Spatial Distribution of Infant Mortality in Ethiopia: Using Demographic Health Survey, the Ethiopia

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Abstract

Background

Mortality is one of the demographic variables that affect population trends. Among mortality of children, Infant mortality contributed to more than 75% of all under-five deaths globally. It disproportionately affects those living in the different regions of countries and within the region. Exploring the spatial distribution and identifying associated factors is important to design effective intervention programs to reduce infant mortality. Thus, this study aimed to assess the spatial distribution and associated factors of infant mortality in Ethiopia using the 2016 Ethiopian Demographic and Health Survey (EDHS).

Method

The Data this study were used Ethiopian Demographic and Health Survey in 2016. A total of 11,023 live births from the EDHS data were included in the analysis. Spatial analysis was done to explore spatial distribution of infant mortality using ArcGIS version 10.4.

Results

This study revealed that the spatial distribution of infant mortality was non-random in the country with Moran's index 0.1546 (P-value=0.0185). The Afar and Somali regions of Ethiopia were identified in this study on the hot spot of infant mortality.

Conclusions

The spatial distribution of infant mortality varies across the country. ANC usage, sex of a child, birth interval, birth size, birth type, birth order, wealth index, residence, region, and the spatial variable (Si) were significant predictors of infant mortality. Therefore, it needs interventions in the hot spot areas. Focusing on maternal health care services, rural residences, multiple births, infants having a smaller birth size, and male infants deserves special attention.

Introducation

Infant mortality is the death of a child before his or her first birthday. The infant mortality rate (IMR) is defined as the number of children who die before reaching their first birthday in a given year, expressed per 1000 live births [1]. The IMR is not only a key indicator of maternal and child health, it is also considered an important indicator of population health and development [2, 3]. For the last three decades, infant and child mortality has remained a global priority. According to the world health organization report, the chance of a child dying before the age of one was highest in the African Region (51 per 1000 live births), which is over six times higher than that in the European Region (8 per 1000 live births) [4]. In

Africa, the main risk factors related to a high number of infant deaths include lack of access to funds, and infrastructure, access to education, lack of medical professionals, poverty, and discrimination [5].

The Sub-Saharan African countries have achieved remarkable improvement in infant survival rates since the introduction of the Millennium Development Goals (MDGs), However, infant mortality was higher compared to others, an estimated 5.2 million children died in 2019 more than half of those deaths occurred in Sub-Saharan Africa [6]. Ethiopian Demographic and Health Survey (EDHS,2016) result indicated that the infant mortality rate for the 5 years preceding the survey was 48 deaths per 1000 live births [7]. It was a large share among under-five mortality. About 72% of under-five mortality in our country occurs before the first birthday.Infant mortality varies in the country in space and time by changing its magnitude. Deaths occurring in children under one year of age measured by the infant mortality rate are nonrandom. Therefore, this study tries to address the spatial distribution of infant mortality and explore the major risk factors of infant death taking into consideration possible spatial correlations.

Materials And Methods

The source of data for this study was the 2016 EDHS. The data were downloaded from DHS website by this link www.meauredhs.com. The survey covered all nine regions and two city administrations of Ethiopia, and regions are divided into 68 zones, and zones, into administrative units called districts (817). Each district is further subdivided into the 16,253 lowest administrative units, called kebele [7].

Study variables

Outcome variable.The outcome variable of this study is infant mortality that refers to the death of an infant before his or her first birthday.

Explanatory variables. The predictor is characteristics by individual-level and community/cluster-level(Figure 1).

Statistical Data Analysis

In this study, the data were analyzed using SAS version 9.4 with Proc Glimmix by using the method of LAPLACE approximation. In addition to SAS software to analyze the data, this study was used the ArcGIS version for spatial data analysis. In this study, infant mortality was considered as response variable. Henceforth, from a statistical viewpoint, the outcome variable is given by a binary variable.

$$y_{ij} = \begin{matrix} 1 = \text{infantwhodied} \\ 0 = \text{infantwhoarealive} \end{matrix}$$

The most protuberant logistic model for this condition is the binary logit model. Y_{ij} be a dichotomous outcome random variable with categories 1 (infant who died) and 0 (infant who are alive) in the first year of life before the survey. The $X_{(n\times(k+1))}$ denote the collection of k-predictor variables of the response. Then, the conditional probability that the ith infant has died given the vector of predictor variables X_i is denoted by $P_i = P(y_i = 1 \mid X_i)$. The expression P_i in logistic regression model written in linear combinations of predictors can be expressed in the form of [8, 9]:

$$logit(P_i) = \log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ik}, i = 1,2,\ldots,n$$

Whereβ's are the regression coefficient for the explanatory variable

Geospatial data processing

In this study, we extended the binary logistic regression models by allowing random effects accommodating spatial correlations. The model was considered hierarchical logistic regression model for the infant mortality dataset was arranged in spatial form. Different spatial covariance structures were explored in datasets on mortality of infants giving due attention to the various implementation issues of the models. his study was used spatial models to discern spatial patterns of infant mortality. The study was explored different spatial covariance structures.

Geostatistical methods such as spatial autocorrelation, kriging and semivariograms were applied to create a prediction grid surface from a scattered set of points. Kriging assumes that the distance or direction between sample points reflects a spatial correlation that can be used to explain variation in the surface

Results

Exploratory Data Analysis

Among 645 clusters, 622 were included in this study, 21 clusters were excluded due to zero GPS longitude and latitude coordinate readings for spatial analysis while the rest two of them were not included initially from the EDHS coordinate file. A total weighted 11,023 live births within five years preceding the 2016 EDHS was included in the analysis, and the infant mortality rate (IMR) in Ethiopia was 48 per 1000 live births in 2016. The majority of 9,807(89.0%) in this study participants were from rural dwellers. Among the respondents, 4,851(44.0%) were from the Oromia region and 2,296(20.8%) were from SNNPR. The infant mortality rate (IMR) varies across the regions of the country. The highest IMR was observed in Harari (76.9 per 1000 live birth) and Afar (70.2 per 1000 live birth). The lowest was observed in Tigray (29.3 per 1000 live birth) and Addis Ababa (32.8 per 1000 live birth) (Figure 2).

Figure 3below showsthatthe proportion of infant mortality varies from cluster to cluster. That means the enumeration area is considered as a random effect for this study (Figure 3).

Spatial Analysis of Infant Mortality

The estimated Global Moran's Index in this study was 0.1546; indicates that the spatial distribution of infant mortality significantly clustered by in Ethiopia. In addition to looking at the Moran's *I* to identify whether there is a spatial correlation, the *P*-value (<0.0185) was found to be less than 0.05, suggesting significant evidence of unexplained spatial autocorrelation in the risk of infant mortality (Figure 4). Similarly, the incremental spatial autocorrelation graph identified the maximum peak distance value (30000 meters), which indicates distances where spatial processes promoting clustering are most pronounced. The color of each point on the graph corresponds to the statistical significance of the z-score values (Figure 5).

Spatial Autocorrelation by Distance

A total 622 clusters were included in this study to analyze the spatial of infant mortality. Each point in the map characterizes one enumeration area with the proportion of infant mortality in each cluster. The green color indicates that the areas with a low proportion of infant mortality whereas the red color indicates enumeration areas with a high proportion of infant mortality. The highest proportions of infant mortality occurred in a majority part of the Harari region, East part of Afar, border of Benishangul Gumuz and Oromia, the central part of Somali, border of Amhara and Benishangul Gumuz, and central part of Oromia. Whereas the low proportion of infant mortality was accumulated in Tigray, Dire Dawa, Gambela, the entire part of Addis Ababa, and the Northeast part of SNNPR (Figure 6).

Cluster and Outlier Analysis of Infant Mortality

Cluster and outlier analysis was conducted to identify the nature of clustering by using Anselin local Moran's I. The red color (cluster- low) indicates that the low rate of infant mortality is surrounded by a low rate of infant mortality, and the dark green color (cluster-high) indicates a high rate of infant mortality surrounded by the high rate of infant mortality. Whereas the green color (high outlier) indicates a high rate of infant mortality surrounded by the low rate of infant mortality and the yellow color (low outlier) shows a low rate of infant mortality surrounded by the high rate of infant mortality. Significant clusters were found in Afar, Addis Ababa, border of Benishangul Gumuz and Oromia. High outliers were observed on Harari, Dire Dawa, South Tigray, border of Amhara and Oromia, border of Oromia and SNNPR while the low outliers were found in the Somali region (Figure 7).

Hot Spot Analysis of Infant Mortality

The Local Getis-Ord Gi* statistics identified significant hot spot and cold spot areas of infant mortality. The red color indicates that significant hot spot (high-risk) areas for infant mortality and found in Afar and Somali regions. The blue color indicates the cold spot (low risk) areas of infant mortality. These cold spot areas were observed in Addis Ababa, the central part of the Oromia and Amhara regions (Figure 8).

Spatial Interpolation of Infant Mortality

The spatial kriging interpolation analysis was used to predict infant mortality for unsampled areas of the country based on sampled enumeration area measurements. Prediction of the high-risk areas was indicated by red predictions. Afar, Somali, Harari, Southwest SNNPR, East Benishangul Gumuz, South and central part of Oromia were predicted as more risky areas compared to other regions. Whereas, Tigray, Amhara, Addis Ababa, Northwest Oromia, North Somali, Dire Dawa, Northwest Benishangul Gumuz, Northeast SNNPR, border of Gambela and SNNPR, border of Gambela and Oromia were predicted as having less risk for infant mortality (Figure 9).

Spatial distribution of the spatial autocorrelation term: autocovariate variable

Figure 10 shows the spatial distribution of the autocovariate variable in equation , which represents the spatial autocorrelation term in the GLMM. The autocovariate variable has the same unit as the dependent variable, which also represents the incidence of death occurrence, but it is just a macro spatial trend. Figure 10 show that the spatial distribution of incidence of death occurrence has a strong spatial tendency and heterogeneity, which presents a transitional and gradual change throughout the country. The incidence is very high in the Northern and central part of Afar, the entire part of Harari, the central part of Somali, Southern and Western SNNPR, Eastern Oromia, and Western Benishangul Gumuz regions that is consistent with what we observed in Figure 6 that these areas were characterized by a high proportion of infant mortality.

Spatial Covariance Structures

Figure 4 show that the spatial distribution of infant mortality exhibit spatial correlations and this study investigate various possible spatial covariance structures. Based on statistical software SAS offers several possible spatial covariance structures: Exponential, Gaussian, Linear, Spherical, etc. each represents a particular pattern of changes in spatial covariance among residuals as observations grow in distance from one another. Below We utilized the DIC and AIC fit statistics to examine Spherical and Gaussian spatial covariance structures. Our first observation is that the fit statistics drop in value, indicating a better fit to the data(Table 1).

Results of this study indicated that the Spherical and Gaussian spatial covariance structures were fit to the residuals from the GLMM. Focusing on the AIC fit statistics, we observe a drop from 4146.12 to 4039.27 in Gaussian covariance structure compared to a model with an unstructured covariance structure. This is an improvement, but as part of our model building process, we consider the two spatial covariance structures. When comparing the Gaussian and Spherical models, the fit statistics do now show a meaningful drop, suggesting that perhaps a Gaussian covariance structure is not appropriate. As a result, the Spherical spatial covariance structure better fits the data. We used this covariance structure for modeling in this study, since it has smaller DIC and AIC fit statistics as compared to the other(Table 1).

Table 1 Goodness of fit statistics for different covariance structures

	DIC	AIC	BIC
Without spatial correlation (unstructured)	4137.08	4146.12	4156.35
Gaussian	4031.19	4039.27	4051.46
Spherical	4028.52	4034.75	4047.82

The intercept-only model without explanatory variable was constructed to measure the effect of community variation on infant mortality.

The variance of random effects at the cluster is (=3.6413, p-value<0.0001) which was statistically significant and reflects there is statistically significant variation in the infant mortality among infants across the community (see Table 2).

The estimated intra-class correlation computed(ICC)was 52.5%. This indicates about 52.5% of the total variation for infant mortality was due to the difference between communities, leaving 47.5% of the variability to be accounted for the infants or other unknown factors.

The covariance parameter estimates in Table 2 indicates that the estimated higher-level error variance goes down from 3.6413 to 2.7646. The proportion of explained variance at infant-level computed as

$$\mathrm{PCV} = R_1^2 = \frac{\sigma^2_{e|b} - \sigma^2_{e|m}}{\sigma^2_{e|b}}$$

$$= \frac{3.6413 - 2.7646}{3.6413} = 0.241 = 24.1\%$$

This indicates that the proportion of explained variation at the individual level for infant mortality with level-1 predictor is about 24.1%. Similarly, the Wald test value 9.17 with a p-value<.0001 was statistically significant and suggested that there is statistically significant variation in the infant mortality among infants across the community (Table 2).

The cluster or community level residual goes down to 1.7692 from 2.7646, so the community level R_2^2 becomes $R_2^2 = \frac{2.7646 - 1.7692}{2.7646}$ = 0.360=36%.The proportion of explained variance at the community level for infant mortality is about 36%. This indicates that 36% of variability at the community level for infant mortality was explained by individual-level and community-level predictors. The Wald value (Z=6.45, and p-value<.0001) indicates that the random effects were statistically significant (Table 2).

In this model, the individual-level variables, community-level variables, and spatial autocovariate variables were introduced. The proportion of explained variance at community-level computed as: $R_3^2 = \frac{1.7692 - 0.7579}{1.7692}$= 0.572=57.2. It indicates that about 57.2% of the variability at the community level for infant mortality was explained by the individual-level, community-level, and spatial autocovariate variables. The random effects were statistically significant with a Wald value of 5.04 and p-value<.0001

(Table 2). In this study the random coefficients model does not converge; as a result, we exclude the random coefficients model.

Table 2
Covariance parameter estimate for models in the study

Cov Parm		Subject	Estimate	Standard Error	Z Value	Pr > Z
Model I	Variance	PSU	3.6413	0.5126	7.10	<.0001
Model II	Variance	PSU	2.7646	0.3015	9.17	<.0001
Model III	Variance	PSU	1.7692	0.2741	6.45	<.0001
Model IV	Variance	PSU	0.7579	0.1505	5.04	<.0001
	SP(SPH)	PSU	92.0000	0	.	.

Factors Of Infant Mortality

The result of the selected model Table 3 shows that individual-level factors such as birth size, birth type, sex of a child, breastfeeding status, birth order, birth interval, ANC usage, and wealth index were found to be significantly associated with the odds of infant mortality. On the other hand, community-level factors such as place of residence and region had significant effects (P-value<0.05) on the log-odds of the ith infant in the jth cluster experiences death. In addition to the individual and community level factors, the spatial autocovariate variable (Si) was also significantly associated with infant mortality (Table 3).

Table 3
Parameter estimate for models in the study using individual-level, community-level, and spatial autocovarite variable

Variables	Category	Estimate	SE	(95%CI)
Intercept		-4.9958*	0.46	(-5..89,-4.09)
ANC usage	**No**	**0.3739****	**0.13**	**(0.16,0.58)**
	Yes	**0**		
Birth interval	**<=24 month**	**0.8324****	**0.15**	**(0.58,1.07)**
	25-36	**0.1497****	**0.13**	**(-0.11,0.40)**
	>36	0		
Birth order	2-3	0.3262	0.17	(0.01,0.64)
	4-5	0.1880	0.22	(-0.20,0.57)
	6 and more	**1.1331****	**0.22**	**(0.73,1.53)**
	First	0		
Breastfeeding status	**No**	**1.3701****	**0.14**	**(1.16,1.57)**
	Yes	0		
Family size	4-6	-1.1150	0.17	(-1.42,-0.80)
	7 and more	-2.0979	0.23	(-2.50,-1.69)
	1-3	0		
Marital status	Married	-0.3946	0.25	(-0.84,0.05)
	Unmarried	0		
Mothers education	No education	0.3491	0.28	(-0.16,0.85)
	Primary	0.1653	0.25	(-0.33,0.66)
	Secondary & higher	0		
Sex of child	**Male**	**0.4668****	**0.13**	**(0.26,0.67)**
	Female	0		
Sex of household head	Male	0.7174	0.18	(0.37,1.07)
	Female	0		
Birth size	**Average**	**-0.2798**	**0.12**	**(-0.51,-0.04)**
	Small	**0.2417****	**0.13**	**(-0.23,0.47)**

Variables	Category	Estimate	SE	(95%CI)
	Large	0		
Type of birth	**Multiple**	**1.9205****	**0.21**	**(1.56,2.38)**
	Single	**0**		
Wealth index	Medium	-0.2736	0.16	(-0.58,0.03)
	Poor	**0.3074***	**0.14**	**(0.04,0.57)**
	Rich	0		
Region	Addis Abeba	0.2438	0.25	(-0.24,0.73)
	Afar	**0.4322***	**0.22**	**(0.01,0.86)**
	Amhara	0.4276	0.32	(-0.20,1.06)
	Benishangul	0.7658	0.24	(0.29,1.24)
	Dire Dawa	0.6528	0.30	(0.06,1.24)
	Gambela	0.3823	0.28	(-0.17,0.93)
	Harari	**0.4454***	**0.25**	**(-0.04,0.94)**
	Oromia	0.4293	0.31	(-0.18,1.04)
	SNNPR	0.3189	0.32	(-0.31,0.94)
	Somali	**0.4160***	**0.23**	**(-0.03,0.87)**
	Tigray	0		
Residence	**Rural**	**0.4867****	**0.29**	**(-0.05,1.02)**
	Urban	**0**		
Si (P-value=0.0028)		-0.5778*	0.19	(-0.95,-0.20)

ANC usage: Ifants of mothers who did not received ANC during the last pregnancy were 45% higher likely to die in their first year of life compared with infants whose mothers did receive ANC, AOR = 1.45 ,95% CI: 1.17, 1.78). This indicated the mothers who did not use ANC1.45 times more likely as compared to those who did during their pregnancy.

Breastfeeding: The reference group here was mothers who breastfed their children. Infants, who were not breastfed died at a rate which was about 3.93 times more likely as compared than infants who were breastfed. The estimated odds of infant death were 3.93 with 95%.(CI:3.19,4.80).

wealth index:Among mothers who belong to the poor wealth index, the estimated odds of infant death were 1.36 (OR=1.36, 95% CI:1.04,1.77) times more likely as compared to their counterpart rich wealth index in the same clusters.

Sex of infant: The ods ratio for male infants was 1.59 found to be (95% CI:1.29,1.95) meaning that the risk of males dying was about 59% higer than that for female infants. The confidence interval indicated that the risk of death for female infants could be as low as 29% and as high as 95%.

Birth order: The reference group, in this case, was taken as a single birth. Infants belonging to the 6 and more birth order category were about 13% more likely to die relative to the reference group (OR= 1.1331 95%,CI:0.73,1.53).

Birth size :The estimated odds of infant death among infants born with birth size perceived by their mothers as small was 1.27 (OR=1.27, 95% CI:0.79,1.60) times more likely than infants born with birth size perceived by their mothers as large.

Preceding Birth:The estimated odds of death among infants born with a preceding birth interval of less than or equal to 24 months were 2.29 (OR=2.29, 95% CI:1.78,2.91) times more likely to die as compared to infants born with a birth interval of more than 36 months in the same clusters keeping other covariates constant. Whereas the estimated odds of dying among infants born with a preceding birth interval of between 25-36 months was 1.16 (OR=1.16, 95% CI:0.89,1.49) times more likely to die as compared to infants born with a birth interval of more than 36 months in the same clusters keeping other covariates constant.

Type of birth:: The predictable value of odds of infant mortality among multiple births was 6.82 with, 95% CI:4.75,10.80. This showed that infant mortality among multiple 6.82 times more likely than singletons of the same.

In addition to the individual-level characteristics, community-level characteristics (such as the ways of life in the regions, and **residence** in Ethiopia) were significantly associated with infant mortality.

Residenc: The estimated odds of infant mortality among rural residents were 62%, higher as compared to their counterpart urban residents keeping other covariates constant.

Regions: Infants living in pastoralist regions (Afar, Somali, and Harari) were significant to compare tigray region. The odds ratio of afar 1.54 times more likely to die in their first year compared with infants living in Tigray regions with, AOR=1.54, (95% CI:0.67,5.20). In addition this,, Somali, and Harari regions were 1.51 (OR=1.51, 95% CI:0.77,3.63), and 1.56 (OR=1.56, 95% CI:0.31,4.31) times more likely as compared to infants from the Tigray region. Respectively(see Table 3).Furthermore, the spatial autocorrelation between clusters. In Table 3 the P=0.0028 also proves that it was true, in a sense that there was a spatial correlation of infant mortality between clusters. The spatial variable correlation with infant death was a negative value, -0.5778, which indicates that clusters with a low incidence of infant mortality were usually surrounded by clusters with a high incidence of infant mortality. Bear in mind that during the interpretation of one variable so far it is assuming that the other variables are held constant (Table 3).

Discussion

This study aimed to assess the spatial distribution and associated factors of infant mortality in Ethiopia using 2016 EDHS data. The spatial analysis in different methods consistently verified hot and cold spot areas of infant mortality among infants in Ethiopia. The spatial analysis indicated that Afar and Somali regional states were statistically significant hot spot areas for infant mortality. The possible justification could be is the variation in ANC utilization across regions. The lowest ANC utilization rate was reported in the hot spot areas (Afar and Somali regions) as compared to cold spot areas [7]. This could be attributed to the discrepancy in the distribution of maternal health services, and environmental factors across the area [10]. This implies that identifying regions with high infant mortality is important for prioritizing areas for analysis of cause and planning of remedial actions. In contrast, the cold spot areas were observed in the entire part of Addis Ababa, the central part of the Oromia and Amhara regions. The possible justification could be these regions are urban as compared to the hot spot areas. They have good access to health facilities, mothers may have awareness about ANC utilization, and its benefits compared to other regions.

The findings of this study show that ANC usage, preceding birth interval, birth order, breastfeeding status, sex of a child, birth size, type of birth, wealth index, region, residence, and the spatial autocovariate variable (Si) were determinants of infant mortality.

ANC usage has a significant association with infant mortality. The odds of infant death among infants from mothers who did not use ANC more likely as compared to infants born from mothers who did during their pregnancy in the same clusters. This finding is consistent with studies conducted in Ethiopia [11], Pakistan [12], and Brazil [13].

The birth order of a child is another factor of infant death. The odds of dying among infants with sixth or higher birth was more likely than first-born infants in the same clusters. This finding is consistent with the studies conducted in Ethiopia [11], and South Africa [14].

The sex of a child significantly influenced the occurrence of infant mortality. The risk of death among male infants was more likely as compared to female infants in the same clusters. This result is in line with studies conducted in Ethiopia [15], and Bangladesh [16].

Concerning birth interval, infants born with a preceding birth interval of between 25-36 months and less than or equal to 24 months was more likely to die as compared to infants born with a birth interval of more than 36 months in the same clusters. This result is similar to studies done in Ethiopia [17], and Nepal [18].

This study also demonstrated that the odds of death among multiple births were 6.82 times more likely than singletons in the same clusters. This finding is consistent with studies conducted in Ethiopia [15, 19], Kenya [20] and Brazil [21]. Multiple births are at high risk for numerous negative birth outcomes, and these outcomes contribute to a higher rate of mortality during the infancy period [22].

This study indicated that breastfeeding status has a significant association with infant mortality. Among mothers who did not breastfeed their child, the odds of infant death were 3.93 times more likely as compared with mothers who did in the same clusters. This finding is supported by previous studies done in Ethiopia [23], and Kenya [24].

Our finding shows that the wealth index has a significant association with infant mortality. Among mothers who belong to the poor wealth index, the odds of infant death were 1.36 times more likely as compared to their counterpart rich wealth index categories in the same clusters. This result is in line with studies done in Bangladesh [16].

This study revealed that place of residence is significantly related to infant mortality. The odds of infant death among rural residents was more likely as compared to their counterpart urban residents. This finding is consistent with studies conducted in Ethiopia [15], Nigeria [25], and Pakistan [12]. The reason may be that mothers living in rural areas lack access to health institutions to have ANC follow-ups or lack of media exposure which in turn affects their knowledge and practice of care for the infant.

This study revealed that region has a significant association with infant mortality. The odds of dying during the infancy period in the Afar, Somali, and Harari regions were more likely as compared to infants from the Tigray region. This finding is in line with studies conducted in Ethiopia [19]. The difference in mortality between regions may be due to variations in service accessibility and coverage. The national Universal Health Coverage (UHC) service capacity and access coverage were lowest in Somali and Afar regions 3.7% and 4.1% respectively as compared to the Tigray region (22.0%) [26]. These regions are also known for socio-economic vulnerability and food insecurity leading to malnutrition and infant death [27] (Sileshi et al., 2019) .

This study reveals that the spatial variable has a negative significant effect where clusters with a low incidence of infant mortality were usually surrounded by clusters with a high incidence of infant mortality. Whereas, clusters with a high incidence of infant mortality were usually surrounded by clusters with a low incidence of infant mortality, which is in line with studies in Brazil [28].

Conclusions

The spatial distribution of infant mortality was found significantly clustered in Ethiopia. This study investigated that high-risk areas of infant mortality were found in Afar and Somali regions of the country. In contrast, the cold spot (low risk) areas were identified in Addis Ababa, the central part of the Oromia and Amhara regions.

The result of multilevel GLMM that adjusted for spatial effects better accounted for geographical variability and provided more accurate information on the spatial distribution of infant mortality than non-spatial multilevel models. Therefore, the model that adjusted for spatial effects performed better in this study. The study showed that there was a variation in infant mortality among the regions of Ethiopia.

About 57.2% of the variability at the community level for infant mortality was explained by the individual-level and community-level variables.

This study identified the risk factors of infant mortality at the individual level and community level. At individual-level variables are: being male, multiple birth type, having a smaller birth size, born from mothers who did not attend ANC, born from mothers with poor wealth index, and having a higher birth order were significant factors that increase the risk of death during infancy period. Whereas, having a large birth interval and initiating breastfeeding early were factors that decrease the risk of infant death. At the community level, being a rural residence, born in Afar, Harari, and Somali regions were factors that increase the risk of infant mortality. There was a significant spatial correlation of infant mortality between clusters in which clusters with a low incidence of infant mortality were usually surrounded by clusters with a high incidence of infant mortality and vice versa.

Declarations

Ethical Considerations

Permission for data access was obtained from a major demographic and health survey through an online request from http://www.dhsprogram.com to download and use the raw data for this study. The data used in this study were available without individual identifiers. The Institutional Review Board approved procedures for DHS public-use datasets do not allow specific households or sample clusters to be identified. The geographic identifiers are available only for the enumeration areas (EAs) as a whole, not for particular household addresses. The measured GIS coordinates are randomly displaced in a large geographic area so that particular EAs cannot be identified. Each enumeration area or primary sampling unit has a number in the data file, but these numbers do not have any labels to indicate their names or locations.

Consent for Publication

Not applicable.

Competing interests

We the authors declared that we have no competing interest.

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Availability of Data and Materials

The datasets used and analyzed during this study are available from the corresponding author on reasonable request. The contact person is Ashenafi Abate ashu.abate@gmail.com.The statement to confirm that all methods were carried out in accordance with relevant guidelines and regulations.

Author contributions

All authors made substantial contributions to conception and design, acquisition of data, or analysis and interpretation of data; took part in drafting the article or revising it critically for important intellectual content; agreed on the journal to which the article will be submitted; gave final approval of the version to be published; and agreed to be accountable for all aspects of the work.

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Figures

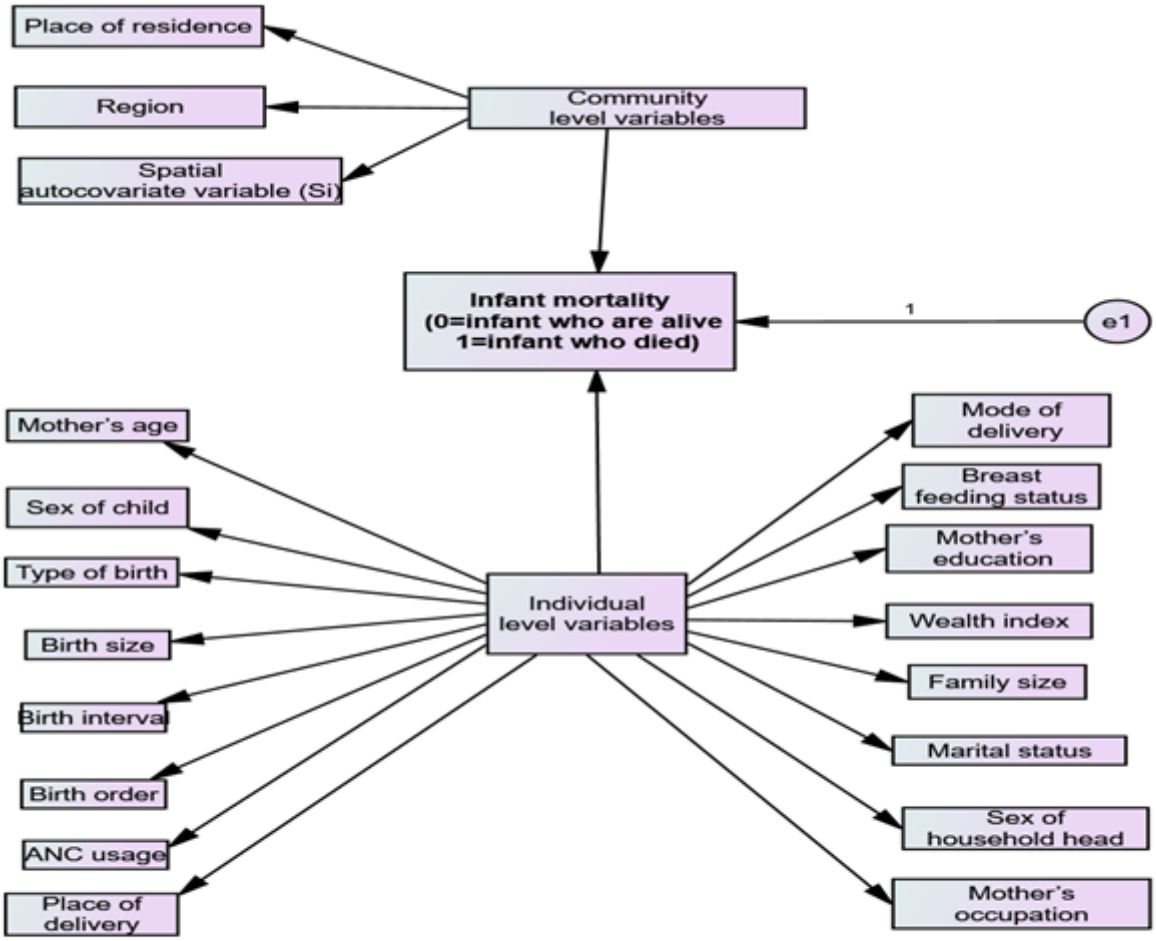


Fig. 1 variables included in the mode

Figure 1

The predictor is characteristics by individual-level and community/cluster-level

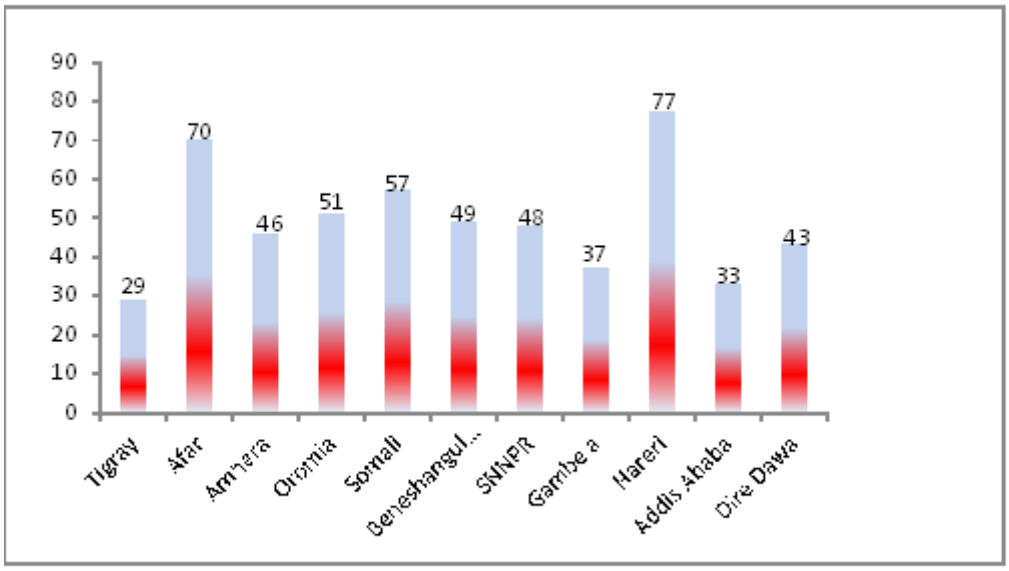


Fig .2 Regional infant mortality rate in Ethiopia, 2016

Figure 2

The highest IMR was observed in Harari (76.9 per 1000 live birth) and Afar (70.2 per 1000 live birth). The lowest was observed in Tigray (29.3 per 1000 live birth) and Addis Ababa (32.8 per 1000 live birth)

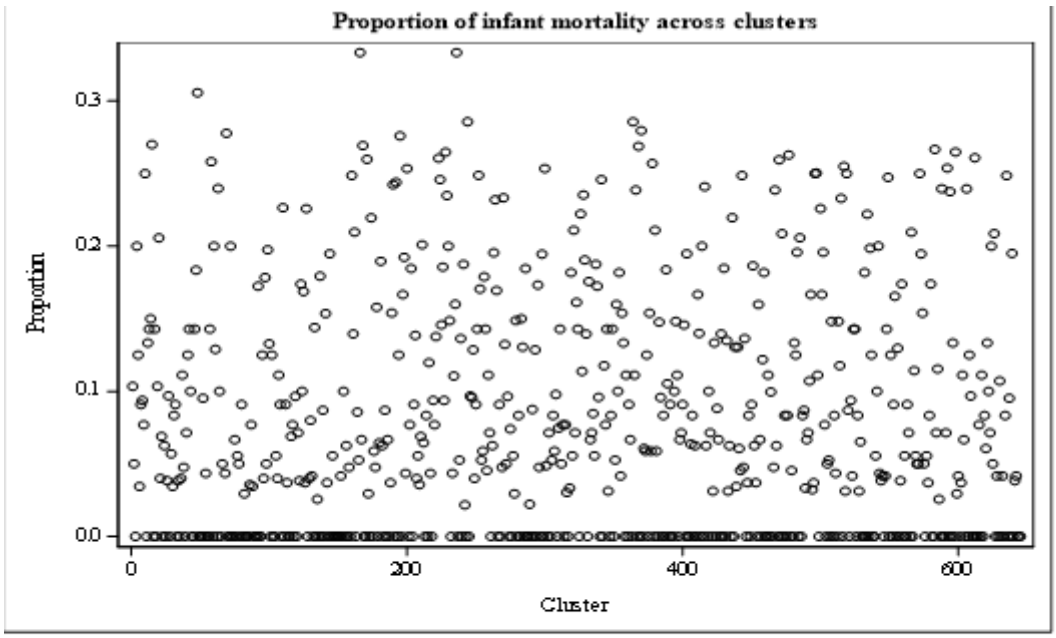


Fig . 3 The proportion of infant mortality across the clusters

Figure 3

The proportion of infant mortality varies from cluster to cluster. That means the enumeration area is considered as a random effect for this study

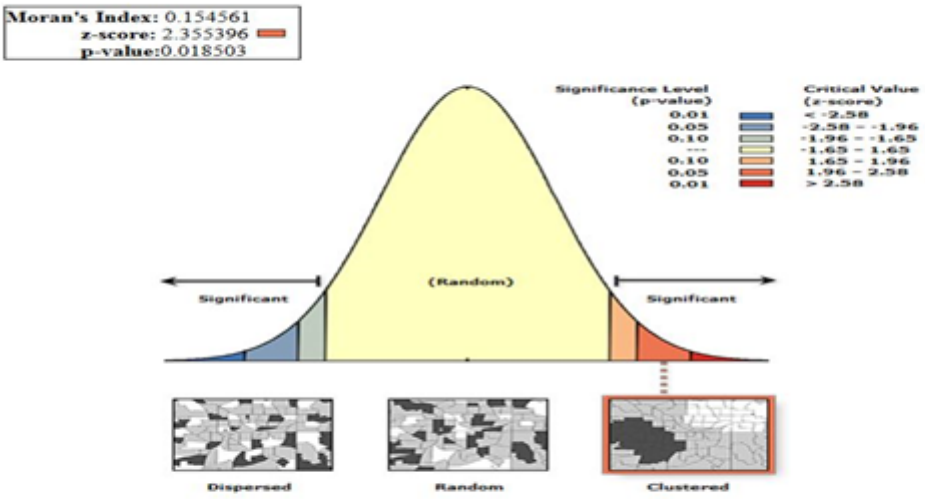
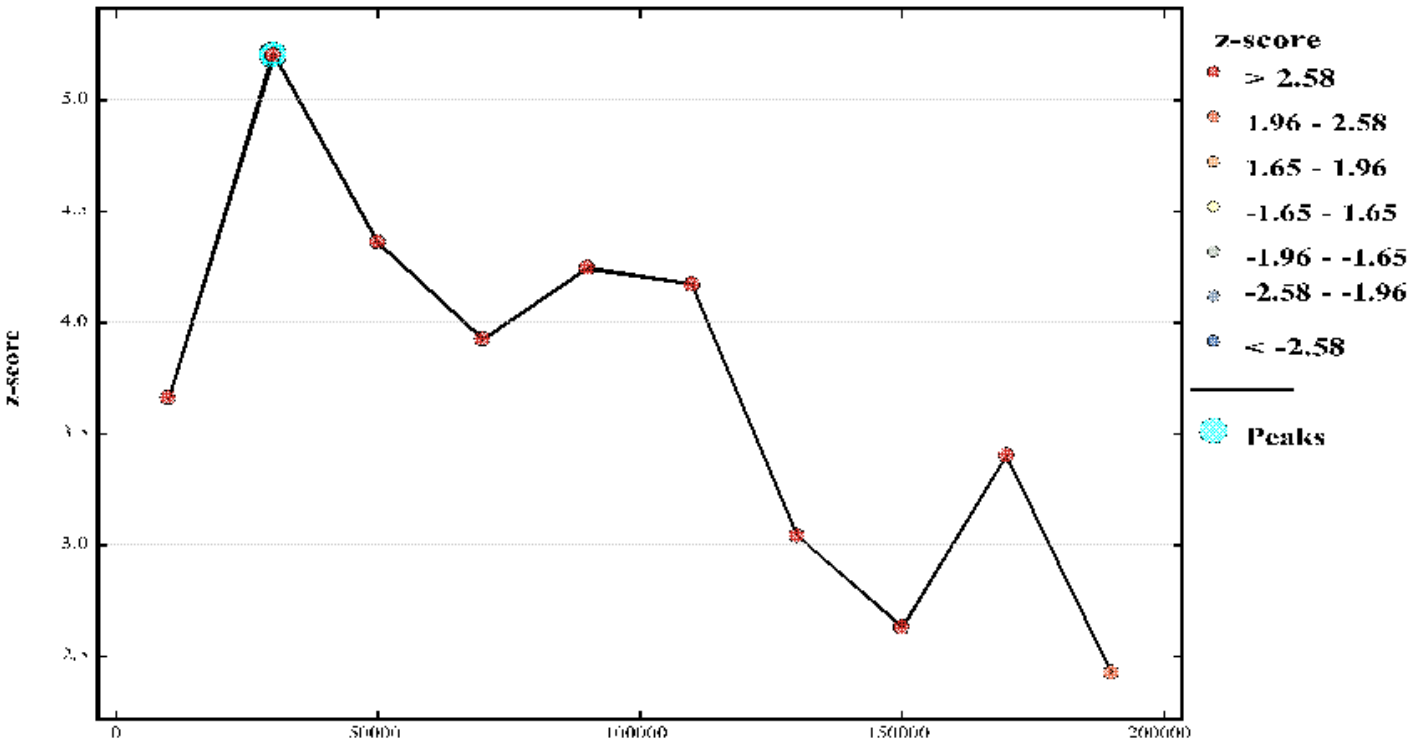


Fig . 4 Spatial autocorrelation for distribution of infant mortality in Ethiopia, 2016

Figure 4

The estimated Global Moran's Index in this study was 0.1546; indicates that the spatial distribution of infant mortality significantly clustered by in Ethiopia. In addition to looking at the Moran's *I* to identify whether there is a spatial correlation, the *P*-value (<0.0185) was found to be less than 0.05, suggesting significant evidence of unexplained spatial autocorrelation in the risk of infant mortality



First Peak (Distance, Value): 30000.00, 5.203618

Max Peak (Distance, Value): 30000.00, 5.203618 Distance measured in meters

Fig. 5Incremental spatial autocorrelation by distance

Figure 5

The incremental spatial autocorrelation graph identified the maximum peak distance value (30000 meters), which indicates distances where spatial processes promoting clustering are most pronounced. The color of each point on the graph corresponds to the statistical significance of the z-score values

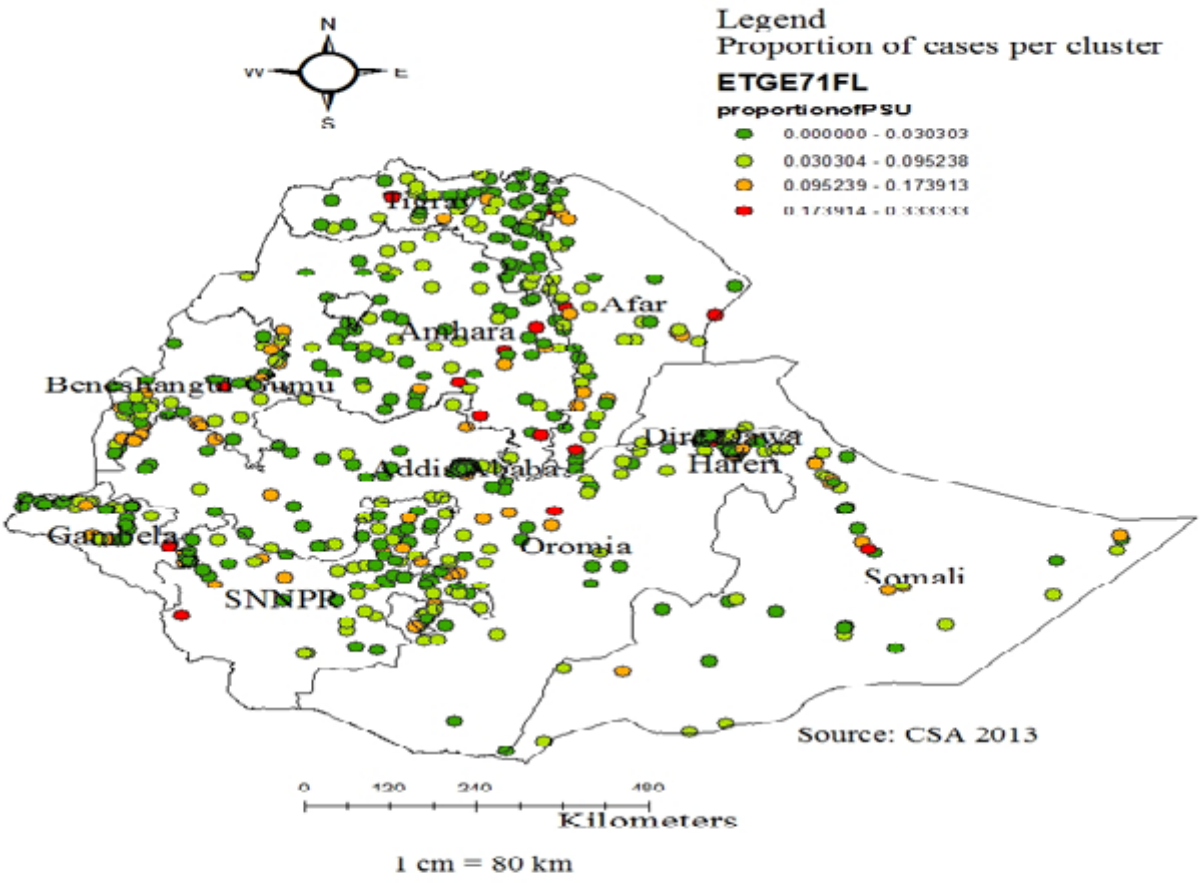


Fig. 6 Spatial distribution of infant mortality among infants in Ethiopia, 2016

Figure 6

The highest proportions of infant mortality occurred in a majority part of the Harari region, East part of Afar, border of Benishangul Gumuz and Oromia, the central part of Somali, border of Amhara and Benishangul Gumuz, and central part of Oromia. Whereas the low proportion of infant mortality was accumulated in Tigray, Dire Dawa, Gambela, the entire part of Addis Ababa, and the Northeast part of SNNPR

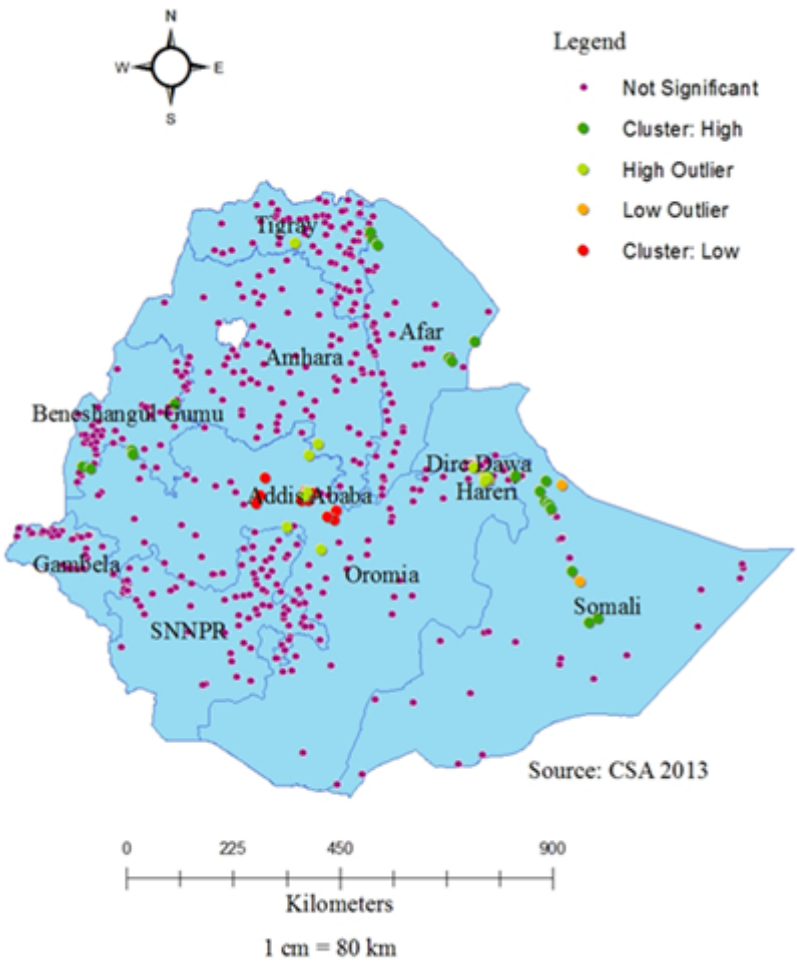


Fig .7 Cluster and outlier analysis of infant mortality in Ethiopia, 2016

Figure 7

Cluster and outlier analysis was conducted to identify the nature of clustering by using Anselin local Moran's I. The red color (cluster- low) indicates that the low rate of infant mortality is surrounded by a low rate of infant mortality, and the dark green color (cluster-high) indicates a high rate of infant mortality surrounded by the high rate of infant mortality. Whereas the green color (high outlier) indicates a high rate of infant mortality surrounded by the low rate of infant mortality and the yellow color (low outlier) shows a low rate of infant mortality surrounded by the high rate of infant mortality. Significant clusters were found in Afar, Addis Ababa, border of Benishangul Gumuz and Oromia. High outliers were observed on Harari, Dire Dawa, South Tigray, border of Amhara and Oromia, border of Oromia and SNNPR while the low outliers were found in the Somali region

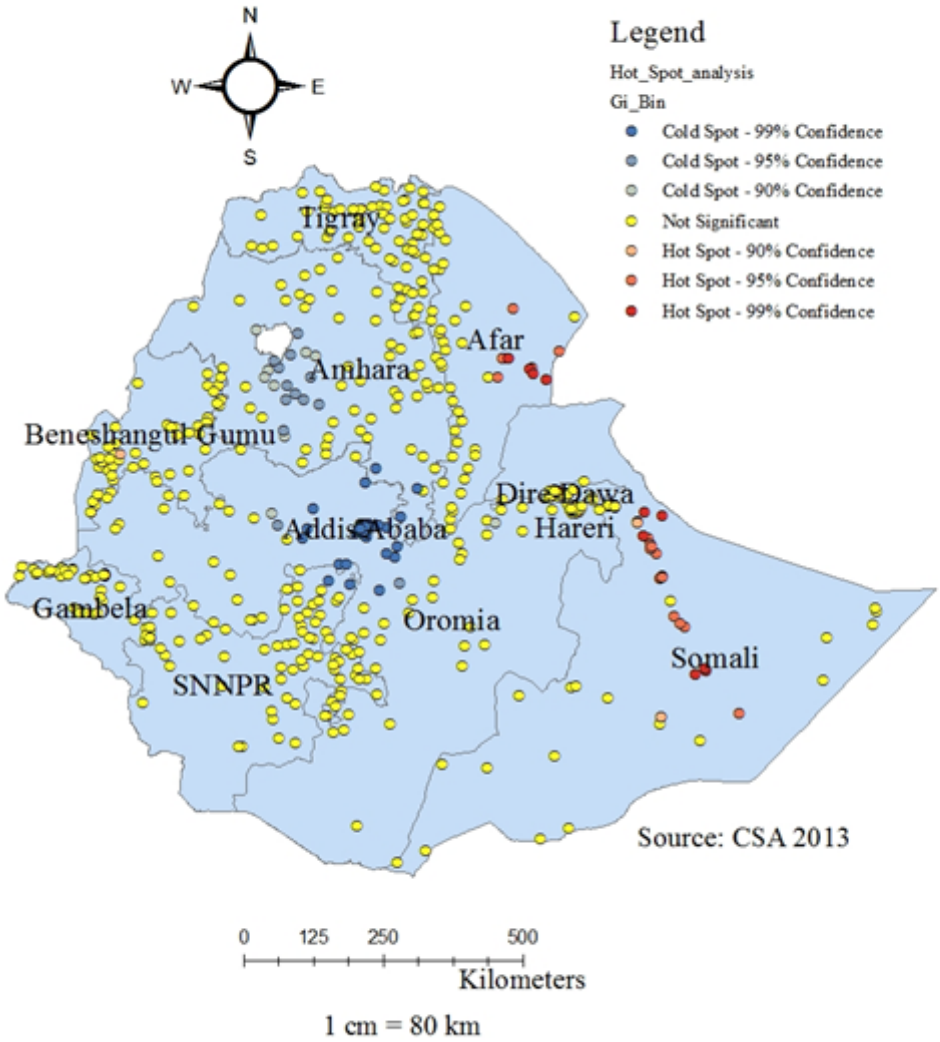


Fig . 8 Hot spot and cold spot identification of infant mortality in Ethiopia, 2016

Figure 8

The Local Getis-Ord Gi* statistics identified significant hot spot and cold spot areas of infant mortality. The red color indicates that significant hot spot (high-risk) areas for infant mortality and found in Afar and Somali regions. The blue color indicates the cold spot (low risk) areas of infant mortality. These cold spot areas were observed in Addis Ababa, the central part of the Oromia and Amhara regions

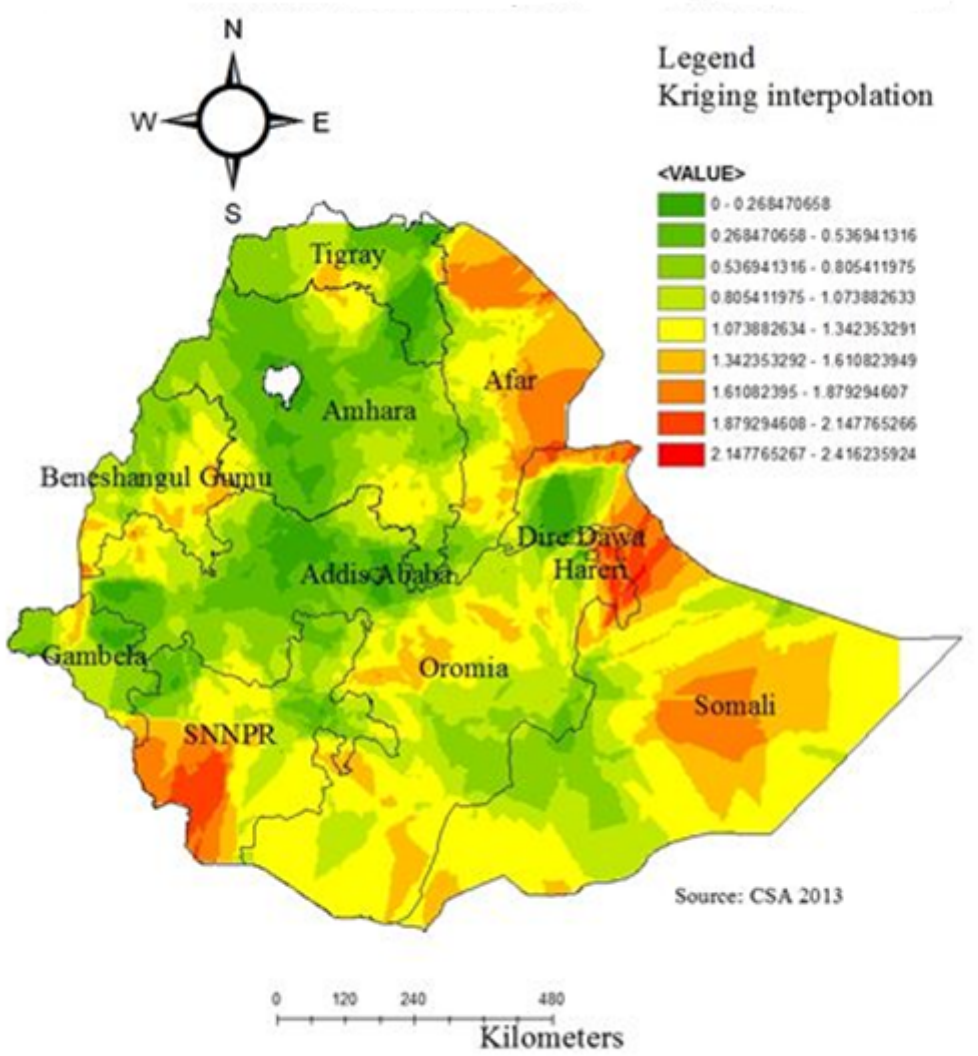


Fig. 9 Kriging interpolation of infant mortality among infants in Ethiopia, 2016

Figure 9

Afar, Somali, Harari, Southwest SNNPR, East Benishangul Gumuz, South and central part of Oromia were predicted as more risky areas compared to other regions. Whereas, Tigray, Amhara, Addis Ababa, Northwest Oromia, North Somali, Dire Dawa, Northwest Benishangul Gumuz, Northeast SNNPR, border of Gambela and SNNPR, border of Gambela and Oromia were predicted as having less risk for infant mortality

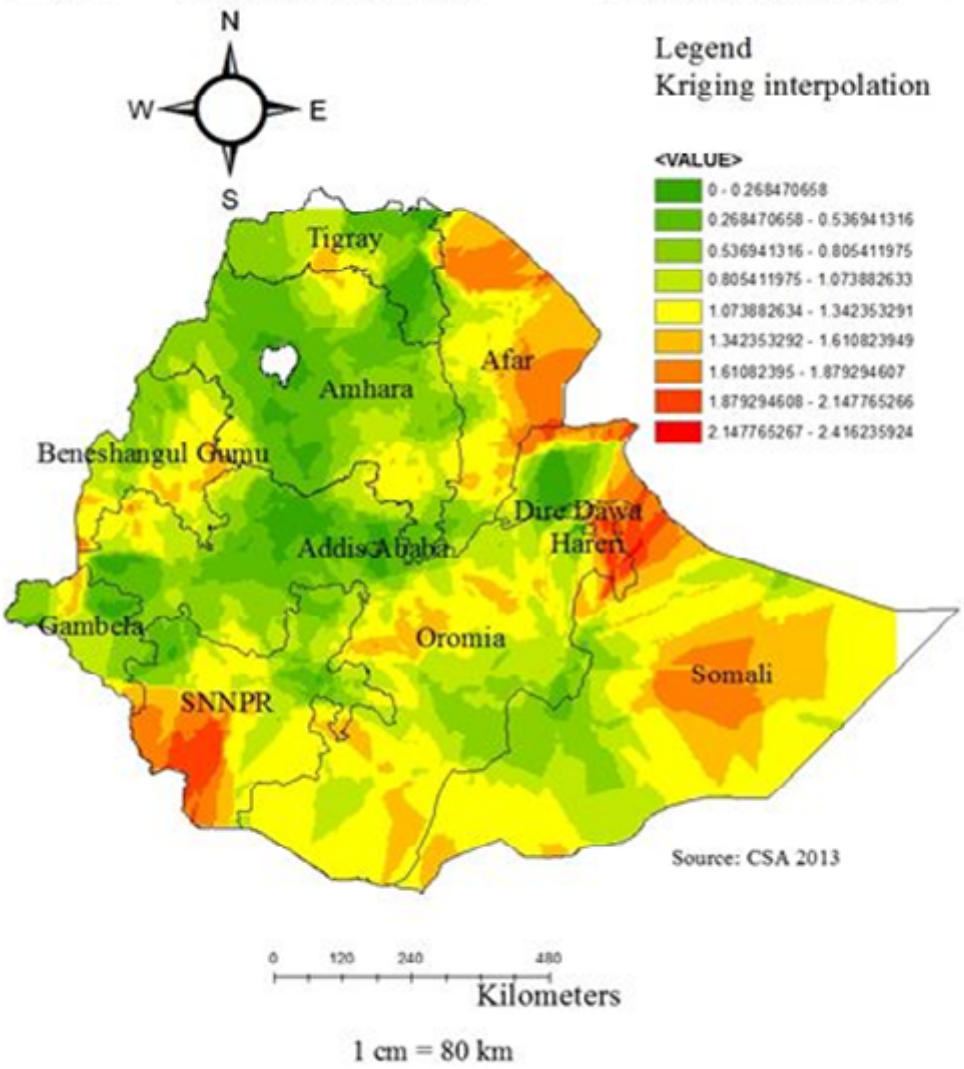


Fig . 10 Spatial distribution of the autocorrelation term: the autocovariate variable

Figure 10

The spatial distribution of the autocovariate variable in equation , which represents the spatial autocorrelation term in the GLMM. The autocovariate variable has the same unit as the dependent variable, which also represents the incidence of death occurrence, but it is just a macro spatial trend