



Review

A Scoping Review of Spatial Analysis Approaches Using Health Survey Data in Sub-Saharan Africa

Samuel Manda ^{1,2,3,*} , Ndamonaoghenda Haushona ^{1,4} and Robert Bergquist ⁵

¹ Biostatistics Research Unit, South African Medical Research Council, Pretoria 0001, South Africa; ndamonahaushona@gmail.com

² Department of Statistics, University of Pretoria, Pretoria 0002, South Africa

³ School of Mathematics, Statistics and Computer Science, University of KwaZulu-Natal, Pietermaritzburg 3209, South Africa

⁴ Division of Epidemiology and Biostatistics, University of Stellenbosch, Cape Town 8000, South Africa

⁵ Ingerod, SE-454 94 Brastad, Sweden; robert.bergquist@outlook.com

* Correspondence: samuel.manda@mrc.ac.za

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Abstract: Spatial analysis has become an increasingly used analytic approach to describe and analyze spatial characteristics of disease burden, but the depth and coverage of its usage for health surveys data in Sub-Saharan Africa are not well known. The objective of this scoping review was to conduct an evaluation of studies using spatial statistics approaches for national health survey data in the SSA region. An organized literature search for studies related to spatial statistics and national health surveys was conducted through PMC, PubMed/Medline, Scopus, NLM Catalog, and Science Direct electronic databases. Of the 4,193 unique articles identified, 153 were included in the final review. Spatial smoothing and prediction methods were predominant ($n = 108$), followed by spatial description aggregation ($n = 25$), and spatial autocorrelation and clustering ($n = 19$). Bayesian statistics methods and lattice data modelling were predominant ($n = 108$). Most studies focused on malaria and fever ($n = 47$) followed by health services coverage ($n = 38$). Only fifteen studies employed nonstandard spatial analyses (e.g., spatial model assessment, joint spatial modelling, accounting for survey design). We recommend that for future spatial analysis using health survey data in the SSA region, there must be an improve recognition and awareness of the potential dangers of a naïve application of spatial statistical methods. We also recommend a wide range of applications using big health data and the future of data science for health systems to monitor and evaluate impacts that are not well understood at local levels.

Keywords: spatial methods; disease mapping; health surveys; Sub-Saharan Africa

1. Introduction

Spatial analysis concerns the use of statistical methods to analyze spatial data by accounting for location-specific information, elevation, distance, spatial relationships and association between the data [1,2]. These methods are prominent statistical tools in the health and epidemiological sciences where the study of the impact of geographical distribution with respect to health data and outcomes is a major research undertaking. For example, the analysis may identify areas of elevated risk of a disease incidence and prevalence. Such a finding could generate scientific questions and hypotheses about the disease aetiology or provide enough supporting scientific evidence to guide public health recommendations on the disease and geography.

In the context of the United Nation's sustainable development goals (SDGs) to be achieved by 2030 [3], those related to ending poverty, terminating malnutrition and improving health in general are

of interest here. A focus across the SDG goals and targets is on monitoring progress at the sub-national level to avoid national-level statistics masking local heterogeneities. Increased focus on sub-national assessments, efficient targeting of resources and improved accuracy for health and development metrics have prompted an emphasis on the development of spatial analyses to provide estimates at lower national levels [4–6]. To meet the need of supporting local-level policies, the implementation and application of spatial techniques have grown exponentially in recent times. This has been made possible by a rise in the availability of nationally representative household and health survey data and high-performance computers to fit spatial statistics methods. Classic spatial statistics methods can now be fitted to larger and more complex spatial datasets in several spatial analysis computer software programs such as SaTScan [7], GeoDa [8] and ArcGIS [9]. Even Bayesian spatial inference, which was intractable before, is now routinely being used to analyze complex spatial models and datasets. Bayesian approaches rely on increased access to spatial statistics software, for example, BayesX [10], WinBUGS/OpenBUGS [11] and Integrated Nested Laplace Approximations (INLA) [12], all freely available applications.

On the other hand, health surveys such as demographic and health surveys (DHS), Malaria Indicator Surveys (MIS), AIDs Indicator Surveys (AIS) and Multiple Indicator Cluster Surveys (MICS) cover a wide range of health topics. Analyses of data from nationally representative households and population health surveys have been done and the findings have provided enough evidence to track the progress of health and socio-demographic indicators to meet local, national and international goals. Even though these surveys are implemented at comparatively enormous costs, their usage has remained sub-optimal since such analyses demand advanced data management and often complicated statistical techniques [13]. A comprehensive analysis using appropriate spatial statistical methods can provide appropriate supporting scientific evidence to guide policy recommendations on health disparities and place.

Even though the application of spatial statistics to map health outcomes and processes have grown in Sub-Saharan Africa (SSA) over the past two decades, reviews summarizing a body of research studies that have employed spatial analysis methods based on nationally representative health survey data are scarce. One previous review on spatial analysis methods on health issues in Africa only applied to HIV research and was general in its coverage of data sources [14]. We set out to review all published literature that employed spatial analysis techniques to nationally representative health survey data in the SSA region. An identification and a description of the spatial analysis methods, software and health discipline used in the applications of spatial statistics to health survey data would be useful to health science researchers including spatial statisticians. We also wanted to identify knowledge gaps and provide useful recommendations for carrying out improved spatial analysis using health survey data in the SSA region. A useful methodology for qualitatively exploring the content of literature through concepts and thematic mapping is conducted using scoping, as opposed to systematic, reviews [15].

2. Methods

2.1. Eligibility Criteria

Inclusion criteria: articles published in English during the period 1990–2018 employing spatial statistic methods in the SSA region to analyze nationally representative household and health survey data.

Exclusion criteria: articles published outside the 1990–2018 period and all publications based on data from health surveys conducted outside the SSA region, systematic reviews and meta-analyses, publications that only referenced health surveys but did not analyze the data obtained, studies that used non-nationally representative local or regional health surveys data and those that had utilized non-spatial statistical methods such as multilevel/random-effects models. Spatial analyses that used surveillance data were also excluded.

2.2. Search Methods

We conducted this scoping review according to the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) extension for Scoping Reviews (PRISMA-ScR) guidelines [16]. A Checklist for Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) is provided as supplementary material (Table S1). However, it has no published protocol. An organized literature search for articles that applied spatial statistical methods and that were published from 1990 to 2018 using data from household and population health surveys was done through PubMed Central (PMC), PubMed/Medline, Scopus, NLM Catalog, and Science Direct electronic databases. Three different searches were conducted for the three NLM literature resources (PMC, PubMed/Medline and NLM Catalog). Our search strategy was formulated using the following keywords to broaden the retrieval of relevant articles: spatial statistics; spatial modelling; spatial variation; small areas estimation; demographic and health survey; AIDS indicator survey; malaria indicator survey; multiple indicator cluster survey; health survey; Sub-Saharan Africa. The search strategy was built using Boolean operators “AND/OR” with keyword combinations, e.g., “spatial statistics” OR “spatial modelling” OR “spatial variation” OR “small areas estimation” OR “demographic health survey” OR “AIDS indicator survey” OR “malaria Indicator survey” OR “multiple indicator cluster survey” OR “health survey” OR “MIS” AND “sub-Saharan Africa”. Correspondingly, filters were applied to restrict our search to the inclusion criteria. A rigorous search of the Cochrane library was done to confirm whether there were existing or ongoing systematic reviews related to this review.

2.3. Study Selection

All potential studies retrieved were first imported to Mendeley and duplicates were removed. The remaining articles were imported to Covidence, a web-based systematic review software-designed process of screening, data extraction and analysis [17] for screening. Using the pre-specified inclusion criteria, the article’s titles and abstracts were screened by two independent reviewers. Articles deemed irrelevant were removed during the screening of abstracts and titles. For articles that could not be clearly depicted as relevant or irrelevant during the screening of abstracts and titles, their full-text articles were retrieved for further scrutiny. Full-text articles meeting the inclusion criteria were assessed further, and the following information answering the review’s objectives were abstracted from each paper: spatial statistical method and computer software packages used; data source; health discipline and themes; demographic group studied; and study country or countries. Discrepancies from independent reviewers were resolved through a discussion.

2.4. Data Extraction

Data extraction was performed using Microsoft Excel, which produced a master table with the following information extracted from each paper: spatial statistical methods and software; data source; public health outcomes and themes; and demographic focus groups. Spatial analysis techniques were categorized as spatial descriptive or aggregation method; spatial autocorrelation and clustering; spatial regression and interpolation and spatial modeling and prediction. The categories for health disciplines and themes were health service coverage; mortality; malaria and fever; diarrhea; malnutrition; non-communicable diseases; TB and HIV/AIDS; and others. Articles were permitted to be sorted into more than one methodological class and public health themes deemed appropriate. Counts and proportions were primarily used to summarize the study findings. The demographic focus groups were categorized into children (<15 years old) or adults (≥ 15 years of age) and gender. The study quality was not assessed.

3. Results

3.1. Study Characteristics

A total of 4193 unique articles were identified after excluding 4318 duplicates. Out of the remaining articles, 3992 were excluded because their abstracts and titles did not meet the eligibility requirements (Figure 1). From a full-text review of the remaining 201 articles a total of 153 were identified for the final review. The reasons for excluding 48 studies were that they had used non-spatial statistical methods (29 articles) or local or regional health survey data (18 articles), while one article was a systematic review (1 article).

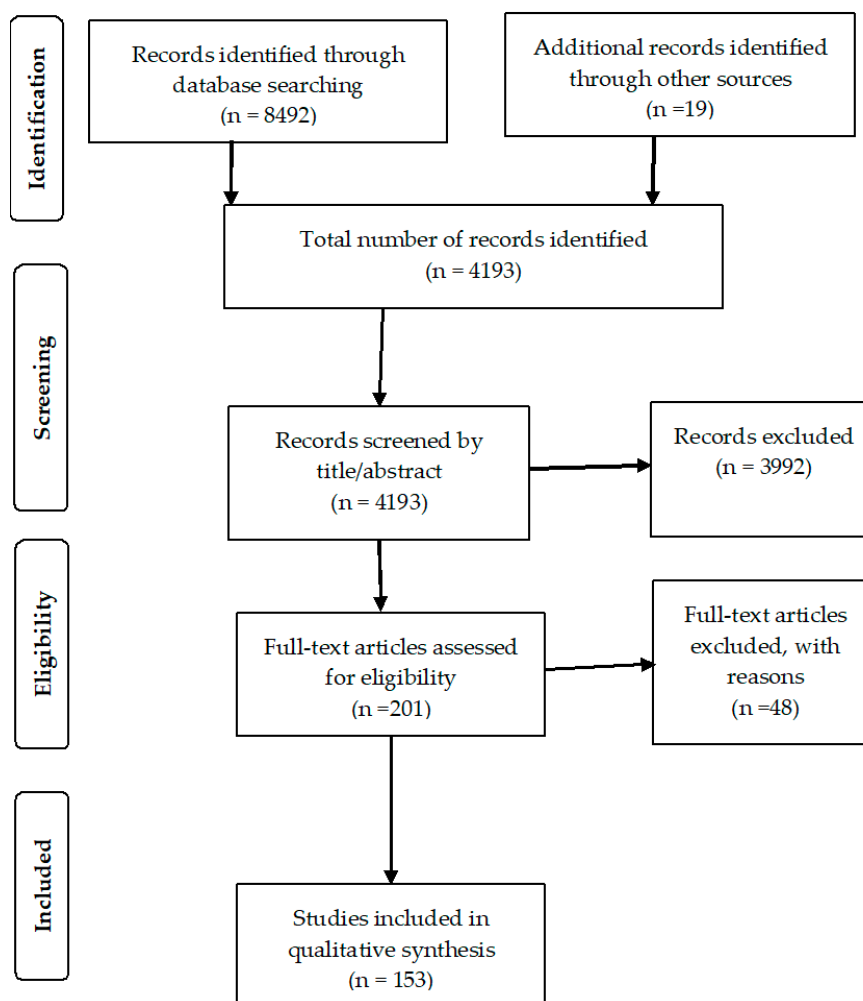


Figure 1. PRISMA flow diagram of the article selection process.

3.2. Spatial Methods Used

In the set of articles chosen for review, the spatial methods that were used for disease mapping are shown in Table 1. Spatial smoothing and predictions were frequently employed ($n = 108$) and of which 32 and 76 articles made use of geostatistical data modelling and lattice data modelling, respectively. Spatial description aggregation methods ($n = 25$) and statistical spatial autocorrelation or clustering ($n = 19$) were the next most used spatial analysis methods.

Most of the articles included in this review used data from DHS ($n = 93$). Country-specific surveys ($n = 23$), MIS ($n = 17$), MICS ($n = 5$), AIDS Indicator Surveys ($n = 4$) were used in the other papers, and 11 articles used data from multiple surveys. All these surveys used multistage sampling designs that encompasses stratification, cluster sampling, and unequal selection probabilities. These three complex

sample design considerations have implications for statistical analyses of the survey data. There were 37 multicounty studies and country-specific articles, Malawi and Nigerian each contributed 17 studies, followed by South Africa with 11 studies, then Kenya with 10 studies.

3.3. Spatial Autocorrelation/Clustering

Nineteen (19) studies used at least one spatial autocorrelation or clustering technique to assess non-random spatial patterns and quantify correlation of spatial observations (Table 1). Kulldorff's spatial scan statistics ($n = 7$), and Getis-Ord GI^* statistic ($n = 7$) were most frequently used, followed by Global Moran's I , Local Moran's I and Anselin Local Moran's I that were each used in three studies. K-function ($n = 1$) was also used (Table 2).

Table 1. Classification of the articles selected for review ($n = 153$).

Focus of the Publication	Number	Percentage	Reference
<i>Spatial Analysis Method</i>			
Description or Aggregation methods	25	16.3%	[4,18–41]
Autocorrelation/Clustering	19	12.4%	[42–60]
<i>Spatial Regression and Interpolation</i>			
Kriging	8	5.2%	[61–68]
Inverse Distance Weighting	1	0.7%	[69]
Weighted Kernel Regression	1	0.7%	[70]
Geographically Weighted Regression (GWR)	4	2.6%	[71–74]
<i>Spatial Smoothing and Prediction</i>			
Geostatistical data modelling	32	20.9%	[6,41,61,62,64–68,72,75–96]
Lattice data modelling	76	49.7%	[5,6,69–71,74,97–167]
<i>Application Techniques</i>			
Nonstandard applications (e.g., spatial analysis model assessment, joint spatial modelling, accounting for survey design)	15	9.8%	[5,6,74,122,123,128,132,142,150,151,153,155,157,159,160]
<i>Survey design and inadequacy</i>			
Survey design	4	2.6%	[74,122,153,160]
Non-response/missing	2	1.3%	[122,159]
<i>Computer Software Package</i>			
BayesX	32	20.9%	[88,108,110,113–120,123,124,127,129,131,133,135,138,140,142–145,147–150,154,156,161,167]
WINBUGS/OPENBUGS	23	15.0%	[47,61,65,67,75,80,91,92,104,112,119,123,128,130,134,142,146,147,155,159–161,165]
ArcGIS	29	19.9%	[22,23,28,31,39,42–46,48,49,51,53,54,57,58,71–73,75,76,98,101,103,105–107,109]
R-prev package	3	1.3%	[5,6,102]
QGIS	1	0.7%	[20]
GeoDA	4	2.6%	[21,43,59,71]
SaTSCAN	9	5.9%	[45,48,50–52,54,103,108,109]
R-survey and mgcv package	1	0.7%	[34]
ArcView	1	0.7%	[36]
MapInfo professional	2	1.3%	[47,104]
GeoR	1	0.7%	[59]
INLA	16	10.4%	[4,46,74,82,89,93–95,122,126,132,134,136,139,162,163]
Own code: Fortran	4	3.0%	[63,64,68,78]

Table 1. Cont.

Focus of the Publication	Number	Percentage	Reference
<i>Study Population</i>			
<i>Age group</i>			
Children (<15 years old)	82	53.6%	[19,21,25,27,29,31,33,35,37,40,42–45,54–57,60–62,64–68,70,71,75,76,79,81,84,86,87,89,91,92,94,95,98,101,104,106,110–113,115,117–122,125–127,131–146,154–157,161–163,167]
Adults (≥15 years old)	50	32.7%	[4–6,18,22,23,28,30,32,34,36,39,43,46–50,52,58,63,65,69,74,83,85,96,97,99,100,102,105,107–109,114,116,123,124,128,129,147–151,153,158–160]
All age groups	17	11.1%	[20,24,26,38,53,72,77,80,82,88,90,103,130,152,165–167]
<i>Gender</i>			
Male	1	0.7%	[34]
Female	23	15%	[18,23,28,32,36,46,58,59,74,88,96,99,100,107,109,114,116,124,128,148,150,154,160]
Both genders	125	81.6%	[4–6,19–22,24–27,29–31,33,35,37–45,47–57,60,62–73,75–79,81–87,89–95,97,98,101–106,108,110–113,115,117–123,125–127,129–146,149,151–153,155–159,161–167]
<i>Health Surveys</i>			
Demographic Health Survey	93	60.8%	[4,5,18,20–23,25–28,30,33,36,38–40,42,44,45,48–50,52,54–62,68,69,71,76,81,82,85–88,95,97–100,102,103,105,106,109–111,113,115,116,118,120–124,127,129,131,133,135,137,140–144,146–148,150,151,153–159,162,163,167]
Malaria Indicator Survey	17	11.1%	[31,37,60,63,64,67,70,77–80,89,92,93,101,107,136]
Multiple Indicator Cluster Survey	5	3.3	[75,113,125,140,145]
AIDS Indicator survey	4	2.6%	[74,153,160,166]
Multi-Surveys	12	7.8%	[6,20,24,53,66,90,96,108,119,130,159,165]
Country-Specific Surveys	23	15.0%	[29,32,43,46,47,51,65,72,73,82,83,91,96,104,112,126,128,132,134,139,149,152,164]
<i>Country of Study</i>			
Angola	1	0.7%	[78]
Burkina Faso	3	2%	[88,89,134]
Cameroon	2	1.3%	[103,119]
Democratic Republic of Congo	9	6.5%	[30,38,42,69,98,114,120,127,138]
Ethiopia	7	4.6%	[45,50,55,58,105,109,167]
Equatorial Guinea	1	0.7%	[51]
Egypt	1	0.7%	[140]
Ghana	2	1.3%	[4,29]
Kenya	10	6.5%	[20,31,34,46,72,74,90,122,153,160]
Lesotho	2	1.3%	[22,97]
Madagascar	1	0.7%	[136]
Malawi	17	11.1%	[77,102,110,113,114,120,121,123,133,134,145,154,156–158,161,162]

Table 1. Cont.

Focus of the Publication	Number	Percentage	Reference
Mali	1	0.7%	[68]
Mozambique	2	1.3%	[32,43]
Multi-Country	37	24.2%	[5,6,10,19–22,24–26,28,33,37,39,40,44,48,49,53,54,60–62,66,71,76,83,84,86,87,91,95,96,119,144,163,165]
Namibia	2	1.3%	[101,155]
Nigeria	17	11.1%	[32,46,77,83,87,97,111,114,125,126,130,134,136,138,139,143,144]
Rwanda	3	2.0%	[97,100,116]
Senegal	2	1.3%	[81,82]
Somalia	5	3.3%	[75,126,132,139,164]
South Africa	11	6.5%	[47,52,73,104,123,128,146,147,150–152]
Sudan	1	0.7%	[130]
Tanzania	4	2.6%	[63,70,106,166]
Uganda	6	3.9%	[56,57,65,67,92,108]
Zambia	5	3.3%	[80,93,96,107,129]
Zimbabwe	2	1.3%	[36,119]

INLA: Integrated Nested Laplace Approximations.

Table 2. Main spatial analysis techniques used in data analysis.

Method Category	Method	No. of References	Reference
Spatial Clustering and regression	Global Moran's <i>I</i>	3	[42,44,45]
	Local Moran's <i>I</i> (LISA)	3	[30,46,47]
	Kulldorff's spatial scan statistic	7	[45,48–50,52–54]
	Getis-Ord G_i^* statistic	7	[43,45,51,55–58]
	Anselin Local Moran's <i>I</i>	3	[44,45,59]
	K-function	1	[60]
	Spatial Prediction and Interpolation	10	[61–70]
Spatial modelling and prediction	Generalized Weighted Regression	4	[71–74]
	Bayesian geostatistical models	32	[6,41,61,62,64–68,72,75–96]
	Bayesian conditional autoregressive (CAR) models	76	[5,6,69–71,74,97–167]
	Joint modelling	12	[5,74,126,128,132,142,150,151,155,157,159,160]

3.4. Spatial Modelling and Prediction

Of the 153 studies included in this review, most—138(90.1%)—used a standard or routine application of spatial methods. These involved studies that used spatial analysis methods embedded in GIS or spatial statistics software to measure spatial clustering and cluster detection and perform spatial modelling and predictions. Numerous studies (122 articles) used spatial modelling to describe relationships between the spatial health data and contextual factors to model and predict health data in space (Tables 1 and 2). Out of these 122 studies, 76 (62.3%) concentrated on lattice data modelling, while 32 (26.2%) dealt with geostatistical data modelling. Almost all lattice and geostatistical analyses were implemented using Bayesian statistics. Only 15 studies endeavored to perform the spatial analysis using nonstandard methods (including joint spatial models and model assessment) or accounted for the survey design. Regarding spatial statistics software packages, BayesX was commonly used ($n = 32$) for modelling and prediction, followed by ArcGIS ($n = 29$), WINBUGS/OPENBUGS ($n = 23$), Integrated Laplace Approximation package ($n = 16$), and SaTSCAN ($n = 9$).

3.5. Spatial Methods Used

In this scoping review, several spatial statistical methods have been used in the extracted publications. These methods include descriptive spatial methods where features within a given area

are simply summarized as totals or averages and then presented on that area (these are aggregation methods). These methods pose a challenge in the choice of the underlying population exposed, which may be problematic in SSA where data on population totals could be inadequate. Several forms of identifying specific observations or areas exhibiting spatial autocorrelation or clustering with their neighbors have been identified in the extracted articles. The spatial autocorrelation statistics methods employed included classic global statistics, such as Moran's *I*, Geary's *C* and Getis's *G* [168,169], which estimate the overall degree of spatial autocorrelation in a dataset. They test for the presence and absence of non-random spatial patterns across the whole studied geographic area. On the other hand, local spatial autocorrelation analysis (also known as hotspot analysis) provides estimates disaggregated to the level of the spatial analysis units to identify local regions of strong autocorrelation. These are often identified by equivalent local spatial autocorrelation measures of Moran's *I*, Geary's *C* and Getis's *G*. However, the most commonly used hotspot analysis is based on Anselin's local indicator of spatial association (LISA) [168] and Kulldorff's spatial scan statistic [170].

The widely used spatial statistics methods are the spatial regression (e.g., spatial lag in observed data and error terms, and geographically weighted regression (GWR)), spatial smoothing, and spatial interpolation, often employed by spatial epidemiologists to improve the estimation of health outcomes and burden. These methods have tools for deriving spatial surfaces from sampled data points or to smooth across polygons to create more robust estimates. Spatial interpolation or spatial prediction methods incorporate geographic information and values at a network of observed locations to estimate values at unobserved locations. In the traditional spatial analysis, the main spatial interpolation techniques include inverse distance weighting (IDW), Kriging, spline interpolation, and interpolating polynomials [171,172]. However, as the evidence shows, Bayesian spatial hierarchical modelling is becoming more effective than the conventional classical spatial analysis method, thanks to advanced computing power and Markov chain Monte Carlo (MCMC) methods [173]. They are now routinely being applied to model complex spatial relationships in large and multiple datasets using Bayesian statistical packages, which are freely available [10–12]. Most of the applications of disease mapping have been based on modelling lattice and "geostatistical" data. The former uses the so-called convolution model of Besag, York and Mollie (BYM) [174] and the latter uses the distance-based geostatistical model as expounded Diggle et al. [175].

3.6. Health Discipline and Themes

Before reviewing the articles included in this review, a list of research topics reflecting major health problems or themes in the SSA region was drawn. Eight major research themes were identified (Table 3). Some publications included at least two public health themes. Malaria or fever were predominately studied ($n = 47$), followed by health services/interventions coverage ($n = 38$), HIV/AIDS ($n = 24$), and mortality ($n = 21$).

Table 3. Application areas of spatial methods.

Health Discipline	Frequency
Mortality	21
Malaria and fever	47
HIV/AIDS	24
Non-communicable diseases	9
Malnutrition	12
Diarrhoea	7
Health services coverage	38
Other *	5

* birth intervals; sexual debut; schistosomiasis; pneumonia.

3.7. Demography

More than half (54.9%) of the articles focused on populations aged less than 15 years, about 34.6% were aged above or equal to 15 years and 10.5% of the articles included all age groups (Table 1). We found limited literature items focusing on public health issues concerning males (<1%) and females (15%) exclusively, as most articles (84.3%) did not differentiate between the genders.

4. Discussion

This scoping review has demonstrated a variety of applications of spatial analysis techniques to household and health survey data in the SSA region. Spatial smoothing and prediction using Bayesian spatial statistics were predominantly used. Spatial autocorrelation and cluster detection were mostly fitted using frequentist methods and routines in GIS software. The most frequently studied health disciplines were malaria and fever followed by health services coverage and HIV/AIDS and health-related to mother and child health.

Despite the wide application of spatial methods in SSA, studies that only concentrated on men were scant (<1%). Additionally, there was a lack of studies concentrating on health program evaluation, possibly because data in this field might be sparse or not well captured in nationally representative health surveys. Most studies failed to account for complex survey design and data insufficiency, possibly due to data inadequacy about non-response, defective sampling frames, and missing information in addition to adjustments for clustering to ensure data representativeness and unbiased inferences. Few studies have developed and applied spatial statistics methods accounting for health survey design, but these were for data outside of SSA [176–179]. There is a lack of systematic and rigorous interrogation of spatial statistics, survey data, and software despite the need for new spatial analysis methods for validation, diagnostics, and predictions. Thus, the utilization of rich survey data sets remains sub-optimal because optimal analyses of such data demand in-depth assessment and the process and design collection of this kind of data must first be further developed. Most have tended to base their study papers with a “data analysts” mindset, with a heavy reliance on the implementation of developed biostatistics techniques in the widely available statistical software. Seldom have the authors thought critically around the development and validation of methods relevant to the problem being investigated. There will be a need for biostatistical expertise in analytical and innovative research, as well as adaptive skills to manage, analyze, and generate the data needed, including the use of existing data, to inform policymakers and local health service implementers [180]. A lack of these biostatistical skills could adversely affect the extent to which analyses and formulation of locally relevant scientific questions have been undertaken [5].

4.1. Limitations

Though the review was conducted adhering to PRIMSA-ScR guidelines, the search strategy used strategy might have missed studies that focused on some countries in SSA because our research included the term SSA only. We excluded studies that analysed health survey data, but the surveys were not nationally representative. We also did not interrogate sufficiently the methods used and the resulting findings. Most of the studies failed to account for the complex sampling design, which could have influenced the findings and conclusions drawn because standard spatial analyses generally underestimate the estimated variance of spatial estimates. Indeed, blind usage of available packages may adversely affect the extent to which analyses follow PRIMSA-ScR guidelines, and our search strategy might have missed studies that deployed spatial analysis techniques because we excluded papers published in languages other than English. There might also have been a risk of publication bias, which we did not assess. This review also excluded published research work that used spatial analyses on sentinel surveillance data. For example, spatial autocorrelation and inverse distance-weighted interpolation were used in [171–183] when spatial statistics were used to analyze HIV data of pregnant women attending antennal clinics (not health surveys).

4.2. Strengths

To the best of our knowledge, this is the first review to provide the range and depth of published studies using spatial analysis techniques to analyze the rich data obtained in nationally representative health surveys conducted in the SSA region. It includes health disciplines, themes and demographic information covering almost 30 years (1990–2018). Our findings demonstrate a wide range of applications of spatial analysis techniques dominated by modelling and prediction approaches based on Bayesian geostatistical and lattice data modelling.

4.3. Recommendations

Sample survey software should be used, especially for estimation of population parameters, and for descriptive and analytical analyses. Under certain circumstances, standard statistical packages can be used to provide results approximately equal to the results obtained from sample survey software. However, recognition of prevailing circumstances and an awareness of the potential pitfalls of using standard statistical packages require detailed information about the characteristics of the survey dataset used (e.g., sampling plan, weighting scheme, intra-cluster correlation) as well as a knowledge of the formulas and default options in standard software packages for weighted analyses. In the end, it seems easier and less time consuming to use a sample survey software package throughout.

Advanced analytical, innovative, and adaptive skills in spatial statistics should be used to manage and analyze existing survey data to better inform policymakers and local health service implementers. Indeed, new spatial methods might need to be developed for applications. We recommend a wide range of implementation examples from big health data, data future science and health systems to monitor and evaluate health program impacts, which are not well understood at the local level. Gender-specific studies focusing on an assessment of health interventions need to be conducted in the SSA region to provide further insights and enable profoundly informed decisions to improve public health concerning new areas of direction and research in SSA. Other obstacles in the region include the financial costs to obtain new data, the prolonged time before data become available for public use due to slow publication and/or bureaucratic processes that hinder data access and use.

Rigorous and coherent quality assessment of survey data is highly important, including design and coverage of sampling. Survey comparisons were often made when sample sizes, item measurement and context varied across years and were at times substantially and not necessarily congruent with national population numbers. Also, age ranges of respondents for the same data items differed across surveys, or across years within a survey. More could have been gained in studies had attempted to tackle key issues including data quality, data and methods triangulation and validation. A challenging, but potentially very fruitful undertaking could come from integrating household surveys with data from routine health information gathering, monitoring and surveillance systems. A focused agenda is recommended for data triangulation and contestability via linkage and validation studies that would allow drawing on complementary properties of different sources, assist in completeness estimations and improve our understanding of the accuracy attribution in the phenomena being studied. Such improved understanding holds clear gains for improved small area estimates, enhanced resource and service distribution, and, eventually, better meeting the health needs of the population.

Refinements of spatial methods and mapping levels are needed, e.g., by updating accessibility layers to include more recent and detailed road networks and settlement layers. This could also involve modelling key driving factors of the phenomena under study, such as poverty or access to sanitation, and then using these as covariates themselves. The effect that a country-specific focus, tailored as much as possible to a specific indicator, can have on mapping accuracies rather than using globally consistent covariates should be explored. Also, many socio-economic factors, not captured by the suite of covariates used, and often available at aggregate levels such as administrative units, could be obtained and their ability to improve mapping accuracy tested. The rising international focus on inequalities in the SDG-era requires a detailed and strong evidence base with an explicit quantification of uncertainties. Some studies provided sufficiently accurate prediction at an administrative unit that

is relevant for policymaking and the allocation of resources. However, none of the studies looked at the issue of the Modifiable Areal Unit Problem (MAUP) in spatial analyses where an analysis based on a grouping unit may accidentally misrepresent or overstate actual risk variations [184]. Even if the data are grouped at the same level for analysis, the way the grouping scheme is used for spatial analysis may accidentally lead to misinterpretation of the spatial patterns. We recommend that studies consider, as part of sensitivity analysis, changing boundaries of levels to assess changes to the overall spatial patterns in the estimated phenomena.

Finally, we have already discussed at length how non-response, missing data, and self-reporting of health conditions pose statistical challenges when estimating small area spatial health variation. Missing data reduces the representativeness of the sample and can, therefore, distort the spatial inferences about a health measure. Perhaps a major feature of these survey data is their representativeness at national and regional levels, but not at the lower geographic level, which may not have been systemically covered sufficiently. Reliable estimates are highly associated with the number of observations falling into these lower levels. Conducting surveys that could generate representative data at the desired geographic level would be highly costly (due to an increase in sample sizes). Others have recommended choosing an appropriate spatial model after performing a systematic evaluation and validation of several spatial models for generating small area estimates [3–6]. Yet others have been novel by developing and validating non-standard spatial models, for example, those based on multivariate spatial models to model multiple health phenomena [95,105,153,154].

5. Conclusions

Comparisons and assessments of public health interventions and control programs at the sub-national level based on health survey data should consider survey design aspects when undertaking spatial analyses. Additionally, future research should focus on developing and evaluating spatial methods that leverage survey data in providing local estimates of health burdens. Several recommendations are made in this scoping review but most of them require strong skills and analytic capacity. Thus, further expansion and strengthening of analytic capacity in the development and application of spatial analysis methods relating to health survey data constitute the main message of our critical and overarching recommendation.

Supplementary Materials: The following are available online at <http://www.mdpi.com/1660-4601/17/9/3070/s1>, Table S1: Checklist for Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist.

Author Contributions: S.M. conceived and conceptualize the study design and methodology, contributed to interpretation of selected articles, writing and editing and provided critical insight. N.H. carried out the scoping review, information extraction and drafted the original version of the paper. R.B. contributed to writing and critical insight. All authors contributed to the revision of the manuscript. All authors have read and agree to the published version of the manuscript.

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References

1. Cressie, N.; Wikle, C.K. *Statistics for Spatio-Temporal Data*; Wiley: Hoboken, NJ, USA, 2011.
2. Bergquist, R.; Manda, S. The world in your hands: GeoHealth then and now. *Geospat. Health* **2019**, *14*, 3–16. [[CrossRef](#)] [[PubMed](#)]
3. United Nations Department of Economic and Social Affairs (UN DESA). *The Sustainable Development Goals Report 2016*; UN: New York, NY, USA, 2016.
4. Abekah-Nkrumah, G. Spatial variation in the use of reproductive health services over time: A decomposition analysis. *BMC Pregnancy Childbirth* **2018**, *18*, 63. [[CrossRef](#)] [[PubMed](#)]

5. Subnational Estimates Working Group of the HIV Modelling Consortium. Evaluation of geospatial methods to generate subnational HIV prevalence estimates for local level planning. *AIDS* **2016**, *30*, 1467–1474. [[CrossRef](#)] [[PubMed](#)]
6. Larmarange, J.; Bendaud, V. HIV estimates at second subnational level from national population-based surveys. *AIDS* **2014**, *28* (Suppl. 4), S469–S476. [[CrossRef](#)]
7. Kulldorff, M.; Information Management Services, Inc. SaTScan™ v8.0: Software for the Spatial and Space-Time Scan Statistics. Available online: <http://www.satscan.org/> (accessed on 1 October 2019).
8. GeoDa Center for Geospatial Analysis and Computation. *GeoDa and Methods for Geospatial Analysis*; Arizona State University: Tempe, AZ, USA, 2010; Available online: <http://geodacenter.asu.edu/> (accessed on 15 February 2020).
9. Esri. *ArcGIS Desktop Version 10.1*; Environmental Systems Research Institute: Redlands, CA, USA, 2011.
10. Belitz, C.; Brezger, A.; Kneib, T.; Lang, S. BayesX Methodology Manual. 2003. Available online: <https://pdfs.semanticscholar.org/346d/56bb6aa017a043a8a9e19e619430e68838a6.pdf> (accessed on 19 October 2019).
11. Lunn, D.; Thomas, A.; Best, N.; Spiegelhalter, D. WinBUGS—A Bayesian modelling framework: Concepts, structure, and extensibility. *Stat. Comput.* **2000**, *10*, 325–337. [[CrossRef](#)]
12. Rue, H.; Martino, S.; Chopin, N. Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *J. R. Stat. Soc. Ser. B Stat. Methodol.* **2009**, *71*, 319–392. [[CrossRef](#)]
13. Manda, S.O.M.; Kandala, N.B.; Ghilagaber, G. Advanced Techniques for Modelling Maternal and Child Health in Africa. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N., Ghilagaber, G., Eds.; Springer: Berlin/Heidelberg, Germany, 2014; pp. 1–7.
14. Boyda, D.C.; Holzman, S.B.; Berman, A.; Grabowski, M.K.; Chang, L.W. Geographic Information Systems, spatial analysis, and HIV in Africa: A scoping review. *PLoS ONE* **2019**, *14*, e0216388. [[CrossRef](#)]
15. Munn, Z.; Peters, M.; Stern, C.; Tufanaru, C.; McArthur, A.; Aromataris, E. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC Med. Res. Methodol.* **2018**, *18*, 143. [[CrossRef](#)]
16. Tricco, A.C.; Lillie, E.; Zarin, W.; O’Brien, K.K.; Colquhoun, H.; Levac, D.; Moher, D.; Peters, M.D.M.; Horsley, Y.; Weeks, L.; et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann. Intern. Med.* **2018**, *169*, 467–473. [[CrossRef](#)]
17. Veritas Health Innovation. *Covidence Systematic Review Software*; Veritas Health Innovation: Melbourne, Australia, 2019.
18. Hounton, S.; Winfrey, W.; Barros, A.J.D.; Askew, I. Patterns and trends of postpartum family planning in Ethiopia, Malawi, and Nigeria: Evidence of missed opportunities for integration. *Glob. Health Action* **2015**, *8*, 29738. [[CrossRef](#)]
19. Nubé, M.; Sonneveld, B.G.J.S. The geographical distribution of underweight children in Africa. *Bull. World Health Organ.* **2005**, *83*, 764–770. [[PubMed](#)]
20. Brdar, S.; Gavrić, K.; Čulibrk, D.; Crnojevic, V. Unveiling Spatial Epidemiology of HIV with Mobile Phone Data. *Sci. Rep.* **2016**, *6*, 19342. [[CrossRef](#)] [[PubMed](#)]
21. Yourkavitch, J.; Burgert, C.; Assaf, S.; Delgado, S. Using geographical analysis to identify child health inequality in sub-Saharan Africa. *PLoS ONE* **2018**, *13*, e0201870. [[CrossRef](#)] [[PubMed](#)]
22. Okano, J.T.; Okano, J.T.; Blower, S. Using geospatial mapping to design HIV elimination strategies for sub-Saharan Africa. *Sci. Transl. Med.* **2017**, *9*, eaag0019. [[CrossRef](#)]
23. Ruktanonchai, C.W.; Ruktanonchai, N.W.; Nove, A.; Lopes, S.; Pezzulo, C.; Bosco, C.; Alegana, V.A.; Burgert, C.R.; Ayiko, R.; Charles, A.S.E.K.; et al. Equality in Maternal and Newborn Health: Modelling Geographic Disparities in Utilisation of Care in Five East African Countries. *PLoS ONE* **2016**, *11*, e0162006.
24. VanderElst, D.; Speybroeck, N. An adjusted bed net coverage indicator with estimations for 23 African countries. *Malar. J.* **2013**, *12*, 457. [[CrossRef](#)]
25. Tenikue, M.; Shapiro, D.; Tenikue, M. Women’s education, infant and child mortality, and fertility decline in urban and rural sub-Saharan Africa. *Demogr. Res.* **2017**, *37*, 669–708.
26. Tansley, G.; Schuurman, N.; Amram, O.; Yanchar, N. Spatial Access to Emergency Services in Low- and Middle-Income Countries: A GIS-Based Analysis. *PLoS ONE* **2015**, *10*, e0141113. [[CrossRef](#)]
27. Burroway, R.; Hargrove, A. Education is the antidote: Individual- and community-level effects of maternal education on child immunizations in Nigeria. *Soc. Sci. Med.* **2018**, *213*, 63–71. [[CrossRef](#)]

28. Chikandiwa, A.; Burgess, E.; Otwombe, K.; Chimoyi, L. Use of contraceptives, high risk births and under-five mortality in Sub Saharan Africa: Evidence from Kenyan (2014) and Zimbabwean (2011) demographic health surveys. *BMC Womens Health* **2018**, *18*, 173. [[CrossRef](#)]
29. Bosomprah, S.; Tatem, A.J.; Dotse-Gborgbortsi, W.; Aboagye, P.; Matthews, Z. Spatial distribution of emergency obstetric and newborn care services in Ghana: Using the evidence to plan interventions. *Int. J. Gynecol. Obstet.* **2015**, *132*, 130–134. [[CrossRef](#)] [[PubMed](#)]
30. Carrel, M.; Janko, M.; Mwandagalirwa, M.K.; Morgan, C.; Fwamba, F.; Muwonga, J.; Tshetu, A.K.; Meshnick, S.; Emch, M. Changing spatial patterns and increasing rurality of HIV prevalence in the Democratic Republic of the Congo between 2007 and 2013. *Health Place* **2016**, *39*, 79–85. [[CrossRef](#)] [[PubMed](#)]
31. Gitonga, C.W.; Karanja, P.; Kihara, J.; Mwanje, M.T.; Juma, E.; Snow, R.W.; Noor, A.; Brooker, S. Implementing school malaria surveys in Kenya: Towards a national surveillance system. *Malar. J.* **2010**, *9*, 306. [[CrossRef](#)]
32. Brodish, P.H.; Singh, K. Association between Schistosoma haematobium Exposure and Human Immunodeficiency Virus Infection among Females in Mozambique. *Am. J. Trop. Med. Hyg.* **2016**, *94*, 1040–1044. [[CrossRef](#)] [[PubMed](#)]
33. Østby, G.; Urdal, H.; Tollefsen, A.F.; Kotsadam, A.; Belbo, R.; Ormhaug, C. Organized Violence and Institutional Child Delivery: Micro-Level Evidence From Sub-Saharan Africa, 1989v2014. *Demography* **2018**, *55*, 1295–1316. [[CrossRef](#)] [[PubMed](#)]
34. Akullian, A.; Onyango, M.; Klein, D.; Odhiambo, J.; Bershteyn, A. Geographic coverage of male circumcision in western Kenya. *Medicine* **2017**, *96*, e5885. [[CrossRef](#)]
35. Kotsadam, A.; Østby, G.; Rustad, S.A.; Tollefsen, A.F.; Urdal, H. Development aid and infant mortality. Micro-level evidence from Nigeria. *World Dev.* **2018**, *105*, 59–69. [[CrossRef](#)]
36. Gonese, E.; Dzangare, J.; Gregson, S.; Jonga, N.; Mugurungi, O.; Mishra, V. Comparison of HIV Prevalence Estimates for Zimbabwe from Antenatal Clinic Surveillance (2006) and the 2005–06 Zimbabwe Demographic and Health Survey. *PLoS ONE* **2010**, *5*, e13819. [[CrossRef](#)]
37. Pond, B.S. Malaria indicator surveys demonstrate a markedly lower prevalence of malaria in large cities of sub-Saharan Africa. *Malar. J.* **2013**, *12*, 313. [[CrossRef](#)]
38. Carrel, M.; Patel, J.; Taylor, S.M.; Janko, M.; Kashamuka, M.; Tshetu, A.K.; Escalante, A.A.; McCollum, A.; Alam, M.T.; Udhayakumar, V.; et al. Social Science & Medicine The geography of malaria genetics in the Democratic Republic of Congo: A complex and fragmented landscape. *Soc. Sci. Med.* **2014**, *133*, 233–241.
39. Cuadros, D.F.; Li, J.; Branscum, A.J.; Akullian, A.; Jia, P.; Mziray, E.N.; Tanser, F. Mapping the spatial variability of HIV infection in Sub-Saharan Africa: Effective information for localized HIV prevention and control. *Sci. Rep.* **2017**, *7*, 9093. [[CrossRef](#)] [[PubMed](#)]
40. Soares, R.J.; Ca, A. Spatial heterogeneity of haemoglobin concentration in preschool-age children in sub-Saharan Africa. *Bull. World Health Organ.* **2011**, *89*, 459–468. [[CrossRef](#)] [[PubMed](#)]
41. Noor, A.; Mutheu, J.J.; Tatem, A.J.; Hay, S.; Snow, R.W. Insecticide-treated net coverage in Africa: Mapping progress in 2000–07. *Lancet* **2008**, *373*, 58–67. [[CrossRef](#)]
42. Taylor, S.M.; Messina, J.P.; Hand, C.C.; Juliano, J.J.; Muwonga, J.; Tshetu, A.K.; Atua, B.; Emch, M.; Meshnick, S. Molecular Malaria Epidemiology: Mapping and Burden Estimates for the Democratic Republic of the Congo, 2007. *PLoS ONE* **2011**, *6*, e16420. [[CrossRef](#)] [[PubMed](#)]
43. Yao, J.; Murray, A.T.; Agadjanian, V.; Hayford, S.R. Geographic influences on sexual and reproductive health service utilization in rural Mozambique. *Appl. Geogr.* **2011**, *32*, 601–607. [[CrossRef](#)] [[PubMed](#)]
44. Brownwright, T.; Dodson, Z.; Van Panhuis, W. Spatial clustering of measles vaccination coverage among children in sub-Saharan Africa. *BMC Public Health* **2017**, *17*, 957. [[CrossRef](#)] [[PubMed](#)]
45. Bogale, G.G.; Alemu, K.; Degefe, D.T.; Gelaw, Y.A. Spatial patterns of childhood diarrhea in Ethiopia: Data from Ethiopian demographic and health surveys (2000, 2005, and 2011). *BMC Infect. Dis.* **2017**, *17*, 426. [[CrossRef](#)]
46. O'Meara, W.P.; Platt, A.C.; Naanyu, V.; Cole, D.C.; Ndege, S. Spatial autocorrelation in uptake of antenatal care and relationship to individual, household and village-level factors: Results from a community-based survey of pregnant women in six districts in western Kenya. *Int. J. Health Geogr.* **2013**, *12*, 55. [[CrossRef](#)]
47. Sartorius, B.; Sartorius, K. Identifying and Targeting Mortality Disparities: A Framework for Sub-Saharan Africa Using Adult Mortality Data from South Africa. *PLoS ONE* **2013**, *8*, e71437. [[CrossRef](#)]
48. Cuadros, D.F.; Abu-Raddad, L.J. Geographical Patterns of HIV Sero-Discordancy in High HIV Prevalence Countries in Sub-Saharan Africa. *Int. J. Environ. Res. Public Health* **2016**, *13*, 865. [[CrossRef](#)]

49. Cuadros, D.F.; Awad, S.F.; Abu-Raddad, L.J. Mapping HIV clustering: A strategy for identifying populations at high risk of HIV infection in sub-Saharan Africa. *Int. J. Health Geogr.* **2013**, *12*, 28. [[CrossRef](#)]
50. Lakew, Y.; Benedict, S.; Haile, D. Social determinants of HIV infection, hotspot areas and subpopulation groups in Ethiopia: Evidence from the National Demographic and Health Survey in 2011. *BMJ Open* **2015**, *5*, 008669. [[CrossRef](#)] [[PubMed](#)]
51. Gómez-Barroso, D.; García-Carrasco, E.; Herrador, Z.; Ncogo, P.; Romay-Barja, M.; Eka, M.; Nseng, G.; Rivas, M.R.; Santana, M.A.; Valladares, B.; et al. Spatial clustering and risk factors of malaria infections in Bata district, Equatorial Guinea. *Malar. J.* **2017**, *16*, 146. [[CrossRef](#)] [[PubMed](#)]
52. Namosha, E.; Sartorius, B.; Tanser, F. Spatial Clustering of All-Cause and HIV-Related Mortality in a Rural South African Population (2000–2006). *PLoS ONE* **2013**, *8*, e69279. [[CrossRef](#)] [[PubMed](#)]
53. Cuadros, D.F.; Abu-Raddad, L.J. Spatial variability in HIV prevalence declines in several countries in sub-Saharan Africa. *Health Place* **2014**, *28*, 45–49. [[CrossRef](#)]
54. Dunn, G.; Johnson, G.D. Spatial and Spatio-temporal Epidemiology The geo-spatial distribution of childhood diarrheal disease in West Africa, 2008–2013: A covariate-adjusted cluster analysis. *Spat. Spatio-Temporal Epidemiol.* **2018**, *26*, 127–141. [[CrossRef](#)]
55. Haile, D.; Azage, M.; Molla, T.; Rainey, R. Exploring spatial variations and factors associated with childhood stunting in Ethiopia: Spatial and multilevel analysis. *BMC Pediatr.* **2016**, *16*, 36. [[CrossRef](#)]
56. Hirai, M.; Roess, A.; Huang, C.; Graham, J. Exploring geographic distributions of high-risk water, sanitation, and hygiene practices and their association with child diarrhea in Uganda. *Glob. Health Action* **2016**, *9*, 32833. [[CrossRef](#)]
57. Turi, K.N.; Christoph, M.J.; Grigsby-Toussaint, D. Spatial Distribution of Underweight, Overweight and Obesity among Women and Children: Results from the 2011 Uganda Demographic and Health Survey. *Int. J. Environ. Res. Public Health* **2013**, *10*, 4967–4981. [[CrossRef](#)]
58. Lakew, Y.; Reda, A.A.; Tamene, H.; Benedict, S.; Deribe, K. Geographical variation and factors influencing modern contraceptive use among married women in Ethiopia: Evidence from a national population based survey. *Reprod. Health* **2013**, *10*, 52. [[CrossRef](#)]
59. Uthman, O.A. Geographical variations and contextual effects on age of initiation of sexual intercourse among women in Nigeria: A multilevel and spatial analysis. *Int. J. Health Geogr.* **2008**, *7*, 27. [[CrossRef](#)] [[PubMed](#)]
60. Takahashi, S.; Metcalf, C.J.E.; Ferrari, M.J.; Tatem, A.J.; Lessler, J. The geography of measles vaccination in the African Great Lakes region. *Nat. Commun.* **2017**, *8*, 15585. [[CrossRef](#)] [[PubMed](#)]
61. Burke, M.; Heft-Neal, S.; Bendavid, E. Sources of variation in under-5 mortality across sub-Saharan Africa: A spatial analysis. *Lancet Glob. Health* **2016**, *4*, e936–e945. [[CrossRef](#)]
62. López-Carr, D.; Mwenda, K.M.; Pricope, N.G.; Kyriakidis, P.; Jankowska, M.M.; Weeks, J.; Funk, C.; Husak, G.; Michaelsen, J. Climate-Related Child Undernutrition in the Lake Victoria Basin: An Integrated Spatial Analysis of Health Surveys, NDVI, and Precipitation Data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote. Sens.* **2016**, *9*, 2830–2835. [[CrossRef](#)]
63. Gosoni, L.; Msengwa, A.; Lengeler, C.; Vounatsou, P. Spatially Explicit Burden Estimates of Malaria in Tanzania: Bayesian Geostatistical Modeling of the Malaria Indicator Survey Data. *PLoS ONE* **2012**, *7*, e23966. [[CrossRef](#)]
64. Adigun, A.B.; Gajere, E.N.; Oresanya, O.; Vounatsou, P. Malaria risk in Nigeria: Bayesian geostatistical modelling of 2010 malaria indicator survey data. *Malar. J.* **2015**, *14*, 156. [[CrossRef](#)]
65. Stensgaard, A.-S.; Vounatsou, P.; Onapa, A.W.; Utzinger, J.; Pedersen, E.M.; Kristensen, T.K.; Simonsen, P.E. Ecological Drivers of *Mansonella perstans* Infection in Uganda and Patterns of Co-endemicity with Lymphatic Filariasis and Malaria. *PLoS Negl. Trop. Dis.* **2016**, *10*, e0004319. [[CrossRef](#)]
66. Giardina, F.; Kasasa, S.; Sié, A.; Utzinger, J.; Tanner, M.; Vounatsou, P. Effects of vector-control interventions on changes in risk of malaria parasitaemia in sub-Saharan Africa: A spatial and temporal analysis. *Lancet Glob. Health* **2014**, *2*, e601–e615. [[CrossRef](#)]
67. Ssempiira, J.; Nambuusi, B.; Kissa, J.; Agaba, B.; Makumbi, F.; Kasasa, S.; Vounatsou, P. Geostatistical modelling of malaria indicator survey data to assess the effects of interventions on the geographical distribution of malaria prevalence in children less than 5 years in Uganda. *PLoS ONE* **2017**, *12*, e0174948. [[CrossRef](#)]

68. Gemperli, A.; Vounatsou, P.; Kleinschmidt, I.; Bagayoko, M.; Lengeler, C.; Smith, T.A. Spatial patterns of infant mortality in Mali: The effect of malaria endemicity. *Am. J. Epidemiol.* **2004**, *159*, 64–72. [[CrossRef](#)] [[PubMed](#)]
69. Messina, J.; Taylor, S.M.; Meshnick, S.R.; Linke, A.M.; Tshefu, A.K.; Atua, B.; Mwandagalirwa, M.K.; Emch, M. Population, behavioural and environmental drivers of malaria prevalence in the Democratic Republic of Congo. *Malar. J.* **2011**, *10*, 161. [[CrossRef](#)] [[PubMed](#)]
70. Mmbando, B.; Kamugisha, M.L.; Lusingu, J.; Francis, F.; Ishengoma, D.S.; Theander, T.G.; Lemnge, M.M.; Hviid, T.V.F. Spatial variation and socio-economic determinants of Plasmodium falciparum infection in northeastern Tanzania. *Malar. J.* **2011**, *10*, 145. [[CrossRef](#)] [[PubMed](#)]
71. Grady, S.C.; Frake, A.N.; Zhang, Q.; Bene, M.; Jordan, D.R.; Dossantos, T.C.; Kadhim, A.; Namanya, J.; Pierre, L.M.; Fan, Y.; et al. Neonatal mortality in East Africa and West Africa: A geographic analysis of district-level demographic and health survey data. *Geospat. Health* **2017**, *12*, 501. [[CrossRef](#)] [[PubMed](#)]
72. Homan, T.; Maire, N.; Hiscox, A.; Di Pasquale, A.; Kiche, I.; Onoka, K.; Mweresa, C.; Mukubana, W.R.; Ross, A.; Smith, T.A.; et al. Spatially variable risk factors for malaria in a geographically heterogeneous landscape, western Kenya: An explorative study. *Malar. J.* **2016**, *15*, 1. [[CrossRef](#)] [[PubMed](#)]
73. Wabiri, N.; Shisana, O.; Zuma, K.; Freeman, J. Assessing the spatial nonstationarity in relationship between local patterns of HIV infections and the covariates in South Africa: A geographically weighted regression analysis. *Spat. Spatio-Temporal Epidemiol.* **2016**, *16*, 88–99. [[CrossRef](#)]
74. Okango, E.; Mwambi, H.; Ngesa, O.; Achia, T. Semi-Parametric Spatial Joint Modeling of HIV and HSV-2 among Women in Kenya. *PLoS ONE* **2015**, *10*, e0135212. [[CrossRef](#)]
75. Noor, A.M.; Clements, A.C.A.; Gething, P.W.; Moloney, G.; Borle, M.; Shewchuk, T.; Hay, S.I.; Smow, R.W. Spatial prediction of Plasmodium falciparum prevalence in Somalia. *Malar. J.* **2008**, *7*, 159. [[CrossRef](#)]
76. Jones, A.D.; Acharya, Y.; Galway, L.P. Urbanicity Gradients Are Associated with the Household- and Individual-Level Double Burden of Malnutrition in Sub-Saharan Africa. *J. Nutr.* **2016**, *146*, 1257–1267. [[CrossRef](#)]
77. Chipeta, M.G.; Terlouw, A.; Phiri, K.; Diggle, P. Adaptive geostatistical design and analysis for prevalence surveys. *Spat. Stat.* **2016**, *15*, 70–84. [[CrossRef](#)]
78. Gosoniu, L.; Veta, A.M.; Vounatsou, P. Bayesian Geostatistical Modeling of Malaria Indicator Survey Data in Angola. *PLoS ONE* **2010**, *5*, e9322. [[CrossRef](#)]
79. Diboulo, E.; Sié, A.; Vounatsou, P. Assessing the effects of malaria interventions on the geographical distribution of parasitaemia risk in Burkina Faso. *Malar. J.* **2016**, *15*, 228. [[CrossRef](#)]
80. Riedel, N.; Vounatsou, P.; Miller, J.M.; Gosoniu, L.; Chizema-Kawesha, E.; Mukonka, V.; Steketee, R.W. Geographical patterns and predictors of malaria risk in Zambia: Bayesian geostatistical modelling of the 2006 Zambia national malaria indicator survey (ZMIS). *Malar. J.* **2010**, *9*, 37. [[CrossRef](#)] [[PubMed](#)]
81. Fronterre, C.; Giorgi, E.; Diggle, P. Geostatistical inference in the presence of geomasking: A composite-likelihood approach. *Spat. Stat.* **2018**, *28*, 319–330. [[CrossRef](#)]
82. Giorgi, E.; Diggle, P.; Snow, R.W.; Noor, A. Geostatistical methods for disease mapping and visualization using data from spatio-temporally referenced prevalence surveys. *Int. Stat. Rev.* **2018**, *86*, 571–597. [[CrossRef](#)]
83. Schur, N.; Hürlimann, E.; Garba, A.; Traoré, M.S.; Ndir, O.; Ratard, R.C.; Tchuem Tchuenté, L.A.; Kristensen, T.K.; Utzinger, J.; Vounatsou, P. Geostatistical Model-Based Estimates of Schistosomiasis Prevalence among Individuals Aged <= 20 Years in West Africa. *PLoS Negl. Trop. Dis.* **2011**, *5*, e1194.
84. Amoah, B.; Giorgi, E.; Heyes, D.J.; Van Buuren, S.; Diggle, P. Geostatistical modelling of the association between malaria and child growth in Africa. *Int. J. Health Geogr.* **2018**, *17*, 7. [[CrossRef](#)] [[PubMed](#)]
85. Bosco, C.; Alegana, V.; Bird, T.; Pezzulo, C.; Bengtsson, L.; Sorichetta, A.; Steele, J.; Hornby, G.; Ruktanonchai, C.; Ruktanonchai, N.; et al. Exploring the high-resolution mapping of gender-disaggregated development indicators. *J. R. Soc. Interface* **2017**, *14*, 20160825. [[CrossRef](#)] [[PubMed](#)]
86. Utazi, C.E.; Thorley, J.; Alegana, V.A.; Ferrari, M.J.; Takahashi, S.; Metcalf, C.J.E.; Lessler, J.; Tatem, A.J. High resolution age-structured mapping of childhood vaccination coverage in low and middle income countries. *Vaccine* **2018**, *36*, 1583–1591. [[CrossRef](#)] [[PubMed](#)]
87. Golding, N.; Burstein, R.; Longbottom, J.; Browne, A.J.; Fullman, N.; Osgood-Zimmerman, A.; Earlm, I.; Bhatt, S.; Cameron, E.; Casey, D.C.; et al. Mapping under-5 and neonatal mortality in Africa, 2000–2015: A baseline analysis for the Sustainable Development Goals. *Lancet* **2017**, *390*, 2171–2182. [[CrossRef](#)]

88. Kneib, T. Mixed model-based inference in geospatial hazard regression for interval-censored survival times. *Comput. Stat. Data Anal.* **2006**, *51*, 777–792. [[CrossRef](#)]
89. Samadoulougou, S.; Maheu-Giroux, M.; Kirakoya-Samadoulougou, F.; De Keukeleire, M.; De Castro, M.C.; Robert, A. Multilevel and geo-statistical modeling of malaria risk in children of Burkina Faso. *Parasites Vectors* **2014**, *7*, 350. [[CrossRef](#)]
90. Noor, A.; Alegana, V.A.; Patil, A.P.; Snow, R.W. Predicting the unmet need for biologically targeted coverage of insecticide-treated nets in Kenya. *Am. J. Trop. Med. Hyg.* **2010**, *83*, 854–860. [[CrossRef](#)] [[PubMed](#)]
91. Brooker, S.; Clements, A.C. Spatial heterogeneity of parasite co-infection: Determinants and geostatistical prediction at regional scales. *Int. J. Parasitol.* **2008**, *39*, 591–597. [[CrossRef](#)] [[PubMed](#)]
92. Ssempiira, J.; Nambuusi, B.; Kissa, J.; Agaba, B.; Makumbi, F.; Kasasa, S.; Vounatsou, P. The contribution of malaria control interventions on spatio-temporal changes of parasitaemia risk in Uganda during 2009–2014. *Parasites Vectors* **2017**, *10*, 450. [[CrossRef](#)] [[PubMed](#)]
93. Bennett, A.; Yukich, J.; Miller, J.M.; Keating, J.; Moonga, H.; Hamainza, B.; Kamuliwo, M.; Andrade-Pacheco, R.; Vounatsou, P.; Steketee, R.W.; et al. The relative contribution of climate variability and vector control coverage to changes in malaria parasite prevalence in Zambia 2006–2012. *Parasites Vectors* **2016**, *9*, 431. [[CrossRef](#)]
94. Oluwole, A.S.; Ekpo, U.F.; Karagiannis-Voules, D.A.; Abe, E.M.; Olamiju, F.O.; Isiyaku, S.; Okoronkwo, C.; Saka, Y.; Nebe, O.J.; Braide, E.I.; et al. Bayesian Geostatistical Model-Based Estimates of Soil-Transmitted Helminth Infection in Nigeria, Including Annual Deworming Requirements. *PLoS Negl. Trop. Dis.* **2015**, *9*, e0003740. [[CrossRef](#)] [[PubMed](#)]
95. Alegana, V.A.; Atkinson, P.M.; Pezzulo, C.; Sorichetta, A.; Weiss, D.; Bird, T.; Erbach-Schoenberg, E.; Tatem, A.J. Fine resolution mapping of population age-structures for health and development applications. *J. R. Soc. Interface* **2015**, *12*, 20150073. [[CrossRef](#)]
96. Colson, K.E.; Dwyer-Lindgren, L.; Achoki, T.; Fullman, N.; Schneider, M.; Mulenga, P.; Hangoma, P.; Ng, M.; Masiye, F.; Gakidou, E. Benchmarking health system performance across districts in Zambia: A systematic analysis of levels and trends in key maternal and child health interventions from 1990 to 2010. *BMC Med.* **2015**, *13*, 69. [[CrossRef](#)]
97. Coburn, B.J.; Okano, J.T.; Blower, S. Current drivers and geographic patterns of HIV in Lesotho: Implications for treatment and prevention in Sub-Saharan Africa. *BMC Med.* **2013**, *11*, 224. [[CrossRef](#)]
98. Aoun, N.; Matsuda, H.; Sekiyama, M. Geographical accessibility to healthcare and malnutrition in Rwanda. *Soc. Sci. Med.* **2015**, *130*, 135–145. [[CrossRef](#)]
99. Messina, J.P.; Mwandagalirwa, M.K.; Taylor, S.M.; Emch, M.; Meshnick, S.R. Spatial and social factors drive anemia in Congolese women. *Health Place* **2013**, *24*, 54–64. [[CrossRef](#)]
100. Kpienbaareh, D.; Atuoye, K.N.; Ngabonzima, A.; Bagambe, P.G.; Rulisa, S.; Luginaah, I.; Cechetto, D.F. Social Science & Medicine Spatio-temporal disparities in maternal health service utilization in Rwanda: What next for SDGs? *Soc. Sci. Med.* **2019**, *226*, 164–175. [[PubMed](#)]
101. Alegana, V.A.; Wright, J.; Uusiku, P.; Noor, A.; Snow, R.W.; Atkinson, P.M. Spatial modelling of healthcare utilisation for treatment of fever in Namibia. *Int. J. Health Geogr.* **2012**, *11*, 6. [[CrossRef](#)] [[PubMed](#)]
102. Palk, L.; Blower, S. Geographic variation in sexual behavior can explain geospatial heterogeneity in the severity of the HIV epidemic in Malawi. *BMC Med.* **2018**, *16*, 22. [[CrossRef](#)]
103. Tewara, M.A.; Mbah-fongkimeh, P.N.; Dayimu, A.; Kang, F. Small-area spatial statistical analysis of malaria clusters and hotspots in Cameroon; 2000–2015. *BMC Infect. Dis.* **2018**, *18*, 636. [[CrossRef](#)] [[PubMed](#)]
104. Sartorius, B.K.D.; Sartorius, K.; Chirwa, T.F.; Fonn, S. Infant mortality in South Africa—Distribution, associations and policy implications, 2007: An ecological spatial analysis. *Int. J. Health Geogr.* **2011**, *10*, 61. [[CrossRef](#)] [[PubMed](#)]
105. Ejigu, B.A.; Wencheko, E.; Berhane, K. Spatial pattern and determinants of anaemia in Ethiopia. *PLoS ONE* **2018**, *13*, e0197171. [[CrossRef](#)]
106. Acheson, E.S.; Kerr, J.T. Nets versus spraying: A spatial modelling approach reveals indoor residual spraying targets Anopheles mosquito habitats better than mosquito nets in Tanzania. *PLoS ONE* **2018**, *13*, e0205270. [[CrossRef](#)]
107. Kamuliwo, M.; Kirk, K.E.; Chanda, E.; ElBadry, M.A.; Lubinda, J.; Weppelmann, T.A.; Mukonka, V.; Zhang, W.; Mushingi, G.; Mwanza-Ingwe, M.; et al. Spatial patterns and determinants of malaria infection during pregnancy in Zambia. *Trans. R. Soc. Trop. Med. Hyg.* **2015**, *109*, 514–521. [[CrossRef](#)]

108. Chimoyi, L.; Musenge, E. Spatial analysis of factors associated with HIV infection among young people in Uganda, 2011. *BMC Public Health* **2014**, *14*, 555. [[CrossRef](#)]
109. Birhanu, A.Y.; Alemu, K.; Dadi, A.F.; Alamirrew, A. Spatial distribution of antenatal care utilization and associated factors in Ethiopia: Evidence from Ethiopian demographic health surveys. *BMC Pregnancy Childbirth* **2018**, *18*, 242.
110. Kandala, N.B.; Magadi, M.A.; Madise, N.J. An investigation of district spatial variations of childhood diarrhoea and fever morbidity in Malawi. *Soc. Sci. Med.* **2006**, *62*, 1138–1152. [[CrossRef](#)]
111. Adebayo, S.B. A Bayesian semiparametric multilevel survival modelling of age at first birth in Nigeria Ezra Gayawan Table of Contents. *Demogr. Res.* **2013**, *28*, 1339–1372.
112. Sacko, M.; Landoure, A.; Dembe, R.; Clements, A.C.A.; Bosque, E.; Coulibaly, G.; Gabrielli, A.F.; Fenwick, A.; Brooker, S. A Comparative Study of the Spatial Distribution of Schistosomiasis in Mali in 1984–1989 and 2004–2006. *PLoS Negl. Trop. Dis.* **2009**, *3*, e431.
113. Kazembe, L.N. An additive regression model for investigating the relationship between childhood health and socio-economic status. *Spat. Spatio-Temporal Epidemiol.* **2013**, *6*, 71–84. [[CrossRef](#)] [[PubMed](#)]
114. Chirwa, T.; Mantempa, J.N.; Kinziunga, F.L.; Kandala, J.D.; Kandala, N.-B. An exploratory spatial analysis of geographical inequalities of birth intervals among young women in the Democratic Republic of Congo (DRC): A cross-sectional study. *BMC Pregnancy Childbirth* **2014**, *14*, 271. [[CrossRef](#)] [[PubMed](#)]
115. Adebayo, S.B.; Fahrmeir, L.; Klasen, S. Analyzing infant mortality with geoadditive categorical regression models: A case study for Nigeria. *Econ. Hum. Boil.* **2004**, *2*, 229–244. [[CrossRef](#)]
116. Niragire, F.; Achia, T.N.O.; Lyambabaje, A.; Ntaganira, J. Bayesian Mapping of HIV Infection among Women of Reproductive Age in Rwanda. *PLoS ONE* **2015**, *10*, e0119944. [[CrossRef](#)]
117. Ngwira, A.; Kazembe, L.N. Bayesian random effects modelling with application to childhood anaemia in Malawi. *BMC Public Health* **2015**, *15*, 161. [[CrossRef](#)]
118. Tsiko, R.G. Bayesian spatial analysis of childhood diseases in Zimbabwe. *BMC Public Health* **2015**, *15*, 842. [[CrossRef](#)]
119. Tonye, S.G.M.; Kouambeng, C.; Wounang, R.; Vounatsou, P. Challenges of DHS and MIS to capture the entire pattern of malaria parasite risk and intervention effects in countries with different ecological zones: The case of Cameroon. *Malar. J.* **2018**, *17*, 156. [[CrossRef](#)]
120. Kandala, N.-B.; Ghilagaber, G. A Geo-Additive Bayesian Discrete-Time Survival Model and its Application to Spatial Analysis of Childhood Mortality in Malawi. *Qual. Quant.* **2006**, *40*, 935–957. [[CrossRef](#)]
121. Ngwira, A.; Stanley, C.C. Determinants of Low Birth Weight in Malawi: Bayesian Geo-Additive Modelling. *PLoS ONE* **2015**, *10*, e0130057. [[CrossRef](#)] [[PubMed](#)]
122. Wakefield, J.; Fuglstad, G.-A.; Riebler, A.; Godwin, J.; Wilson, K.; Clark, S.J. Estimating under-five mortality in space and time in a developing world context. *Stat. Methods Med. Res.* **2018**, *28*, 2614–2634. [[CrossRef](#)] [[PubMed](#)]
123. Kandala, N.-B.; Tigbe, W.; Manda, S.O.; Stranges, S. Geographic Variation of Hypertension in Sub-Saharan Africa: A Case Study of South Africa. *Am. J. Hypertens.* **2013**, *26*, 382–391. [[CrossRef](#)]
124. Kandala, N.-B.; Stranges, S. Geographic Variation of Overweight and Obesity among Women in Nigeria: A Case for Nutritional Transition in Sub-Saharan Africa. *PLoS ONE* **2014**, *9*, e0101103. [[CrossRef](#)]
125. Kazembe, L.N.; Kamndaya, M.S. Spatial and Spatio-temporal Epidemiology Hierarchical spatial modelling of pneumonia prevalence when response outcome has misclassification error: Applications to household data from Malawi. *Spat. Spatio-Temporal Epidemiol.* **2016**, *16*, 35–42. [[CrossRef](#)]
126. Kinyoki, D.K.; Kandala, N.; Manda, S.O.; Krainski, E.T.; Fuglstad, G.; Moloney, G.M.; Berkley, J.A.; Noor, A.M. Assessing comorbidity and correlates of wasting and stunting among children in Somalia using cross-sectional household surveys: 2007 to 2010. *BMJ Open* **2016**, *6*, e009854. [[CrossRef](#)]
127. Kandala, N.; Madungu, T.P.; Emina, J.B.O.; Nzita, K.P.D.; Cappuccio, F.P. Malnutrition among children under the age of five in the Democratic Republic of Congo (DRC): Does geographic location matter? *BMC Public Health* **2011**, *11*, 261. [[CrossRef](#)]
128. Manda, S.O.M.; Lombard, C.L.; Mosala, T. Divergent spatial patterns in the prevalence of the human immunodeficiency virus (HIV) and syphilis in South African pregnant women. *Geospat. Health* **2012**, *6*, 221. [[CrossRef](#)]
129. Kandala, N.; Brodish, P.; Buckner, B.; Foster, S.; Madise, N. Millennium development goal 6 and HIV infection in Zambia: What can we learn from successive household surveys? *AIDS* **2011**, *25*, 95–106. [[CrossRef](#)]

130. Noor, A.M.; ElMardi, K.A.; Abdelgader, T.M.; Patil, A.P.; Amine, A.A.A.; Bakhiet, S.; Mukhtar, M.M.; Snow, R.W. Malaria risk mapping for control in the republic of Sudan. *Am. J. Trop. Med. Hyg.* **2012**, *87*, 1012–1021. [[CrossRef](#)] [[PubMed](#)]
131. Khatab, K.; Kandala, N.-B. Latent variable modelling of risk factors associated with childhood diseases: Case study for Nigeria. *Asian Pac. J. Trop. Dis.* **2011**, *1*, 169–176. [[CrossRef](#)]
132. Kinyoki, D.K.; Manda, S.O.; Moloney, G.M.; Odundo, E.O.; Berkley, J.A.; Noor, A.M.; Kandala, N. Modelling the Ecological Comorbidity of Acute Respiratory Infection, Diarrhoea and Stunting among Children Under the Age of 5 Years in Somalia. *Int. Stat. Rev.* **2017**, *85*, 164–176. [[CrossRef](#)] [[PubMed](#)]
133. Kazembe, L.N.; Mpeketula, P.M.G. Quantifying Spatial Disparities in Neonatal Mortality Using a Structured Additive Regression Model. *PLoS ONE* **2010**, *5*, e11180. [[CrossRef](#)]
134. Ouédraogo, M.; Samadoulougou, S.; Rouamba, T.; Hien, H.; Sawadogo, J.E.M.; Tinto, H.; Alegana, V.A.; Speybroeck, N.; Kirakoya-Samadoulougou, F. Spatial distribution and determinants of asymptomatic malaria risk among children under 5 years in 24 districts in Burkina Faso. *Malar. J.* **2018**, *17*, 460. [[CrossRef](#)]
135. Odwa, D.; Mkandawire, P. Spatial variation of management of childhood diarrhea in Malawi. *Health Place* **2014**, *29*, 84–94. [[CrossRef](#)]
136. Kang, S.Y.; Battle, K.E.; Gibson, H.S.; Ratsimbasoa, A.; Randrianariveolosia, M.; Ramboarina, S.; Zimmerman, P.A.; Weiss, D.J.; Cameron, E.; Gething, P.W.; et al. Spatio-temporal mapping of Madagascar's Malaria Indicator Survey results to assess Plasmodium falciparum endemicity trends between 2011 and 2016. *BMC Med.* **2018**, *16*, 71. [[CrossRef](#)]
137. Kandala, N.; Ji, C.; Stranges, S.; Stallard, N.; Cappuccio, F.P. Spatial analysis of risk factors for childhood morbidity in Nigeria. *Am. J. Trop. Med. Hyg.* **2007**, *77*, 770–779. [[CrossRef](#)] [[PubMed](#)]
138. Kandala, N.; Emina, J.B.; Nzita, P.D.K.; Cappuccio, F.P. Diarrhoea, acute respiratory infection, and fever among children in the Democratic Republic of Congo. *Soc. Sci. Med.* **2009**, *68*, 1728–1736. [[CrossRef](#)]
139. Kinyoki, D.K.; Berkley, J.A.; Moloney, G.M.; Odundo, E.O.; Kandala, N.-B.; Noor, A.M. Environmental predictors of stunting among children under-five in Somalia: Cross-sectional studies from 2007 to 2010. *BMC Public Health* **2016**, *16*, 654. [[CrossRef](#)]
140. Khatab, K. Childhood Malnutrition in Egypt using Geoadditive Gaussian and Latent Variable Models. *Am. J. Trop. Med. Hyg.* **2010**, *82*, 653–663. [[CrossRef](#)] [[PubMed](#)]
141. Adebayo, S.B.; Yahya, W.B. Modelling Immunization Coverage in Nigeria Using Bayesian Structured Additive Regression BT. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N.-B., Ghilagaber, G., Eds.; Springer: Dordrecht, The Netherlands, 2014; pp. 123–145.
142. Manda, S.O.M.; Feltbower, R.G.; Gilthorpe, M.S. A Multivariate Random Frailty Effects Model for Multiple Spatially Dependent Survival Data BT. In *Modern Methods for Epidemiology*; Tu, Y.-K., Greenwood, D.C., Eds.; Springer: Dordrecht, The Netherlands, 2012; pp. 157–172.
143. Ghilagaber, G.; Antai, D.; Kandala, N.-B. Modeling Spatial Effects on Childhood Mortality Via Geo-additive Bayesian Discrete-Time Survival Model: A Case Study from Nigeria BT. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N.-B., Ghilagaber, G., Eds.; Springer: Dordrecht, The Netherlands, 2014; pp. 29–48.
144. Khatab, K. Bayesian Geoadditive Mixed Latent Variable Models with Applications to Child Health Problems in Egypt and Nigeria BT. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N.-B., Ghilagaber, G., Eds.; Springer: Dordrecht, The Netherlands, 2014; pp. 49–81.
145. Kazembe, L.N. Mapping Socio-economic Inequalities in Health Status among Malawian Children: A Mixed Model Approach BT. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N.-B., Ghilagaber, G., Eds.; Springer: Dordrecht, The Netherlands, 2014; pp. 83–106.
146. Manda, S.O.M. Macro Determinants of Geographical Variation in Childhood Survival in South Africa Using Flexible Spatial Mixture Models BT. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N.-B., Ghilagaber, G., Eds.; Springer: Dordrecht, The Netherlands, 2014; pp. 147–168.
147. Kandala, N.-B. Spatial Variation of Predictors of Prevalent Hypertension in Sub-Saharan Africa: A Case Study of South-Africa BT. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N.-B., Ghilagaber, G., Eds.; Springer: Dordrecht, The Netherlands, 2014; pp. 211–237.

148. Adebayo, S.B.; Gayawan, E. Stepwise Geoadditive Regression Modelling of Levels and Trends of Fertility in Nigeria: Guiding Tools towards Attaining MDGs BT. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N.-B., Ghilagaber, G., Eds.; Springer: Dordrecht, The Netherlands, 2014; pp. 253–277.
149. Abiodun, A.A.; Adebayo, S.B.; Oyejola, B.A.; Anyanti, J. A Spatial Analysis of Age at Sexual Initiation Among Nigerian Youth as a Tool for HIV Prevention: A Bayesian Approach BT. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N.-B., Ghilagaber, G., Eds.; Springer: Dordrecht, The Netherlands, 2014; pp. 279–302.
150. Kandala, N.-B.; Manda, S.O.M.; Tigbe, W. Assessing Geographic Co-morbidity Associated with Vascular Diseases in South Africa: A Joint Bayesian Modeling Approach BT. In *Advanced Techniques for Modelling Maternal and Child Health in Africa*; Kandala, N.-B., Ghilagaber, G., Eds.; Springer: Dordrecht, The Netherlands, 2014; pp. 303–320.
151. Kandala, N.-B.; Manda, S.; Tigbe, W.W.; Mwambi, H.; Stranges, S. Geographic distribution of cardiovascular comorbidities in South Africa: A national cross-sectional analysis. *J. Appl. Stat.* **2013**, *41*, 1203–1216. [[CrossRef](#)]
152. Sartorius, K.; Sartorius, B. A spatial model to quantify the mortality impact of service delivery in Sub-Saharan Africa: An ecological design utilizing data from South Africa. *Int. J. Health Geogr.* **2013**, *12*, 8. [[CrossRef](#)]
153. Ngesa, O.; Mwambi, H.; Achia, T. Bayesian Spatial Semi-Parametric Modeling of HIV Variation in Kenya. *PLoS ONE* **2014**, *9*, e103299. [[CrossRef](#)]
154. Kazembe, L.N.; Appleton, C.C.; Kleinschmidt, I. Choice of treatment for fever at household level in Malawi: Examining spatial patterns. *Malar. J.* **2007**, *6*, 40. [[CrossRef](#)] [[PubMed](#)]
155. Kazembe, L.N.; Kandala, N.-B. Estimating areas of common risk in low birth weight and infant mortality in Namibia: A joint spatial analysis at sub-regional level. *Spat. Spatio-Temporal Epidemiol.* **2015**, *12*, 27–37. [[CrossRef](#)] [[PubMed](#)]
156. Kazembe, L.N.; Appleton, C.C.; Kleinschmidt, I. Geographical disparities in core population coverage indicators for roll back malaria in Malawi. *Int. J. Equity Health* **2007**, *6*, 5. [[CrossRef](#)] [[PubMed](#)]
157. Kazembe, L.N.; Muula, A.S.; Simoonga, C. Joint spatial modelling of common morbidities of childhood fever and diarrhoea in Malawi. *Health Place* **2009**, *15*, 165–172. [[CrossRef](#)]
158. Kazembe, L.N.; Muula, A.; Appleton, C.C.; Kleinschmidt, I. Modelling the effect of malaria endemicity on spatial variations in childhood fever, diarrhoea and pneumonia in Malawi. *Int. J. Health Geogr.* **2007**, *6*, 33. [[CrossRef](#)]
159. Manda, S.; Masenyetse, L.; Cai, B.; Meyer, R. Mapping HIV prevalence using population and antenatal sentinel-based HIV surveys: A multi-stage approach. *Popul. Health Metr.* **2015**, *13*, 22. [[CrossRef](#)]
160. Okango, E.; Mwambi, H.; Ngesa, O. Spatial modeling of HIV and HSV-2 among women in Kenya with spatially varying coefficients. *BMC Public Health* **2016**, *16*, 355. [[CrossRef](#)] [[PubMed](#)]
161. Chitunhu, S.; Musenge, E. Spatial and socio-economic effects on malaria morbidity in children under 5 years in Malawi in 2012. *Spat. Spatio-Temporal Epidemiol.* **2016**, *16*, 21–33. [[CrossRef](#)] [[PubMed](#)]
162. Mtambo, O.P.; Masangwi, S.; Kazembe, L.N. Spatial quantile regression using INLA with applications to childhood overweight in Malawi. *Spat. Spatio-Temporal Epidemiol.* **2015**, *13*, 7–14. [[CrossRef](#)] [[PubMed](#)]
163. Ruktanonchai, C.W.; Nilsen, K.; Alegana, V.A.; Bosco, C.; Ayiko, R.; Seven Kajeguka, A.C.; Matthews, Z.; Tatem, A.J. Temporal trends in spatial inequalities of maternal and newborn health services among four east African countries, 1999–2015. *BMC Public Health* **2018**, *18*, 1339. [[CrossRef](#)]
164. Kinyoki, D.K.; Berkley, J.A.; Moloney, G.M.; Odundo, E.O.; Kandala, N.; Noor, A.M. Space—Time mapping of wasting among children under the age of five years in Somalia from 2007 to 2010. *Spat. Spatio-Temporal Epidemiol.* **2016**, *16*, 77–87. [[CrossRef](#)]
165. Pullan, R.L.; Freeman, M.C.; Gething, P.W.; Brooker, S.J. Geographical Inequalities in Use of Improved Drinking Water Supply and Sanitation across Sub-Saharan Africa: Mapping and Spatial Analysis of Cross-sectional Survey Data. *PLoS Med.* **2014**, *11*, e1001626. [[CrossRef](#)] [[PubMed](#)]
166. Acheson, E.S.; Plowright, A.A.; Kerr, J.T. Where have all the mosquito nets gone? Spatial modelling reveals mosquito net distributions across Tanzania do not target optimal Anopheles mosquito habitats. *Malar. J.* **2015**, *14*, 322. [[CrossRef](#)]
167. Ayele, D.G.; Zewotir, T.T.; Mwambi, H.G. Structured additive regression models with spatial correlation to estimate under-five mortality risk factors in Ethiopia. *BMC Public Health* **2015**, *15*, 268. [[CrossRef](#)]

168. Anselin, L.; Getis, A. Spatial statistical analysis and geographic information systems. *Ann. Reg. Sci.* **1992**, *26*, 19–33. [CrossRef]
169. Cliff, A.D.; Ord, J.K. *Spatial Autocorrelation*; Pion Press: London, UK, 1973.
170. Kulldorff, M. A spatial scan statistic. *Commun. Stat.-Theory Methods* **1997**, *26*, 1481–1496. [CrossRef]
171. Schloeder, C.A.; Zimmermann, N.E.; Jacobs, M. Comparison of Methods for Interpolating Soil Properties Using Limited Data. *Soil Sci. Soc. Am. J.* **2001**, *65*, 470–479. [CrossRef]
172. Wu, Y.H.E.; Hung, M.C. Comparison of Spatial Interpolation Techniques Using Visualization and Quantitative Assessment. 2016. Available online: <https://www.intechopen.com/books/applications-of-spatial-statistics/comparison-of-spatial-interpolation-techniques-using-visualization-and-quantitative-assessment> (accessed on 20 March 2020).
173. Banerjee, S.; Carlin, B.P.; Gelfand, A.E. *Hierarchical Modeling and Analysis for Spatial Data*; Chapman and Hall/CRC Press: Boca Raton, FL, USA, 2004; 452p.
174. Besag, J.; York, J. Bayesian image restoration, with two applications in spatial statistics. *Ann. Inst. Stat. Math.* **1991**, *43*, 1–20. [CrossRef]
175. Diggle, P.J.; Ribeiro, P. *Model-Based Geostatistics*; Springer: New York, NY, USA, 2007; pp. 1–656. Available online: <https://link.springer.com/book/10.1007/978-0-387-48536-2> (accessed on 1 November 2019).
176. Mercer, L.; Wakefield, J.; Chen, C.; Lumley, T. A comparison of spatial smoothing methods for small area estimation with sampling weights. *Spat. Stat.* **2014**, *8*, 69–85. [CrossRef] [PubMed]
177. Watjou, K.; Faes, C.; Lawson, A.; Kirby, R.S.; Aregay, M.; Carroll, R.; Vandendijck, Y. Spatial small area smoothing models for handling survey data with nonresponse. *Stat. Med.* **2017**, *36*, 3708–3745. [CrossRef]
178. Chen, C.; Wakefield, J.; Lumley, T. The use of sampling weights in Bayesian hierarchical models for small area estimation. *Spat. Spatio-Temporal Epidemiol.* **2014**, *11*, 33–43. [CrossRef]
179. Vandendijck, Y.; Faes, C.; Kirby, R.; Lawson, A.; Hens, N. Model-based inference for small area estimation with sampling weights. *Spat. Stat.* **2016**, *18*, 455–473. [CrossRef]
180. Joubert, J.; Rao, C.; Bradshaw, D.; Dorrington, R.E.; Vos, T.; Lopez, A.D. Characteristics, availability and uses of vital registration and other mortality data sources in post-democracy South Africa. *Glob. Health Action* **2012**, *5*, 19263. [CrossRef]
181. Zulu, L.C.; Kalipeni, E.; Johannes, E. Analyzing spatial clustering and the spatiotemporal nature and trends of HIV/AIDS prevalence using GIS: The case of Malawi, 1994–2010. *BMC Infect. Dis.* **2014**, *14*, 285. [CrossRef]
182. Moise, I.; Kalipeni, E. Applications of geospatial analysis to surveillance data: A spatial examination of HIV/AIDS prevalence in Zambia. *GeoJournal* **2010**, *77*, 525–540. [CrossRef]
183. Kalipeni, E.; Zulu, L.C. HIV and AIDS in Africa: A geographic analysis at multiple spatial scales. *GeoJournal* **2010**, *77*, 505–523. [CrossRef]
184. Heywood, I.D.; Cornelius, S.; Carver, S. *An Introduction to Geographical Information Systems*; Addison Wesley Longman: New York, NY, USA, 1998.

