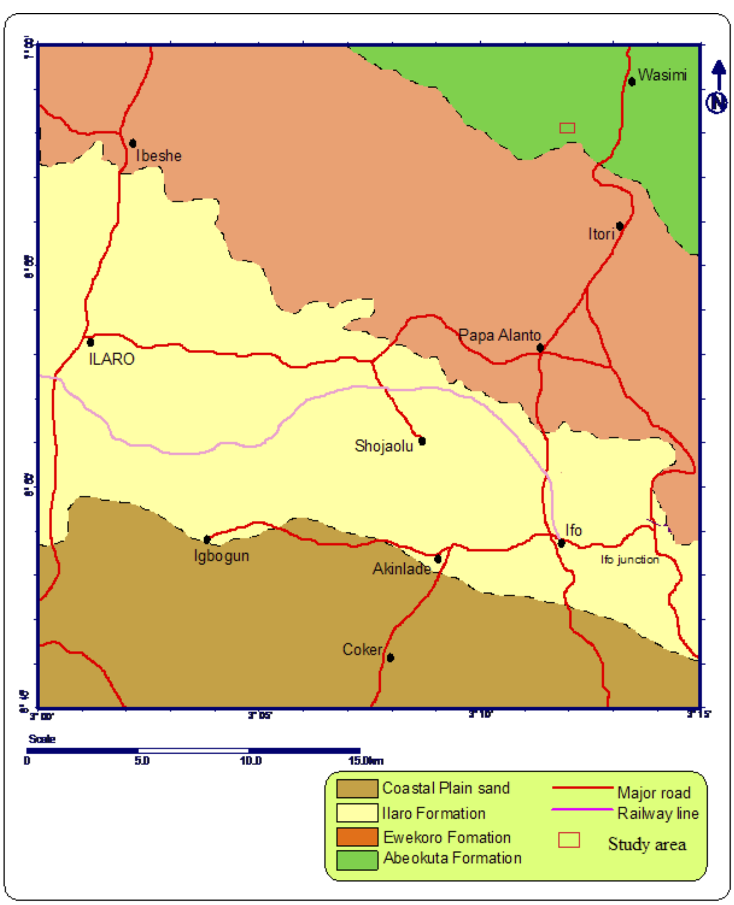


Figure 2: *Geological map of Ifo and environs showing the study area.*

Figure 3: *KD 2 Pro thermal analyser.*

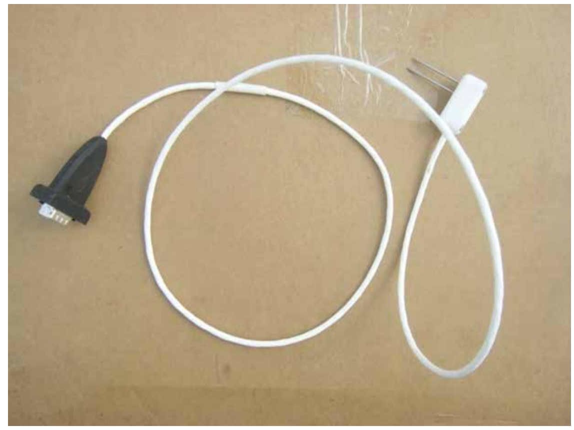


Figure 4: *SH-1 sensor.*

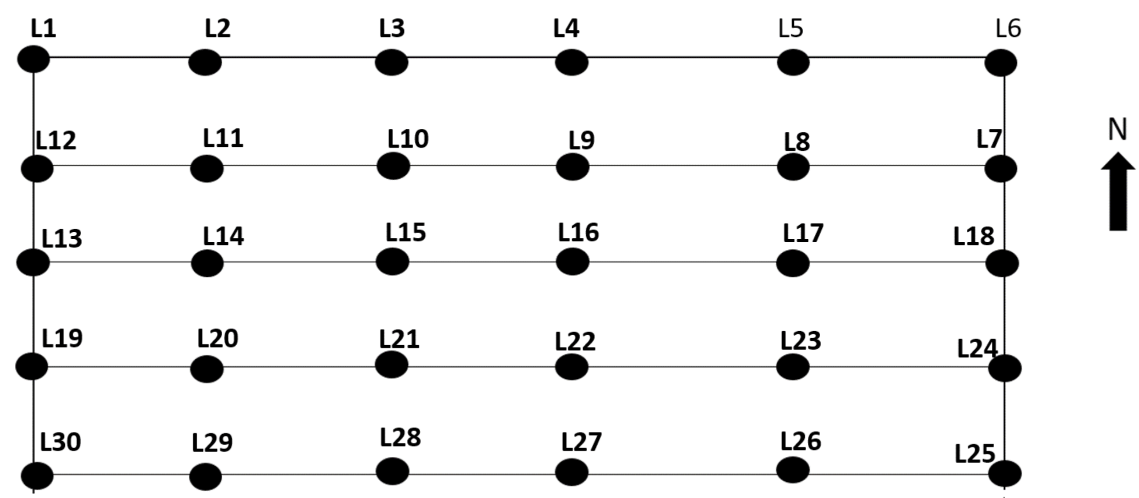


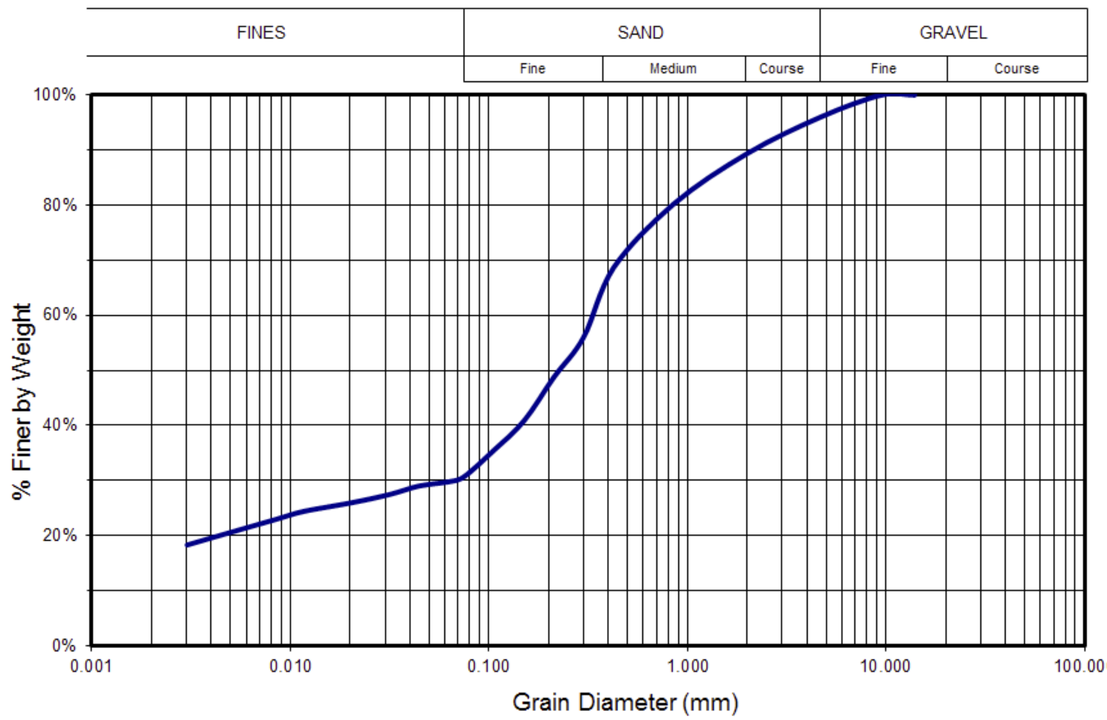
Figure 5: *Sampling points within the study area.*

temperature of materials. This sensor uses the heat pulse methodology and produces dependable soil thermal conductivity, thermal diffusivity as well as estimations of volumetric specific heat using non-linear least squares procedures. The SH-1 sensor is 30 mm long and 1.28 mm in diameter. The spacing between the two needles is 6 mm (Figure 4).

Field procedure

Field sampling design was carried out prior to measurements on the field. Regular sampling measurements were carried out in the area. The top surface of the ground was first scooped to remove the effects of top soils. The thermal sensor was calibrated using standard glycerol. This action was performed in order to test the functionality of the sensor [3, 13]. In order to measure thermal conductivity using the KD-2 Pro, the SH-1 sensor was connected to KD-2 Pro and it was turned on. We ensured that the sensor was correctly placed into the soil and the dual needles of the sensor were maintained parallel to each other during insertion to the ground. The probe was then turned on, and measurements of thermal properties were carried out. After the first measurement, the probe was rested for almost 15 minutes before taking subsequent readings.

Thirty sample points at intervals of 20 m (Figure 5) were tested for various thermal properties, while samples were collected from 20 points (L1–L20) to measure the dry density of soil in the laboratory. The samples were put in polythene bags and stored in a cool dry place, after which the necessary laboratory analyses were carried out on them.



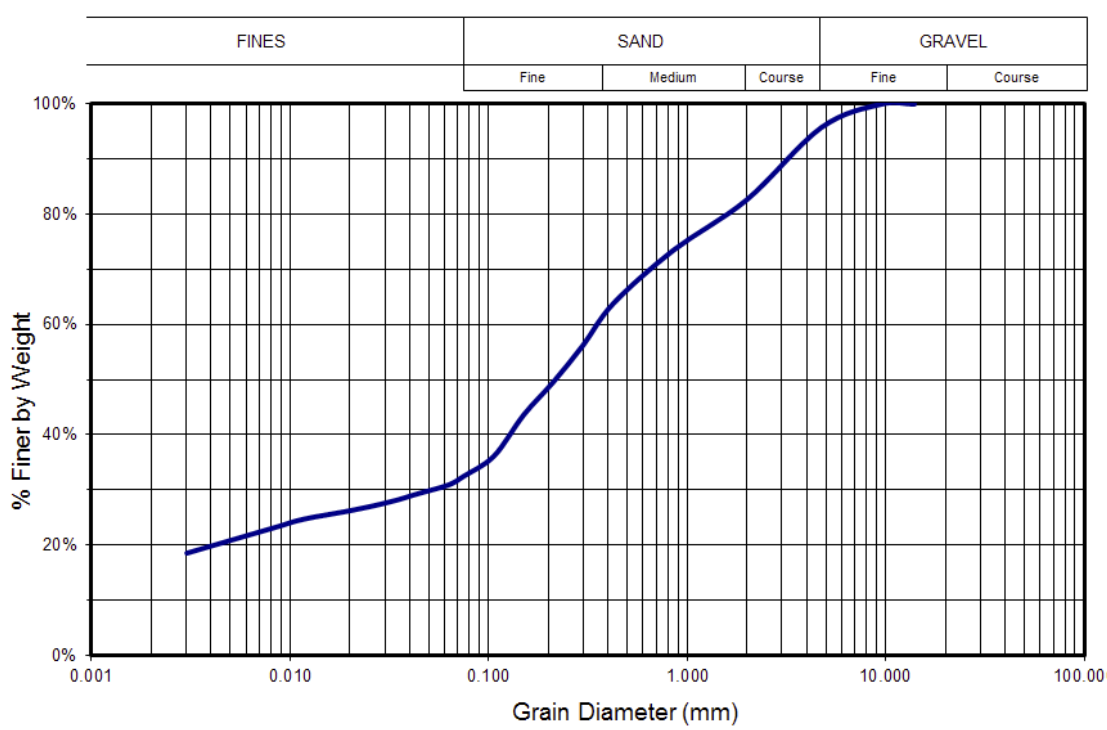


Figure 6: *Grain size analysis for locations 1 and 2.*

Laboratory procedure

In order to understand the characteristics of the soil in the area, grain size analysis was conducted on the samples.

Grain size

This analysis involves the use of mechanical shakers to determine the particle size distribution of the coarse-grained soil. Hydrometer analysis was used to obtain an estimate of the distribution of soil particle sizes for fine-grained soil, i.e. particles finer than 0.063 mm such as clayey and silty particles [14, 15]. The results from both the mechanical sieving and the hydrometer analysis were combined together to give the general result of the grain size distribution.

It is presented in the form of a distribution curve obtained by plotting the particle size against percentage finer on a semi-logarithmic chart, as shown in Figure 6a–b. The shape of the chart suggests that the soil samples are generally well graded.

Determination of dry density

Dry density was determined by the compaction test. The essence of laboratory compaction is to determine the moisture content that would produce a soil with maximum dry density. The procedure is given as follows. An air-dried soil sample weighing 3 kg was mixed thoroughly with 3 kg of water. The soil was compacted into a pre-weighed mould in five layers, with each layer subjected to 27 blows in West African standards and 55 blows in modified American Association of State Highway and Transportation Officials (AASHTO) levels [10, 16]. The compaction mould and the soil were reweighed when the collar and the mould were removed. The extruder was used to remove the compacted soil from the mould after moisture content determination was carried out on representative samples from the top, middle and bottom portions of the specimen.

The procedure was repeated after addition of water (3% by weight) until the weight of the compacted soil in the mould was determined. Dry density was plotted against the moisture content, from which the optimum moisture content (OMC) and the maximum dry density (MDD) were obtained (Figure 7).

ANN analysis

ANN is a type of artificial intelligence technique that mimics the behaviour of the human brain [17]. ANNs possess the expertise to model linear and non-linear systems without making assumptions implicitly as in the case of most traditional statistical approaches.

ANNs have been applied in various aspects of science and engineering [18, 19]. The type of neural network used in our study is the multilayered perception (MLP). An MLP neural network is composed of three layers: (1) input layer, (2) hidden layer and (3) output layer. The input layer is used to present data to the network, and the hidden layer serves as a collection of feature detectors, while the output layer is used to produce an appropriate response to the given inputs. Each layer in a network has sufficient numbers of neurons based on the specific applications. The neurons in a layer are joined to the neurons in the next successive layer, and each connection carries a weight [19]. MATLAB software environment was used for the prediction of dry density. Backpropagation training algorithm was used in the feed-forward network trained using the Levenberg–Marquardt algorithm.

We also used a non-linear hyperbolic tangent sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. A manual trial and error approach was used in our ANN model developed to estimate the number of neurons in the hidden layer. The numbers of neurons were increased in each stage of analyses to obtain the optimum model. In order to avoid the trapping of the learning process in local minima since weights were randomly assigned, the developed network was trained several times (minimum of 15 times) and we selected the best model. The training process terminates when the sum of the mean squared error falls within an acceptable range. The developed model has a three-layer feed-forward network, which is made up of an input layer, one hidden layer and one output layer (Figure 8). The neural network structures were used to construct a model, represented in Equation 2.

$$\text{Dry density} = \text{function}\ (\lambda) \qquad (2)$$

where λ is the thermal conductivity.

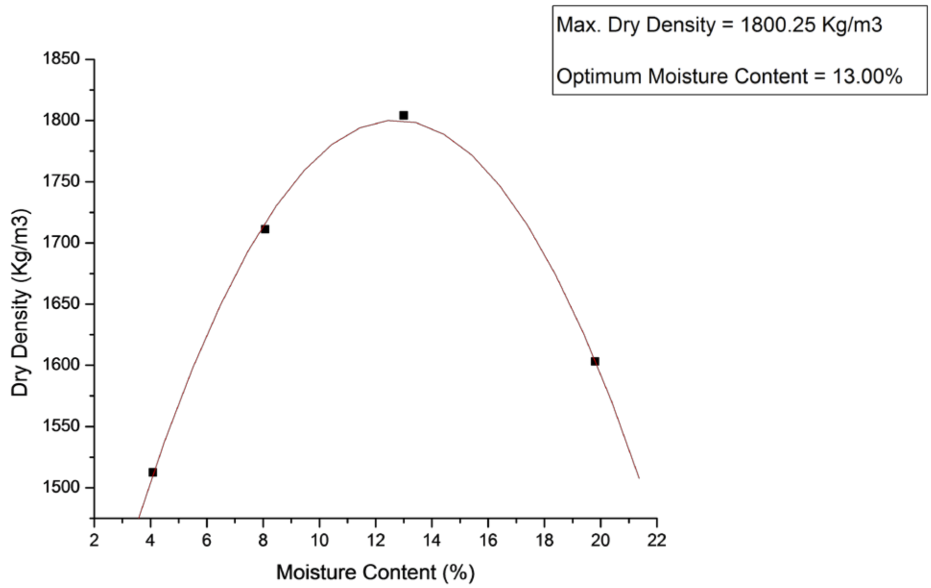


Figure 7: *Plots of compaction results for Locations 3 and 4.*

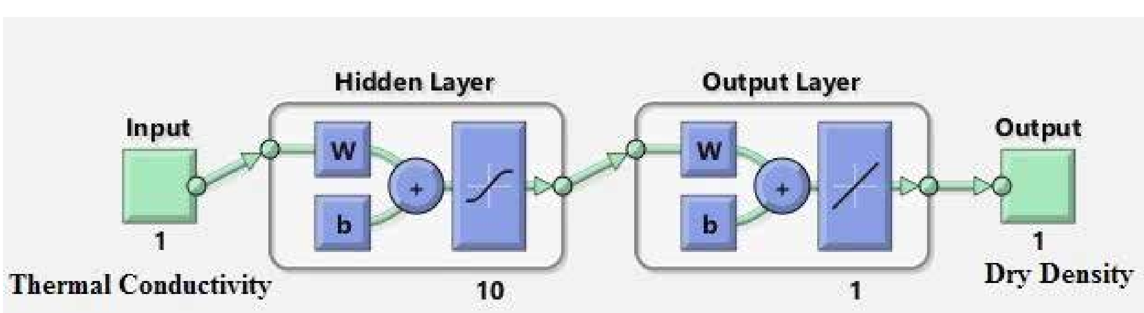


Figure 8: *Architecture of artificial neural network.*

Table 1: *Results of thermal conductivity and dry density in the area*

Locations	Thermal conductivity (W/m·K)	Dry density (kg/m^3)
1	1.996	1850.10
2	1.779	1920.25
3	1.433	1800.25
4	2.933	1840.25
5	1.504	1725.05
6	1.471	1930.00
7	1.953	1880.20
8	1.842	1810.00
9	2.37	1890.02
10	1.391	1910.02
11	1.61	1850.20
12	1.393	1906.28
13	2.37	1903.89
14	2.874	1914.87
15	1.466	1883.58
16	2.028	1875.19
17	1.381	1903.73
18	1.217	1725.27
19	1.848	1835.85
20	1.603	1923.25

Results and discussion

The results from the analyses of the thermal conductivity and dry density are presented in Table 1.

Thermal conductivity ranges between 1.217 and 2.933 W/m·K, with an average of 1.823 W/m·K, while dry density varies between 1725.05 and 1930.00 kg/m^3, with a mean of 1863.91 kg/m^3.

Figures 9–12 show the regression models for the training, testing and validation phases that contain all networks for the ANN model generated for dry density. Figure 9 shows that the degree of correlation between predicted dry density and measured values is moderately high for our training data, having correlation coefficient (R) of 0.86.

The testing model gives high correlation coefficient between predicted dry density and measured dry density, and the value is found to be 0.99 (Figure 10).

The validation model shows the correlation coefficient between the predicted and measured dry densities, which was found to be very high,

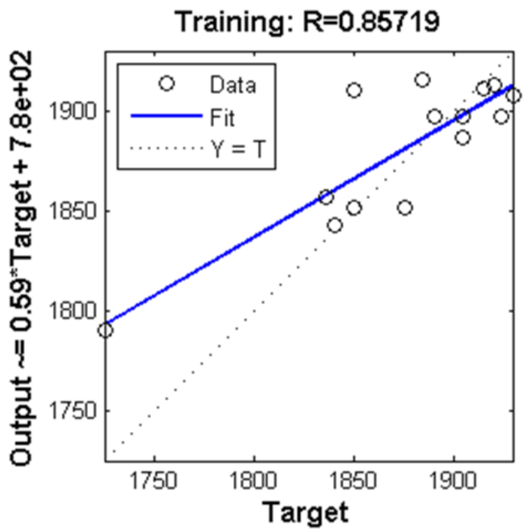


Figure 9: *Regression model for the training network.*

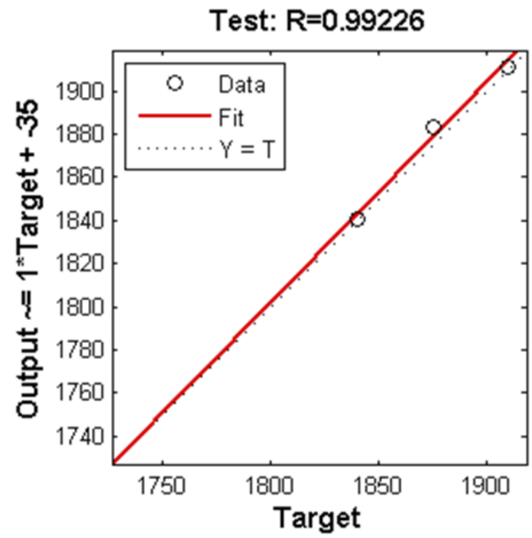


Figure 10: *Regression model for the testing network.*

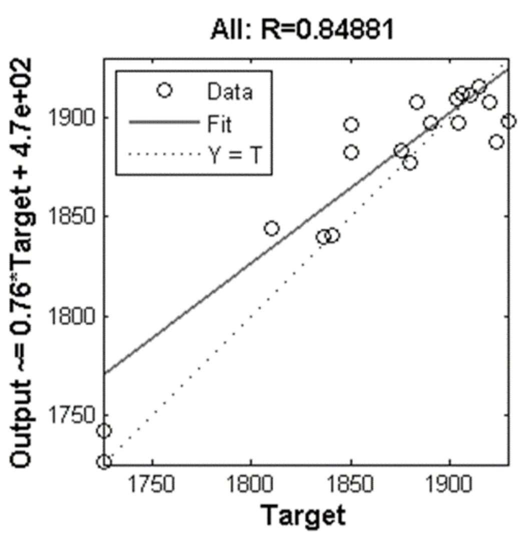


Figure 11: *Regression model for the validation network.*

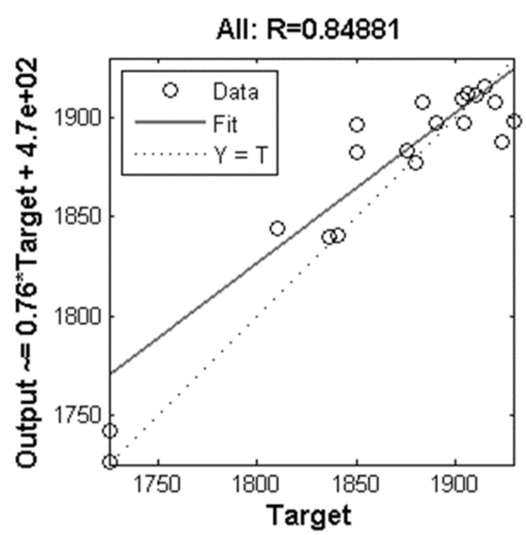


Figure 12: *Regression model for the network phase.*

with *R* value of 0.99 (Figure 11). This model is the model used to check the performance of our ANN [20].

The network phase (i.e. combination of training, testing and validation models) for the ANN model gives moderately high correlation coefficient between predicted and measured dry densities, with *R* of 0.85 (Figure 12).

We compared the measured and predicted dry densities generated by our ANN model (Table 2). The deviation of the simulated results from the actual measurements is within the acceptable limit, which we set at maximum of 5%. Root–mean-square error (RMSE) was estimated for the predicted and measured dry densities using Equation 2 in order to check the performance of the model developed in this study [21]. The RMSE was found to be 0.50, which indicates good prediction performance of the model [21]. Therefore, we could say that based on the high values of *R* and the low value of RMSE, our model shows high prediction performance and that the generalised model

Table 2: *Measured versus predicted dry densities*

Measured dry density (kg/m³)	Predicted dry density (kg/m³)	Error (%)
1850.10	1850.18	−0.004
1920.25	1920.23	+0.001
1800.25	1800.38	−0.007
1840.25	1840.05	+0.011
1725.05	1725.14	−0.005
1930.00	1930.37	−0.019
1880.20	1880.20	0.000
1810.00	1810.28	−0.015
1890.02	1890.24	−0.012
1910.02	1910.27	−0.013
1850.20	1849.97	+0.012
1906.28	1906.57	−0.015
1903.89	1903.24	+0.034
1914.87	1913.32	+0.081
1883.58	1884.43	−0.045
1875.19	1875.03	+0.009
1903.73	1903.72	+0.001
1725.27	1725.4	−0.008
1835.85	1835.89	−0.002
1923.25	1924.17	−0.048

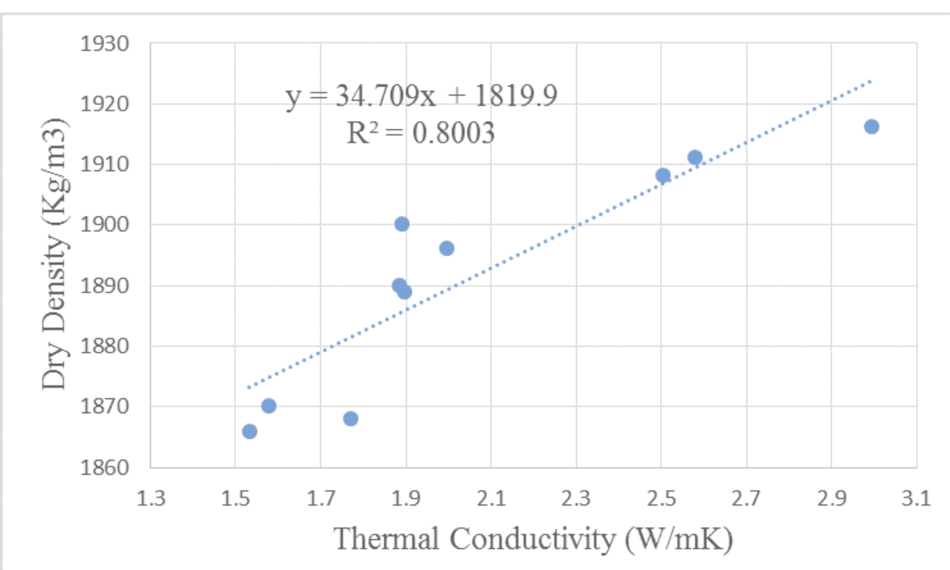


Figure 13: *Relationship between thermal conductivity and dry density in the study area.*

Table 3: *Predicted dry density*

Locations	Measured thermal conductivity (W/m·K)	Predicted dry density (kg/m^3)
21	1.896	1889.01
22	1.579	1870.26
23	1.533	1866.02
24	2.993	1916.32
25	2.504	1908.24
26	1.771	1868
27	1.996	1896.24
28	1.886	1890.02
29	2.58	1911.14
30	1.891	1900.22

is efficient in predicting the dry density using thermal conductivity.

$$RMSE = \sqrt{\frac{\sum_1^n (y - \bar{y})^2}{n}} \ldots\ldots\ldots\ldots\ldots. \qquad (3)$$

where y is the measured value, $\bar{y}$ is the predicted value and n is the total number of measured data points.

The model developed was then used to simulate the dry density for the remaining 10 locations where the dry densities were not measured in the laboratory but whose thermal conductivities were known (Table 3; Figure 13). The relationship between the dry density and thermal conductivity was moderately high, with R^2 of 0.80.

Conclusions

We have demonstrated the use of ANN in the prediction of dry density of soil in a farmland in Abeokuta using the thermal conductivity as a function. Our ANN was able to predict the parameter with high degree of correlation between the actual and predicted dry densities. Analysis of RMSE also showed high performance of the predictive model. Therefore, the predictive model can be implemented to predict the dry density of soil in study areas where thermal conductivities are known. We suggested linear regression analysis from the ANN to predict the dry density of soil in the study area. However, it should be noted that the predicted equations developed in this study are only valid for soils that have the same characteristics as the soil in the study area. More studies are required to verify these relationships.

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