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Performance Evaluation of Some Noise Prediction Modelling Approaches: Multiple Linear Regressions and a Hybrid Approach

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ABSTRACT: *Noise prediction models are very useful for urban planning and environmental management. As a result, researchers are always searching for methods that are practically applicable in predicting noise levels accurately. It is therefore important to implement systems that could be employed to predict accurately, noise pollution levels in an urban area. In this study, two land-use regression methods was used to formulate two models namely, multiple linear regression (MLR) and a hybrid of analytical hierarchy process-multiple linear regression (AHP-MLR) to predict noise pollution levels in the Tarkwa mining community. The performance of the two models was evaluated using statistical indicators. The statistical findings indicate that the MLR model achieved a RMSE, standard deviation (SD), R^2 and R values of 1.569 dB(A), 1.585 dB(A), 0.961 and 0.980, respectively. The hybrid model (AHP-MLR), on the other hand, produced 1.774 dB(A), 1.758 dB(A), 0.955 and 0.977 as its corresponding RMSE, SD, R^2 and R values. Plotted box-and-whisker and range plots further confirmed the performance of the two models. The overall analysis showed that the MLR outperformed the AHP-MLR. The resulting noise map based on the noise predictions from the two models suggested that with the appropriate data and useful tools the noise pollution levels of an urban area could be well predicted and mapped for urban planning and environmental management.*

KEYWORDS: *Noise Level; Noise Pollution, Noise Models; Land Use Regression Models*

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I. INTRODUCTION

The levels of environmental noise pollution are increasing at an alarming rate in our urban cities, especially the mining communities. This is primarily due to infrastructural development, industrial activities, and social activities. Studies have confirmed in literature that the increase in noise pollution brings about increase in risk factor for cardiovascular dysfunction, ear problems, sleep disturbances and others (Ylikoski, 1988; Satterfield, 2001). Other studies have contributed to the fact that noise pollution affects job performance and satisfaction (Benfield, 2012; Goines and Hagler, 2007; Ighoroje *et al*., 2004; Passchier-Vermeer and Passchier, 2000). In some cases of high noise pollution levels, intolerable reactions and negative impact become a threat to the well-being of humans and the environment (Goines and Hagler, 2007). Since there is a continuous population growth and increasing urbanization, noise pollution levels will automatically continue to increase; and this calls for comprehensive studies in this area of environmental pollution. This will aid in getting abreast of prevailing noise pollution levels and be able to predict future noise levels for proper planning of our cities and environmental management.……………

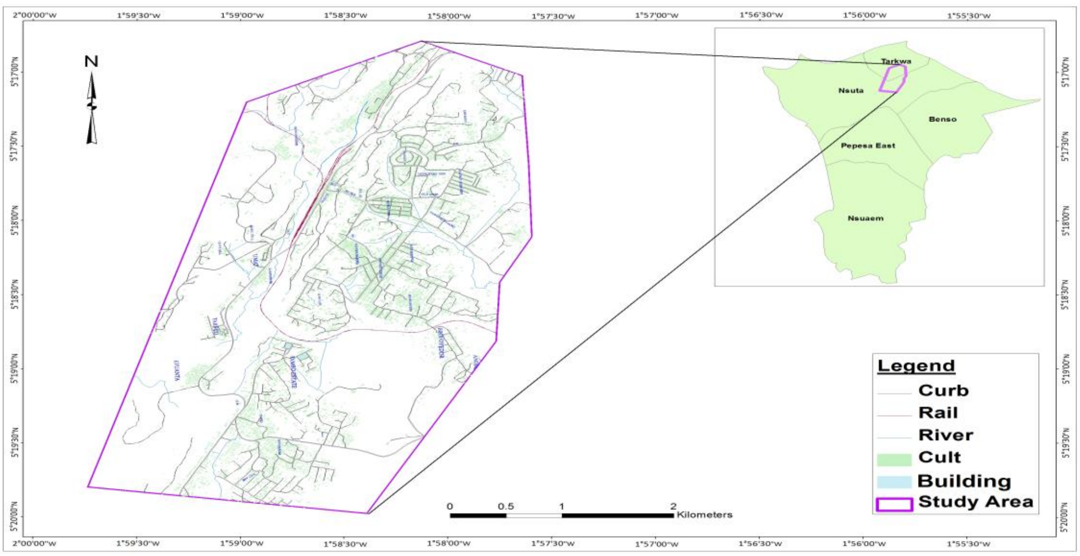
Predicting future noise pollution levels requires specialised customised modelling software and user know-how and as such make it difficult to obtain prediction models for a given location, especially in the developing world. Thus, noise prediction has become a major challenge in urban planning and environmental management (Xie et al., 2015) where it is required to relate changes in spatial distribution of noise pollution levels for future urban expansion at the planning stage and environmental management. Therefore, mapping and forecasting of intraurban noise pollution change for urban development layout, still remains a very difficult task, since the formulation and application of the model depends on several factors, including the size of the area, availability of input data, which are largely land-use variables. Current efforts are mainly experiment-based, statistical models and noise mapping (Xie et al., 2015), and most literature focus on specific sources on noise such as transportation, industry, construction, and other social sources. Therefore, all-inclusive models are required and efforts in this direction are largely dependent on land-use regression (LUR) modeling.

Land-use regression modelling approaches have mostly been used for assessing the exposure of the urban communities to air pollutions (Henderson, et al., 2015 and references therein). LUR methods use least-squares approach to model and predict air pollution levels based on the available predictor variables. In the field of noise levels prediction, LUR modelling has been the least explored. Currently, only two studies have applied this technique, the first one was applied in China (Xie et al., 2015) and the other was applied in three European cities (Aguilera, 2015). In this present study, a generic LUR model was developed to predict noise pollution levels in the Tarkwa mining community (TMC) using multiple linear regression (MLR). Having the notion of improving the modelling capabilities of the developed MLR approach in the noise prediction field, the analytical hierarchy process (AHP) was applied to formulate a hybrid model namely, AHP-MLR. The reason for the choice of the AHP was based on its reported strengths and capabilities in the literature to solve multi-criteria decision problems. This was directly in line with the several land use variables at the modeler's disposal which are usually used in the MLR model development phase. Hence, in order to make an informed and better decision on the variables utilised, the AHP was selected (see Akinlalu et al., 2017; Xishang et al., 2014). The main idea here was to explore the noise prediction potential and reliability of utilizing MLR via AHP particularly in the TMC since such kind of study to the best of our knowledge has not been comprehensively investigated. Therefore, the aim of this presented study was to compare and contrast the efforts of the two developed models (i.e. MLR and AHP-MLR) in noise prediction. This will help in getting a better understanding on the effectiveness of the proposed AHP-MLR as well as its being a supplementary technique to the MLR in predicting noise pollution levels in our communities, using the TMC as a case study. The developed MLR and AHP-MLR were evaluated using root mean square error, standard deviation, coefficient of determination and correlation coefficient.

II. MATERIALS AND METHODS USED

2.1 Study Area

The study area is the Tarkwa Mining Community (TMC). It is found within the Tarkwa Nsuaem Municipality in the Western Region of Ghana. The study area is geographically located between latitudes 5º 17' 00" N and 5º 20' 00" N and longitudes 1º 55' 30" W and 2º 00' 00" W, about 89 km north of Takoradi, the Capital of the Western Region (Mantey and Tagoe, 2012). The community is situated in an area well noted for the mining of minerals such as gold and manganese. Goldfields Ghana limited, Anglo-gold Ashanti, and Ghana Manganese Company are some of the large scale mining companies found in the TMC. There are also numerous allied mining companies located there. Several small scale mining activities are also going on in the TMC. Over the past few years, TMC has seen infrastructural developments including road constructions, building of health posts, education, industries, banking, hospitality services and private business development (Kumi-Boateng, 2012). Figure 1 shows a map of the Tarkwa Mining Community.



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Figure~~.~~ 1 Location of the Study Area

2.2 Field Measurements

The spatial positions of the precise monitoring stations (PMS) in the TMC were measured using Garmin GPS 60CSx handheld Global Positioning System (GPS) of 2 m accuracy. A calibrated Larson Davis's SoundTrack LxT (Trade Mark) Sound Level Meter was also used to measure the noise levels in the TMC. The noise levels were measured from August 2014 to January 2015, which were outdoor nature. The measurements of the PMS were taken at street level and were also determined with the aid of the city digital map of the area.

The standard regulations for measuring noise levels were strictly adhered to. In order to avoid noise reflections, the instrument for measuring noise level was set on a tripod at about 1.5 m above the ground and also separated from the source by at least 1.5 m. This decision was in consonance with what has been reported and accepted in the literature, including Mehdi *et al*., (2010) who used 1.5 m above ground level and 1.22-1.52 m from the source of the noise. The tolerance of the calibrated Larson Davis's SoundTrack LxT trademark device is ±0.6 dB(A). A-weighted instantaneous sound pressure levels were also recorded three times daily at the selected positions in the study area. The total number of the PMS used in this study for the modeling was 50.

III. MATERIALS AND METHODS USED

The materials and methods employed in this paper are discussed in the following sections.

3.1 Noise Prediction Models

Land use regression models have been useful applications to predicting noise pollution levels in intraurban cities, but in this study the multiple linear regression (MLR) approach was applied. After developing the MLR model, a hybrid approach of AHP-MLR was also developed for forecasting the noise pollution levels in the TMC. In the afore-mentioned formulated models, the noise level was used as the dependent variable and the areas of the various land-uses within the study area were defined as independent variables.

The general equation therefore consisted of five independent variables namely land-use, traffic intensity, road network, distance to the main road, and population density. The AHP of the Multi-Criteria Decision Making (MCDM) was used to solve complex multi-criteria decisions and develop the hybrid model. The equations developed from AHP were solved using matrix notations. Detailed explanations on the methods applied have been given in the subsequent sections.

3.1.1 The MLR Approach

Equation (1) was used to develop the MLR model for the noise pollution levels prediction in the TMC. The formulated observation equations were then solved using matrix notation.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + e_i, \quad i = 1, 2, \ldots, n. \tag{1}$$

Here, y is the noise pollution levels in the TMC; β_1, β_2 and β_k are regression coefficients and β_0 is the intercept.Using the matrix notation, a more compact framework shown in Equation (2) was formed in terms of vectors representing the observations, levels of regressor variables, regression coefficients, and random errors.

$$Y = X\beta + \acute{\varepsilon} \tag{2}$$

Where, Y is the noise pollution levels, X represents the design variables, β represents the unknown regression coefficients to be determined and $\acute{\varepsilon}$ is the residuals.

The least square estimator of β is given by Equation (3) as:

$$\beta = (X^TX)^{-1}(X^TY) \tag{3}$$

Since X is not usually a squared matrix, it is multiplied by the transpose of X, that is (X^TX) and the inverse of (X^TX).

The predicted pollution noise levels were projected for ten years and were then used to develop the spatial distribution of the estimated noise levels.

3.1.2 The Hybrid Approach (AHP-MLR)

It was observed in literature that AHP of MCDM is useful for solving multi criteria problems assigning weights to variables (Akinlalu et al., 2017, Xishang et al., 2014) in solving useful equations. Looking at the strengths and the capabilities of AHP, a hybrid model was formulated in combination of MLR. The AHP is a theory of comparative judgements through pairwise comparisons that relies on a comparison matrix at each level of the hierarchy. The comparisons are made using a scale of absolute judgements that represents how much more one element dominates another with respect to a given attribute (Saaty, 2008). Thus, the AHP helps in making decisions using conflicting criteria (Xu and Yang, 2001) of which each criterion has a particular level of importance in the final decision, hence the need to quantify them.

One of the most crucial steps in many decision-making approaches is the accurate estimation of the pertinent data. The approach based on pairwise comparisons as proposed by Saaty (1980) has long attracted the interest of

many researchers. In this study, pairwise comparison was used to create a ratio matrix. This was done by creating pairwise comparison inputs and producing relative weights as outputs.
The levels of comparison are graduated on a scale of 1 to 9. The quantity 1 normally represents two factors of the same importance, whiles the quantity 9 represent a factor of extreme importance (Saaty, 2008). Based on literature as well as experts' advice, the judgements for the independent variables were formulated. Each independent variable has five alternatives and five decision criteria. Each of the alternative was assessed in terms of the decision criteria and the relative importance (or weight) of each criterion. The results are thus represented in a normalized pairwise comparison matrices in the proceeding Equations (4) and (5).

$$\bar{a}_{jk} = \frac{a_{jk}}{\sum_{l=1}^{m} a_{lk}}. \quad (4)$$

After creating the normalized pairwise comparison matrices for the independent variables, the criteria weight vector, w was built by averaging the entries on each row of A_{norm} that is,

$$w_j = \frac{\sum_{l=1}^{m} \bar{a}_{jl}}{m}. \quad (5)$$

The whole processes were then summarised and then the judgment tables was represented by a 5 x 5 matrices. After that, they were then squared to obtain the eigenvectors. The obtained result was then normalised by summing the eigenvectors and dividing each value of the eigenvector by the sum. The weights for the individual independent variables were obtained after the normalisation process. The process was then iterated a number of times until the weights assigned to each factor were consistent. A consistency ratio of 0.012 was achieved which is less than the maximum allowable ratio of 0.10.

3.2 Models Performance Evaluation

To evaluate the accuracies of the models applied in this study, the under listed statistical indicators were calculated using Equations (6) to (8). These equations are indicators helping to make unprejudiced evaluation of the models and they include Root Mean Square (RMSE), coefficient of determination (R^2), correlation coefficient (R), and Standard Deviation (SD).

$$RMSE = \sqrt{\sum \frac{E^2}{n}} \quad (6)$$

$$MBE = \sum \frac{E}{N} \quad (7)$$

Where E is the error and N is the number of observation points. The SD was calculated using Equation 8:

$$SD = \sqrt{\sum \frac{(E - \ddot{E})^2}{n-1}} \quad (8)$$

Where n is the number of observation points, E is the error value, Ë is the mean error and n is the number of observation points.

IV. RESULTS AND DISCUSSION

4.1. Results of the Errors in the Predictions

The results of the observed and the predicted noise levels by the MLR and AHP-MLR are presented in Table 1. The residuals produced by comparing the observed and the predicted noise level are also presented (Table 1).

Table 1 Predicted Noise level and residuals

Observed	Predicted (AHP-MLR)	AHP-MLR (Error)	Predicted (MLR)	MLR (Error)
65	64.585	0.415	65.049	-0.049
78	78.335	-0.335	77.741	0.259
84	84.529	-0.529	83.497	0.503
84	83.639	0.361	82.54	1.46
75	75.668	-0.668	75.31	-0.31
86	85.204	0.796	84.635	1.365
79	78.335	0.665	77.741	1.259
88	88.595	-0.595	87.254	0.746
85	84.927	0.073	83.821	1.179
86	84.927	1.073	83.821	2.179
89	91.755	-2.755	90.995	-1.995
90	91.755	-1.755	90.995	-0.995
91	93.059	-2.059	92.183	-1.183
98	98.823	-0.823	98.151	-0.151
96	93.801	2.199	92.887	3.113
94	95.295	-1.295	95.77	-1.77
83	84.198	-1.198	83.995	-0.995
81	82.894	-1.894	82.807	-1.807
84	84.198	-0.198	83.995	0.005
85	86.563	-1.563	85.916	-0.916
75	72.883	2.117	74.28	0.72
76	72.883	3.117	74.28	1.72
74	72.883	1.117	74.28	-0.28
77	78.704	-1.704	78.649	-1.649
79	78.704	0.296	78.649	0.351
74	73.329	0.671	73.749	0.251
73	73.329	-0.329	73.749	-0.749
86	87.142	-1.142	87.281	-1.281
88	90.678	-2.678	89.6	-1.6
84	85.83	-1.83	84.965	-0.965
89	92.254	-3.254	91.951	-2.951
87	85.385	1.615	85.058	1.942
89	92.239	-3.239	91.328	-2.328
90	92.239	-2.239	91.328	-1.328
95	96.977	-1.977	95.626	-0.626
98	98.456	-0.456	96.996	1.004
97	96.977	0.023	95.626	1.374
87	84.274	2.726	85.415	1.585
86	84.274	1.726	85.415	0.585
89	88.359	0.641	88.42	0.58
93	93.733	-0.733	93.321	-0.321
95	93.733	1.267	93.321	1.679
94	92.254	1.746	91.951	2.049
96	98.456	-2.456	96.996	-0.996
92	92.239	-0.239	91.328	0.672
88	84.594	3.406	84.282	3.718
80	78.704	1.296	78.649	1.351
76	78.704	-2.704	78.649	-2.649
68	71.835	-3.835	71.756	-3.756

These are presented with locations of the PMS indicated along the major road and the computed values of noise level descriptors for the various locations in the TMC. Figure 2 shows the trend of errors as generated by both prediction models.

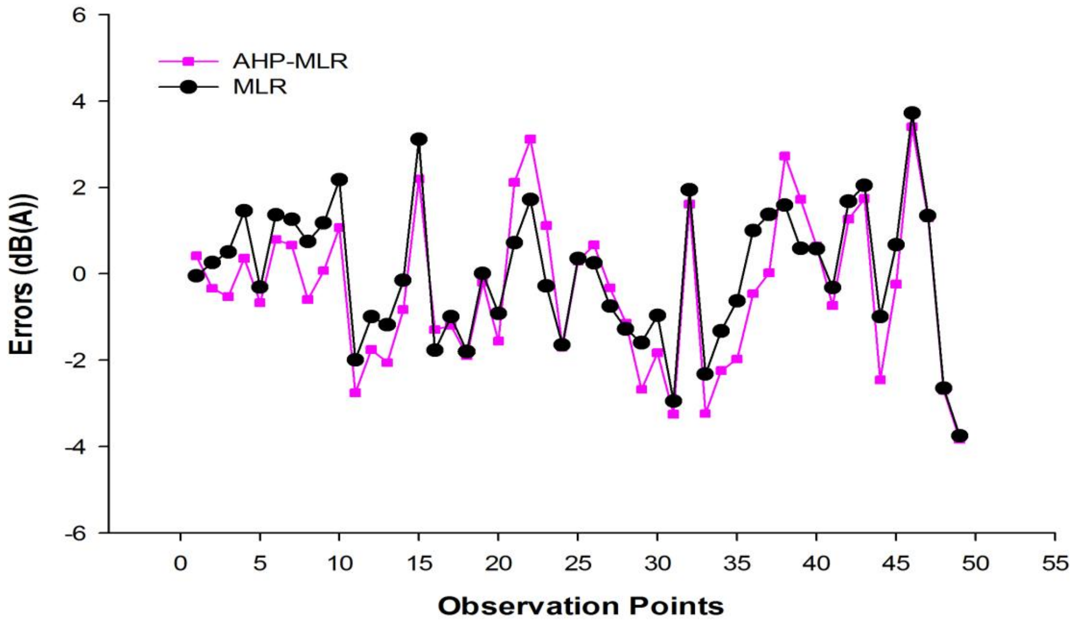

Figure 2 Trend of Errors Generated from MLR and AHP-MLR Models

The performances indicators of both models based on statistical analysis are presented in Table 2.

Table 2 Statistics of the residuals produced by MLR and AHP-MLR

Mathematical Model	Performance Indicators						
	RMSE	**Mean**	**SD**	**Maximum**	**Minimum**	**R^2**	**R**
AHP-MLR	1.774	3.15	1.758	3.406	-3.835	0.955	0.977
MLR	1.569	2.462	1.585	3.718	-3.756	0.961	0.98

The performance evaluation comparison was further illustrated in Figure 3 using the box-and-whisker plots. The box-and-whisker plot presented is an exploratory graphic showing the spatial distribution of the errors achieved by each model. The comparison in this case stem from outliers, through lower and upper whiskers, lower and upper quartiles, and the median. The box-and-whisker of course shows you more than just four split groups. One can also see which way the data sways by comparing both models.

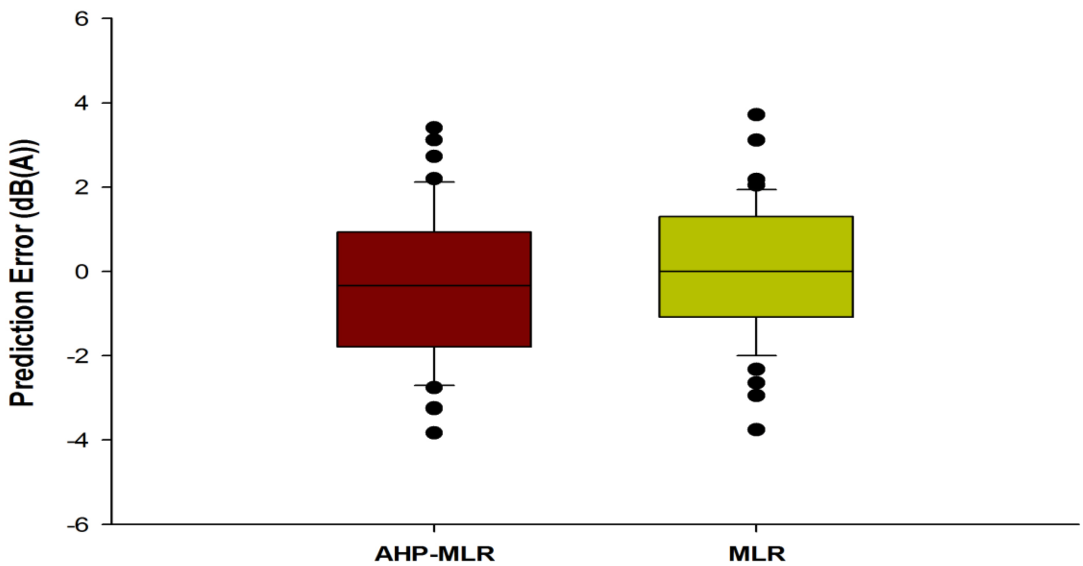

Figure 3 Error Variability of the MLR and AHP-MLR

The evaluation of the performances of the designed and implemented models was also presented in range plots (Figure 4) for further analysis. Range plots also illustrated the minimum, maximum and average errors propagated when the MLR and AHP-MLR approaches were applied to predict noise pollution levels for the TMC.

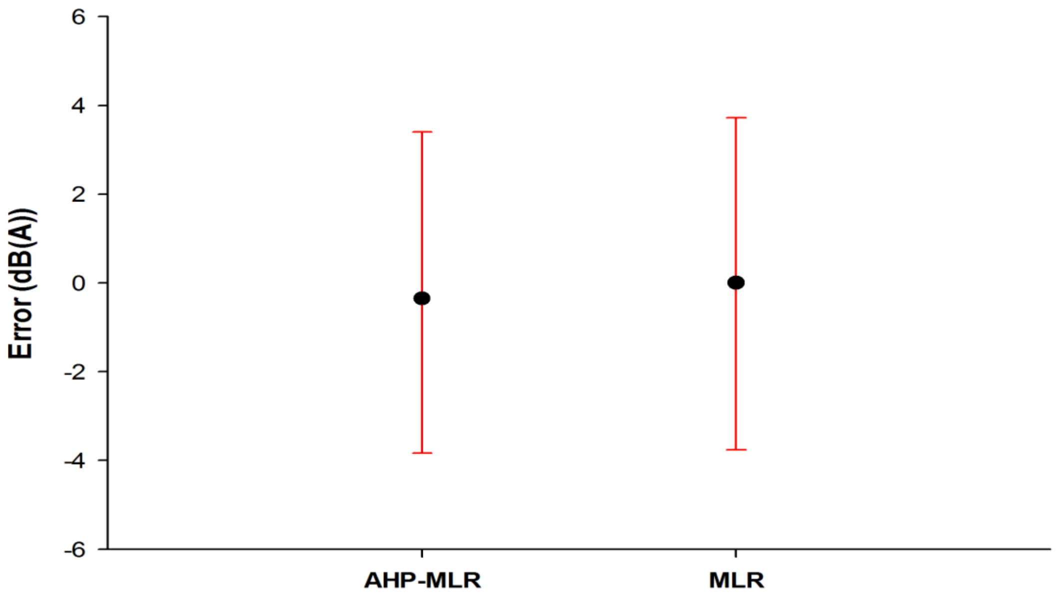

Figure 4 Error Bar for MLR and AHP-MLR Models

The developed MLR and AHP-MLR models results were used to plot the spatial distribution of the noise levels of the study area. The spatial distribution of the forecasted noise pollution levels from the monitoring stations in the TMC are presented in Figure 5. This demonstrates that GIS could be used for noise mapping.

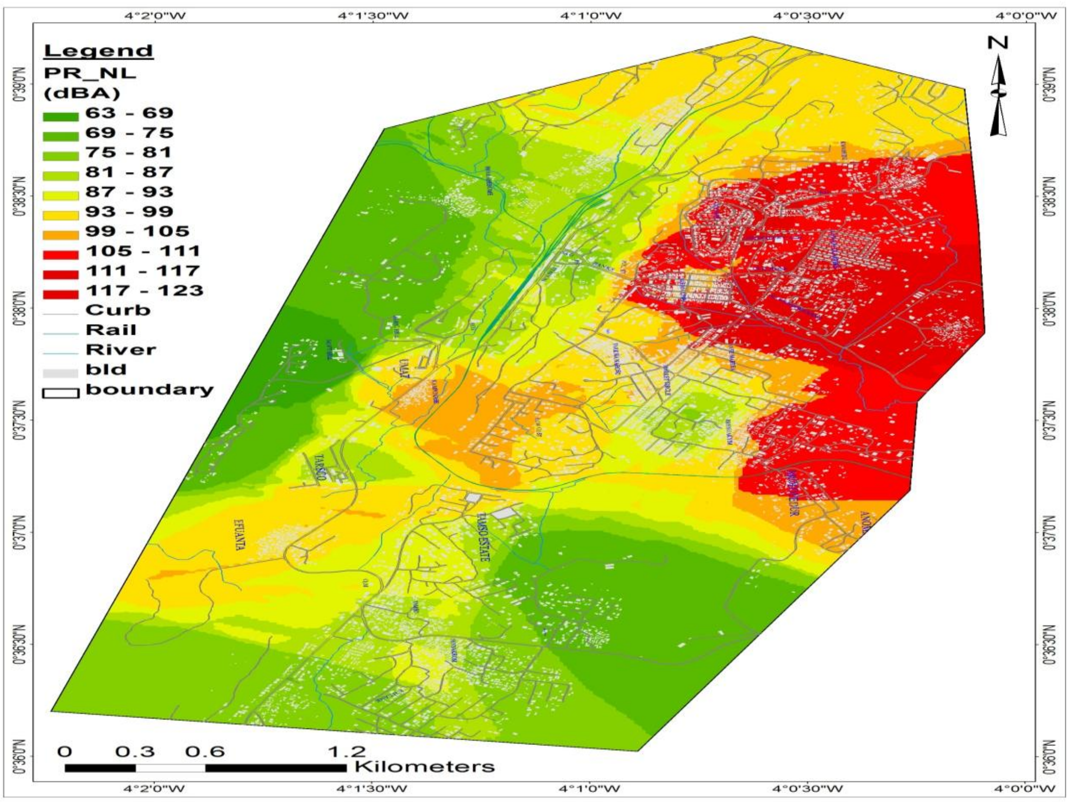

Figure 5 Noise Map for the Predicted Noise Levels using MLR

4.2. Discussion

From Table 1, the residuals presented indicate the degree at which the predicted outputs produced by the MLR and AHP-MLR depart from the corresponding measured noise data. These residuals suggest the prediction inadequacy of the methods utilized in this study. This will further give the modeller and the user the opportunity to know evidently the quantitative predictive strength of the two methods. This assertion was clearly demonstrated from the analysis of Table 1 and Figure 2 where it was shown that the MLR technique produced more satisfactory results than the AHP-MLR. The inference made here is that the MLR was able to model appropriately on the measured noise data as compared with the AHP-MLR. In the light of these, it could be stated that the predicted outputs rendered by the MLR are in better agreement to the measured noise level data than the AHP-MLR. These assertions are further confirmed by Fig. 2 where it can be observed that the extent of error variability for the MLR appears to be better across the ideal zero value than the AHP-MLR, respectively.

With reference to Table 2, it is noticeable that the MLR produced the best performance in relation to the statistical findings presented. It is a well-known fact that to determine the extent of fit of a model, the RMSE is a good estimator. Thus, the closer the RMSE value is to zero the better the model prediction strength. On the basis of the RMSE results, it can be seen that the MLR outperformed the AHP-MLR. Moreover, the high R^2 and R values (Table 2) produced further affirmed the quality of the prediction performance of the two methods. Here, the R^2 values obtained indicate the level of tolerance of the prediction values from MLR and AHP-MLR. Thus, 96.1% changes in the measured noise level data are explained by the variation in the MLR predicted output values while, the AHP-MLR could explain only 95.5% variability. The R findings, on the other hand, show the degree at which the predicted noise data fall closely to the line of best fit. Judging from the R outcomes in Table 2, the MLR model delineate discrepancy in the predicted data with high precision and accuracy. This precision capability of the models can also be seen from the standard deviation values (Table 2).

The analysis performed on the two models by comparing the box-and-whisker plots (Figure 3) helps to understand the spread of error distribution with respect to the predicted noise level data. On each plot, the central mark is the error median, the edges of the box is the first and third quartile, and the lower and upper whiskers signify the minimum and maximum error range not considered as outliers. The essence of the box-whisker plot (Figure 3) is to provide a graphical rendition of the summary statistics based on the residuals achieved by the MLR and AHP-MLR. With reference to Fig. 3, it can be observed that the MLR achieved less error variability than the AHP-MLR model. It is also evident from Figure 3 where it can be noticed that the interquartile range length for the MLR is smaller than the AHP-MLR.

Furthermore, the range plot (Figure 4) gave further confirmation of the previous assessment of the performance indicators. The range plot showed the minimum (lower whisker), mean (middle) and maximum (upper whisker) errors for both developed models (Figure 4). Due to the strength of the MLR model developed, it was used to forecast long-term variability of urban noise levels in the Tarkwa mining communities. Additionally, the noise map developed from the forecasted noise levels brought to bear the ample use of GIS for noise mapping. The results obtained, as shown in Figure 5, indicate that it is possible to develop a LUR model using the MLR technique with independent variables; and that the results could be used for noise mapping (Figure 5).

It is interesting to know that the noise prediction models developed in this research are exclusively different from the already existing LUR models developed by (Xie et al., 2015, Aguilera et al., 2015). Since in these current applications the variety of independent variables is applied both of the MLR and AHP-MLR equations were entirely different from the previous LUR models developed. It is also different from other basic prediction models by the consideration of land-use and other relevant variables. The results from this modelling processes show that, with accurate data, noise prediction models are now promising tools, as demonstrated, for noise exposure assessment with potential applications in urban planning, environmental management, particularly in areas where noise predictions models or noise maps from competent authorities are not available.

V. CONCLUSION

Noise prediction models have been developed and their performance evaluated, from MLR and then AHP-MLR methods, using statistical indicators. Based on the strengths and the capabilities of AHP, a hybrid model of AHP-MLR was designed to augment the inefficiencies of MLR and improve on it. However, comparing their performances of both models using statistical indicators, MLR rather performed better than the hybrid AHP-MLR. The difference reflected in the indicators whereby RMSE of MLR is 1.569 and that of AHP-MLR is 1.774. Moreover, R^2 and R of MLR was 0.961 and 0.980 respectively whiles those of AHP-MLR are 0.955 and 0.977 respectively. Furthermore, visual inspection of the box-and-whisker plot cum that of the range plot further confirms the performances of the two developed models.

In such situation, to be able to set up a standard practice of noise prediction especially in Ghana, the hybrid approach of AHP-MLR and MLR are proposed over the traditional models. This will further accelerate effective and accurate prediction models for noise predictions. The spatial distribution of the long-term predicted noise levels demonstrates the values of these models to mapping urban noise levels in relation with urban land use change at the same time being feasible for different applications. The application of land-use variables also shows that the developed models can be easily applied to predict noise pollution levels and also identify potential areas that are violating the regulatory requirements.

In conclusion, the developed models have also confirmed its ability in mapping intraurban noise in relation to urban land-use as changes occur. This rather will very much aid in urban planning and environmental noise management. It could also be applied predict environmental noise changes with time and epidemiological studies as well as decision-making tool. It was observed from this study that the more the positional monitoring stations observed, the better the model performance. Therefore, the model performs better for large scale area like the study area and vice versa.

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