Spatial Modeling of Risk Factors of Maternal Mortality in Kenya

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ABSTRACT

Spatial modeling is important for conducting geospatial analysis to understand the world and guide decision-making. This study conducts spatial modeling of risk factors of maternal mortality. Spatial means that each data item has a geographical reference. Perinatal and maternal mortality are significant health concern among nations. The specific objectives are to estimate the national and county prevalence of maternal mortality in Kenya, to identify the most influential risk factors associated with maternal mortality in Kenya, and to model spatial variations of maternal mortality and produce a Kenyan atlas of maternal mortality by county. Secondary data was sourced from KNBS and Africa open Data for the 2019 KPHC and Kenyan Counties shape files, respectively. The study used maternal death as the dependent variable. The study considered four models: the logistic regression, the normal unstructured heterogeneity (UH) random effects, ICAR Spatial random effects, and the convolution model. Best subset selection was achieved using the forward stepwise selection method, where the best model was determined using AIC. The study compared the spatial models using the DIC. The study estimated the models using the Bayesian approach. The descriptive results revealed that countrywide, maternal mortality has a prevalence of 10.7%. The comparison results showed that the convolution model performed better than the logistic regression, normal UH random effects, and ICAR spatial random effects models. The study concluded that Wajir, Mandera, Laikipia, Nyandarua, Nyeri, Tharaka Nithi, Elgeyo Marakwet, Siaya, and Migori had the greatest prevalence indices. Isiolo, Embu, and Machakos had the lowest Maternal Mortality prevalence indices. The coun-ties with considerably low risks of maternal mortality included Isiolo, Embu, and Machakos, The counties with moderate risks of maternal mortality included West Pokot, Narok, and Lamu.

Keyword: - *Maternal Mortality, Spatial Modelling*

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1. INTRODUCTION

1.1 Background Information

Maternal mortality refers to deaths that occur because of pregnancies or childbirth complications [31]. Globally, perinatal and maternal mortality are major public health concerns. According to UN inter-agency estimates, the gloabl ratio of maternal mortal-ity dropped from 342 to 211 deaths per 100,000 live births, translating to a percentage drop of 38% [16]. The global projected cost from 2022 to 2030 for completely ending or significantly minimizing preventable maternal deaths is $115.5 billion for 120 priority nations (Institute for Health Metrics and Evaluation (IHME) 2022). Fig 1.1 shows that maternal mortality remains high in Africa. For example, in 2017, the African region recorded 66% of the maternal deaths globally [24]. Other regions with high risks of maternal mortality include South America and Asia. In the Caribbean and Latin America, the lifetime risks of women dying from maternal causes are 1 in 570 and 1 in 2020, respectively. Although the risks compare favorably with the average risk in all developing regions (of 1 in 160), they are relatively high when compared to Canada (1 in 5200) and the United States (1 in 1800) [16].

The Kenyan government has, over the years, focused on reducing the health care cost burden, as a way to end maternal mortality and other health threatening diseases. In 1989, Kenya introduced the health care services' user fee (Dindi et al., 2020). The fees was meant to sup-port management and general operations within public health facilities. Critics of this move argued that the fees would increase the level of social inequity and exclusion in services access. The critics saw the suspension of the user fee in 1990 (Ghosh et al., 2022). Due to the economic constraints in Kenya, the fees was re-introduced in 1991. However, the re-introduction included exemptions of including tuberculosis, malaria, and sexually transmitted diseases treatment charges, and immunization charges, that were applicable to children aged below

5 years. [11]. In 2004, the government of Kenya implemented a policy that proposed a minimal fee of Ksh. 10 and a registration fee of Ksh. 20 at any public dispensary and health center, respectively [15]. Additionally, in 2003, the government set a free maternity services in all public health institutions, asa way of promoting social protection. The policy implementation was done immediately following its declaration and a follow up during process implementation through memos and circulars [15].

Kenya is divided into 47 counties, which were established through a process of devolution that began in 2010. Before this, the country was divided into eight provinces, further subdivided into districts. The formation of Kenyan counties was part of a broader constitutional reform process that aimed to decentralize power and resources and promote greater participation and representation at the local level [18]. This process was driven by a desire to address historical inequalities and marginalization and to promote more equitable development across the country. The new constitution, which was adopted in 2010, created a two-tier system of government, with power and resources shared between the national government and the counties. The counties were given significant autonomy and control over their affairs, including the power to raise revenue and manage their development programs [23]. The process of establishing the counties involved several steps, including the identification of county boundaries, the establishment of county governments, and the allocation of resources and powers between the national government and the counties. The boundaries of the counties were determined through a consultative process that involved local communities, stakeholders, and experts. The process considered geographic, economic, and cultural factors, population size, and density [23].

The establishment of county governments involved the election of governors, deputy governors, and county assembly members [26]. The county governments were given broad powers and responsibilities, including managing health, education, agriculture, infrastructure, and social services. The allocation of resources and powers between the national government and the counties was determined through negotiation and consultation. The move involved the establishment of a formula for revenue sharing between the national government and the counties, as well as identifying areas of responsibility and the government levels' co-ordination. Overall, the formation of Kenyan counties was a complex and ambitious process that aimed to transform the country's governance and development landscape [18]. While the process has faced several challenges and controversies, it has also generated significant gains in local empowerment, service delivery, and democratic participation.

Nonetheless, each county has its unique characteristics and social-economic profile that may affect health outcomes. Counties in arid and semi-arid regions, such as Turkana and Marsabit, may experience higher malnutrition rates and waterborne diseases due to limited access to water and food [13]. On the other hand, counties located in coastal regions, such as Mombasa and Kilifi, may have higher malaria rates due to the prevalence of mosquitoes in the area. Counties with higher population densities, such as Nairobi and Mombasa, may have higher rates of infectious diseases due to increased person-to-person contact [30]. Counties with high poverty levels, such as Mandera and Wajir, may experience higher malnutrition rates and infectious diseases due to poor sanitation, inadequate healthcare, and limited access to nutritious food [20]. Also, counties with well-established healthcare facilities and trained healthcare workers, such as Nairobi and Kiambu, may have better health outcomes than counties with limited healthcare facilities and personnel, such as Turkana and Samburu [30]. Further, counties with high levels of education and literacy, such as Nairobi and Kiambu, may have better health outcomes due to increased health awareness and better healthcare-seeking behaviors. Counties with low levels of education and literacy, such as Mandera and Wajir, may experience higher rates of preventable diseases due to limited knowledge and understanding of health risks [14]. Above all, counties with higher levels of poverty and unemployment, such as Mandera and Tana River, may experience higher rates of malnutrition and infectious diseases due to inadequate housing, poor sanitation, and limited access to healthcare [20].

This study conducts a spatial modelling of risk factors of maternal mortality. Spatial means that each data item has a geographical reference. Spatial data contain location, time and attribute information [10]. The analysis of spatial data entails analyzing locations of an object or different locations of events occurrences. The spatial process can be indexed over continuous space (Geo-Statistics), over lattices in space and spatial point process [29]. In simple terms, spatial data represents observations that identify the geographic location of features and boundaries. Knowledge of spatial variations is a very important for both the national and county governments to plan, evaluate, monitor and execute projects that will improve the socio-economic status. Spatial modeling is the most suitable analysis technique to handle this spatial variations across regions [32]. Therefore, this study considers the 47 counties as the spatial units, and analysed data from all counties to cater for the discrepancies.

1.2 Statement of the Problem

Globally, maternal deaths average at 810 women per day [16]. In addition to the loos of live, it is also costly to deal with the maternal mortality issue. The global cost for ending preventable maternal deaths is increasing, with a projection of $115.5 billion for 120 priority countries (IHME, 2022). For the same projection period, ICPD has set $11.9 billion to enhance assistance towards eliminating preventable maternal deaths at the country level. As noted by IHME (2022), the world requires a total new investment of $103.6 billion to end preventable maternal deaths. Ideally, consensus exists among nations on the need to minimize maternal deaths. However, there are limited funds and other resources, which necessitate thorough assessment of most affected countries [1].

Sub-Saharan Africa and Southern Asia recorded more than 86% (254,000) of the global maternal deaths. Sub-Saharan Africa alone recorded 67% (196,000) of the global maternal deaths, while Southern Asia accounted for more than 20% (58,000) [24]. De-spite the notable progress of about 40% reduction in maternal deaths between 1990 and 2019, Africa remains the continent with the greatest maternal mortality rate. However, the maternal mortality in Africa varies significantly from county to country [2].

In Kenya, the average number of maternal mortality cases per day is 13.70, translating to approximately 5000 women who die annually due to childbirth and pregnancy complications [25]. In Kenya, the ratio of maternal mortality is 355 deaths per a hundred thousand live births [9]. Ideally, maternal and perinatal mortality are significant threats to public health in the country, despite the abolishing of maternity care user fee under the Free Maternity Service policy, in all public health facilities in June, 2013. This is an indication that hospital cost was not the only major factor leading to high maternal mortality rate in Kenya.

The high mortality rate in Kenya has dire consequences. The consequences ripple out from the spouse to the children and later to the household, running across generations [15]. Women perform most household tasks when healthy. However, after death, their responsibilities for such tasks is moved to the husbands, mother-in-law, mothers, or children. Children's survival is also threatened. Mwaura, Kamanu, and Kulohoma, (2023) observed that only 37% of live births to mothers who die of maternal causes survive for 1 year, compared to 65% and 93% of live births of their counterparts who die from non-maternal causes and surviving women, respectively [25]. The children who survive to school age often miss school or have little time for school work, due to factors such as increased housework and loss of household income.

Ending maternal mortality in Kenya remains a major focus by the Ministry of Health and a significant indicator in the SDG as well as the vision 2030 (Mathai et al., 2022). However, despite the global agreement, commitment by the Kenyan government, and several decades of progress, more than 300 deaths per a hundred thousand live births, from preventable maternal deaths, are recorded in Kenya [25]. Like other nations, Kenya faces limited funds and other resources for ending preventable maternal deaths. Therefore, there is a fundamental need for a spatial Model for risk factors of maternal mortality in Kenya, to identify counties that require deliberate focus and allocation of most resources.

2. RESEARCH METHODOLOGY

2.1 Research Method and Design

The study adopted a descriptive research design and a quantitative research method. The design entailed investigating the respondents in their natural lives. The adopted research strategy was approached through the involvement of quantitative data collection and analysis techniques. The data was collected once from the participants and this helped in describing their characteristics as they naturally occur. Also, the study followed a highly structured methodology which aimed at facilitating the hypothesis with a reliance on quantifiable observations that was subjected to statistical analysis. As described by Sekaran and Bougie (2016), unlike the qualitative approach, the quantitative method uses numerical facts where trends are identified using statistical modeling to reveal the correlative and causal links between variables. This research approach emphasizes on objective measurement and the statistical, numerical, or mathematical analysis of data (Martelli, and Greener, S. (2018). A significant justification for the choice of the quantitative research approach is that the method allows for a better generalization of the results [29]. Also, the method yields unbiased results because it does not rely on the skills and interpretation of the researcher as the case of qualitative studies, but standard data analysis processes. As presented by Sekaran and Bougie (2016), a significant characteristic of the quantitative research study is that data collection is done using a struc-tured research instrument. Hence, uniform data is obtained, which enhances comparison among studies done in the previous times, different organizations, or from different regions. Above all, given the high reliability and the fact that all aspects of the study are carefully designed before data is collected, researchers can replicate or repeat the study [9].

2.2 Target Population

The study targets a population of all households in Kenya. The households were expected to state whether they had a maternal mortality case. The first volume of the 2019 Census re-ports were published in November 2019, presenting the population by country and sub-country. According to the report, Kenyaâs population is 47.5 million, with 12.2 million households. Therefore, the target population was of size N=12.2 million. The countryâs average household size is 3.9.

2.3 Data Description

2.3.1 Data Source

The study used data from the 2019 KPHC, as provided by the KNBS. The 2019 KPHC market significant improvements from the previous census projects, including the use of mobile tech-nology during mapping and enumeration. The census was conducted under the provisions of the constitution of Kenya, 2010 (Fourth Schedule Part 1 item 11), the Statistics (Amendment) Act, 2019 and the Statistics (Census of Population) Order, 2018-Legal Notice No. 205. The enumeration process took plcae from 24th/25th to 31st August 2019 followed by a mop-up exercise on 1st and 2nd of September 2019. The general overview of the 2019 KPHC report showed that the study enumerated a total of 47,564,296 persons of which 23,548,056 (49.5%), 24,014,716 (50.5%), and 1,524 (0.0%) were males, females and intersex, respectively. Data quality was achieved through field supervision which followed a three tier structure from coordinators, ICT, to Content Supervisors. Also, independent observers drawn from the national statistics and international communities' offices monitored the enumerators. A secure ICT infrastructure was utilized for data transmission.

2.3.2 Dependent Variable

The study used maternal death as the dependent/response variable. Maternal death occurs when a pregnant or birthing woman dies when pregnant, during birth or 42 days after the end of pregnancy from pregnancy related health problems. The variable was a derived variable obtained after combining data from three variables, namely, death during pregnancy (variable H18_1), death during delivery (variable H18_2), and death within 6 weeks or 42 days after delivery (variable H18_3).

2.3.3 Covariates

Covariates are explanatory variables that exist naturally within research units. During the data collection, these variables were not collected with the primary interest of investigating the maternal mortality, but are believed to have effects on the likelihood of maternal mortality. The covariates included various prostate cancer risk factors highlighted in the literature. The study used a total of 20 covariates. Table 3.1 describes the variables used in the study by stating their codes, descriptions, names, and responses.

2.4 Model Specification

In this subsection, the study considered some of the frequently used models when modeling the Bernoulli data. The response variable was the presence or absence of maternal death, implying that y_{ij} had value 1 (one), if the jth household in county i had maternal death and 0 (zero) if otherwise, i = 1, 2, · · · , 47, for the 47 counties. Therefore, the dependent variable was Bernoulli with unknown probability p that a household had a maternal death. Mathematically;

$$y_{ij} \sim \text{Bernoulli}(p_{ij}) \quad (1)$$

The study considered four models that estimated the amount of spatial heterogeneity in ma-ternal mortality and the association between risk factors and maternal death using spatial correlation. The model fit were compared using AIC and DIC criteria.

2.4.1 Model 1: Logistic Regression model

$$\text{logit}(p_{ij}) = X^T \beta \quad (2)$$

Where; X was the vector of the unknown covariates and β the model parameters, i.e the model's fixed effects.

2.4.2 Model 2: Normal unstructured heterogeneity (UH) random effects model

$$\text{logit}(p_{ij}) = X^T \beta + v_i \quad (3)$$

Where; v_i is the unstructured random effect added to the logistic regression model.

Overall, the UH model allowed for both fixed and random effects to be estimated. This provided providing a more comprehensive understanding of the relationships between the predictor and response variables while accounting for heterogeneity across different groups in the data.

2.4.3 Model 3: ICAR Spatial random effects model

$$\text{logit}(p_{ij}) = X^T \beta + u_i \quad (4)$$

Where; u_i is the structured random effects added to the logistic regression model

2.4.4 Model 4: Convolution model

$$\text{logit}(p_{ij}) = X^T \beta + u_i + v_i \qquad (5)$$

Where; u_i and v_i are the structured and unstructured random effects, respectively, added to the logistic regression model.

The study modelled the random effects u and v using conditional autoregressive priors and normal distribution, respectively. The study used Bayesian inference based on the posterior distributions of the regression parameters, which was implemented using a random samples via MCMC simulation to all the fitted models.

2.5 Best Subset Selection

The study determined the predictive model using best subset selection criteria. The criteria provided the best n variables models. The selection of the best n variables model was done using forward selection method. The selection technique entailed a selection approach that begun with a null model, then started to add the most significant variables one after the other until all variables under consideration were included in the model. The best model was chosen based on the AIC. The study used AIC to compare models produced from the forward stepwise selection method, and determined the best for the data. The AIC was calculated using the number of independent variables, and the maximum likelihood estimate of the model

$$\text{AIC} = -2\log L(\theta) + 2P \qquad (6)$$

Where; L is the likelihood function and p the number of parameters.

In general, a model with smaller AIC is a better model.

2.6 Predictive Model Selection

The study was interested in the spatial modeling of risk factors of maternal mortality in Kenya. Therefore, the model comparison procedure only involved the two spatial models, ICAR spatial random effects model and convolution model, and excluded the non-spatial models. The normal UH (Unstructured Heterogeneity) random effects model is not necessarily a spatial model. While the model can be used to analyze spatial data, it does not incorporate explicit spatial structure or dependence among the observations. Ideally, it is a statistical model used in the analysis of panel data, which are observations collected over time on multiple individuals or entities. The model assumed that the data followed a normal distribution with a mean that varied across counties and a constant variance. The variations in the mean across counties was captured by the random effects, which were assumed to be independently and identically distributed with a normal distribution. Hence, this study never considered the normal UH random effects model as a spatial model. Similarly, while logistic regression can be extended to incorporate spatial structure and dependencies among observations, it is not inherently a spatial model.

The models were compared using the DIC. DIC is a measure used to compare the fit of different models to a set of data set. A lower DIC value implies a better model fit to the data. The DIC was calculated using the formula;

$$\text{DIC} = -2\log(p(y|\theta)) + C \qquad (7)$$

Where; y represented the data,

θ the unknown parameters,
p is the likelihood function and,

C is a constant.

2.7 Parameter Estimation

Model estimation was carried out using the Bayesian approach. The study specified an appropriate prior distributions for all parameters. Also, the researcher assigned non-informative priors to the regression coefficients where the covariate coefficients were set to have a highly dispersed normal distribution priors. Hence,

$$p(\beta) \sim N(0, 10000) \qquad (8)$$

Bayesian inference was used to estimate the parameters in all the models with MCMC method. Parameters were treated as random variables and were given prior distributions.

3. ANALYSIS RESULTS AND DISCUSSIONS

3.1 Descriptive Results

The descriptive statistics investigated the proportion of households with maternal mortality in the three scenarios. The first scenario was the death of the mother during pregnancy. According to the analysis, most of the households, with a frequency of 1906 (94.4%), did not experience any death of a mother during pregnancy, while the minority, with a frequency of 114 (5.6%), had a death of a mother during pregnancy. The second scenario was the death of the mother during delivery. According to the analysis, most households, with a frequency of 1860 (92.1%), did not experience the death of a mother during delivery, while the minority, with a frequency of 46 (2.3%), had a death of a mother during delivery. The third scenario was the mother's death within 6 weeks after delivery. According to the analysis, most of the households, with a frequency of 1804 (89.3%), did not experience any death of a mother within 6 weeks after delivery, while the minority, with a frequency of 56 (2.8%), recorded at least one death of a mother within 6 weeks after delivery. The study combined the data from the three scenarios to create a derived variable called maternal death. The analysis of the maternal death variable produced frequencies equal to 1804 (89.3%) and 216 (10.7%) for the households that did not record a maternal mortality case and those that did, respectively. The analysis revealed that maternal mortality was a rare event in the population of Kenya.

Table -1: Frequency distribution of Maternal Mortality Variables

Event occurrence	Death during pregnancy	Death during delivery	Death within 6 weeks after delivery
Yes	114 (5.6%)	46 (2.3%)	56 (2.8%)
No	1906 (94.4%)	1860 (92.1%)	1804 (89.3%)
Missing	0 (0.0%)	114 (5.6%)	160 (7.9%)
Total	2020 (100%)	2020 (100%)	2020 (100%)

3.2 Best Subset Selection Results

As discussed in the methodology section, the study used the best subset selection criteria to determine the variables to include in the predictive model. The criteria will provide the best n variables models. The best n variables model was selected using the forward selection method. From the analysis results, the null model had an AIC of 1375.8. The best 1-variable model contained the age at death as the independent variable, with an AIC of 1335.1. The results implied that death age was the most significant factor explaining the likelihood of maternal death.

The best 2-variable model contained death age and county as the independent variables, with an AIC of 1332.3. The analysis revealed that the best 3-variable model had the variables in the best 2-variable model with the death notified variable added. The model produced an AIC of 1333.0. The best 4-variable had the variables in the best 3-variable model, plus the EA status variable added, which produced an AIC of 1329.6. The best 5-variable had the variables in the best 4-variable model, with EA type variable added, and it produced an AIC of 1324.1. The best 6-variable had the variables in the best 5-variable model, with EA type variable added to the model, and had an ACI of 1322.9. The best 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, and all-variable models were obtained by stepwise adding relationship to the head, habitable rooms, wealth quintile, irrigation, aquaculture, livestock rearing, area of agriculture, dwelling units, the period in the household, purpose of Agriculture, and where the death occurred, respectively. The AIC values for the best 7, 8, and 9-variable models were 1322.9, 1324.0, and 1324.5, respectively. The model with all the independent variables produced an AIC of 1334.9.

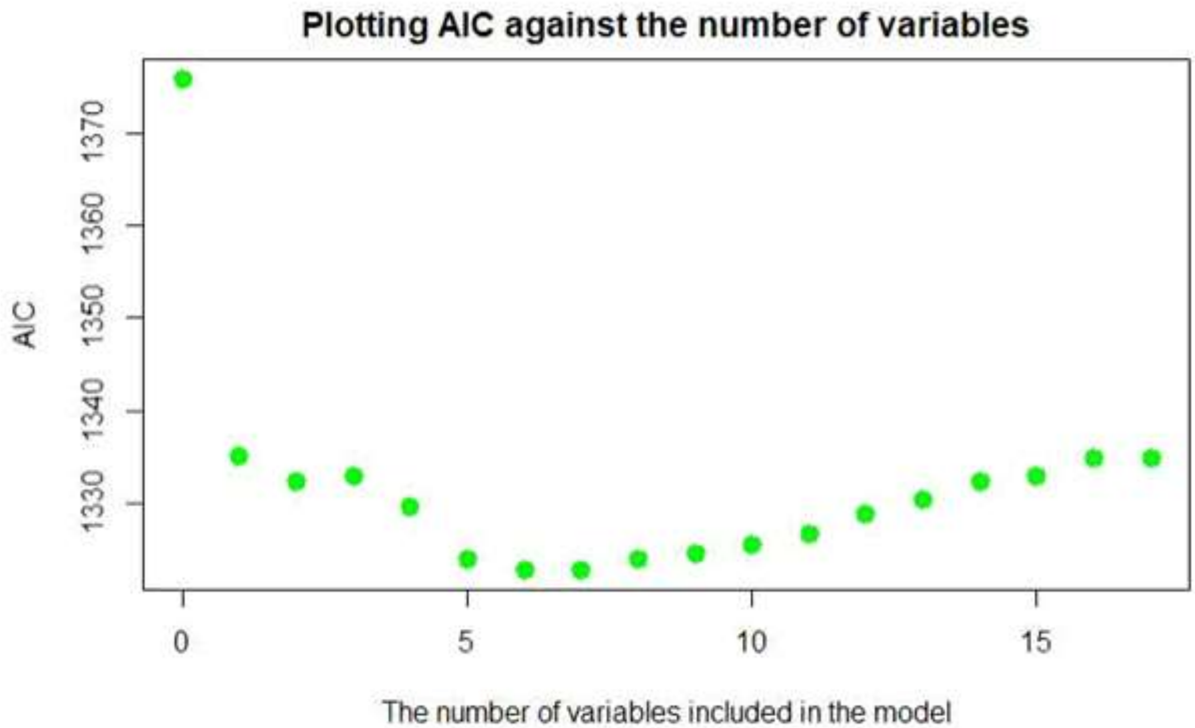

Fig -1: Plot of AIC against the number of variables

The study plotted the AIC against the number of variables included in the model subsets to graphically show the model subset with the lowest AIC. The graph in figure 4.1 showed that the 6 and 7-variable models had the lowest AIC of 1322.9. Hence, at an accuracy of one decimal point, it was not possible to determine the best subset. Hence, the researcher broke the tie using the residual deviance. The 6-variable model had a residual deviance of 1308.9, while the 7-variable model had a residual deviance of 1306.9. Table 4.2, showed that the best n-variable model was the model with 7 dependent variables, since it recorded the lower residual deviance. The independent variables which yielded the best model included death age, county, death notified, AE status, AE type, water source, relationship to the head and habitable rooms.

3.3 Logistic Regression model Results

The study ran a logistic regression model to the data to reveal how the selected variables influenced the likelihood of maternal mortality. The results indicated that the most significant independent variables were the EA type-Urban and death age, with coefficients equal to - 0.5729 ($p=0.00509$) and -0.0515 ($p<0.001$), respectively. The coefficient of EA type-Urban was negative, indicating that living in an urban set up reduced the risk of maternal mortality. Similarly, the coefficient of death age was negative, indicating that having old age reduced the risk of maternal mortality. Other variables with negative coefficients included relationship to the head-grandparent, death notified-No, water source-bottled, water source-piped to yard/plot, water source-piped into dwelling, water source-pond, water source-public tap/standpipe, water source-rain/harvested water, water source-stream/river, water source-unprotected well, and water source-water vendor. All these variable levels reduced the likelihood of maternal mortality.

Table -2: Logistic Model's Coefficients Analysis Results

Variable	Category	Estimate	Standard Error	z-value	p-value
Intercept		-11.4500	1.455e+03	-0.008	0.99372

EA type	Urban	-0.5729	2.045e-01	-2.801	0.00509
EA Status	Informal	0.6631	5.012e-01	1.323	0.18585
Relationship to the head	Daughter	11.6400	1.455e+03	0.008	0.99362
	DK	-0.3354	2.058e+03	0.000	0.99987
	Grandchild	11.3200	1.455e+03	0.008	0.99379
	Grandparent	-0.6551	1.541e+03	0.000	0.99966
	Inlaw	12.4900	1.455e+03	0.009	0.99315
	Mother	11.5200	1.455e+03	0.008	0.99369
	Niece	12.1400	1.455e+03	0.008	0.99335
	Non-relative	12.3100	1.455e+03	0.008	0.99325
	Other relative	12.9400	1.455e+03	0.009	0.99290
	Sister	12.6000	1.455e+03	0.009	0.99309
	Spouse	12.3400	1.455e+03	0.008	0.99323
Death notified	No	-0.1877	6.175e-01	-0.304	0.76121
	Yes	-0.8453	5.936e-01	-1.424	0.15448
Death age		-0.0515	7.999e-03	-6.440	1.19e-10
Water Source	Bottled water	-0.0671	1.174e+00	-0.057	0.95445
	Dam	0.0094	3.075e-01	0.031	0.97566
	Piped to yard/plot	-0.816	5.387e-01	-1.612	0.10697
	Piped into dwelling	-0.2638	5.522e-01	-0.490	0.62382
	Pond	-0.2043	3.034e-01	-0.673	0.50073
	Protected Spring	0.0816	6.310e-01	0.129	0.89709
	Protected well	-0.2638	4.084e-01	-0.646	0.51841
	Public tap/standpipe	-0.6114	3.175e-01	-1.926	0.05414
	Rain/Harvested water	-0.8871	7.908e-01	-1.122	0.26191
	Stream/river	-0.5491	4.419e-01	-1.243	0.21401
	Unprotected spring	0.2548	5.324e-01	0.479	0.63225
	Unprotected well	-0.9197	4.105e-01	-2.240	0.02508

	Water vendor	-1.0500	7.794e-01	-1.348	0.17775
Habitable rooms		0.0440	3.394e-02	1.297	0.19457

3.4 Normal UH Random Effects Model Results

The results of the normal UH random effects model were presented using the fixed effects table and the random effects table. The fixed effects analysis table revealed that urban EA type lowered the likelihood of maternal mortality with a negative coefficient equal to 0.0235327. Having some relationships with the head, including in-laws, other relatives, sisters, and spouses, increased the risks of maternal mortality with coefficients equal to 0.0549445, 0.0723978, 0.0389401, and 0.0183531, respectively. Other factors that increased maternal mor-tality risk included those related to a water source, such as protected and unprotected springs, with coefficients equal to 0.0058728 and 0.0355590, respectively. Further, the study revealed that an increase in the number of habitable rooms increased the risk of maternal mortality, with a coefficient of 0.0043484.

Table -3: Fixed Effects Analysis Results for the Normal UH Random Effects Model

Variable	Category	Estimate	Standard Error	t-value
(Intercept)		0.3356424	0.3101393	1.082
EA Type	Urban	-0.0235327	0.0192474	-1.223
EA Status	Informal	0.1112164	0.0519163	2.142
Relationship to the head	Daughter	-0.0301255	0.3003881	-0.100
	DK	-0.0573978	0.4209698	-0.136
	Grandchild	-0.0603598	0.3035097	-0.199
	Grandparent	-0.0919395	0.3180239	-0.289
	In-Law	0.0549445	0.3008496	0.183
	Mother	-0.0377325	0.3009344	-0.125
	Niece	-0.0039233	0.3053307	-0.013
	Non-relative	-0.0232147	0.3086059	-0.075
	Other relative	0.0723978	0.3024618	0.239
	Sister	0.0389401	0.3010831	0.129
	Spouse	0.0183531	0.3002433	0.061
Death Notified	No	-0.0488835	0.0690438	-0.708
	Yes	-0.0496101	0.0656863	-0.755
Death Age		-0.0037717	0.0006892	-5.473
Water source	Bottled water	-0.0196739	0.1086704	-0.181

	Dam	-0.0100852	0.0340289	-0.296
	Piped to yard/plot	-0.0748640	0.0449298	-1.666
	Piped into dwelling	-0.0411911	0.0519509	-0.793
	Pond	-0.0345840	0.0329092	-1.051
	Protected Spring	0.0058728	0.0682093	0.086
	Protected Well	-0.0333029	0.0386471	-0.862
	Public tap/Standpipe	-0.0579938	0.0330585	-1.754
	Rain/Harvested water	-0.0773011	0.0614215	-1.259
	Stream/River	-0.0532285	0.0412107	-1.292
	Unprotected Spring	0.0355590	0.0572185	0.621
	Unprotected Well	-0.0788914	0.0355965	-2.216
	Water Vendor	-0.0741146	0.0549758	-1.348
Habitable rooms		0.0043484	0.0031878	1.364

In addition to the fixed effects coefficients, the UH model includes random effects coefficients that estimate the variation in the intercept. Random effects in a normal UH random effects model refer to unobserved individual-specific effects that are assumed to be normally distributed with mean zero and constant variance. These effects captured the unobserved heterogeneity across counties that the observed covariates in the model cannot explain. According to the analysis, the residuals had a variance of 0.086043 (SD=0.29333). The UH model allowed for heteroscedasticity, implying that the error term variances are not constant across counties. Instead, it allowed varying according to some function of the observed covariates or the unobserved individual-specific effects. The estimated variance of the random effects provided information about the amount of unobserved heterogeneity in the data.

Table -4: Random Effects

Groups	Name	Variance	Standard Deviation
Counties Residual	Intercept	0.008388 0.086043	0.09158 0.29333
Number of obs Groups	2020 Counties= 47		

3.5 ICAR Spatial Random Effects Model Results

The results of the ICAR Spatial random effects model were presented using the coefficients table. The coefficient estimates for the explanatory variables represented the expected change in the outcome variable for a one-unit increase in the corresponding explanatory variable, holding all other variables constant. According to the analysis, living in an urban setup lowered the risk of maternal mortality, with a coefficient of -0.0230288. Having some relationships with the head, including in-laws, other relatives, sister, and spouse, increased the risks of maternal mortality with coefficients equal to 0.0479417, 0.0665658, 0.0308861, and 0.0116957, respectively. Other factors that increased maternal mortality risk included those related to a water source, such as protected and unprotected springs, with coefficients equal to 0.0026693 and 0.0365032, respectively. Further, the study revealed that an increase in the number of habitable rooms increased the risk of maternal mortality, with a coefficient of 0.0036327.

Table -5: Coefficients Analysis Results for the ICAR Spatial Random Effects Model

Variable	Category	Estimate	Standard Error	t-value
(Intercept)		0.2776709	0.3749571	0.741
EA Type	Urban	-0.0230288	0.0192598	-1.196
EA Status	Informal	0.1109974	0.0522223	2.125
Relationship to the head	Daughter	-0.0368401	0.3004633	-0.123
	DK	-0.0575176	0.4210012	-0.137
	Grandchild	-0.0671379	0.3035869	-0.221
	Grandparent	-0.1002602	0.3181240	-0.315
	In-Law	0.0479417	0.3009287	0.159
	Mother	-0.0440977	0.3010111	-0.146
	Niece	-0.0086897	0.3053809	-0.028
	Non-relative	-0.0301653	0.3086808	-0.098
	Other relative	0.0665658	0.3025224	0.220
	Sister	0.0308861	0.3011796	0.103
	Spouse	0.0116957	0.3003186	0.039
Death Notified	No	-0.0515726	0.0690824	-0.747
	Yes	-0.0506884	0.0656981	-0.772
Death Age		-0.0037662	0.0006894	-5.463
Water source	Bottled water	-0.0188554	0.1086816	-0.173
	Dam	-0.0112896	0.0340488	-0.332
	Piped to yard/plot	-0.0757868	0.0449436	-1.686
	Piped into dwelling	-0.0406887	0.0519582	-0.783
	Pond	-0.0348162	0.0329258	-1.057
	Protected Spring	0.0026693	0.0682707	0.039

	Protected Well	-0.0329093	0.0386515	-0.851
	Public tap/Standpipe	-0.0580395	0.0330651	-1.755
	Rain/Harvested water	-0.0791334	0.0614465	-1.288
	Stream/River	-0.0541198	0.0412235	-1.313
	Unprotected Spring	0.0365032	0.0572318	0.638
	Unprotected Well	-0.0802041	0.0356170	-2.252
	Water Vendor	-0.0727989	0.0549917	-1.324
Habitable rooms		0.0036327	0.0032414	1.121

3.6 Convolution Model Results

The results of the Convolution Model were presented using coefficient estimates. Like the ICAR Spatial random effects model's coefficients, the Convolution Model's coefficients represented the expected change in the outcome variable for a one-unit increase in the corresponding explanatory variable, holding all other variables constant. According to the analysis, living in an urban setup lowered the risk of maternal mortality, with a coefficient of -0.0245459. Conversely, an informal EA status increased the risk of maternal mortality, with a coefficient of 0.1120484. Having some relationships to the head, including in-law, niece, other relative, sister, and spouse, increased the risks of maternal mortality with coefficients equal to 0.0720437, 0.0129696, 0.0877023, 0.0556658, and 0.0357864, respectively. Other factors that increased maternal mortality risk included those related to a water source, such as protected and unprotected springs, with coefficients equal to 0.0054072 and 0.0364031, respectively. Further, the study revealed that an increase in the number of habitable rooms increased the risk of maternal mortality, with a coefficient of 0.0045287.

Table -6: Fixed Effects Analysis Results for the Convolution Model

Variable	Category	Estimate	Standard Error	t-value
(Intercept)		0.1594770	0.4282486	0.372
EA.Type	Urban	-0.0245459	0.0193004	-1.272
EA Status	Informal	0.1120484	0.0519146	2.158
Relationship to the head	Daughter	-0.0131648	0.3008326	-0.044
	DK	-0.0396516	0.4212693	-0.094
	Grandchild	-0.0432397	0.3039968	-0.142
	Grandparent	-0.0735717	0.3185109	-0.231
	In-Law	0.0720437	0.3013060	0.239
	Mother	-0.0194829	0.3014617	-0.065

	Niece	0.0129696	0.3057959	0.042
	Non-relative	-0.0077024	0.3089983	-0.025
	Other relative	0.0877023	0.3028595	0.290
	Sister	0.0556658	0.3015311	0.185
	Spouse	0.0357864	0.3007248	0.119
Death Notified	No	-0.0498226	0.0690362	-0.722
	Yes	-0.0502495	0.0656876	-0.765
Death Age		-0.0037951	0.0006901	-5.499
Water source	Bottled water	-0.0177572	0.1086717	-0.163
	Dam	-0.0088662	0.0340759	-0.260
	Piped to yard/plot	-0.0723044	0.0449966	-1.607
	Piped into dwelling	-0.0406778	0.0519624	-0.783
	Pond	-0.0337239	0.0329494	-1.024
	Protected Spring	0.0054072	0.0682090	0.079
	Protected Well	-0.0344546	0.0386573	-0.891
	Public tap/Standpipe	-0.0567298	0.0331000	-1.714
	Rain/Harvested water	-0.0765070	0.0614220	-1.246
	Stream/River	-0.0573331	0.0413899	-1.385
	Unprotected Spring	0.0364031	0.0572161	0.636
	Unprotected Well	-0.0786715	0.0355972	-2.210
	Water Vendor	-0.0742557	0.0549799	-1.351
Habitable rooms		0.0045287	0.0031971	1.417

3.7 Model Comparison

The results of the model comparison produced DIC values of 1248.6 and 1246.3 for the ICAR spatial random effects and convolution models, respectively. Hence, the convolution model (DIC=1246.3) was the best model.

Table 4.8: Random Effects

Statistics	Model 3: ICAR Spatial Random Effects Model	Model 4: Convolution Model
$^{\sigma}u$		0.06154
σ_v	0.087052	0.36343

DIC	1248.6	1246.3

3.8 Mapping of Maternal Mortality across different counties in Kenya

The mapping of the Maternal Mortality prevalence across different counties using the convo-lution model showed that Wajir, Mandera, Laikipia, Nyandarua, Nyeri, Tharaka Nithi, Elgeyo Marakwet, Siaya, and Migori had the greatest prevalence indices. Isiolo, Embu and Machakos had the lowest Maternal Mortality prevalence indices.

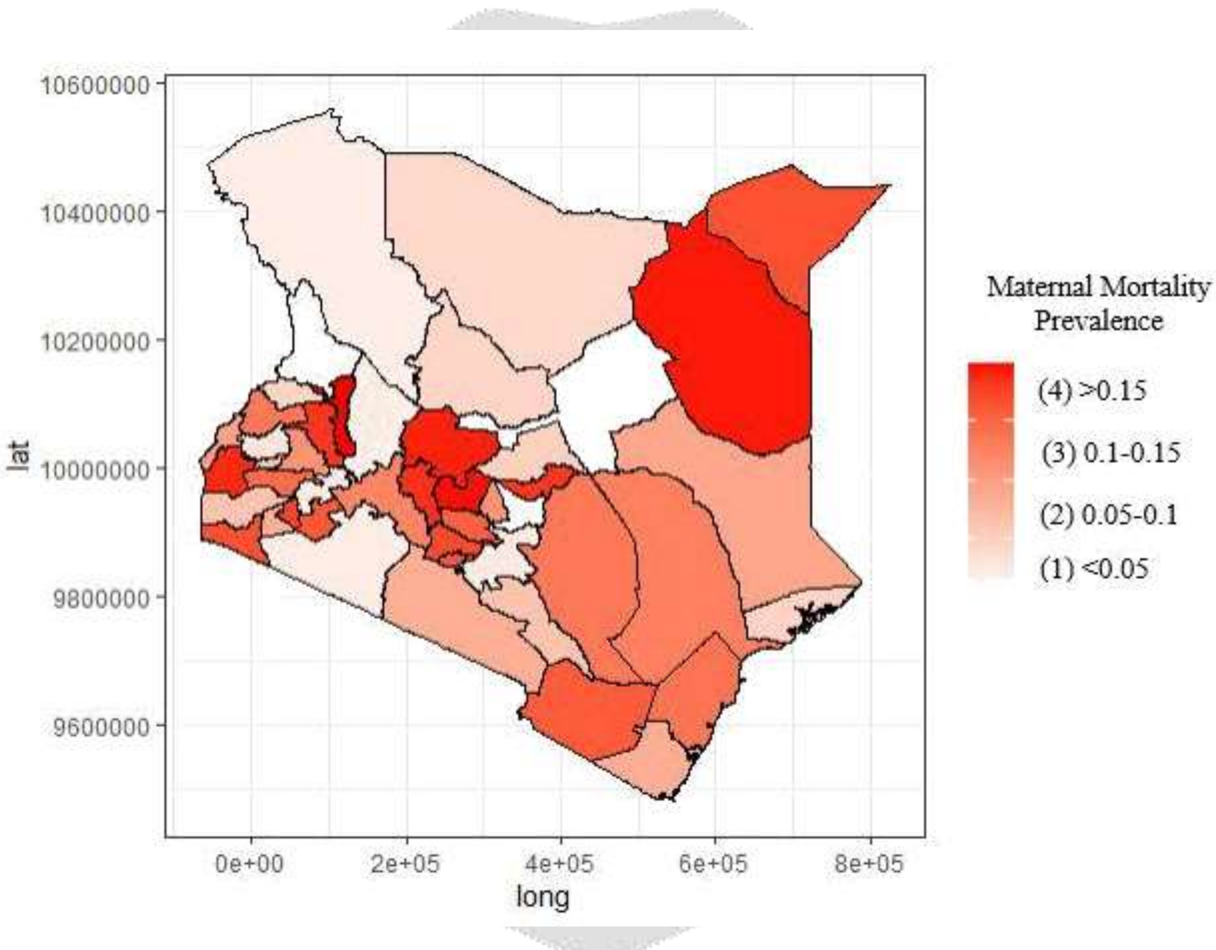

Fig -2: Maternal Mortality prevalence map

According to the analysis, the counties with considerably low risks of maternal mortality in-cluded Isiolo, Embu, and Machakos. The counties with moderate risks of maternal mortality included West Pokot, Narok, and Lamu.

4. CONCLUSIONS AND RECOMMENDATIONS

4.1 Conclusion

The study concluded that maternal and perinatal mortality was a significant threat to the global public health, particularly in Kenya. The preliminary investigations revealed that the average number of maternal mortality cases per day is 13.70, translating to approximately 5000 women annually who die due to childbirth and pregnancy complications. However, the study noted significant efforts to minimizing the problem with the ICPD setting $11.9 billion for development assistance at the country level.

The descriptive statistics revealed that the country-wide maternal mortality prevalence was 10.7%. The occurrence of maternal death was distributed varyingly across the three scenarios that resulted in maternal mortality. The first scenario was the death of the mother during pregnancy. The study revealed that most of the households did not experience any death of a mother during pregnancy, while the minority (with a frequency of 114 (5.6%)) had a death of a mother during pregnancy. The second scenario was the death of the mother during delivery. According to the analysis, most households did not experience the death of a mother during delivery, while the minority, with a frequency of 46 (2.3%), had a mother’s death during delivery. The third scenario was the motherâs death within 6 weeks after delivery. According to the Marakwet, Siaya, and Migori had the greatest prevalence indices. Isiolo, Embu, and Machakos had the lowest Maternal Mortality prevalence indices. The counties with considerably low risks of maternal mortality included Isiolo, Embu, and Machakos, The counties with moderate risks of maternal mortality included West Pokot, Narok, and Lamu.

4.2 Recommendations

The study concluded that in many counties in Kenya, pregnant women do not have access to basic healthcare services, which can lead to complications that may result in death during pregnancy. Other factors may include poor maternal health, complications during pregnancy, and cultural or social factors. Therefore, the government of Kenya is recommended to address these challenges using a multi-faceted approach that includes improving access to healthcare, promoting maternal health and nutrition, increasing the availability of skilled birth attendants, providing emergency obstetric care, and addressing cultural and social factors that contribute to maternal mortality.

In particular, the government of Kenya should focus its support on Wajir, Mandera, Laikipia, Nyandarua, Nyeri, Tharaka Nithi, Elgeyo Marakwet, Siaya, and Migori, which were found to have the greatest risks of maternal mortality. In particular, the government should support the county governments, especially those with greater risks of maternal mortality, to ease the access to quality and timely health services.

Further, the study made recommendations for future research. This study used a logistic regression model to select the best n-variable model. However, the study later used the convolution model to conduct a spatial model of risk factors of maternal mortality in Kenya. This provides a limitation since some factors could have been more significant if the spatial variations were considered than when no spatial variations were considered. Therefore, this study recommends that future researchers find a way of conducting subset selection using the convolution model, highlighted as the best spatial model for the data.

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