Mathematical Modelling and Applications
2026; 11(1): 1-17
http://www.sciencepublishinggroup.com/j/mma
doi: 10.11648/j.mma.20261101.11

Small Area Risk Mapping of Under-five Mortality: A District-level Analysis using Parametric Approach

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To cite this article:
Salyungu Mabula, Robert Too, Gregory Kerich. (2026). Small Area Risk Mapping of Under-five Mortality: A District-level Analysis using Parametric Approach. *Mathematical Modelling and Applications, 11*(1), 1-17. https://doi.org/10.11648/j.mma.20261101.11

Received: 30 November 2025 ; **Accepted:** 20 December 2025; **Published:** 20 January 2026

Abstract: Mortality of under-five children remains a pressing public health concern in Tanzania, with spatial disparities contributed by the intersection of socioeconomic, health and environmental factors. This study employs Bayesian techniques and epidemiological spatial methods to estimate and map district-level under-five mortality, focusing on malaria prevalence, maternal education and source of drinking water. The districts with high risk are identified using georeferenced data of under-five mortality from recent Tanzania Demographic and Health Survey. We estimated the relative risk (RR) of under-five mortality within a hierarchical Bayesian spatial framework using three priors namely Besang-York-Mollie (BYM), Dean & Cressie (DC) and Leroux (BMY2). The model performance was evaluated using Watanabe-Akaike Information criterion (WAIC) to identify the best, from which the relative risk of under-five mortality was estimated and visualized using interactive and static maps. The Leroux (BYM2) model effectively estimated the relative risk compared to BYM and DC. The findings reveal that there are disparities of under-five mortality even across districts of the same region. The top ten districts with higher relative risk of under-five mortality based on model estimates are Ifakara (RR = 3.2), Nyasa (RR = 3.0), Babati (RR = 2.74), Rungwe (RR = 2.58), Songea (RR = 2.58), Mbarali (RR = 2.55), Rorya (RR = 2.36), Namtumbo (RR = 2.36), Mbulu (RR = 2.11) and Mbogwe (RR = 2.11). The findings advocate for targeted interventions in these districts that may reduce under-five mortality and consequently increase child survival rates in Tanzania.

Keywords: Under-five Mortality, Bayesian Hierarchical Model, Relative Risk, Small Area Estimation, Tanzania

1. Introduction

In public health, particularly maternal and childcare areas, under-five mortality (U5M) is one of the key indicators that defines health of the population. As a result, in attempt to have a healthy population, U5M is one of the enshrined priorities in the Sustainable Development Goal (SDG) 3 target 2, which calls for ending preventable deaths of children under five by 2030 [1]. The latest Tanzania Demographic and Health Survey (DHS) that was conducted in 2022 indicate that 43 out 1000 children who are born alive still die before celebrating their fifth birthday [2, 3]. These statistics are slightly higher compared to the global record of 37 deaths per every 1000 live births in the same survey. Although this U5M statistics is a significant improvement in Tanzania since 2000 [4], it is still above global average and far from achieving the expected SDG 3 target 2 of atmost 25 deaths per 1000 live births by the year 2030 [5].

Further statistics indicate significant disparities of U5M at global, regional and national levels, with more than 80% of the global burden being distributed in Sub-Saharan Africa and small parts of Southern Asia [6]. Within Sub-Saharan Africa, Western and Central Africa regions are still leading with more than 90 deaths per 1000 live births on average. The Eastern Africa region statistics, where Tanzania is found, is also exceptionally high, with 55.5 deaths per 1000 live births, compared to global averages and the anticipated SDG 3 targets [4]. This spatial disparity trickles down to national levels. In Tanzania, for instance, evidence from both official reports and empirical studies indicate that U5M is predominant in Western, Southern highlands and parts of Coastal regions [7, 8]. This predominance of U5M has been associated with several environmental, sociodemographic, health and socioeconomic factors such as wealth index, water access, residence type, media access, age and disease transmissions to mention a few. In resource-constrained countries including Tanzania, national surveys like DHS and National Panel Survey (NPS) have been utilized to study the effect of space on various health outcomes, U5M among others. However, these surveys tend to be representative at high administrative levels only, particularly zones and regions. Although these surveys have produced enormous evidence of spatial variation of health outcomes at higher levels, the spatial variation of health outcomes, in most of the finer levels like districts or divisions, may have been either overestimated or underestimated [6, 9, 10]. This is due to the fact that, geographically, mortality patterns even within one region tend to differ based on factors like household income, maternal education, disease prevalence, access to health facilities, and access to water and sanitation [11, 12]. This suggests that techniques like Small Area Estimation (SAE) may be relevant in understanding patterns of health outcomes at finer levels. Based on this viewpoint, in this study, we applied epidemiological methods and three Bayesian spatial models to analyze the variation of U5M at district-level in Tanzania using latest DHS data. The main contributions of this paper are as follows;

1. To advance the application of geospatial epidemiology by evaluating a spatial Bayesian framework using three priors (BMY, DC and Leroux (BMY)) to estimate under-five mortality risk across 195 districts in Tanzania. This approach allows to identify high-risk districts accounting for both uncertainty and the effect of space.
2. The identification of districts with elevated under-five mortality helps to align health resources with the neediest children through targeted interventions. This provides policymakers with actionable insights to make powerful decisions towards reducing child mortality using data-driven strategies.

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2. Literature on Spatial Modelling and Small Area Estimation

Under-five mortality risk has been extensively analyzed in Africa, and Tanzania in particular, using traditional statistical approaches as well as contemporary ones like AI-based frameworks. Most of the studies tend to analyze U5M at higher levels like country, zone and region leaving a gap at finer levels like districts and divisions where most of the interventions and decisions are implemented. This section focuses on methodological literature with justification of spatial modelling and relevance of SAE in studying U5M patterns.

SAE on U5M sparked interest among researchers during Millenium Development Goals (MDGs) era after realizing that progress of finer level estimates was masked by the national-level estimates [10, 13]. Among the studies that explored application of SAE for estimating U5M in Africa, some used mixed methodological approaches [14] while others specifically incorporated space and time covariates to capture and quantify the geographic and temporal variation effects [13, 15]. The findings of previous studies on spatial and spatial-temporal dimensions reveal significant variation of U5M at small area level in Zambia [13]; in Ethiopia and Nigeria [11]; and regional variations in all 54 countries in Africa [9, 10]; in Ethiopia [16]. In addition, numerous studies applied traditional statistical methods to analyze U5M without focusing on SAE, and excluding spatial-temporal dimensions. These studies include the multilevel Weibull regression modeling in Eastern and Southern Africa on predictors of U5M [17]; multiple linear and multinomial regression models focusing on interaction effect of anemia and carbon dioxide in Benin [18]; as well as Single level binary logistic and multilevel logistic regression models in Ghana [19].

Despite the rich insights of research in spatial modelling on health outcomes, much of it, particularly in Tanzania, do not exclusively focus in applying Bayesian spatial modelling especially using recent DHS data. In addition, while [13], one of the well-known studies on spatial analysis of U5M in Tanzania, explore on small area estimation, the spatial estimates maps presented are the ones at regional level, limiting the small-level insights like that of [14] who did a similar study in Zambia but presented the estimates at district-level. In light of the limitations of the previous studies on spatial analysis of U5M that mostly are not conducted in Tanzania, this study aimed to exclusively provide insights on the spatial distribution of U5M in Tanzania using recent DHS data by evaluating a hierarchical Bayesian framework using three priors namely BMY, DC and Leroux (BYM2). The insights of this study can help policy and decision makers in optimizing the healthcare interventions that could lead to increased child survival.

3. Materials and Methods

3.1. Data Source

This study utilized Tanzania 2022 DHS data, specifically the Kids Under 5 (KR) file. The data were obtained from Tanzania National Bureau of Statistics (NBS) with permission from DHS Archive program, ICF. The DHS data has information of a nationally representative sample of 10783 under-five children that were collected retrospectively from women of age 15-49 years. The Sample was drawn from 628 clusters. For confidentiality purposes, the cluster-level GPS points for DHS data are normally displaced up to 2 km in urban areas and up to 5 km in rural areas, with 1% displaced up to 10 km from their true location [20]. Since cluster displacement necessary

Table 1. *List of the Selected Variables from the Demographic and Health Survey (DHS) Questionnaire.*

S/N	Variable Name	Risk Category
1	Under Five Mortality Status	-
2	Maternal Age-group	15-24
3	Malaria Prevalence	Tested positive
4	Type of Residence	urban
5	Mother's education	no education
6	Source of drinking water	unimproved source
7	Type of Toilet	unimproved toilet
8	Sex of Child	female
9	Child Age-group	4-4.9
10	Household Size	1-4
11	Number of under-five children in a household	0-2
12	Sex of household head	male
13	Age of household head	40-49, 50+
14	Access to news papers	not at all
15	Access to radio news	not at all
16	Access to television news	not at all
17	Access to internet	not at all
18	Wealth Index	poor
19	Marital Status	widowed/divorced
20	Under-five children sleeping in mosquito net	no mosquito net
21	Respondent slept in mosquito net last night	no
22	Mother gets permission for medical help	big problem
23	Mother gets money for medical help	big problem
24	Is distance to health facility a problem?	big problem
25	Mother Accompanied to Medical Treatment	not a big problem
26	Use of Contraceptives	no
27	Child lives with who?	relatives or others
28	Mother working status	no
29	Breastfeeding Status	never breastfed

introduces location bias, we sourced GPS data for each of the 628 clusters from DHS archive and overlaid them with the latest Tanzania shapefile to assign each cluster to its district of origin. This district aggregation provides a larger geographic area that reduces the misclassifications of cluster locations, which consequently minimizes the bias of spatial displacement [20, 21]. Using jittering procedure to mimic the DHS displacement, we conducted a sensitivity check of proportion of deaths of under-five children for each of the 195 districts using 100 simulations, and compared the results to the baseline proportions. The results are presented in Appendix 1 and discussed in section 4.4. In addition to this approach, the Bayesian framework, using Leroux (BMY2) model, that we applied in estimating the relative risk in sections 4.3 and 4.4 accounts for spatial correlation across districts. This approach helps to absorb the small misalignment caused by spatial displacement, since the model borrows strength from neighboring districts.

It is worthy to note two issues in Appendix 1. First that relative standard deviation (Rel.SD %) is calculated as;

$$\text{Rel. SD } (\%) = \frac{\text{SD of simulated proportion}}{\text{Baseline proportion} + \epsilon} \times 100 \qquad (1)$$

Where ϵ is a very small constant added to avoid division by zero when the baseline proportion is 0. Second, the standard deviations (SD) of the simulated proportions appear in 3 decimal points but the calculations were done in 18 decimal points. For instance, SD for Arusha DC and Arusha MC are 0.001 and 0.000 which are approximations from 0.000700410460120541 and 0.000408448523565538 respectively. The same logic applies to absolute deviations. This is why most of relative SD are not zero despite having most 0.000 values in the SD column.

3.2. Data Management and Variable Selection

Initially, we explored all 1324 variables that were in the KR file using SPSS and identified that there was missingness of between 0% and 99.9%. Since higher missingness can introduce significant biases and lead to loss of data integrity [22-25], the first step was to exclude all variables with missingness of more than 10% following [22], where only 392 variables were retained. Following [22, 25], the Little's MCAR test was conducted, and confirmed that missingness in the 392 variables was completely at random. The next step was data cleaning. The cleaning process had two steps; first, imputing all missing values by KNN technique using R package, with a 5-folds cross-validation. The second step was to re-code variables that had a long list of categories so that they had atmost five. The variables were further subjected to dimensionality reduction using Principal Component Analysis (PCA), with factor loading of 0.5 being a cut point, from which 29 variables were extracted as indicated in Table 1. Finally, the Pearson (χ^2) test was applied to identify the factors that are significantly associated with under-five mortality. Fifteen of the twenty eight predictor variables had significant association with under-five mortality as indicated in Table 2, which were used for evaluating the three priors. All covariates were categorical, where the risk category of each variable was identified, and quantified as a proportion for modelling purposes [26]. The proportions were computed based on the category that exhibited higher percentage of death among the categories of a particular variable as indicated in Table 2. For instance, the maternal age group "15-24" was selected as a risk category because 6% of children within that age-group died compared to 2.8% and 2.4% in "25-34" and "35-49" respectively. The proportions for children who tested positive for malaria were extracted from GPS data that was downloaded from DHS program archive.

3.3. Modelling and Data Analysis Techniques

3.3.1. Parametric Spatial Modelling

Parametric modelling is well documented in literature including [11, 27-29], in which the outcome variable is expected to assume a specific distribution like Poisson or exponential. This implies that these models are only valid if the distribution fits well the data of interest. The assumptions help in simplifying both computations and interpretation. In contrast, non- and semi-parametric models have relaxed assumptions giving much flexibility in structures [29, 30]. By adding a spatial component in either a parametric or semi-parametric model, it helps in accounting for variation in the outcome variable across different districts. Since under-five mortality was aggregated at district level, it basically provides count data with a well behaved Poisson distribution allowing to use parametric approach within the Bayesian spatial framework [28]. To achieve this, we applied the R package namely R-INLA that was developed by Rue and Martino [31]. We conducted the analysis using HP ProBook 445 Generation 9, U88 version 01.17.00, with a Windows 10Pro 64-bit system and an AMD Ryzen 7 5825U processor, 16CPUs of 2.0GHz and 16.384GB RAM.

3.3.2. Model Specification

In the current study the outcome variable, under-five mortality, follows a Poisson distribution which is modelled within a hierarchical Bayesian framework. The Poisson model had no problem of over-dispersion making it more suitable for the aggregated data compared to Negative Binomial model. All statistical analyses, except exploratory analysis using SPSS, were conducted in an open-source R software version 4.4.3. In particular, hierarchical Bayesian spatial modelling was done using Integrated Nested Laplace Approximation popularly referred to R-INLA [26, 28].

The Spatial Bayesian framework was specified based on previous studies that focus on Small Area Estimation [26, 28, 32, 33]. We specified a general hierarchical Bayesian model based on [26] as follows;

$$Y_i \sim \text{Poisson}(E_i\theta_i), \quad i = 1, \ldots, n \tag{2}$$

$$\log(\theta_i) = \alpha + u_i + v_i \tag{3}$$

Where; in equation (1), Y_i represents observed deaths of under five children in district i; $E_i\theta_i$ is the mean where E_i is the expected deaths and θ_i is the relative risk in district i. In equation (2), α is the overall mortality risk; u_i is the random effect of district i and v_i represents unstructured noise with its distribution given as $v_i \sim N(0, \sigma_v^2)$.

To implement a spatial hierarchical Bayesian framework, we used three widely applied priors namely BYM, DC and Leroux (BMY2) [28], which are specified in equations (3), (4) and (5) respectively. The performance of the priors was evaluated using WAIC statistic. The suitable model for spatial mapping was Leroux (BMY2) based on its lower value of WAIC. The three priors are specifies as follows;

In the Besag-York-Mollie (BYM) prior, the structured spatial effect u_i follows an intrinsic conditional autoregressive distribution, borrowing strength from neighboring districts through the weights w_{ij}.

$$u_i \mid u_{-i} \sim N\left(\frac{\sum_{j\in\delta_i} w_{ij}u_j}{\sum_{j\in\delta_i} w_{ij}}, \frac{\sigma_u^2}{\sum_{j\in\delta_i} w_{ij}}\right), \quad v_i \sim N(0, \sigma_v^2) \tag{4}$$

The unstructured effect v_i is modeled as independent Gaussian noise. Together, these components allow the model to capture both spatial correlation and local heterogeneity.

The Leroux prior in equation (4) defines the vector of spatial random effects u with a proper CAR multivariate normal distribution $u_i \sim \text{MVN}(0, D)$. The adjacency matrix R and diagonal matrix D encode neighborhood structure.

$$D^{-} = \frac{(1-\rho)I + \rho R}{\sigma^2} \tag{5}$$

On the other hand, the parameter $\rho \in [0, 1]$, introduced as a spatial dependence parameter, controls the balance between independent Gaussian variation ($\rho = 0$) and full CAR dependence ($\rho = 1$). The variance parameter σ^2 scales the overall variability.

$$R = \rho(D - W) + (1 - \rho)I \tag{6}$$

In DC prior, the vector of spatial effects u follows a multivariate normal distribution with mean m and covariance $\sigma^2 Q^{-1}$, where Q is the precision matrix induced by the neighborhood graph.

$$u_i \sim \text{MVN}\big(m,\ \sigma^2 Q^{-1}\big) \tag{7}$$

The parameter σ^2 scales overall variability, and m is a mean vector (often $m = \mathbf{0}$). In equation (8), Q_{ij} encodes adjacency; n_i is the number of neighbors of area i; $i \sim j$ indicates that i and j are neighbors; $r \in [0, 1]$ controls the strength of spatial dependence.

$$Q_{ij} = \begin{cases} n_i, & \text{if } i = j, \\ -r, & \text{if } i \sim j, \\ 0, & \text{otherwise,} \end{cases} \tag{8}$$

The off-diagonal entries are $-r$ for neighboring pairs and 0 otherwise, yielding $Q = D - rW$ with $D = \text{diag}(n_i)$ and W the adjacency matrix. The conditional form of the DC prior is given by;

$$u_i \mid u_{-i} \sim N\left(\frac{r}{n_i}\sum_{j\sim i} u_j,\ \frac{\sigma^2}{n_i}\right) \tag{9}$$

These methodological procedures allowed to produce results that are presented in section 4.0 along with discussions. We present the results in three subsections namely selected factors associated with under-five mortality, Summaries of Regression Parameters as well as Tanzania regional and district-level Spatial Maps showing Standard Mortality Rates (SMR) and Relative Risk (RR). RR maps are considered relevant as they address the weakness of SMR map, which may mislead, in case a district has very low or no deaths recorded in the sample.

4. Results and Discussions

4.1. Association of Selected Factors with Under-five Mortality

We applied Pearson (χ^2) test to identify the factors that are significantly associated with under-five mortality as indicated

Table 2. Distribution of Selected Variables Associated with Under-five Mortality in Tanzania.

			Child's survival status? [b5R]			
Variable Name	**Variable Code**	**Category**	**Overall N[%]**	**Alive N[%]**	**Died N[%]**	**p-value**
Type of residency	v025R	rural	7845[72.8]	7579 [96.6]	266 [3.4]	0.048
		urban	2938[27.2]	2815 [95.8]	123 [4.2]	
Maternal age	v013R	15-24	3024[28.0]	2832 [94.0]	182 [6.0]	< 0.001
		25-34	4954[45.9]	4814 [97.2]	140 [2.8]	
		35-49	2815[26.1]	2748 [97.6]	67 [2.4]	
Mother's education	educationR	no education	2274[21.1]	2139 [94.1]	135 [5.9]	< 0.001
		primary	5621[52.1]	5429 [96.6]	192 [3.4]	
		secondary and above	2888[26.8]	2826 [97.9]	62 [2.1]	
Marital status	maritalstatusR	married/living with a partner	9024[83.7]	8716 (96.6)	306 [3.4]	0.023
		never in union	643[6.0]	614 [95.5]	29 [4.5]	
		widowed/divorced/separated	1116[10.3]	1062 [95.2]	54 [4.8]	
Source of drinking water	watersourceR	improved source	5723[53.1]	5579 [97.5]	144 [2.5]	< 0.001
		unimproved source	5060[46.9]	4815 [95.2]	245 [4.8]	
Mosquito net use among U5 children	underfive_netR	all or some	7772[72.1]	7568 [97.4]	204 [2.6]	< 0.001
		no	2793[25.9]	2670 [95.6]	123 [4.4]	
		no mosquito net in household	218[2.0]	156 [71.6]	62 [28.4]	
Respondent slept under net	v461R	no	2888[26.8]	2781 [96.3]	107 [3.7]	0.743
		yes	7895[73.2]	7613 [96.4]	282 [3.6]	
Type of toilet	toiletR	improved	5106[47.4]	4977 [97.5]	129 [2.5]	< 0.001
		unimproved	5677[52.6]	5477 [95.4]	2630[4.6]	
Child sex	b4R	male	5294[49.1]	5138 (97.1)	156 (2.9)	< 0.001
		female	5489[50.9]	5256 [95.8]	233 [4.2]	
Child age [years]	b8R	0-1.9	4481[41.6]	4342 [96.9]	139 [3.1]	< 0.001
		2-3.9	4129[38.3]	3990 [96.9]	139 [3.4]	
		4-4.9	2173[20.2]	2062 [94.9]	111 [5.1]	
Household size	HH_membersR	1-4	3047[28.3]	2884 [94.7]	163 [5.3]	< 0.001
		5-8	5469[50.7]	5306 [97.0]	163 [3.0]	
		9 and above	2267[21.0]	2204 [97.2]	63 [2.8]	
Number of U5 children	number_childR	0-2	8510[78.9]	8165 [95.9]	345 [4.1]	< 0.001
		3-5	2055[19.1]	2013 [98.0]	42 [2.0]	
		6 and above	218[2.0]	216 [99.1]	2 [0.9]	
Sex of household head	v151R	male	2280[21.1]	2187 [95.9]	93 [4.1]	0.174
		female	8503[78.9]	8207 [96.5]	296 [3.5]	
Age of household head	v152R	15-29	1811[16.8]	1744 [96.3]	67 [3.7]	0.340
		30-39	3617[33.5]	3469 [96.7]	121 [3.3]	
		40-49	2609[24.2]	2500 [95.8]	109 [4.2]	
		50-59	1362[12.6]	1312 [96.3]	50 [3.7]	
		60 and above	1384[12.8]	1342 [97.0]	42 [3.0]	
Access to newspapers	newspapersR	at least once a week	621[5.8]	604 [97.3]	17 [2.7]	0.358
		less than once a week	1481[13.7]	1432 [96.7]	49 [3.3]	
		not at all	8681[80.5]	8358 [96.3]	323 [3.7]	
Access to radio news	radioR	at least once a week	3273[30.4]	3133 [95.7]	140 [4.3]	0.090
		less than once a week	2510[23.3]	2413 [96.1]	97 [3.9]	
		not at all	5000[46.4]	4848 [97.0]	152 [3.0]	
Access to television news	tvR	at leats once a week	2605[24.2]	2517 [96.6]	88 [3.4]	0.470
		less than once a week	1612[14.9]	1546 [95.9]	66 [4.1]	
		not at all	6566[60.9]	6331 [96.4]	235 [3.6]	
Access to internet	internetR	at least once a week	9468[87.8]	9120 (96.3)	348 (3.7)	0.406
		less than once a week	162[1.5]	155 [95.7]	7 [4.3]	
		not at all	1153[10.7]	1119 [97.1]	34 [2.9]	
Wealth index	v190R	poor	2051[19.0]	1960 [95.6]	91 [4.4]	0.042
		middle	4482[41.6]	4339 [96.8]	143 [3.2]	
		rich	4250[39.4]	4095 [96.4]	155 [3.6]	
Permission for medical treatment	v467bR	big problem	742[6.9]	720 [97.0]	22 [3.0]	0.331
		not a big problem	10041[93.1]	9674 [96.3]	367 [3.7]	
Distance to health facility	v467dR	big problem	3407[31.6]	3284 [96.4]	123 [3.6]	0.992
		not a big problem	7376[68.4]	7110 [96.4]	266 [3.6]	

			Child's survival status? [b5R]			
Variable Name	**Variable Code**	**Category**	**Overall N[%]**	**Alive N[%]**	**Died N[%]**	**p-value**
Mother accompanied to treatment	v467fR	big problem	1785[16.6]	1725 [96.6]	60 [3.4]	0.541
		not a big problem	8998[83.4]	8669 [96.3]	329 [3.7]	
Use of contraceptives	v464R	no	825[7.7]	6427 [95.9]	275 [4.1]	< 0.001
		yes	9958[92.3]	3967 [97.2]	114 [2.8]	
Child lives with who?	b9R	relatives or others	6702[62.2]	566 [68.6]	259 [31.4]	< 0.001
		respondent	4081[37.8]	9828 [98.7]	130 [1.3]	
Mother working status	v714R	no	4182[38.8]	4033 [96.4]	149 [3.6]	0.843
		yes	6601[61.2]	6361 [96.4]	240 [3.6]	
Breastfeeding status	m4_1R	ever breastfed	8800[81.6]	8562 [97.3]	238 [2.7]	< 0.001
		never breastfed	1983[18.4]	1832 [92.4]	151 [7.6]	

in Table 2. Out of 28 factors, 15 of them were found to be significantly associated with under-five mortality, 12 at 1% and 3 of them at 5%. The total sample comprised 10783 under-five children, 49.1% boys and 50.9% girls, of which 72.8% of them resided in rural areas and 27.2% in urban areas of Tanzania. There are slightly more deaths among children in urban areas (4.2%) compared to rural areas (3.4%), and most of them deaths occur among girls (4.2%) compared to boys (2.9%). Lower maternal age is associated with high death proportions (6%) just like mothers without formal education (5.9%). As expected, children from widowed, divorced or separated partners have higher proportions of deaths (4.8%) compared to children with both parents living together (3.4%). Households that use unimproved source of drinking water experience about two times more under-five deaths (4.8%) compared to households with improved sources (2.5%).

Although the sample had only 2% of under-five children did not use beds with mosquito nets, 28% of them died before celebrating the fifth birthdays compared to only 2.6% among those who used mosquito nets. This makes under-five children without mosquito nets to be about nine times more risky than their counterparts.

While it may not be expected, households with few members and fewer number of under-five children were found to have higher proportions of deaths with 5.3% and 4.1% compared to 2.8% and 0.9% respectively. This may be attributed to the fact that larger households often have more adults and older siblings who can share caregiving and responsibilities [34]. In addition, smaller households may coincide with younger mothers or unstable unions which both increase the risk of child death. Results further indicate that, among children from poor households, 4.4% of them die before reaching age of five years compared to 3.2% and 3.6% from middle and rich households respectively. Mothers who use contraceptives reduce the risk of death among their children by 1.3% compared to those who do not use.

One unexpected result in Table 2 is that, among children who live with their relatives experience more deaths (31%), about 30 compared to those who live with respondents, mostly mothers (1.3%). The main reason could be attributed to both maternal factors like breastfeeding, that protect children against infections and malnutrition; and social factors like children living with relatives may not receive the same level of attention or immediate care [6, 34]. It is also evident that majority of under-five children live wit relatives or other (62.2%) compared to those who live with their mothers (respondents), a characteristic which reflect that majority of the sample was drawn from rural areas where community caregiving for children is still common. These circumstances themselves are risk factors for child mortality, so the higher proportions of death reflect underlying vulnerability.

Following the identification of the factors that are significantly associated with under-five mortality, in the next section we illustrate the spatial distribution of Standardized Mortality Rates (SMR) in Figure 1. We begin with regional-level estimates of the current study, and contrast the results

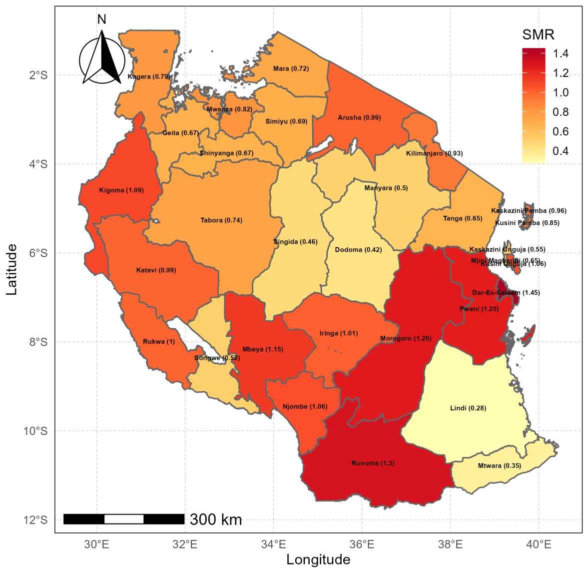
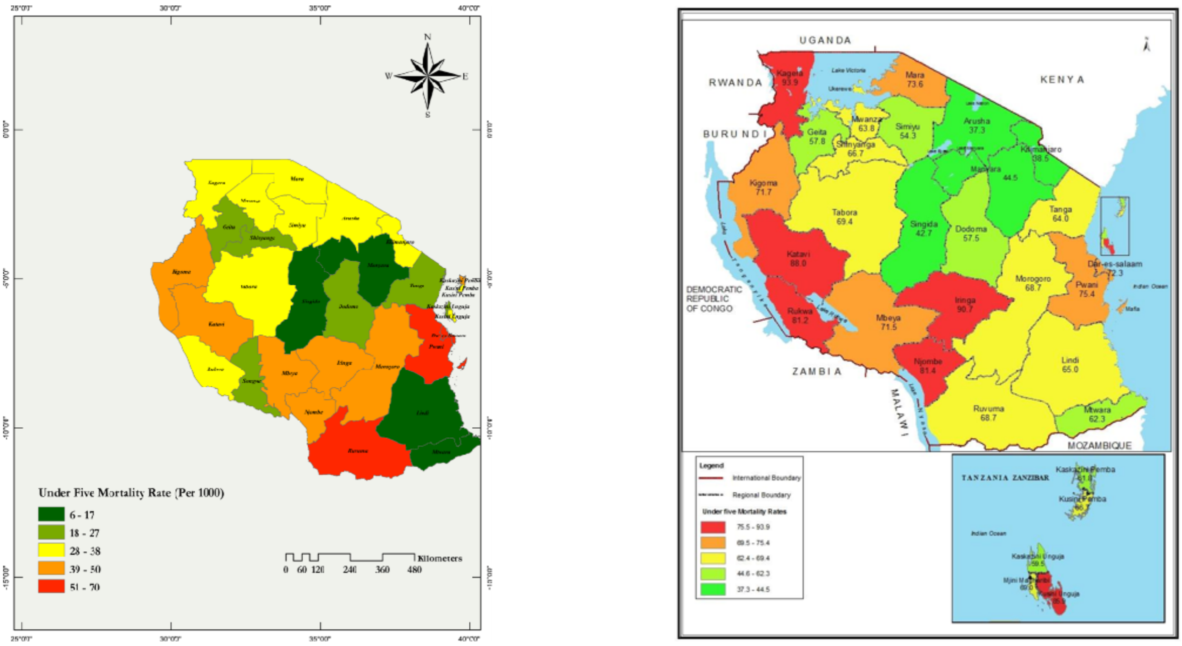


Figure 1. *Spatial Distribution of U5M at Regional-level from the Current Study, Tanzania.*



(a) Source: [8] *(b) Source: [35]*

Figure 2. *Spatial Distribution of U5M at Regional-level of Two Prior studies, Tanzania.*

with two prior studies[1] on the same subject, one is a child mortality report from Tanzania Bureau of Statistics based on 2012 Population and Housing Census [35], and the second is a recent article that estimated regional-level under-five mortality in Tanzania using a different methodology [8].

4.2. Spatial Dynamics of Under-five Mortality at Regional-level

Results in Figure 1 indicate that under-five mortality risks are higher in most of the southern highlands regions like Ruvuma, Njombe, Mbeya and Iringa along with eastern regions of Morogoro, Pwani, Dar es Salaam and Kusini Unguja. In these regions, under-five mortality rate exceed the expected rate by 45% in Dar es Salaam, 30% in Ruvuma, 27% in Morogoro, 25% in Pwani and 15% in Mbeya. We also observe that in Kigoma and Kusini Unguja regions there is a higher number of under-five deaths with 9% and 6% of standardized mortality above average respectively.

The remaining regions are below average. These results compare closely to findings by Sujon [8] in Figure 2(a) who recently identified all the regions, except Rukwa, as areas with under-five mortality in Tanzania. All regions in the lake and north zones have mortality below expected average, but they are slightly higher compared to the regions in the central zone and southern part, especially Lindi and Mtwara. Comparing these results to official NBS report of 2015 [35] as revealed in Figure 2(b), under-five mortality patterns seem to have slightly shifted based on 2022 DHS data.Particularly, Ruvuma and Morogoro have emerged as new areas of concern in terms of under-five mortality risk while Kagera and Mara have slightly improved. While we attribute these changes to time passage and the dynamics of the factors associated to under-five mortality, the prior studies reported using counts of deaths per region while in the current study we used standardized mortality. This also may imply to the slight differences we have discussed. In the next section, we show how regional-level estimates may musk finer-level disparities by first, modelling district level estimates using a three hierarchical Bayesian models, and then plot the posterior estimates of the best model to show the distribution of under-five mortality relative risk, which is a major departure from the prior studies that have been presented.

4.3. Modelling Observed Data to Obtain Mortality Relative Risk at District-level

In order to get under-five mortality risks, as explained in section 3.3.2, we specified a Bayesian hierarchical framework using three priors; BMY, Deand & Cressie and Leroux. The comparison of the estimates is presented in Table 3. Three of

[1] The spatial maps from the two studies are included in order to; (i) show how under-five mortality patterns have changed since 2012 at regional-level and; (ii) Compare when raw counts are used to plot maps instead of standardized mortality rates. The two approaches have limitations as they can mislead especially when the number of cases sampled in each area is very small or missing at all. Bayesian modelling addresses this weakness

Table 3. *Posterior Estimates and Precision Parameters across three Spatial Models using Tanzania 2022 DHS Data.*

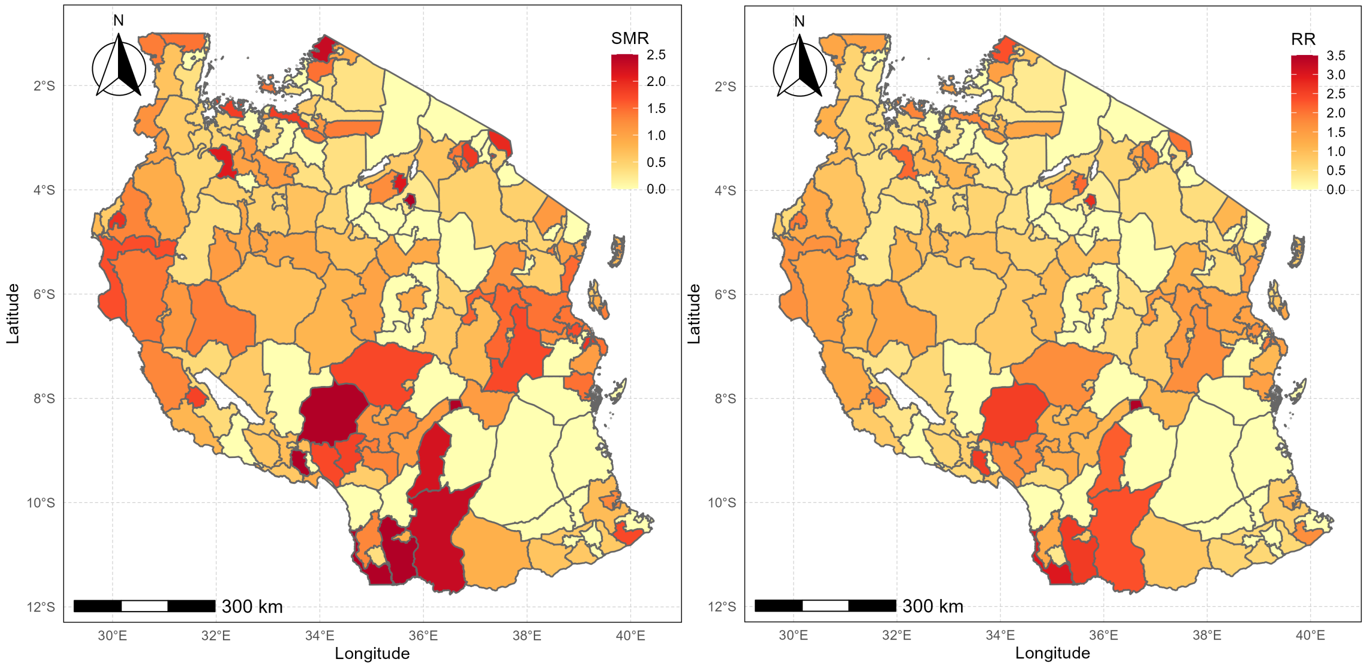
Variable	BMY Model				Dean & Cressie Model				Leroux (BYM2) Model			
			95% CI				95% CI				95% CI	
	mean	sd	Lower	Upper	mean	sd	Lower	Upper	mean	sd	Lower	Upper
(Intercept)	-0.242	0.853	-1.917	1.431	-0.243	0.870	-1.950	1.463	-0.260	0.854	-1.938	1.413
malariaP	5.141	1.900	1.457	8.923	5.116	1.925	1.361	8.920	4.984	1.863	1.373	8.698
v013R2	-0.378	0.622	-1.605	0.837	-0.400	0.631	-1.642	0.835	-0.403	0.617	-1.620	0.803
educationR2	0.465	0.114	0.229	0.810	0.464	0.113	0.382	0.640	0.434	0.107	0.237	0.547
watersourceR2	0.369	0.106	0.223	0.762	0.370	0.101	0.232	0.774	0.259	0.091	0.234	0.652
toiletR2	0.019	0.340	-0.643	0.693	0.023	0.342	-0.645	0.697	-0.009	0.336	-0.662	0.656
b4R2	-0.191	0.995	-2.151	1.752	-0.180	1.009	-2.164	1.795	-0.078	0.997	-2.043	1.872
b8R2	1.107	1.064	-0.979	3.195	1.105	1.083	-1.020	3.230	1.058	1.072	-1.043	3.163
HH_membersR2	0.458	0.669	-0.857	1.767	0.449	0.681	-0.888	1.782	0.451	0.669	-0.866	1.760
number_childR2	-0.107	0.644	-1.370	1.157	-0.095	0.657	-1.383	1.194	-0.138	0.642	-1.399	1.121
v190R2	0.136	0.410	-0.668	0.943	0.125	0.418	-0.693	0.945	0.072	0.408	-0.730	0.873
maritalstatusR2	-0.631	0.705	-2.017	0.749	-0.634	0.719	-2.047	0.775	-0.657	0.709	-2.054	0.730
underfive_netR2	-0.595	0.915	-2.390	1.201	-0.595	0.935	-2.429	1.239	-0.497	0.914	-2.291	1.297
b9R2	0.125	1.132	-2.093	2.348	0.145	1.153	-2.115	2.408	0.191	1.134	-2.032	2.419
v464R2	0.521	0.515	-0.478	1.540	0.525	0.516	-0.480	1.542	0.498	0.511	-0.491	1.514
m4_1R2	-0.822	1.037	-2.852	1.215	-0.817	1.056	-2.887	1.256	-0.858	1.044	-2.904	1.193
WAIC	648.3				647.6				645.1			
iid precision (τ_{iid})	220.318	980.40	8.70	1205.00	23.04	13.45	5.85	70.4				
spatial precision (τ_s)	212.526	10.623	2.72	40.86	13.93	10.21	3.31	40.99				
Total precision (τ)									21.801	18.213	6.16	57.77
Phi (ϕ)									0.504	0.260	0.060	0.941

the factors associated with under-five mortality namely malaria prevalence, mother's education and source of drinking water consistently show that, the 95% credible intervals across all the three models suggest to contain the true parameters. Malaria prevalence has the strongest effect which indicate that a high number of children who test positive for malaria increases the chance of a child dying before celebrating the fifth birthday in a particular district. Likewise, a district with a high proportion of households with mothers who do not have formal education at all increase the risk of under-five mortality and are consisted with findings from UNICEF [6] and a maternal mortality study [36], that both attribute increased mortality to mother's lower education which hinder them from seeking timely medical care and preventive services like immunization. In addition, people from households who drink water from unimproved sources also have more chances to increase under-five mortality via diseases like diarrheal and poor hygiene. The 95% credible intervals of the rest of the factors are wider with each including a zero, which imply that there is weak evidence of credible association with under-five mortality.

The Watanabe-Akaike Information Criterion (WAIC) in Table 3 indicate that Leroux (BYM2) model performed slightly better with lower WAIC (645.1) compared to BMY and Dean & Cressie models with WAIC statistics of 648.3 and 647.6 respectively. As expected, posterior estimates of BMY and Dean & Cressie models exhibit instability due to wider intervals, possibly due to variance trade-off between spatially structured and unstructured components [26, 28, 37]. BMY estimates are the most unstable with 95% CI of [8.70-1205.0] and [2.72-40.86] for precision parameters of unstructured (τ_{iid}) and structured (τ_s) components respectively. Although precision parameters of Dean & Cressie model are small, [5.85-70.4] for unstructured (τ_{iid}) and [3.31-40.86] for structured (τ_s) components, they are slightly wider than the precision parameter (τ) for Leroux (BYM2) model [6.16-57.77]. To address the weakness of BMY and Dean & Cressie model, the Leroux (BYM2) model use reparameterization where the unstructured (τ_{iid}) and structured (τ_s) components are collapsed into a single precision parameter (τ) and a mixing parameter (ϕ), making it more stable with identifiable posterior estimates. The mixing parameter (ϕ) in the Leroux (BMY2) model with posterior mean (0.504) in Table 3 indicate that, 50.4% of variability in under-five mortality is spatially structured while 49.6% is due to district-specific factors. The balanced distribution of variance suggests that the Leroux (BYM2) model performs well, avoiding both over-smoothing and under-smoothing. Following these results, we used the Leroux (BYM2) model, with the three factors, namely malaria prevalence, maternal education and type of water source, which have significant 95% credible interval, to model the relative risk of under-five mortality in all 195 districts in Tanzania. We present the spatial distribution of both standardized mortality rates (SMR) and relative risk (RR) at district-level in Figure 3.

4.4. *Spatial Dynamics of Under-five Mortality at District-level*

Results in Figures 3 (a) and (b) represent standardized mortality ratios and relative risks respectively, across all 195 districts in Tanzania. The SMR map show that most of the districts with high SMR values correspond with the southern highland regions of Ruvuma, Njombe, Mbeya and Iringa along with Morogoro, Pwani and Dar es Salaam in the eastern zone; and Kigoma in the western zone. Although some of the districts have low SMR, this is a similar spatial pattern of under-five mortality we reported in section 4.2. In addition, Figures 3(a) reveals several more spots of higher SMR districts in the following regions; Mwanza (Buchosa and Magu districts), Mara (Rorya and Butiama districts), Kagera (Missenyi and Kyerwa districts) and Shinyanga (Mbogwe district) regions around lake zone; Manyara (Babati and Mbulu districts) and Kilimanjaro (Meru, Rombo and Moshi districts) within the northern zone; and one district, Nanyamba TC to be specific, in Mtwara region within south eastern zone. As discussed earlier, the relative risk map in Figures 3(b) is presented to address the weakness of SMR map which may report under- or over-estimate values in a district.



(a) Map Showing Standardized Mortality Ratio (SMR)

(b) Map Showing Relative Risk (RR)

***Figure 3.** Spatial Distribution of U5M at District-level from the Current Study Using Tanzania 2022 DHS Data.*

The RR map shows the model based values accounting for the effect of covariates associated with under-five mortality at 95% credible interval. It is evident that regional estimates musks the district disparities in two ways. First, regions that are reported to have higher mortality rates have disparities at district level. For example, in Morogoro the SMR were estimated at 1.26, that is 26% more than expected, but the SMR estimates range from 0.01 in Ulanga district to as high as 3.5 and 2.2 in Ifakara and Malinyi districts respectively. Second, even in the regions which were found to have low SMR, the SAE have uncovered noticeable differences among districts. For instance, in Manyara, SMR regional estimates indicated to be around 50% below expected average, but district estimates identify Babati MC (SMR = 2.74) and Mbulu TC (SMR = 2.11) to have higher mortality rates compared to other districts. The trend is similar in Mara region (Rorya district, SMR = 2.33), Geita region (Mbogwe district, SMR = 2.11) and Mtwara region (Nanyamba district, SMR = 1.72). This evidence underscores the importance of finer level estimates using SAE.

After modelling under-five mortality using the Leroux (BYM2) model, we plotted the posterior estimates in Figure 3(b), accounting for variation in malaria prevalence, maternal education and type of water source as discussed in section 4.3. Results indicate that, adjusted for covariates effect, under-five mortality is most prevalent in the following districts; Ifakara (RR = 3.2), Nyasa (RR = 3.0), Babati (RR = 2.74), Rungwe (RR = 2.58), Songea (RR = 2.58), Mbarali (RR = 2.55), Rorya (RR = 2.36), Namtumbo (RR = 2.36), Mbulu (RR = 2.11) and Mbogwe (RR = 2.11). It is further evident that, even children within districts with different mortality rates may have similar risks. For instance, SMR estimates in Buchosa district (SMR = 1.84) and Magu district (SMR = 1.84) were found higher than in Bariadi district (SMR = 1.12) and Itilima district (SMR = 1.35). However, the relative risk in all the four districts is more or less the same; Buchosa (RR = 0.88), Magu (RR = 0.83), Bariadi (RR = 0.82) and Itilima (RR = 0.84).

The higher risk of mortality in these districts may be attributed to geographic and health systems factors as well as socio-economic and environmental drivers. For instance, Ifakara and Nyasa are located relatively remote in southern Tanzania where, historically, malaria prevalence has been high. This is reflecting the high burden of vector-borne diseases that contribute to child mortality. High mortality risk in

Songea and Namtumbo districts, in Ruvuma region, may equally be attributed to limited maternal health coverage and poor road networks that translates into long travel distance to seek medical services. About Rungwe and Mbarali districts, in Mbeya region, despite fertile land, rural poverty and limited maternal health coverage persist [38]. Babati and Mbulu districts are found in Manyara region which is characterized with semi-arid conditions, making these areas prone to seasonal food insecurity that may exacerbate child vulnerability [39]. Mortality risk in Rorya may be attributed to its proximity to Lake Victoria where malaria and water-borne diseases remain significant. Mbogwe districts, on the other hand, is more prone to rural poverty. In addition, mining activities in the two district coexist with other risk factors, culminating to environmental risks that may contribute to increased child mortality.

Based on the sensitivity analysis results presented in Appendix 1 using 100 displacement simulations, proportion of under-five deaths varied minimally with baseline results in each district. All absolute deviations from baseline were less than 1% and all relative variability were less than 2%. This indicates that DHS geomasking introduced negligible bias in estimates of relative risk at district-level. The findings we have presented are robust and can be replicated using similar estimation techniques or by adopting different models and covariates. The evidence we have produced on spatial variation of under-five mortality is crucial for policy implementation, particularly on targeted interventions at sub-national levels.

4.5. Limitations

In this study, we used a parametric analysis with few selected variables based on data completeness. Exploring dynamics of under-five mortality at sub-national levels in Tanzania using non- and semi-parametric approaches may be an avenue to bring more insights as suggested by Jahan [28]. Modelling missingness in order to include more variables may also bring more insights to enable interventions to be more specific to most affect areas. In addition, analysis of under-five mortality in this study is based on TDHS 2022, which is a cross-sectional data, does not capture temporal dynamics. A potential extension of this work would be to incorporate multiple DHS surveys or other longitudinal sources to develop time-series models, which may enable assessment of trends and changes in under-five mortality risk across districts over time.

5. Conclusion

The aim of this study was to map the spatial variation of under-five mortality at district-level using latest Tanzania Demographic and Health Survey data. The findings suggest that there are disparities of under-five mortality among districts of the same region. Making decision based on regional-level estimates may always musk the need for attention of vulnerable children within the most affected districts. According to model-based estimates, top ten districts with higher risk of under-five mortality are Ifakara (RR = 3.2), Nyasa (RR = 3.0), Babati (RR = 2.74), Rungwe (RR = 2.58), Songea (RR = 2.58), Mbarali (RR = 2.55), Rorya (RR = 2.36), Namtumbo (RR = 2.36), Mbulu (RR = 2.11) and Mbogwe (RR = 2.11). Targeted interventions in these districts may significantly reduce under-five mortality and consequently increase child survival rates in Tanzania. We propose streamlining health programmes and interventions to prioritize resource allocation in districts facing higher under-five mortality.

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Abbreviations

BMY	Besag-York-Mollie
SDG	Sustainable Development Goals
IHI	Ifakara Health Institute
DC	Dean & Cressie
WAIC	Watanabe-Akaike Information Creterion
U5M	Under-five Mortality
MDGs	Millenium Development Goals
NPS	National Panel Survey
SAE	Small Area Estimation
NBS	National Bureau of Statistics
ICF	ICF International
SPSS	Statistical Package for the Social Sciences
KNN	K-Nearest Neighbors
MCAR	Missing Completely at Random
INLA	Integrated Nested Laplace Approximation
MoF	Ministry of Finance
CAR	Conditional Autoregressive
SMR	Standardized Mortality Ratio
RR	Relative Risk
PCA	Principal Component Analysis
MAP	Malaria Atlas Project

Acknowledgments

We acknowledge DHS program and ICF for granting permission to use and supplying Tanzania DHS data for the current study. We also acknowledge the MAP project team, Dar es Salaam node, IHI and the University of Dar es Salaam[2].

[2] The three institutions convened a workshop on geospatial modelling, held on 16th - 18th of september 2025 at the University of Dar es Salaam

Author Contributions

Salyungu Mabula: Conceptualization, Investigation, methodology, software implementation, validation, formal analysis, data curation, resources, writing original draft, writing review, editing and visualization.

Robert Too: Conceptualization, validation, writing review, editing and supervision.

Gregory Kerich: Conceptualization, validation, writing review, editing and supervision.

Data Availability Statement

Restrictions apply to the availability of these data. Data were obtained from Tanzania Bureau of Statistics (NBS) via DHS Archive-ICF and are available at https://dhsprogram.com/data/available-datasets.cfm with the permission for access from DHS Program.

Conflicts of Interest

The authors declare no conflict of interest.

Appendix

Table 4. *Sensitivity Check for Proportion of Under-five Deaths by District (100 Simulations.*

S/N	Name of District	Number of Simulations	Baseline Proportion	Simulated Proportion	SD	Min	Max	Abs. Dev.	Rel. SD (%)
1	Arusha DC	100	0.064	0.062	0.001	0.063	0.065	0.002	1.091
2	Arusha MC	100	0.048	0.048	0.000	0.047	0.049	0.000	1.272
3	Babati DC	100	0.011	0.011	0.000	0.011	0.011	0.000	0.888
4	Babati MC	100	0.118	0.119	0.002	0.117	0.120	0.001	1.282
5	Bagamoyo DC	100	0.059	0.059	0.001	0.058	0.060	0.000	1.396
6	Bahi DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
7	Bariadi DC	100	0.013	0.014	0.000	0.013	0.014	0.001	1.400
8	Bariadi TC	100	0.049	0.050	0.000	0.050	0.050	0.001	0.694
9	Biharamulo DC	100	0.024	0.024	0.000	0.024	0.024	0.000	0.785
10	Buchosa DC	100	0.078	0.079	0.000	0.078	0.079	0.001	0.599
11	Buhigwe DC	100	0.024	0.024	0.000	0.024	0.024	0.000	0.716
12	Bukoba DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
13	Bukoba MC	100	0.034	0.035	0.000	0.035	0.035	0.001	0.806
14	Bukombe DC	100	0.019	0.019	0.000	0.019	0.019	0.000	1.241
15	Bumbuli DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
16	Bunda DC	100	0.014	0.014	0.000	0.014	0.014	0.000	0.616
17	Bunda TC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
18	Busega DC	100	0.023	0.024	0.000	0.023	0.024	0.001	0.780
19	Busokelo DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20	Butiama DC	100	0.063	0.063	0.001	0.063	0.064	0.001	0.626
21	Chake Chake	100	0.040	0.040	0.001	0.040	0.041	0.000	1.503
22	Chalinze DC	100	0.062	0.062	0.001	0.061	0.063	0.000	1.493
23	Chamwino DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
24	Chato DC	100	0.019	0.019	0.000	0.019	0.019	0.000	1.412
25	Chemba DC	100	0.040	0.040	0.000	0.040	0.041	0.000	1.083
26	Chunya DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
27	Dodoma CC	100	0.039	0.039	0.000	0.039	0.040	0.000	0.951
28	Gairo DC	100	0.067	0.068	0.001	0.067	0.068	0.001	1.224
29	Geita DC	100	0.019	0.020	0.000	0.020	0.020	0.000	0.589
30	Geita TC	100	0.021	0.021	0.000	0.021	0.021	0.000	0.843
31	Hai DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
32	Hanang DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
33	Handeni DC	100	0.023	0.023	0.000	0.023	0.023	0.000	1.343
34	Handeni TC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
35	Ifakara TC	100	0.154	0.156	0.002	0.155	0.158	0.002	1.012
36	Igunga DC	100	0.028	0.029	0.000	0.028	0.029	0.000	0.787

Table 4 . *Continued*

S/N	Name of District	Number of Simulations	Baseline Mean	Simulated Mean	SD	Min	Max	Abs. Dev.	Rel. SD (%)
37	Ikungi DC	100	0.030	0.030	0.000	0.030	0.030	0.000	0.701
38	Ilala MC	100	0.082	0.083	0.001	0.081	0.084	0.001	1.469
39	Ileje DC	100	0.026	0.026	0.000	0.026	0.026	0.000	0.830
40	Ilemela MC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
41	Iramba DC	100	0.019	0.019	0.000	0.019	0.019	0.000	0.532
42	Iringa DC	100	0.075	0.075	0.001	0.074	0.076	0.000	1.054
43	Iringa MC	100	0.028	0.028	0.000	0.028	0.028	0.000	1.154
44	Itigi DC	100	0.035	0.034	0.000	0.034	0.035	0.001	1.100
45	Itilima DC	100	0.060	0.059	0.000	0.060	0.061	0.001	0.839
46	Kahama TC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
47	Kakonko DC	100	0.043	0.043	0.000	0.042	0.043	0.000	1.131
48	Kalambo DC	100	0.034	0.034	0.000	0.034	0.034	0.000	0.809
49	Kaliua DC	100	0.014	0.014	0.000	0.014	0.014	0.000	0.895
50	Karagwe DC	100	0.029	0.028	0.000	0.028	0.029	0.001	0.670
51	Karatu DC	100	0.024	0.025	0.000	0.024	0.025	0.000	1.376
52	Kaskazini A	100	0.024	0.025	0.000	0.024	0.025	0.000	1.469
53	Kaskazini B	100	0.023	0.023	0.000	0.023	0.023	0.000	1.074
54	Kasulu DC	100	0.056	0.057	0.000	0.056	0.057	0.001	0.838
55	Kasulu TC	100	0.083	0.085	0.001	0.083	0.086	0.001	1.502
56	Kati	100	0.039	0.040	0.001	0.039	0.040	0.001	1.320
57	Kibaha DC	100	0.053	0.054	0.001	0.053	0.054	0.001	1.132
58	Kibaha TC	100	0.073	0.073	0.000	0.073	0.074	0.000	0.610
59	Kibiti DC	100	0.063	0.063	0.000	0.063	0.063	0.000	1.083
60	Kibondo DC	100	0.038	0.039	0.001	0.039	0.039	0.000	1.000
61	Kigamboni MC	100	0.063	0.063	0.000	0.063	0.064	0.001	0.668
62	Kigoma DC	100	0.032	0.033	0.001	0.032	0.033	0.000	1.503
63	Kigoma Municipal-Ujiji	100	0.020	0.020	0.000	0.020	0.020	0.000	0.000
64	Kilindi DC	100	0.052	0.052	0.001	0.052	0.053	0.000	1.242
65	Kilolo DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
66	Kilombero DC	100	0.047	0.047	0.001	0.046	0.047	0.000	1.373
67	Kilosa DC	100	0.031	0.032	0.001	0.031	0.032	0.000	1.222
68	Kilwa DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
69	Kinondoni MC	100	0.059	0.059	0.001	0.059	0.060	0.001	0.654
70	Kisarawe DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
71	Kishapu DC	100	0.014	0.015	0.001	0.014	0.015	0.001	1.197
72	Kiteto DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
73	Kondoa DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
74	Kondoa TC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
75	Kongwa DC	100	0.022	0.022	0.000	0.022	0.022	0.000	0.562
76	Korogwe DC	100	0.020	0.020	0.000	0.020	0.020	0.000	0.741
77	Korogwe TC	100	0.043	0.044	0.001	0.043	0.044	0.001	1.000
78	Kusini	100	0.058	0.059	0.001	0.058	0.060	0.001	1.411
79	Kwimba DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
80	Kyela DC	100	0.040	0.040	0.001	0.040	0.041	0.001	1.252
81	Kyerwa DC	100	0.059	0.059	0.001	0.059	0.060	0.001	0.662
82	Lindi DC	100	0.031	0.032	0.001	0.031	0.032	0.001	0.631
83	Lindi MC	100	0.056	0.056	0.001	0.057	0.057	0.001	1.490
84	Liwale DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
85	Longido DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
86	Ludewa DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
87	Lushoto DC	100	0.048	0.048	0.001	0.048	0.049	0.001	1.095
88	Madaba DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
89	Mafia DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
90	Mafinga TC	100	0.040	0.040	0.000	0.041	0.041	0.001	1.206

Table 4 . *Continued.*

S/N	Name of District	Number of Simulations	Baseline Mean	Simulated Mean	SD	Min	Max	Abs. Dev.	Rel. SD (%)
91	Magharibi A	100	0.028	0.028	0.000	0.028	0.028	0.000	0.789
92	Magharibi B	100	0.041	0.041	0.001	0.041	0.042	0.001	1.331
93	Magu DC	100	0.078	0.080	0.000	0.079	0.080	0.001	0.603
94	Makambako TC	100	0.059	0.060	0.000	0.059	0.060	0.001	1.339
95	Makete DC	100	0.074	0.075	0.001	0.074	0.076	0.001	0.938
96	Malinyi DC	100	0.095	0.096	0.001	0.095	0.097	0.001	1.265
97	Manyoni DC	100	0.043	0.044	0.001	0.044	0.045	0.001	1.182
98	Masasi DC	100	0.026	0.026	0.000	0.026	0.026	0.000	0.951
99	Masasi TC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
100	Maswa DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
101	Mbarali DC	100	0.110	0.111	0.001	0.110	0.111	0.001	0.724
102	Mbeya DC	100	0.031	0.031	0.000	0.031	0.031	0.000	1.211
103	Mbeya MC	100	0.019	0.019	0.000	0.019	0.019	0.000	0.719
104	Mbinga DC	100	0.056	0.056	0.001	0.055	0.057	0.001	1.329
105	Mbinga TC	100	0.015	0.015	0.000	0.015	0.015	0.000	0.815
106	Mbogwe DC	100	0.091	0.091	0.001	0.091	0.092	0.001	1.306
107	Mbozi DC	100	0.027	0.027	0.000	0.027	0.027	0.000	1.498
108	Mbulu DC	100	0.054	0.054	0.000	0.054	0.054	0.000	1.432
109	Mbulu TC	100	0.091	0.091	0.001	0.091	0.092	0.001	0.632
110	Meatu DC	100	0.015	0.015	0.000	0.015	0.015	0.000	0.861
111	Meru DC	100	0.080	0.081	0.001	0.080	0.081	0.001	1.001
112	Micheweni	100	0.034	0.034	0.000	0.034	0.035	0.000	1.354
113	Missenyi DC	100	0.062	0.062	0.001	0.061	0.063	0.001	1.482
114	Misungwi DC	100	0.016	0.016	0.000	0.016	0.016	0.000	0.578
115	Mjini	100	0.017	0.017	0.000	0.017	0.017	0.000	0.962
116	Mkalama DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
117	Mkinga DC	100	0.019	0.019	0.000	0.019	0.019	0.000	0.873
118	Mkoani	100	0.032	0.032	0.000	0.032	0.032	0.000	1.510
119	Mkuranga DC	100	0.046	0.047	0.001	0.046	0.047	0.001	0.671
120	Mlele DC	100	0.059	0.059	0.000	0.059	0.060	0.000	0.555
121	Momba DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
122	Monduli DC	100	0.026	0.026	0.000	0.026	0.027	0.000	1.293
123	Morogoro DC	100	0.074	0.075	0.001	0.074	0.075	0.001	1.863
124	Morogoro MC	100	0.024	0.024	0.000	0.024	0.024	0.000	0.791
125	Moshi DC	100	0.019	0.019	0.000	0.019	0.020	0.000	0.873
126	Moshi MC	100	0.087	0.088	0.001	0.087	0.088	0.001	0.563
127	Mpanda DC	100	0.060	0.062	0.001	0.061	0.062	0.001	0.882
128	Mpanda MC	100	0.034	0.034	0.000	0.034	0.034	0.000	0.688
129	Mpimbwe DC	100	0.018	0.018	0.000	0.018	0.018	0.000	0.781
130	Mpwapwa DC	100	0.023	0.023	0.000	0.023	0.024	0.000	1.014
131	Msalala DC	100	0.044	0.044	0.000	0.044	0.045	0.000	1.453
132	Mtwara DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
133	Mtwara MC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
134	Mufindi DC	100	0.052	0.052	0.000	0.052	0.053	0.001	0.590
135	Muheza DC	100	0.043	0.044	0.001	0.043	0.045	0.000	1.374
136	Muleba DC	100	0.015	0.015	0.000	0.015	0.015	0.000	0.000
137	Musoma DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
138	Musoma MC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
139	Mvomero DC	100	0.065	0.064	0.000	0.065	0.066	0.001	0.957
140	Mtwanga DC	100	0.000	0.000	0.000	0.000	0.000	0.001	0.000
141	Nachingwea DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
142	Namtumbo DC	100	0.100	0.100	0.000	0.099	0.102	0.000	1.319
143	Nanyamba TC	100	0.042	0.042	0.000	0.042	0.043	0.001	1.061
144	Nanyumbu DC	100	0.028	0.028	0.000	0.028	0.028	0.000	0.812

Table 4 *. Continued.*

S/N	Name of District	Number of Simulations	Baseline Mean	Simulated Mean	SD	Min	Max	Abs. Dev.	Rel. SD (%)
145	Newala DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
146	Newala TC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
147	Ngara DC	100	0.051	0.051	0.000	0.051	0.052	0.000	0.539
148	Ngorongoro DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
149	Njombe DC	100	0.057	0.058	0.001	0.057	0.058	0.001	1.188
150	Njombe MC	100	0.023	0.023	0.000	0.023	0.024	0.000	1.407
151	Nkasi DC	100	0.056	0.056	0.000	0.056	0.057	0.001	0.533
152	Nsimbo DC	100	0.049	0.050	0.001	0.049	0.051	0.001	1.520
153	Nyamagana MC	100	0.044	0.044	0.000	0.044	0.044	0.000	0.806
154	Nyang'wale DC	100	0.048	0.049	0.000	0.048	0.050	0.001	1.459
155	Nyasa DC	100	0.129	0.131	0.002	0.129	0.132	0.002	1.204
156	Nzega DC	100	0.022	0.022	0.000	0.022	0.022	0.000	0.958
157	Nzega TC	100	0.038	0.038	0.000	0.038	0.039	0.001	1.010
158	Pangani DC	100	0.037	0.037	0.000	0.037	0.038	0.001	0.998
159	Rombo DC	100	0.086	0.086	0.001	0.085	0.087	0.001	1.323
160	Rorya DC	100	0.100	0.101	0.001	0.100	0.101	0.001	0.545
161	Ruangwa DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
162	Rufiji DC	100	0.040	0.040	0.000	0.040	0.041	0.000	1.308
163	Rungwe DC	100	0.111	0.113	0.001	0.112	0.113	0.001	0.860
164	Same DC	100	0.022	0.022	0.000	0.022	0.023	0.000	1.340
165	Sengerema DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
166	Serengeti DC	100	0.014	0.014	0.000	0.014	0.014	0.000	0.781
167	Shinyanga DC	100	0.047	0.048	0.001	0.047	0.048	0.001	1.321
168	Shinyanga MC	100	0.051	0.051	0.000	0.051	0.051	0.000	0.594
169	Siha DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
170	Sikonge DC	100	0.029	0.030	0.000	0.030	0.030	0.000	0.797
171	Simanjiro DC	100	0.021	0.021	0.000	0.021	0.022	0.000	1.263
172	Singida DC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
173	Singida MC	100	0.019	0.019	0.000	0.019	0.019	0.000	0.589
174	Songea DC	100	0.111	0.112	0.001	0.110	0.113	0.001	1.365
175	Songea MC	100	0.036	0.037	0.000	0.036	0.037	0.000	1.319
176	Songwe DC	100	0.024	0.025	0.000	0.024	0.025	0.000	0.896
177	Sumbawanga DC	100	0.017	0.017	0.000	0.017	0.017	0.000	0.835
178	Sumbawanga MC	100	0.077	0.078	0.001	0.077	0.078	0.001	0.712
179	Tabora MC	100	0.043	0.043	0.000	0.043	0.044	0.000	1.080
180	Tandahimba DC	100	0.025	0.026	0.000	0.025	0.026	0.001	1.417
181	Tanga CC	100	0.042	0.042	0.000	0.041	0.042	0.000	1.036
182	Tarime DC	100	0.040	0.040	0.000	0.039	0.040	0.000	1.092
183	Tarime TC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
184	Temeke MC	100	0.080	0.081	0.001	0.080	0.081	0.001	1.042
185	Tunduma DC	100	0.038	0.038	0.000	0.038	0.039	0.000	1.022
186	Tunduru DC	100	0.037	0.037	0.000	0.037	0.038	0.000	0.520
187	Ubungo MC	100	0.000	0.000	0.000	0.000	0.000	0.000	0.000
188	Ukerewe DC	100	0.061	0.062	0.001	0.061	0.063	0.001	1.453
189	Ulanga DC	100	0.000	0.000	0.000	0.046	0.047	0.000	0.000
190	Urambo DC	100	0.047	0.047	0.000	0.046	0.047	0.000	0.705
191	Ushetu DC	100	0.023	0.023	0.000	0.023	0.023	0.000	1.160
192	Uvinza DC	100	0.072	0.073	0.001	0.072	0.074	0.001	1.164
193	Uyui DC	100	0.041	0.041	0.000	0.041	0.042	0.000	0.999
194	Wanging'ombe DC	100	0.077	0.078	0.001	0.077	0.079	0.001	1.326
195	Wete	100	0.048	0.049	0.001	0.048	0.049	0.001	1.061

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