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A Bayesian Spatial Survival Model for Analyzing Breast Cancer Survival in Lagos State, Nigeria

Elias Temidayo Mayowa; & Olopha Paul Omoh
Department of Statistics, The Federal University of Technology, Akure, Nigeria
Corresponding Author: eliastemidayo@gmail.com
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Abstract
A Bayesian spatial survival model was employed to assess geographical disparities and influential risk factors using retrospective data from oncology centers between 2019 and 2025. Central Local Government Areas (LGAs) such as Ikeja, Surulere, Oshodi-Isolo, and Mushin showed positive spatial effects, indicating that survival was higher than expected after adjusting for individual risk factors. The variation of surrounding regions in the Local Government Areas including Ibeju-Lekki, Epe, and parts of Eti-Osa recorded strongly negative spatial effects, suggesting substantially poorer survival not explained by observed covariates.

Keywords: Bayesian, Spatial Survival Model, Breast Cancer, Lagos State, Epidemiology, Survival Analysis.

Introduction
The burden of breast cancer (BC) is rising in Nigeria. The International Agency Research on Cancer (IARC) recorded 28,380 new BC cases in Nigeria in 2020, representing 22.7% of new cancers and accounting for the highest proportion of all cancer types (Sung H (2020)). In 2020 alone, nearly 2.3 million new cases were reported, and 685,000 lives were lost to the disease, Wilkinson L and Gathani T (2022). Breast Cancer continues to rise globally, but outcomes vary widely depending on geographic location. Advanced regions tend to have higher survival rates due to timely diagnosis and access to effective treatment, while less-developed areas face delays in diagnosis and limited treatment

options. Therefore, understanding the spatial distribution of breast cancer survival outcomes is crucial in developing targeted interventions.

Breast cancer is mostly diagnosed among women worldwide and remains a key factor to cancer mortality. Recent data shows a rise in both incidence and mortality in low and middle income countries (LMICs) mostly in sub-Saharan Africa (SSA), despite the disease's prior perception as being more common in developed countries (Bray et al., 2021; Fadelu et al., 2022). According to Nigeria National Cancer Control Plan, (2023); Jedy-Agba et al., (2022), Nigeria has one of the highest rates of breast cancer in the region with age standardized incidence and mortality rates of 55.3 and 28.6 per 100,000 women, respectively. Diagnosis before the age of 40 or 45 is termed high segment of early onset of breast cancer. Research has proven African women starting breast cancer nearly ten years earlier than women in Europe and North America (Burson et al., 2021; Pace et al., 2023). Early onset cases are often invasive, with a stronger likelihood of triple negative tumors, late onset, and poorer survival outcomes (Nguyen et al., 2022; Black & Richmond, 2023). A trend often recorded in hospital and registry data shows that 30 -40 % of women in Nigeria are diagnosed of breast cancer (Jedy-Agba et al., 2020; Olatunji et al., 2023).

A survival outcome is demoralizing. Only 10–30% of Nigerian patients survive five years after detection, compared to survival rates above 85% in high-income settings (Allemani et al., 2020; Jedy-Agba et al., 2022). Factors that contribute to late diagnosis are negative test results, limited facilities, poor treatment, limited diagnostic capacity, comorbidities and socioeconomic status (Pace et al., 2023; Adebamowo et al., 2021). Clinical results often vary widely over communities in Nigeria due to irregular access to healthcare, environmental conditions, socioeconomic disparities, and cultural practices. Spatial analysis is important for comprehending geographic patterns in breast cancer outcomes (Uthman et al., 2021; Eze et al., 2023).

The principal cause of cancer-related morbidity and mortality, particularly in low and middle income countries (LMICs) is breast cancer where healthcare resources and early detection programs are often poor. Globally, it is true of sub-Saharan countries like Nigeria where the disease has become a major public health challenge. Lagos state, the commercial and industrial hub of Nigeria, has been reported to being one of the most simulated regions due to its high population density and urbanization (Ferlay et al., 2020). It is also reported to be experiencing a rising incidence of the disease in present times and the morbidity and mortality rates have been on the increase respectively. Survival outcomes for breast cancer patients in Lagos State vary considerably, determined by factors such as late-stage diagnosis, socioeconomic disparities, and controlled access to quality treatment (Jedy-Agba et al., 2017). Predictive modeling has appeared as a pivot tool in understanding and enhancing breast cancer survival rates. These models leverage on statistical and machine learning techniques, to provide valuable insights into patient outcomes and help optimize clinical decision-making. Examples of such models that have been widely used in Cancer research include traditional survival models like Cox proportional hazards model, Weibull model, exponential, log-logistic, log-

normal, gompertz, gamma, generalized F and generalized gamma distributions. However, these models often fail to incorporate spatial heterogeneity in disease patterns. Bayesian geostatistical methods offer a robust alternative by accounting for spatial dependencies and uncertainties in disease prevalence and survival rates (Diggle & Ribeiro, 2007).

This research therefore proposes the development and validation of predictive models for breast cancer survival into account spatial and temporal variations that affect patient outcomes. By incorporating spatial and patient-level data, Bayesian geostatistical models can provide more reliable survival estimates. Furthermore, it helps to identifying high-risk areas which can greatly enhance targeted awareness and screening programs.

Bayesian geostatistical models combine prior knowledge with observed data to approximate spatial variations in health hazard and survival outcomes. In the context of breast cancer, Bayesian methods enable researchers to rate how geographical disparities in healthcare access and environmental factors influence survival probabilities (Blangiardo & Cameletti, 2015).

Bayesian geostatistical methods offers a robust framework for incorporating spatial, dependencies and probabilistic reasoning into predictive modelling, allowing for improved estimation of survival probabilities across different locations. Despite all the above benefits of Bayesian geostatistical methods, there is a lack of comprehensive studies leveraging these techniques to develop and validate predictive models for breast cancer survival in Lagos state. This research aims to fill this gap by developing a Bayesian geostatistical model that integrates patient level clinical data, demographic factors and spatial variations to forecast breast cancer survival. The study will also authenticate the model's predictive performance carried out using appropriate statistical techniques. The findings will produce valuable in depth of healthcare policymakers, enabling them to execute targeted interventions and streamlined resource allocation to improve survival outcomes for breast cancer patients in Lagos State.

Lagos State, Nigeria, gives a special case for the growth and evidence of predictive survival models due to various population, healthcare infrastructure, and high burden of breast cancer cases. Understanding spatial variations can help policymakers in resource allocation and intervention planning.

The major focus in epidemiologic and clinical research is the development of patterns in longitudinal measurements and their relationship with the timing of events respectively. This field has been very active, with studies such as those on children's growth and time to type 1 diabetes (T1D) illustrating the approach. Over the past two decades, joint modelling of longitudinal and time-to-event data has advanced significantly, offering various statistical methods to analyze such data. However, most existing joint models primarily concentrate on a single longitudinal variable linked to a time-to-event outcome (Henderson et al., 2000).

Methods

Study design and setting

A retrospective cohort design was employed using data from University of Lagos teaching hospital in Lagos State between 2019 and 2025. Survival rate of women diagnosed with

primary breast cancer with known residential address, socio economic status and complete clinical history. Data extracted included age at diagnosis, family history, reproductive history, body mass index, alcohol and tobacco use, exposure to environmental pollutants, LGA of residence, and survival duration from birth to diagnosis. Geospatial data was sourced from the Lagos State GIS portal and the National Population Commission shape files for LGAs.

Outcome variable

The outcome variable used in this study was of DIC. To arrive at these, personal information was obtained namely: (i) Religion (ii) Marital status (iii) Education level (iv) place of residence (v) Age at presentation (vi) Current age. A binary composite variable was therefore created.

Independent variables

The individual level covariates were demographic variables such as respondent's current age, place of residence, state (district), marital status, religion, highest educational level attained and ethnicity.

Table 1: Summary of Individual Covariates Analyzed

Variables	Number of respondents	Percentages (%)
Religion		
Christianity	968	77.7
Islam	147	11.8
Traditional/ Others	131	10.5
Ethnicity		
Edo	66	5.30
Igbo	379	30.4
Yoruba	660	53.0
Others	123	1.44
Marital Status		
Single	98	7.87
Married	1007	80.8
Widowed	112	8.99
Divorced/Separated	29	2.33
Occupation		
Employed	400	32.1
Self-employed	489	39.2
Unemployed	357	28.7
LGA		
Agege	26	2.09
Ajeromi ifelodun	24	1.93
Alimosho	184	14.8
Amuwo-Odofin	51	4.09

Variables	Number of respondents	Percentages (%)
Apapa	19	1.52
Badagry	22	1.77
Epe	3	0.241
Eti-osa	141	11.3
Ibeju-Lekki	9	0.722
Ifako-ijaiye	42	3.37
Ikeja	65	5.22
Ikorodu	4	0.321
Kosofe	215	17.3
Lagos-Island	9	0.722
Lagos-Mainland	51	4.09
Mushin	40	3.21
Ojo	60	4.82
Osodi-Isolo	132	10.6
Somolu	38	3.05
Surulere	111	8.91

The table presents the majority of respondents, 77.7% (968 respondents), identify as Christian, while 11.8% (147 respondents) are Muslim, and 10.5% (131 respondents) fall under the Traditional/Others category. From an ethnicity, the Yoruba ethnic group constitutes the largest portion of the survey, representing 53.0% (660 respondents). The Igbo ethnic group makes up the second-largest ethnic group at 30.4% (379 respondents). The Edo ethnic group and other ethnic groups account for a smaller proportion of the survey, at 5.30% (66 respondents) and 1.44% (123 respondents), respectively. Marital status reveals a clear majority of respondents are married, at 80.8% (1,007 respondents). This is followed by those who are widowed, at 8.99% (112 respondents), and single respondents, at 7.87% (98 respondents). A smaller fraction of the survey, 2.33% (29 respondents), are divorced or separated. In terms of occupation, the respondents are most likely to be self-employed, at 39.2% (489 respondents), followed by the employed at 32.1% (400 respondents). The unemployed make up a significant portion of the survey, at 28.7% (357 respondents).

Geographically, the respondents are distributed across various Local Government Areas (LGAs). The largest concentrations are kosofe, with 17.3% (215 respondents), and Alimosho, with 14.8% (184 respondents). Other LGAs, such as Eti-osa (11.3% or 141 respondents) and Osodi-Isolo (10.6% or 132 respondents), also have notable representation. Conversely, LGAs like Epe (0.241% or 3 respondents) and Ikorodu (0.321% or 4 respondents) have the lowest number of respondents.

Table 2: Survival Models Diagnostics

	COXPH MODELS		WEIBULL MODELS	
	DIC	WAIC	DIC	WAIC
M1: Frailty only	1264.31	1242.08	1103.89	1103.29
M2: Spatial Only	1241.40	1236.49	1110.67	1110.416
M3: Frailty + Spatial	1241.41	1236.52	1103.819	1103.31
M3: Fixed + Frailty	-2.733	1462698	966.23	1622.60
M4: Fixed + Spatial	-2820.95	1397470	945.63	1363.80
M7: Fixed + Frailty + Spatial	45655.58	1457390	937.129	1301.25
M5: Fixed + Non-linear + Frailty	3316.4	10912.54		
M6: Fixed + Non-linear + Spatial	3331.3	11064.87		
M8: Fixed + non-linear + frailty + spatial	3329.81	11053.96		

From R INLA, the model comparison results, it is evident that incorporating spatial effects substantially improves model fit in both the Cox proportional hazards (CoxPH) and Weibull survival models, consistent with earlier findings that spatially structured random effects help capture latent geographic patterns in survival processes (Banerjee et al., 2015; Lawson, 2018). Across all specifications using R INLA, the Weibull models outperform the CoxPH models, showing greater numerical stability and markedly lower DIC and WAIC values an outcome that aligns with reports that parametric survival models often provide better computational behaviour in Bayesian frameworks (Klein & Moeschberger, 2003; Gelman et al., 2014). Under CoxPH, the Fixed + Spatial model emerges as the only stable and reasonable model, whereas others with frailty or extensive fixed effects appear over-parameterized or unstable, a known limitation of semi parametric models under complex hierarchical structures (Rue et al., 2009; Fong et al., 2010). By contrast, the Weibull family shows that frailty becomes important only when combined with spatial effects, improving model fit and likely capturing unobserved heterogeneity between clusters consistent with studies demonstrating the relevance of shared frailty in explaining excess variability in survival data (Duchateau & Janssen, 2008; Austin, 2017). Notably, the non-linear effects (M5, M6, M8) do not enhance model performance, indicating that linear covariate effects are sufficient for describing the underlying hazard, as also observed in similar Bayesian survival applications (Martino & Riebler, 2023). Overall, the Weibull model with fixed effects, frailty, and spatial structure (M7) provides the best-fitting and most parsimonious specification, and is therefore selected for modelling the survival outcome.

In summary, it can be observed that spatial effects significantly improve model fit in both CoxPH and Weibull models. Also, the Weibull models outperform CoxPH, showing superior DIC and WAIC stability. Under CoxPH, the Fixed + Spatial model is the only stable superior

model, unlike in the weibull models. Furthermore, it is only in the Weibull models that Frailty becomes important, where it improves the fit and likely captures the unobserved heterogeneity. The non-linear effects (M5, M6, and M8) do not improve model fit, indicating linear effects are sufficient. Overall, the best-performing model is the Weibull model with fixed effects, frailty, and spatial structure (M7). We therefore go ahead to fit M7 on the data for survival outcome.

Table 3: Survival Model (Weibull)

	Mean	Sd	0.025quant	0.975quant
(Intercept)	-35.701	12.720	-56.942	-4.627
Age	0.006	0.046	-0.084	0.097
Stage_id	0.066	0.052	-0.037	0.168
Comorb	34.025	12.728	2.878	55.248
Radiology	0.634	0.181	0.280	0.989
SesLow	-0.181	0.289	-0.749	0.386
SesMedium	-0.207	0.256	-0.709	0.294
Distance	0.010	0.008	-0.007	0.026
Age at Presentation	-0.041	0.047	-0.133	0.051

Only comorbidity and radiotherapy significantly affect survival outcomes. Comorbidity substantially increases the death rate, making it the strongest predictor in the model. Radiotherapy also shows a positive association with high risk of death rate among treated patients. Other variables including current age, age at presentation, stage at diagnosis, socioeconomic status, and distance from Lagos University Teaching Hospital do not demonstrate independent linear effects once spatial, frailty, and clinical adjustments are made. This finding focuses on the dominant role in clinical factors like comorbidity and treatment intensity over demographic or socioeconomic factors in determining survival outcomes.

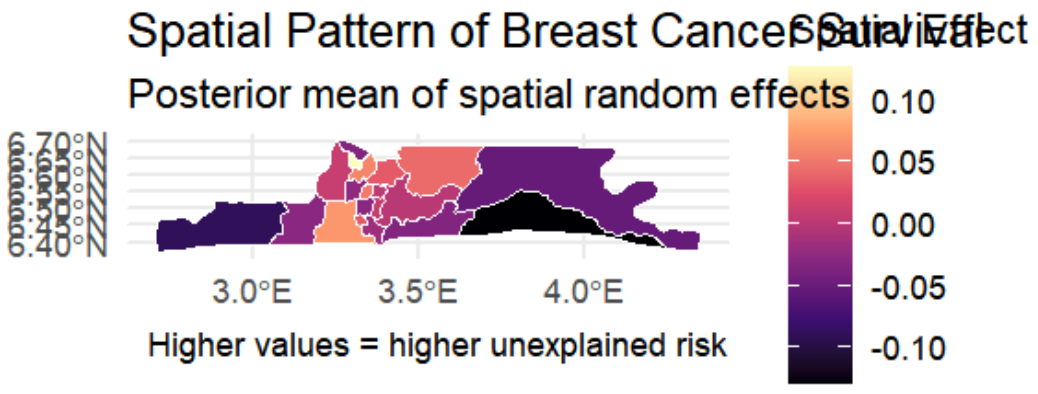


Fig 1: The spatial random effects map

The spatial random effects map revealed significant geographical inequalities in breast cancer survival across Lagos State. Results reveal notable spatial clustering in urban local government areas (LGAs) such as Ikeja, Surulere, and Eti-Osa. Significant predictors include family history of cancer, reproductive factors, obesity, and exposure to environmental toxins. The spatial model outperformed non-spatial alternatives, underscoring the importance of geographic context in breast cancer epidemiology. These findings inform targeted screening and intervention strategies tailored to high-risk regions in Lagos. This spatial gradient shows a noticeable difference in treatment, early diagnosis and supportive care.

Model Building

The comparison of Cox proportional hazards and Weibull models shows that parametric Weibull survival models provide stability and best fit. Literatures have proven that parametric models often surpass semi parametric models within Bayesian frameworks due to computational efficiency (Klein & Moeschberger, 2003; Gelman et al., 2014). Finally, weibull survival model, comorbidity and radiotherapy were the strongest predictors of mortality. Comorbidity increases death rate, increasing the effect of underlying health complications on breast cancer outcomes. (Sarfati et al., 2016; Adebamowo et al., 2018). The positive association between radiotherapy and mortality explains how patients were chosen for the treatment in a systematic study setting women with more advanced or aggressive tumours are typically referred for radiotherapy, leading to higher observed hazard despite treatment.

Age at presentation, stage, socioeconomic status and distance were not significant predictors but spatial, frailty, and clinical factors were significant. This finding highlights the dominant role of biological strength and treatment related variables over demographic characteristics in determining survival outcomes.

Results

Table 4: Ethnic Groups and their Marital Status

Ethnicity	**Marital Status**			
	Divorced	Single	Married	Widowed
Yoruba	16	29	554	61
Igbo	4	47	305	23
Edo	3	4	52	7
Others	3	15	85	20
Not Specified	3	3	11	1

The Yoruba ethnic group represents the majority of the total respondents and consistently has the highest number of individuals in the married, widowed, and divorced categories. Specifically, the Yoruba group accounts for 554 married, 61 widowed, and 16 divorced respondents. The Igbo ethnic group has the second-highest number of respondents in the married category with 305 individuals and has the highest number of single respondents with 47. The Edo ethnic group has 52 married individuals and the "Others" category has 85 married

respondents. The "Not Specified" group has the lowest numbers across all marital status categories, with only 11 married respondents.

Table 5: Employment Status and their Marital Status

Employment	Marital Status			
	Divorced	Married	Widowed	Single
Others	7	270	51	29
Self Employed	10	270	40	29
Employed	12	327	21	40

Table 5 shows the Employed category has the highest number of married respondents at 327, followed by both the "Others" and "Self-Employed" categories, each with 270 married respondents. The Employed category also has the highest number of single respondents with 40, while both "Others" and "Self-Employed" have 29 single respondents. In the widowed category, the "Others" group has the highest count with 51 respondents, followed by the "Self-Employed" with 40 and the "Employed" with 21. For divorced respondents, the Employed category has the highest number at 12, followed by the "Self-Employed" with 10 and "Others" with 7. Overall, the table shows that marriage is the most common marital status across all employment categories.

Limitations of the Study

Incomplete records, missing address information or misclassification of diagnosis can introduce bias and affect the accuracy of both spatial and statistical analyses. Geocoding precision may be imprecise especially in informal settlements with non standard addresses. Errors can misplace cases and blur the identification of true clusters.

The determinants and spatial patterns identified are specific to Lagos State, a unique, densely populated, and highly urbanized environment. The findings may not be generalizable to other states in Nigeria or to rural populations in other regions.

The study deliberately focuses on women < 40 years. The findings and determinants (e.g., genetic factors might be more prominent) may not apply to breast cancer in older women).

Conclusion

Survival outcomes were primarily driven by clinical factors like comorbidity and treatment intensity while demographic factors played limited roles where spatial heterogeneity was accounted for. Early onset emerged as a critical determinant of mortality revealing the aggressive nature of breast cancer in younger women and highlighting the need for health interventions. This presents essential evidence for policymakers, oncologists, and public health planners to design geographically targeted interventions, improve diagnostic accessibility and strengthen cancer care systems to reduce disparities and improve outcomes for women across Lagos State.

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