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Modelling Non Evacuation of Waste Bin in North Western Part of Nigeria using Bayesian Approach

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Abstract **– Municipal public waste bins are commonly positioned at strategic places in the cities to prevent indiscriminate dumping of refuse and to keep it clean. There are currently very litle tools available for site-by-site non evacuation risk of the waste bin inspection requirements in the country which this paper is aimed to address. Bayesian logistic regression is employed in order to allow for the data randomness and for the uncertainty associated with any prediction. The results show that the bayesian model could perform as better option for waste bin non evacuation in the country.**

Keywords **– Waste-bin, Non-evacuation, Prediction, Inspection.**

I. INTRODUCTION

Man in every stage of civilization generates wastes, however, the rate of generation, amount and disposal vary from individual to individual, source, season, geography and time, (Robert, 1999). The generation of waste is an inevitable consequence of man's attempt to survive on the earth's surface through his productive and consumption processes. One of the challenges of the 21st century is how to achieve cost-effective and environmentally sound strategies to deal with the global waste crisis confronting mankind in both developed and developing countries. Rapid increase in volume and types of solid and hazardous waste as a result of continuous economic growth, urbanization and industrialization, is becoming a burgeoning problem for all tiers of government.

Egunlobi (2004), in the early times (pre- colonial days) up till 1970s, the disposal of refuse and other waste did not pose any significant problem. The population was small and enough land was available for assimilation of waste. Solid waste problem started with urban growth, resulted partly from increase in population. Mba (2003) noted that no town in Nigeria especially the urban and semi- urban centres of high population density can boast of having found a lasting solution to the problem of filth and huge piles of solid waste, rather the problem continues to assume monstrous dimensions. In order to address this problem, a truck was developed for the haulage of this waste to designated point. Early garbage removal trucks were simply open bodied dump trucks pulled by a team of horses. They became motorized in the early part of the 20th century. These were soon equipped with "hopper mechanisms" where the scooper was loaded at floor level and then hoisted mechanically to deposit the waste in the truck. The Garwood Load Packer was the first truck in 1938, to incorporate a hydraulic compactor (Herbert, 2007). Today, the use of robin has become widespread in many municipalities and urban centres for the collection and onward transfer of waste to the dumpsite. To this end, this method has been adopted and become a common waste collection strategy in Ilorin municipality for over a decade. However, this method of waste management has not holistically address waste collection and disposal problems in the city due to human and other logistic factors.

Municipal waste bin collector is now common and fashionable among urban waste managers in Nigerian and other parts of world. This is crucial in order to address problems pose by waste in municipalities. It is the same factors that has necessitated the use of waste bin to collect and prevent indiscriminate dumping of waste and refuse in Ilorin metropolis. However, poor management and untimely collection and evacuation of this Municipal Waste Bin (MWB) for onward transfer to the disposal site (Land fill) is now a problem in itself. On many occasions, some of these waste bins were left without been evacuated when it is overdue (filled-up) even at the centre of the city and consequently become cynosures of eyes. Apart from the fact that when it is not evacuated as at when due disfigures the general landscape and aesthetic outlook of its immediate surroundings, it is now a breeding place for rodents in the city. Besides, the impact of climatic factors such as high temperature, rainfall and wind cannot be underestimated when it is overdue for evacuation or filled to the maximum capacity. Such problems include; land and waters contamination, environmental pollution, leakages of hazardous chemical substances deposited inside the waste bin and runoffs contaminations among others. In the same vein, untimely evacuation of waste bin is now impacting negatively on residential properties in the city because people are no more interested in renting houses or engage in commercial activities where waste and its attendant problems manifest. Consequently the problems are now generating untold crisis in the study area. Thus, the multiplier effect of these problems on human health, aquatic animals and other socio-economic activities cannot be overemphasised.

(a)

(b)

(c)

(d)

Fig. 1. Waste Bin in Ilorin Municipality

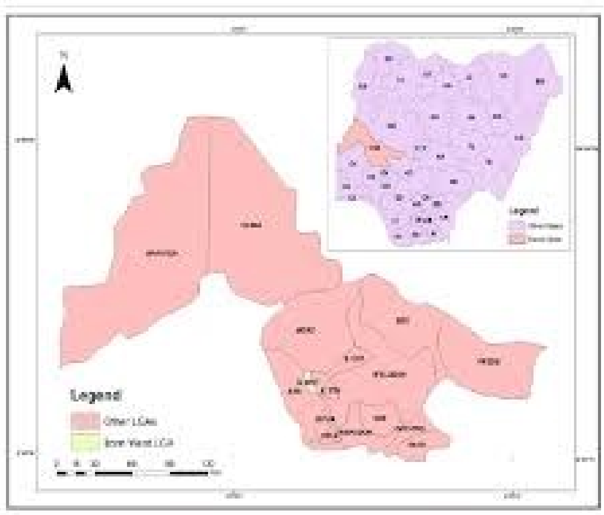

Figure 1. Location of the study area. Source: Ministry of lands and housing, Ilorin

Fig. 2. The Study Area and methodology

The study area is Ilorin metropolis; it is situated on Latitude 8.5^{O}N and Longitude 4.55^{0}E. The waste bins are strategically and spatially located within the city. They are routinely evacuated in order to ensure that the environment is secure from waste and its attendant problems. Therefore, this study modelled non-evacuation of municipal waste bin in Ilorin using The Bayesian Approach.

II. Methodology

To determine the proportion of Robin not evacuated, The raw data from individual Robin was used in the form

$$Yij = \left\{ \begin{matrix} 1 \; if \; Robin \;\; i \; is \; not \; evacuated \; on \; inspection \;\; j \\ 0 \;\; otherwise \end{matrix} \right\} \quad (1)$$

To model and predict the probability of non-evacuation of a particular waste Robin i on inspection j, a logistic model was fitted into the data because it is a generalised linear model that allows binary data to be modelled through a suitable Bernoulli distribution where the probability of occurrence of the binary outcome depends on a number of explanatory variables (Dey*et al*, 2000)

The model

The likelihood = $\pi_{i=1}^{n} p^{x}(1-p)^{1-x}$ for i = 0, 1 (2)

The response function

$$Pij = \frac{e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}}{1+e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}} \quad (3)$$

The likelihood =

$$\pi_{i=1}^{37}\left(\frac{e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}}{1+e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}}\right)^{x}\left(1-\frac{e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}}{1+e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}}\right)^{1-x} \quad (4)$$

$$\text{The prior } = \pi_{j=0}^{5}\frac{1}{\sqrt{2\pi\sigma}}\exp\{-\frac{1}{2}(\frac{\beta_j-\upsilon_j}{\sigma})^2\} \quad (5)$$

The posterior $\propto$ likelihood x prior

The posterior $\propto$

$$\pi_{i=1}^{37}\left(\frac{e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}}{1+e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}}\right)^{x}\left(1-\frac{e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}}{1+e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4}}\right)^{1-x}.$$

$$\pi_{j=0}^{5}\frac{1}{\sqrt{2\pi\sigma}}\exp\{-\frac{1}{2}(\frac{\alpha_j-\upsilon_j}{\sigma})^2\} \quad (6)$$

Since,

Y_{ij}~ Bernoulli (P_{ij})

$$\log it(p_{ij}) = \alpha_0+\alpha_1X_1+\alpha_2X_2+\alpha_3X_3+\alpha_4X_4+e_i \quad (7)$$

Where P_{ij} is the probability of non-evacuation of waste Robin i on inspection j

For i= 1, 2,…37and j= 1, 2,…5

$$\text{logit } (P_{ij}) = \log[\frac{Pij}{1-pij}] \quad (8)$$

Where (α_0 , α_1,…,α_4) = regression coefficient and;

X_1 = Quantity of waste generated.

X_2 = Population of the resident.

X3 = Commercial land location of robin.

X_4 = Residential land location of robin.

To complete the Bayesian setting, a non-informative normal prior was used. Therefore all model variable were given non-informative prior

$\alpha_r \sim N(0, 10^4)$, $r = 0,1,\ldots 4$
$X_1 \sim N(0, 10^4)$,
$X_2 \sim N(0, 10^4)$,
$X_3 \sim N(0, 10^4)$,
$X_4 \sim N(0, 10^4)$,

All the numerical variables (X_1, X_2, X_3, X_4) were standardized to have the mean 0 and variance 1 using the transformation (i.e. variable - mean /standard deviation).

A. Model Variable Selection

To obtain the most appropriate model for predicting probability P_{ij}, a Bayesian stepwise procedure, Deviance Information Criterion (DIC) was used which is related to the negative value of the log-likelihood of the observed data (Spiegehalter et al., 2002). The model was fitted using Markov Chain Monte Carlo (MCMC) methodology which allows estimation of variables in Bayesian setting through stochastic simulation from their posterior distribution.

B. Model Predictive Accuracy using Validation Sample

Five measures were considered for assessing model predictions using the validation sample denoted by y_k, k = 1,2,…,7 In defining these measures a classification rule according to threshold (t,: $0 < t < 1$) for positive non-evacuation was selected, applying a binary classification rule according to which waste bin K was non-evacuated on inspection if $p_k \geq t$ or evacuated if $p_k < t$.

The measures are as follows:

1. Np = total number of Robin not-evacuated on inspection in validation sample.
2. Positive Predictive Value (PPV): Proportion of Robin not-evacuated with positive prediction. This measure express the probability that a given waste binwas not evacuated given that the model predicts that it is likely not evacuated

$$PPV = \frac{\sum_k y_k I(P_K \geq t)}{\sum_k I(P_K \geq t)} \tag{9}$$

For k = 1 … 7, where y_k are the omitted observations and $I(pk < t)$if $P_k \geq t$ or 0 otherwise.

3. Negative Predictive Value (NPV): proportion of waste bin with negative prediction that classified as evacuated. This measure gives the probability that the waste bin were evacuated given that the model predicts that it is evacuated.

$$NPV = \frac{\sum_k (1-y_k) I(P_K < t)}{\sum_k I(P_K < t)} \tag{10}$$

4. True Positive Rate (TPR): proportion of actual waste robin that were correctly classified (also known as sensitivity of the prediction). This determines the probability that the model predicts a robin not evacuated given that it is actually not evacuated.

$$\text{TPR} = TPR = \frac{\sum_k y_k I(P_K \geq t)}{\sum_k Y_k} \tag{11}$$

5. True Negative Rate (TNR): proportion of robin that were correctly classified (also known as the specificity of the prediction). This gives the probability that the model predicts that a waste bin is evacuated given that it is actually evacuated.

$$TNR = \frac{\sum_k (1-y_k) I(P_K < t)}{\sum_k (1-Y_k)} \tag{12}$$

Using a classification threshold of t = 0.3, i.e., considering a model prediction when $P_k \geq 0.3$. This classification threshold was used in this research based on Streftaris *et al.* (2013*)* where they used a threshold of 0.5 in modelling probability of blockage at culvert trash screens using Bayesian approach, however, he opine that the value can be varied in other to improve the efficiency of our prediction.

Where:

y_k = Validation sample set.
t = Robin classification threshold.
P_k = Probability of Robin not evacuated on inspection in the validation sample.

III. Result and Discussion

The diagnostic plot in Fig. 3 shows the point at which the MCMC reach its convergence. This was done in order to ensure that the correct value of posterior estimate was obtained before taken its summary. The plots consist of the density, trace, autocorrelation and history of the plot respectively. The kernel density plot estimates the posterior marginal distribution of parameters. The plots take the shape of a normal distribution before taking the posterior estimate which is assumed by plot in the first column, in the same vein, the trace indicate that two separate chains were initialised in the simulation process and were well mixed and column 3 shows the autocorrelation plot which indicates no high degree of autocorrelation for each of the posterior samples, implying good mixing and lastly the history of the plot in Column 4 shows the mean of the Markov chain has stabilized and appears constant over the graph. Also, the chain has good mixing and is dense, it traverses the posterior space rapidlywhich reflects that convergence was reached. This was carried out for all the parameters under consideration. Therefore the summary of the posterior estimates were taken

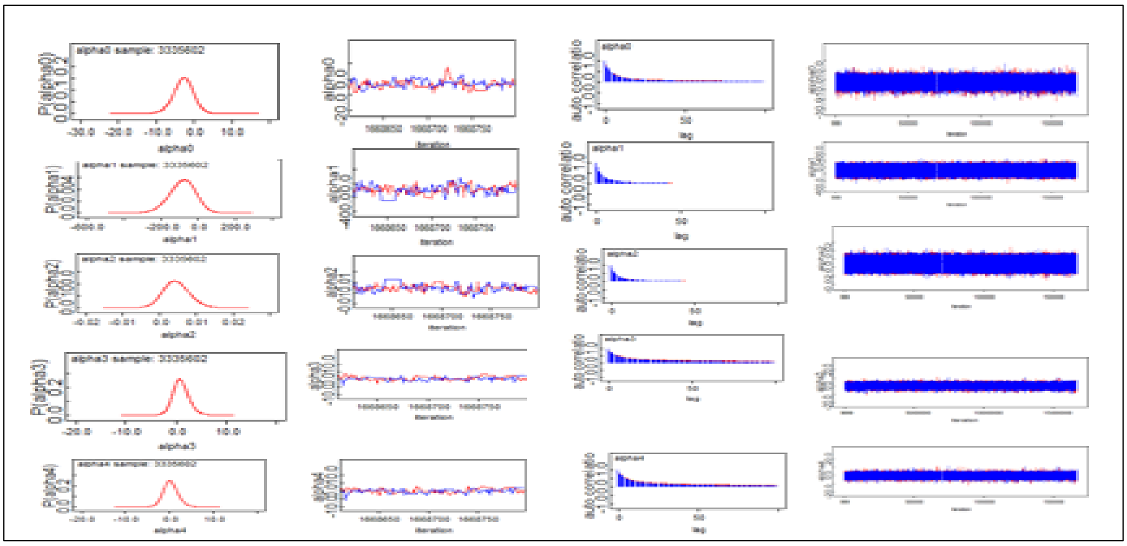

Fig. 3. Diagnostic plot of Convergence of Model Parameters

A. Full Model Fit

In order to fit the model, the posterior estimates of the variable coefficients were considered as shown in Table 1. For the α coefficients, the results in the table show the average effect on the logistic function of non-evacuation probability of the waste bin for an increase of one unit in the corresponding variable (on the standardized scale) (Column 3), together with the corresponding standard deviation (Column 4) and measures of uncertainty as expressed through 25% and 95% credible intervals of the α parameters (Columns 5 and 6). In Bayesian statistics, the credible (or Bayesian) interval plays a role similar to that of confidence intervals in classical statistics such that intervals that do not include zero imply a significant effect of the corresponding variables Strafteris *et al*.(2013) demonstated that significant effects of parameter estimates were presented graphically in Fig. 4. It shows point estimates of the coefficients as represented with their variables.

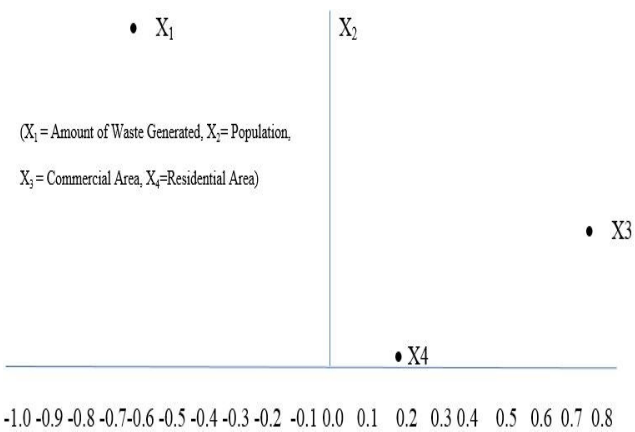

Fig. 4. Posterior Mean Estimates of Coefficients (dots) for the corresponding variables:

The vertical line in Fig. 4 represents the point at which coefficients are not significantly different from zero. Streftaris *et al*. (2013) said that the closer a variable coefficient is to this line, the less influence it has as a model predictor. Thus, Fig. 4 demonstrates that only variables X_2, X_3 and X_4 have positive significant effects on the model predictor, while variable X_1 is not significantly different from zero. Thus, the population, commercial area and residential land use have contributed to the non-evacuation of the waste bin in Ilorin city.

Table 1. Posterior Estimate of Model Variables Coefficient

coefficients	**Variables**	**Mean**	**Standard deviation**	**2.5% CI**	**97.5% CI**
Alpha0		-2.895	2.771	-8.636	2.378
Alpha1	Amount of waste generated	-87.15	73.12	-240.1	48.53
Alpha2	Population of resident using waste bin	0.0045	0.0037	-0.0024	0.0122
Alpha3	Commercial land use location waste bin	0.8477	1.1713	-2.283	4.529
Alpha4	Residential land use location of waste bin	0.184	1.718	-3.125	3.948

B. Model Variable Selection using Deviance Information Criteria

The Deviance Information Criteria (DIC) assumes the posterior mean to be a good estimate of the stochastic parameters. Spiegel halter *et al*. (2002) established that DIC is a measure of model fit and related to the negative value of the log-likelihood of the observed data under the considered model, penalized by the number of variables used. Therefore, small DIC values represent a better model fit. This approach is analogous to commonly used classical stepwise regression procedures. In particular, starting from the full model, a single variable was removed at a time and the model with the lowest DIC value was selected.

In Table 2, the variables were removed one after the other and regressed using backward stepwise regression method, the model with the smallest DIC was estimated as the best to fit the model **DIC = 90.17**. This is in consonance with the method adopted by Strefteris *et a*l. (2013) in which variable x_1 has not contributed to the model. This led to the emergence of the new model.

Table 2. Estimates of Deviance Information Criteria (DIC)

Parameters	Variables	Dbar	Dhat	DIC	pD
α_0		75.93	61.66	90.20	14.27
α_1	X_1	75.99	61.80	**90.17***	14.18
α_2	X_2	76.17	62.11	90.24	14.07
α_3	X_3	76.20	62.09	90.30	14.10
α_4	X_4	75.93	61.61	90.25	14.32

Where, DIC = Dbar + pD, pD = Dbar - Dhat, Dhat = Deviance of the posterior mean, Dbar = posterior mean of the deviance.

C. The New Model

$$\text{Logit}(P_{ij}) = \alpha_0 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + e_i \quad (4.3)$$

Where:

P_{ij} = Probability of non-evacuation of waste bin i on inspection j $\alpha_0 \ldots \alpha_4$ = parameter of the model.

X_2 = Population of people using the waste bin.

X_3 = Commercial land use positioning of the waste bin.

X_4 = Residential land use of the waste bin.

D. Estimation of Model Predictive Accuracy using Validation Sample

To estimate the model predictive accuracy, sample of seven observations were made as validation sample. Streftaris (et al, 2013), experimented different validation data sizes (e.g., 5 or 10%) but did not produce noticeably different results. The essence of this was to make comparison between the observed value and the predicted model value. The validation sample set denoted y_k were randomly selected and run separately in Open BUGS, the following probability of non-evacuation P_k in the validation sample in table 3 were obtained.

Table 3 shows the posterior estimate of the validation sample. The mean and the credible interval are shown in Columns 2, 4 and 5 respectively. From the table, the means lie within the credible interval.

Table 3. Posterior Estimates of Validation Sample

P_k	**Mean**	**SD**	**2.5%CI**	**97.5%CI**
P[1]	0.3065	0.1243	0.05228	0.5765
P[2]	0.426	0.16	0.1732	0.8001
P[3]	0.306	0.1721	0.05066	0.6934
P[4]	0.2547	0.1461	0.00359	0.5309
P[5]	0.5066	0.1893	0.156	0.8632
P[6]	0.2719	0.1505	0.03746	0.6057
P[7]	0.3284	0.1625	0.07188	0.6892

Table 4, depicts the total number of observed non-evacuated waste bin as shown in Colum 2 is 12. Using the non-evacuation threshold, ($p \geq 0.3$) the total number of predicted non-evacuated waste bin as indicated by asterisk (*) sum together in Colum 4 above is 11 indicating that the observed and predicted value are very close which is a measure of how good the predictive strength of the model is. However, we can increase or decrease the value of our threshold in order to improve the efficiency of our model predictive accuracy.

Table 4. Comparison of Probability of Validation Sample with Threshold (0.3)

K	**Observed Out of 5 (j)**	**Proportion of observed (y_k)**	**Probability (P_k) of Validation Samples**
1	1	0.2	0.307*
2	3	0.6	0.426*
3	2	0.4	0.306*
4	0	0	0.255
5	3	0.6	0.507*
6	1	0.2	0.272
7	2	0.4	0.328*

Similarly, other measures such as Positive Predicted Value (PPV), Negative Predicted Value (NPV), True Positive Rate model predictive accuracy (TPR) and True Negative Rate (TNR) could be used as shown in Table 5. It shows the estimates of the predictive measures considered in this study. The values obtained in all the measures indicate that they all lie within the credible intervals. The value of PPV (0.47) indicates that 47% of the waste bin in the study area was predicted to be non-evacuated by the model. While the value of NPV (0.9) indicates that 90% of the waste bin were predicted to be evacuated by the model. In the same vein, if the inspection team were to visit the waste bin, the TPR of (0.4) indicates the actual number of waste bin that will not be evacuated is 40% which is a measure of the probability that on visiting any waste bin, the probability of it non-evacuation is 0.4. Similarly, the TNR of (0.26) indicates that if the inspection team is to visit the waste bin for inspection, only 26% of the waste bin will be evacuated.

Table 5. Predictive Measures for Model Accuracy

Prediction Measures	Mean	25%	97.5%
Np	11	12	15
PPV	0.47	0.40	0.60
NPV	0.90	0.85	0.99
TPR	0.40	0.307	0.491
TNR	0.26	0.259	0.2721

IV. Summary and Conclusion

Waste bin un-evacution is a serious problem in our environment especially in form of air or wind pollution and Consequently, allows different diseases to spread on land. Therefore, this study has developed a model related predictive measures to over come this problem in the north western part of Nigeria. The model has shown that the dominant factors responsible for non - evacuation of the waste bin in Ilorin are population of people using the waste bin and the location of the bin. Also, It has shown a high predictive ability in forecasting the unevacuated waste bins in this part of the country. This can also be extended to any waste bin at a given location (point estimate) if the population using the waste bin and its location are known.

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Moreover, stakeholders in waste management in the city should increase the number of waste bin in commercial, residential and populous areas of the city.

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