(RESEARCH ARTICLE)

Naive Bayesian classifier and random forest approaches for modeling the electrical resistivity of soils in tropical zones by meteorological variables: case of nine sites in Lomé, Togo

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Abstract

The work combined in this article presents the results of modeling the electrical resistivity of soils based on meteorological data such as geo-referenced coordinates (A), the state of nature the day before (B), the state of nature of the day (C), the ambient temperature (D). A total of 9815 data were sampled over three consecutive years in Lomé, Togo. As methods, we carried out the characterization of the electrical resistivities of the soils measured by Wenner – Schlumberger techniques on nine sites selected in Lomé. Random forests and Naive Bayesian Classifiers are the algorithms used. Certain performance evaluation criteria most commonly encountered in the bibliography are taken into account to evaluate the models. The best result is obtained with random forests and gives MAPE = 17.372%, RMSE = 22.419%, RRMSE = 15.185% and R^2 = 70.4%. The result obtained with the naive Bayesian classifier is: MAPE = 24.01%, RMSE = 49.79%, RRMSE = 33.63% and R^2 = 37.34%. We deduce from these results that random forests are well suited to predicting the electrical resistivity of soils in tropical areas using meteorological variables. However, it would be good to explore other algorithms to check if the performance will not be better.

Keywords: Naive Bayesian Classifier; Random Forests; Soil Electrical Resistivity; Classification; Prediction.

1. Introduction

In our time, electrical energy occupies a predominant place in daily life, because it offers a range of services that make life easier for populations by relieving them of certain painful and repetitive tasks. Everything suggests that technological development cannot take place without it. In short, electricity is a basic resource for economic and human development. Its presence also makes it possible to measure the level of social and industrial development of a country.

Despite these many advantages, the use of electrical energy often presents dangers for people and property. These dangers are usually linked to insulation defects in the devices used, [1], [12], [13], [23], [24]. There are also other causes such as lightning and direct contact. To protect users of electrical energy against these faults, a device is necessary: the earthing system, [25].

Earthing is a crucial element which generally plays two roles: maintaining equipotentiality and evacuating earth fault currents, [24]. To effectively carry out earthing, the electrical resistivity of the ground is an important parameter to take into account, [25]. The electrical resistivity of the soil is influenced by intrinsic variables such as porosity, salinity, water

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content, grain size, clay content. For extrinsic variables we can cite the temperature, the nature of the soil, the geo-referenced location, etc.

The nature of the soil varies depending on the location and at all scales, [3]. Within the same plot, it is not uncommon to observe several types of soil presenting very different physical, physicochemical and biogeochemical characteristics [11]. The basic parameter linked to the nature of the ground for the implementation of an earthing system is its electrical resistivity. Several works have been devoted to modeling this electrical resistivity of the ground, [1], [2], [4], [8], [12], [25].

This work used stochastic methods, finite elements, and some artificial intelligence algorithms (RNA, SVM, ANFIS). These methods and algorithms were further explored in Matlab software. As Matlab is software that requires a license, it is time to resume this work using other free software like Python, Anaconda. The advantage is linked to the fact that other artificial intelligence algorithms exist and can be incorporated into this free software. It is also important to emphasize that the ever-increasing climatic anomalies favor the increase in databases for meteorological input variables, hence the need to take them into account.

The objective of this work is to explore algorithms such as random forests and the naive Bayesian classifier, which have proven their worth when the parameters are random in the study of a system, in a python environment to model this resistivity. The implementation and validity of this objective will involve the exploration of some criteria for evaluating the performance of models very often used in the literature [1] such as the Mean Absolute Percentage Error (MAPE), the Root Mean Square Error (RMSE), the Relative Root Mean Square Error (RRMSE) and the correlation coefficient (R^2).

The aim of this work is to consider as input variables the geo-referenced coordinates (A), the state of nature the day before (B), the state of nature of the day (C), the ambient temperature (D) to incorporate it into the aforementioned algorithms to predict the electrical resistivity of the soil particularly in tropical areas. The data samples will be measured at sites chosen as reference in this study.

2. Materials and methods

The data samples used in our study come from nine (09) sites located in the city of Lomé, the capital of Togo. Electrical resistivity values are measured by the Wenner–Schlumberger method. During the measurements, the georeferenced coordinates, the state of nature the day before the measurement, the state of nature on the day of the measurement as well as the ambient temperature in the field were associated with the electrical resistivities thus constituting the variables d entry into the study of our model. We therefore have four variables which will serve as input to the development of our model. Table 1 details these variables, their mathematical explanation and the associated coding system.

Table 1 List of input variables for the simulation

Input variables	Values	Mathematical explanations	Codes
Geo referenced coordinates of the point	Longitude	-	A
	Latitude		
	Altitude		
State of nature the day before the measurement	Very sunny	1	B
	Sunny	2	
	Less sunny	3	
	Partially covered	4	
	Cloudy	5	
	Rainy	6	
State of nature on the day of measurement	Very sunny	1	C
	Sunny	2	

	Less sunny	3	
	Partially covered	4	
	Cloudy	5	
	Rainy	6	
Ambient temperature (in ° C) at the point of measurement	25 ; 26 ; 27 ; 28 ; 29 ; 30 ; 31 ; 32 ; 33 ;34 ; 35.	-	D

Regarding this article, for the construction of our model, we took into account the four input variables simultaneously, which corresponds to the combination [ABCD].

2.1. Random Forests

Random forests are one of the popular techniques for data prediction. They are widely recognized for their ability to provide more accurate predictions on various data sets. In a comparative study carried out by Fernández-Delgado et al. (2014) [22], which looked at 121 datasets and evaluated 179 algorithms, random forests were shown to consistently rank among the best predictive algorithms. In addition, this method has the advantage of having a limited number of parameters, which facilitates their model adjustment processes in order to obtain the best possible performance on a random data set.

A random forest consists of aggregating the prediction of several trees. The idea behind this technique is to group the mean (in the case of regression) of the predictions in order to reduce the variance associated with it. The principle consists of aggregating the prediction of several different regression trees [17]. Figure 1 presents a flowchart for the construction of a basic random forest and Figure 2 shows how its algorithm works.
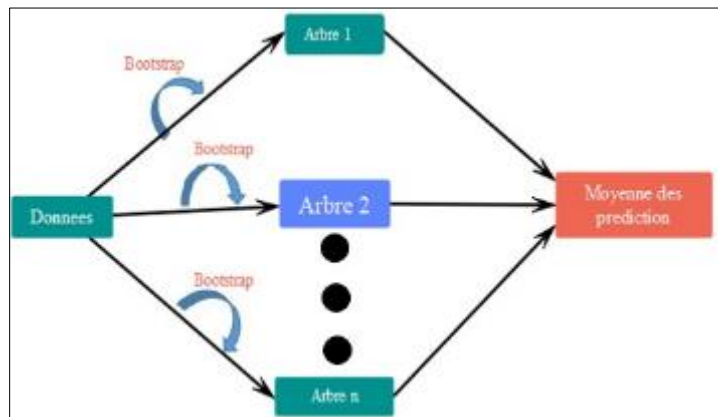

Figure 1 Flowchart for building a basic random forest

The random forest method combines ensemble learning and decision tree construction to improve the accuracy of predictions. A decision tree is structured into classification trees and data regression trees. The target variable used in this work being of continuous type the tree is composed of:

- Decision nodes each containing a test on an attribute;
- Branches generally corresponding to one of the possible values of the selected attribute;
- Sheets including objects that belong to the same class.

Combining multiple decision trees in random forests allows you to create more robust prediction models. Each tree is built using a different training sample, created from the initial sample. When predicting, random forests aggregate predictions from all trees to get a final prediction. Since classification and regression can be exploited, the work presented in this document only takes regression into account.
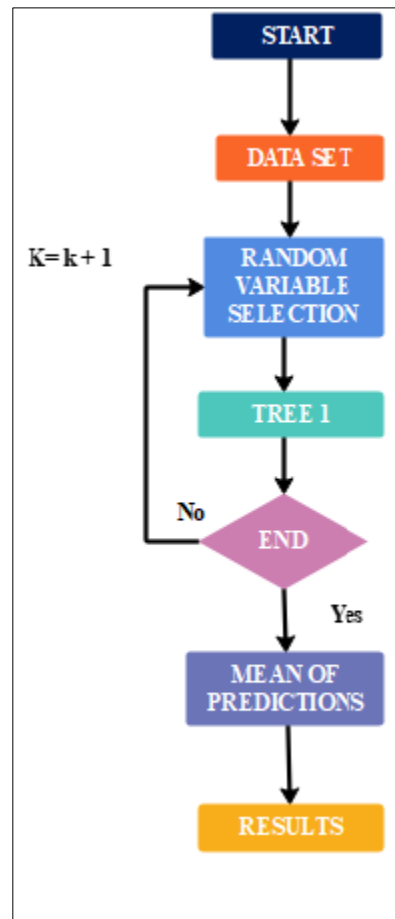
Figure 2 Random forest operating algorithm

2.2. Naive Bayesian classifier

Bayesian classifier is a machine learning method that is based on Bayes' theorem and is widely used for data categorization and classification. Its fundamental principle is to estimate the probability that a data instance belongs to a given class, based on the characteristics (or attributes) of this instance. This process is called "Prior probabilities" [7]. The Naive Bayes Classifier is a variant of the Bayesian classifier that assumes strong conditional independence between features (predictor variables). This simplification allows for faster and more efficient calculations. The term "naive" in the naive Bayesian classifier comes from the simplifying assumption that features are independent of each other, given the class. It has some key principles such as using Bayes' theorem to calculate inverse conditional probabilities, applying the Bayesian decision rule for classification, estimating probabilities from training data, and hypothesis of conditional independence of characteristics.

The naive Bayesian classification algorithm, is made up of several steps (figure 3) which are: preparation of training data, estimation of prior probabilities, estimation of conditional probabilities, calculation of posterior probabilities and prediction class. We note two main variants of the Bayesian classifier. The multinomial Bayesian classifier which is an adaptation of the naive Bayesian classifier for discrete or categorical variables (a discrete or categorical variable represents observations or measurements that can be classified into distinct, unordered categories), [21]. They are defined by a finite or countable set of distinct values and cannot be subjected to continuous mathematical operations.

The Bayesian Gaussian classifier which assumes that the predictor variables (features) follow a Gaussian distribution conditional on each class. Instead of estimating discrete conditional probabilities for categorical features, it estimates Gaussian distributions. Gaussian distribution parameters, such as mean and variance, are estimated from the training data for each class for continuous features.
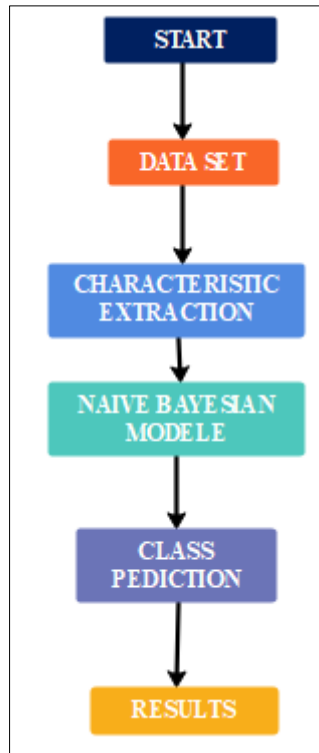
Figure 3 Operating algorithm of the naive Bayesian classifier

2.3. Model performance evaluation criteria

In order to evaluate the prediction performance, we used criteria such as: mean absolute percentage error (MAPE) root mean square error (RMSE), square root of root mean square error average expressed in a relative way (RRMSE) and the correlation coefficient (R^2). They are calculated by the relations (1 to 4)), [22], [23], [24].

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\rho_{j,p} - \rho_{j,r}\right)^2} \tag{1}$$

$$RRMSE = \frac{\sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\rho_{j,p} - \rho_{j,r}\right)^2}}{\frac{1}{N}\sum_{j=1}^{N}P_{j,r}} \tag{2}$$

$$MAPE = \sum_{j=1}^{N}\left|\frac{\rho_{j,p} - \rho_{j,r}}{\rho_{j,r}}\right| \times 100 \tag{3}$$

$$R^2 = \frac{\sum_{j=1}^{N}\left(\rho_{j,P} - \rho_{p,avg}\right) * \left(\rho_{j,r} - \rho_{j,avg}\right)}{\sqrt{\left[\sum_{j=1}^{N}\left(\rho_{j,p} - \rho_{p,avg}\right)^2\right] * \left[\sum_{j=1}^{N}\left(\rho_{j,r} - \rho_{r,avg}\right)^2\right]}} \tag{4}$$

Where :

$\rho_{j,p}$ represent the estimated or predicted values;

$\rho_{j,r}$ are measured values

$P_{p,avg}$ being the predicted mean values

$\rho_{j,avg}$ is the average measured value

N is the number of points sampled

3. Results

The results of the statistical estimation of the electrical resistivity values measured on the nine (9) sites are presented in Table 2.

Table 2 Summary of site characterization

Sites	Mean	Standard deviation	Mode	Median	Minimum	Maximum	Kurtosis	Skewness
1	190.710	23.737	188.495	189.385	106.448	276.462	3.425	0.091
2	104.014	23.002	39.997	105.522	39.997	185.101	3.187	0.040
3	185.632	27.942	100.635	185.242	100.635	277.559	2.608	0.033
4	172.213	20.794	188.495	172.609	95.727	241.948	3.259	-0.026
5	95.248	21.580	35.212	94.267	35.212	166.584	2.918	0.181
6	133.213	21.383	70.494	132.803	70.494	206.447	2.815	0.033
7	164.183	24.917	89.628	164.094	89.628	235.660	2.972	-0.033
8	119.693	26.248	36.526	117.503	36.526	206.902	2.796	0.263
9	168.144	30.819	74.988	168.553	74.988	270.363	3.026	0.007

The information is presented in the form of a histogram of resistivities grouped by class according to their relative frequency, to which we have applied Gauss's normal law and are illustrated by figures going from 4 to 12.
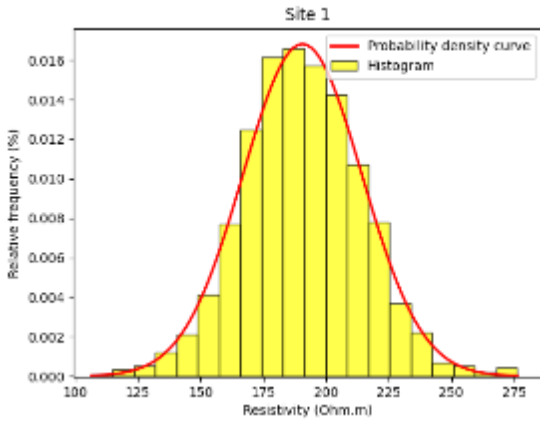
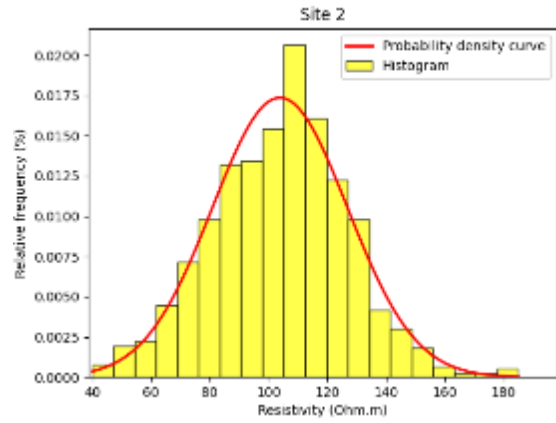**Figure 4** Distribution of values relative to the relative density of site 1

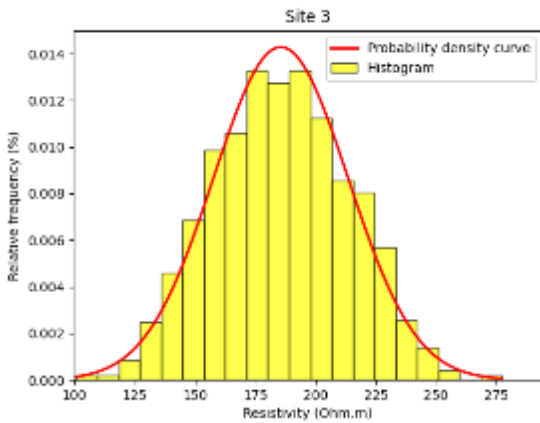**Figure 5** Distribution of values relative to the relative density of site 2

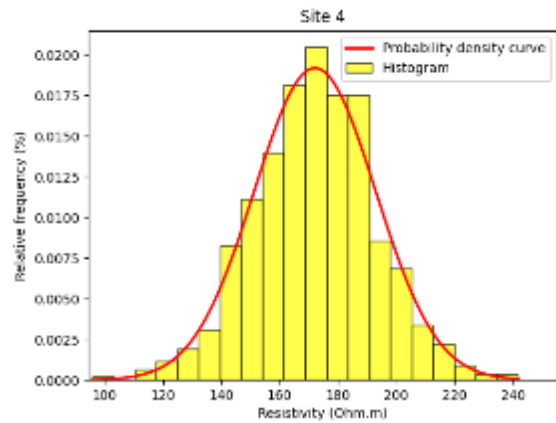**Figure 6** Distribution of values relative to the relative density of site 3

Figure 7 Distribution of values relative to the relative density of site 4
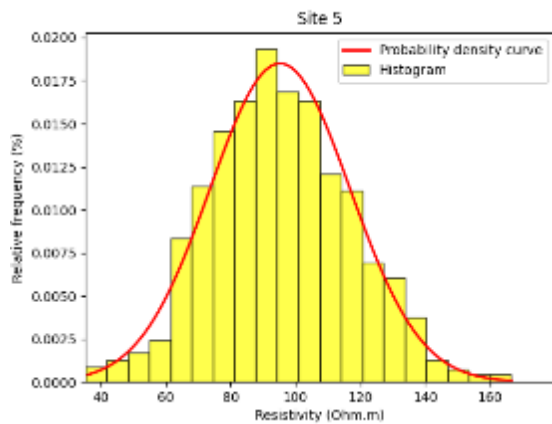

Figure 8 Distribution of values relative to the relative density of site 5

Figure 9 Distribution of values relative to the relative density of site 6

Figure 10 Distribution of values relative to the relative density of site 7

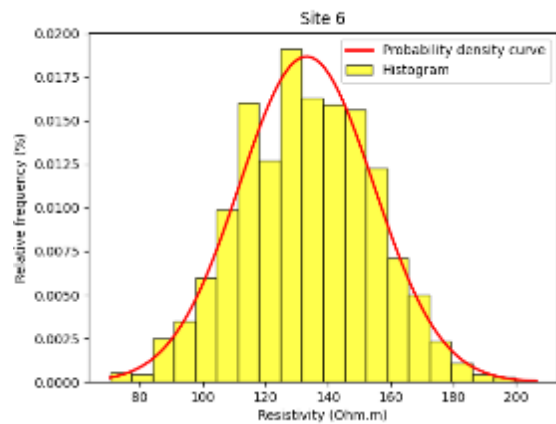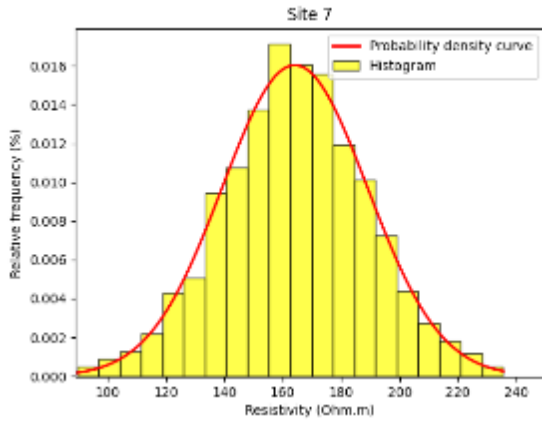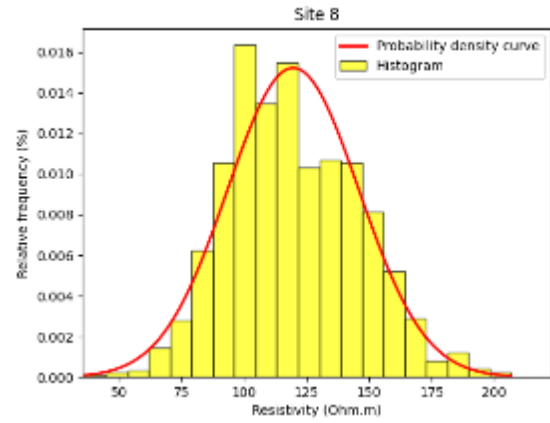**Figure 11** Distribution of values relative to the relative density of site 8
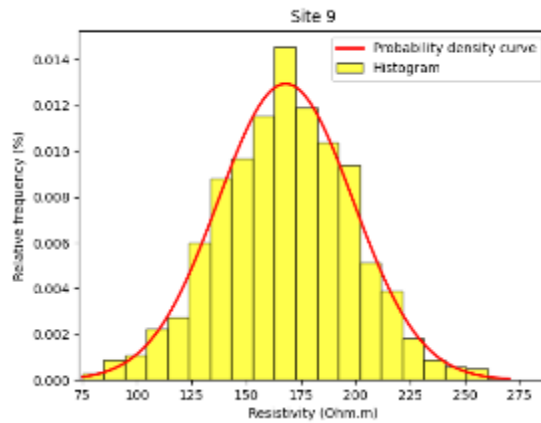

Figure 12 Distribution of values relative to the relative density of site 9

We divided the data into two sets. 80 % dedicated to training and 20 % for testing. Using random forests, we implemented a total of 55 simulations. Table 3 summarizes the results obtained during the various simulations.

Table 3 Simulation results for random forests

		Performance evaluation criteria	Number of trees	1	10	20	30	40	50	75	100	200	300	500
Number of nodes	10	RRMSE	(%)	16.455	15.426	15.313	15.269	15.247	15.229	15.201	15.195	15.186	15.191	15.185
		RMSE (%)		24.305	22.679	22.568	22.524	22.487	22.468	22.452	22.439	22.423	22.422	22.419
		MAPE (%)		18.718	17.551	17.466	17.437	17.405	17.391	17.383	17.376	17.37	17.371	17.372
		R^2	(%)	65.197	69.412	69.859	70.033	70.118	70.19	70.299	70.322	70.359	70.339	70.4
	20	RRMSE	(%)	20.443	16.712	16.407	16.321	16.31	16.243	16.223	16.217	16.144	16.141	16.109
		RMSE (%)		30.521	24.476	24.075	23..52	23.869	23.832	23.794	23.762	23.711	23.682	23.671
		MAPE (%)		23.606	18.83	18.594	18.514	18.438	18.407	18.391	18.358	18.335	18.316	18.306
		R^2	(%)	46.283	64.102	65.401	65.76	65.808	66.087	66.171	66.196	66.498	66.512	66.643
	30	RRMSE	(%)	21.055	16.898	16.58	16.486	16.461	16.337	16.372	16.36	16.284	16.274	16.246
		RMSE (%)		31.3	24.766	24.312	24.181	24.098	24.07	24.037	23.989	23.932	23.903	23.892
		MAPE (%)		24.342	19.117	18.783	18.695	18.631	18.599	18.566	18.531	18.493	18.476	18.467
		R^2	(%)	43.016	63.299	64.668	65.063	65.172	65.524	65.545	65.599	65.917	65.959	66.075
	40	RRMSE	(%)	21.111	16.892	16.609	16.505	16.483	16.394	16.39	16.367	16.29	16.275	16.24
		RMSE (%)		31.321	24.78	24.326	24.202	24.108	24.08	24.045	23.995	23.937	23.907	23.891
		MAPE (%)		24.384	19.122	18.794	18.716	18.639	18.609	18.578	18.536	18.496	18.478	18.464
		R^2	(%)	42.714	63.324	64.544	64.985	65.077	65.453	65.469	65.566	65.892	65.952	66.1
	50	RRMSE	(%)	21.111	16.889	16.607	16.504	16.483	16.394	16.39	16.367	16.291	16.276	16.241
		RMSE (%)		31.321	24.779	24.326	24.202	24.108	24.081	24.045	23.996	23.937	23.908	23.892
		MAPE (%)		24.384	19.122	18.794	18.715	18.639	18.609	18.578	18.538	18.496	18.479	18.465
		R^2	(%)	42.714	63.336	64.551	64.988	65.08	65.455	65.471	65.567	65.889	65.949	66.096

Figure 13 is the graphical visualization of the prediction; Figure 14 presents the residual graph of the best model and Figure 15 shows the evolution curves for training the optimized model and the test.
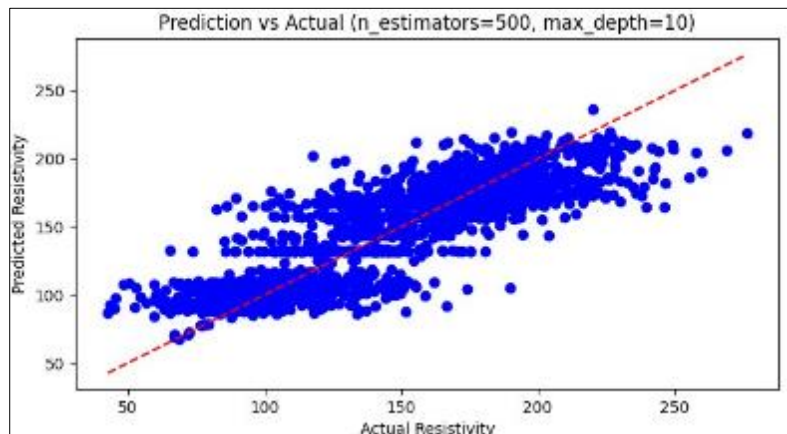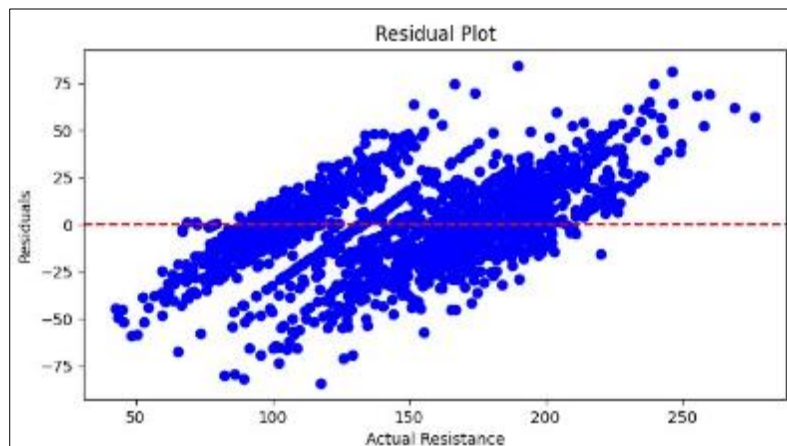

Figure 13 Graphical visualization of the prediction

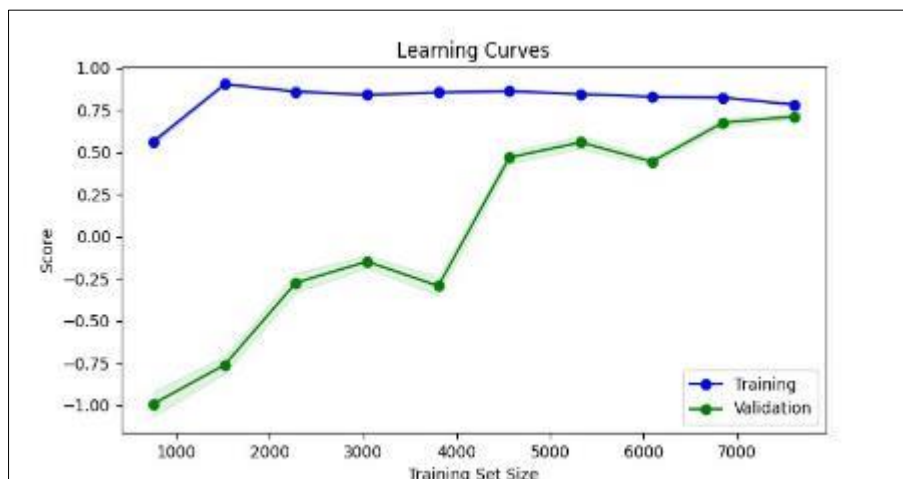**Figure 14** Residual graphs of the best model

Figure 15 Evolution curves for learning the optimized model and the test

It appears that the best model has a maximum forest size of 500 trees each with a maximum depth of 10 nodes. After having made the predictions, we have the various curves which will allow us to analyze the best performance. After the random forest simulations on the 9513 data. we obtained the following results for the best performance as shown in Table 3: MAPE = 17.372 %; RMSE = 22.419 %; RRMSE = 15.185 % and R^2 = 70.4 %.

For the naive Bayesian classifier, we used its Gaussian function and the prediction curve is obtained by Figure 16. Figure 17 shows the curve of the residuals (prediction errors).
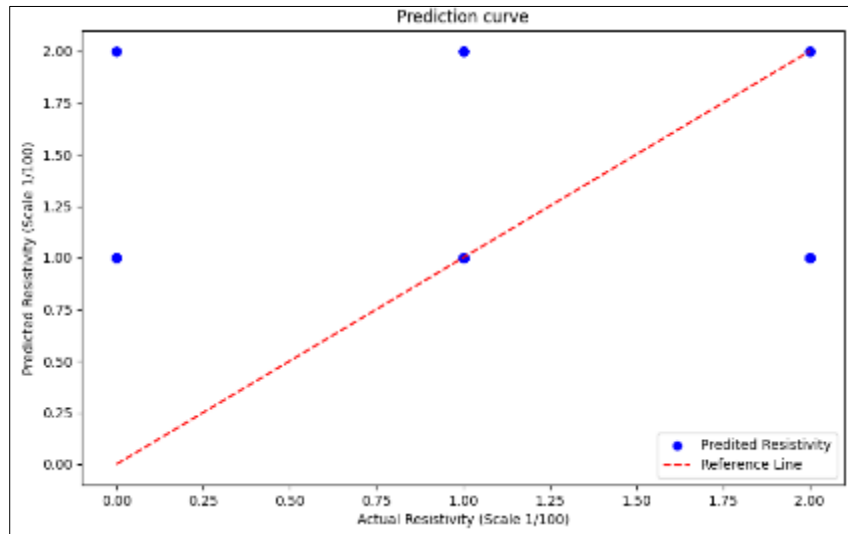

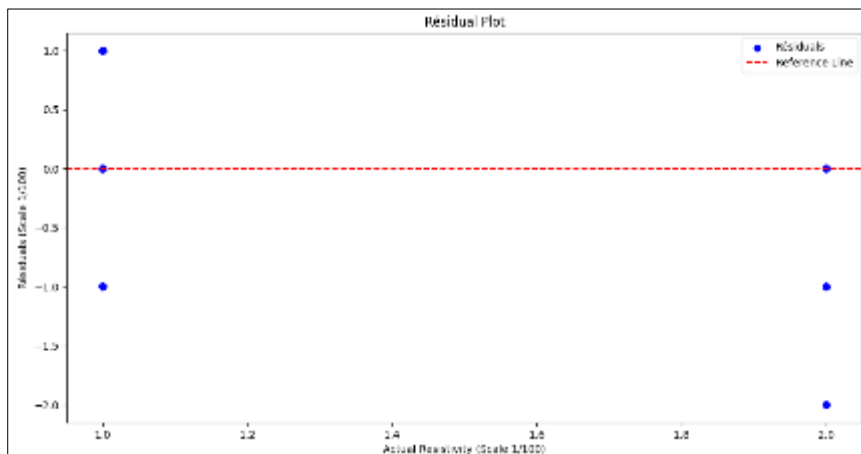**Figure 16** Graphical visualization of the prediction

Figure 17 Graphical representation of residuals

The curves clearly show us that the prediction is not good. The naive Bayesian classifier assumes the independence of the predictive variables. which is a limit to our work. After the simulations on the 9513 data. we redo the calculations of MAPE. RMSE. RRMSE for all the data. We obtained MAPE = 24.75%. RMSE = 49.79%. RRMSE = 51.71% and R^2 = 37.34%.

4. Discussions

The random forest learning curve, also called error curve, is used to represent the learning progress of our model, [17], [18]. It allows you to visualize whether the model learns effectively and improves over time, or whether it reaches a plateau where the improvement in performance is low. To see Figure 13, at the start of training, the error of the model is high because it does not yet know the data to be studied well. As training progresses, the error decreases and the

model better fits the characteristics of the training data. The learning curve shows a steady decrease in error until it converges to a low and stable level. Figure 11 represents the plot of the prediction curves and Figure 12 that of the residuals obtained after simulation for the best model for 500 trees and a depth of 10 nodes. Typically plotted as a smooth line or curve, it shows how the model's predictions vary depending on the values of the predictor variable. The residual curve. for its part. represents the errors (difference between the observed values and the predicted values) as a function of the predicted values. For points above the axis. the residual is positive. For those located below the axis, the residual is negative.

The results obtained by naive Bayesian classifier do not give us the advantage of exploiting this model. Seeing the performance of: MAPE = 24.75%; RMSE = 49.75%; RRMSE = 51.79% and R^2 = 37.34%; we can conclude that it is not an algorithm suitable for this study. It is explored in this work because of the alphanumeric variables contained in our study and coded before exploitation. Indeed, the naive Bayesian classifier algorithm is particularly useful for text classification problems. It takes categorical variables much more into account. We therefore tried to make this prediction with its Gaussian model. We observe that it does not support continuous variables (resistivity which is a real number) as class labels.

In our case, we are performing a regression task to predict a continuous numerical value (the electrical resistivity of the ground) and it is unlikely that the features are independent or follow a Gaussian distribution. Observation of the results obtained previously shows us that those of random forests are satisfactory unlike those of the naive Bayesian classifier.

Performance is better when its correlation coefficient (R^2) is close to 100%. We thus say that its error criterion tends towards 0%. For the optimized random forest model, the correlation coefficient gives 70.4% while for the Gaussian model of the naive Bayesian classifier it is 37.34%, which is not satisfactory. For the RRMSE, we find an excellent value for the prediction, when it is less than 10%. The prediction is good for a RRMSE value between 10% and 20%. In the case where the RRMSE is between 20 and 30%, we say that the prediction is acceptable and it is poor for an RRMSE greater than 30%.

The result obtained by the naive Bayesian classifier of this study is poor given its RRMSE which is worth 51.79%. On the other hand, it is good through random forests which present a prediction with an RRMSE of 15.185%, thus confirming the choice made on random forests as suitable for predicting the electrical resistivities of soils.

5. Conclusion

The work accumulated in this document focused on modeling the electrical resistivity of soils from meteorological data such as the geo-referenced coordinates of the chosen location (A). the state of nature the day before (B). the state of the nature of the day (C) and the ambient temperature (D). Random forests and the naive Bayesian classifier constitute the method implemented in this work.

The data samples used in our study come from nine (09) sites located in the city of Lomé. the capital of Togo. Codifications were carried out on this data because of the numeric variables mixed with alphanumeric variables. Thanks to some performance evaluation criteria of models such as RRMSE. RMSE. MAPE and R^2 we were able to observe some results.

The best result obtained in this work comes from random forests and is given by: MAPE = 17.372%, RMSE = 22.419%, RRMSE = 15.185% and R^2 = 70.4%. Given this performance. random forest modeling can be reliable for a prediction approach linked to the electrical resistivity of soils.

A very poor performance was obtained from the naive Bayesian classifier. given its performances: MAPE = 24.01%, RMSE = 49.79%, RRMSE = 33.63% and R^2 = 37.34%.

Compared to previous studies. we observe that random forests are well rated for modeling the electrical resistivity of soils but the performance of their model does not exceed the best results already obtained.

We thus find the need to retain the models from some previous work while allowing ourselves to explore other input variables and other algorithms if possible. using languages other than PYTHON and MATLAB.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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