Vaccine 89 (2026) 128904

Contents lists available at ScienceDirect

Vaccine

journal homepage: www.elsevier.com/locate/vaccine

Review

Geospatial approaches for mapping zero-dose prevalence and routine childhood immunisation coverage in low- and lower-middle-income countries: A scoping review

Ann M. Njogu [a,b,*], Moses M. Musau [a,c,d], Swati Srivastava [e], Francesco Menegale [f], Emma Clarke [g], Caroline Mudereri [h], Felix R. Kitema [h], Yvonne Opanga [i], Arnold Mmbando [h], Absolomon Gashaija [h], Hassan Sibomana [j], Jeanine Condo [h], Frank Osei [b], Lenka Beňová [a,k], Justine I. Blanford [b], Piero Poletti [f], Aleksandra Torbica [l,m], Alessia Melegaro [l], Carlo Federici [m], Peter M. Macharia [a,c], The REACHOUT Consortium

[a] Department of Public Health, Institute of Tropical Medicine (ITM), Antwerp, Belgium
[b] Faculty of Geoinformation Science and Earth Observation (ITC), University of Twente, Enschede, the Netherlands
[c] Population and Health Impact Surveillance Group, Kenya Medical Research Institute-Wellcome Trust Research Programme, Nairobi, Kenya
[d] Institute of Life, Earth, and Environment (ILEE), University of Namur, Namur, Belgium
[e] Heidelberg Institute of Global Health, Faculty of Medicine and University Hospital, Heidelberg University, Heidelberg, Germany
[f] Center for Health Emergencies, Fondazione Bruno Kessler, Trento, Italy
[g] Swiss Tropical & Public Health Institute, Basel, Switzerland
[h] Centre for Impact, Innovation and Capacity Building for Health Information Systems and Nutrition (CIICHIN), Kigali, Rwanda
[i] Amref Health Africa, Kenya
[j] Rwanda Biomedical Center, Kigali, Rwanda
[k] Faculty of Epidemiology and Population Health, London School of Hygiene and Tropical Medicine, London, United Kingdom
[l] Department of Social and Political Sciences, Bocconi University, Milan, Italy
[m] CERGAS, SDA Bocconi School of Management, Bocconi University, Milan, Italy

ARTICLE INFO

Keywords:
Zero-dose
Immunisation coverage
Vaccination inequity
Spatial
High-resolution
Geostatistics
Geospatial modelling
Mapping
Small-area estimation
Data
Low- and lower-middle-income countries

ABSTRACT

Background: Zero-dose (ZD) children remain a critical public health concern, particularly in low- and lower-middle-income countries (LLMICs), where over 80% of the global ZD population resides, disproportionately concentrated among the most marginalised. Geospatial approaches have emerged as effective tools for identifying and targeting immunisation gaps. However, no review has systematically documented the spatial approaches used to predict or map ZD prevalence and routine immunisation (RI) coverage. This scoping review addresses this gap across LLMICs.

Methods: We searched six databases for peer-reviewed articles published up to 2025, on spatial modelling of childhood vaccination coverage in LLMICs. We extracted details on study characteristics, covariate types and sources, modelling methods, and limitations; stratifying findings between studies mapping RI coverage and those estimating ZD prevalence. Articles were thematically summarised focusing on geospatial data, modelling approaches, and corresponding gaps.

Results: We included 102 articles from 68 LLMICs, with 70% published between 2021 and 2024, and 87% concentrated in Ethiopia, Nigeria, and India. Most studies mapped RI coverage indicators, only 19.6% assessed ZD prevalence, based on two distinct definitions. Studies relied predominantly on survey-based vaccination data. Covariate data were dominated by demographic factors (49%) with limited representation of hard-to-reach contexts such as conflict areas and nomadic populations. Methods included clustering and autocorrelation analysis (54%), spatial interpolation (45%), small-area estimation (13%), and machine learning (8%). Key gaps included inconsistent ZD definitions, data inaccuracies and scarcity, and limited use of routine vaccination data.

Conclusions: Geospatial mapping of RI coverage is expanding across LLMICs but relies predominantly on exploratory approaches insufficient for precise targeting, while dedicated ZD mapping remains sparse. Geospatial

* Corresponding author at: Institute of Tropical Medicine, Nationalestraat 155, 2000 Antwerp, Belgium.
E-mail address: anjogu@itg.be (A.M. Njogu).

https://doi.org/10.1016/j.vaccine.2026.128904
Received 1 April 2026; Received in revised form 27 June 2026; Accepted 30 June 2026

modelling is constrained by overreliance on survey data, limited application of routine data, and underrepresentation of marginalised populations. Addressing these gaps requires integrated data systems, and reproducible modelling approaches underpinned by sustained investment in local analytical capacity.

1. Introduction

Childhood immunisation is a pillar of public health, significantly reducing morbidity and mortality from vaccine-preventable diseases (VPDs) [1]. Since the launch of the World Health Organisation (WHO) Expanded Programme on Immunisation (EPI), global immunization coverage has improved substantially, with approximately 85% of children worldwide now receiving the third dose of diphtheria, tetanus, and pertussis containing vaccine (DTP3), a widely used marker of immunisation system performance [2]. However, even in countries with high immunisation coverage, there are still pockets of zero-dose (ZD) children - those who do not receive any routine immunisation (RI) [3,4].

ZD children are operationally defined by WHO and Gavi as those missing the first dose of DTP-containing vaccine (DTP1) by the end of their first year of life [4,5]. DTP1 serves as a reliable indicator since it is universally administered in RI, recommended at six weeks, marking initial contact with RI services [6]. Years of suboptimal vaccine coverage, compounded by the COVID-19 pandemic, have resulted in an accumulation of ZD and under-immunized populations, fuelling outbreaks of VPDs such as measles, which caused approximately 136,000 deaths in 2022 [7]. Over 80% of global ZD children reside in low- and lower-middle-income countries (LLMICs), with a few countries (e.g., Nigeria, India, and Sudan) accounting for a disproportionate share [2]. These children are mostly concentrated in marginalized areas such as remote rural areas, urban informal settlements, conflict zones and refugee populations [8], and are often among the most under-served populations within health systems. The lack of RI is not only an indicator of missed immunisation but also a proxy for limited or absent contact with routine health services [4]. As such, ZD status often reflects wider patterns of exclusion, including reduced access to primary healthcare, maternal and child health services, and other essential interventions [9].

Structural barriers to vaccination, including inadequate funding for immunisation programs, geographic inaccessibility of immunizing health facilities, armed conflicts, among others, have been cited as longstanding barriers to immunisation uptake in LLMICs [9,10]. The COVID-19 pandemic further exacerbated global declines in RI rates. In India, for instance, the coverage of DTP3 dropped from 91% to 85% during this pandemic [11]. Consequently, global initiatives such as the Immunisation Agenda 2030 (IA2030) [12] and the Gavi Strategy 5.0 aim to achieve immunisation equity, with a particular focus on reaching ZD children [13,14]. To achieve this, it is crucial to precisely identify, target, and reach ZD children with equitable and cost-effective interventions immunisation [15,16].

To map RI coverage and identify ZD children, spatial, statistical, or a combination of both approaches, have been employed [16–18]. These approaches often integrate covariates (factors or determinants of ZD and RI coverage) with vaccination coverage, to generate high-resolution estimates of ZD prevalence or RI coverage. Approaches that incorporate a geospatial lens emerge as effective tools for unmasking disparities in ZD prevalence and RI coverage that are often obscured by regional or national estimates [15,19]. High-resolution geospatial techniques are especially valuable for identifying ZD children who are often found in small clusters masked by national or regional averages, as they can integrate multiple datasets to reveal geographic iniquities [16,17,20]. Spatial approaches used for mapping RI coverage and estimating ZD prevalence have considerably advanced in the last two decades [21–23], fuelled by the increasing availability of immunisation data from routine health information systems (e.g., District Health Information Software-2 (DHIS2)) and household surveys (e.g., Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS)) that incorporate global positioning systems (GPS) [24,25], as well as georeferenced health facility datasets [26], satellite derived variables and development of advanced methods to synthesize these datasets [27]. For example, the number of countries using DHIS2 for health reporting increased from 11 to 99 between 2010 and 2025 [28], while DHS have increased substantially between 1985 and 2025, now covering 92 out of 129 LMICs [28–30]. Integrating spatial analysis with demographic and health data enables design of context-specific interventions, precise targeting and resource allocation, thus improving the efficiency and equity of immunisation strategies.

However, to date, no synthesized evidence has described the geospatial approaches and data used to identify ZD children or RI coverage in LLMICs. Previous literature reviews have mainly focused on factors or determinants [31–33], barriers [34,35], and inequalities [36–38] associated with RI coverage or ZD prevalence. While findings of these reviews highlight disparities in vaccine coverage among vulnerable groups, they lack a geospatial lens, leaving a critical gap in understanding the landscape of spatial mapping of ZD and RI coverage and key spatial determinants. So far, only one narrative review has applied a geospatial lens to examine microplanning, geospatial, and machine learning approaches for reaching ZD and under-immunised children. While it provides an overview of the strengths and limitations of these approaches, it was restricted to 18 publications and reports in SSA only mainly published in 2024 and 2025, did not explicitly focus on spatial methods, and it did not critically assess the methods, data and sources used in the studies [39].

To address this gap, we conducted a scoping review of geospatial approaches used to map immunisation coverage in LLMICs, focusing on both RI coverage and ZD prevalence. Although ZD children represent the most extreme form of immunisation exclusion, they sit within a broader continuum of RI performance, and the geospatial methods used to map each largely overlap. Examining both yields a comprehensive synthesis: RI coverage mapping characterises the overall landscape of immunisation performance, while ZD mapping pinpoints the most excluded communities. Specifically, we aimed to (i) outline the relevant spatial datasets that have been used to map ZD prevalence and RI, (ii) outline the methods used in mapping ZD children and RI coverage and (iii) highlight gaps in both geospatial data and methodological frameworks used and synthesize recommended strategies to address these gaps.

A scoping review was appropriate because evidence on geospatial methods for identifying ZD children and RI coverage is diverse, cross-disciplinary, and evolving. Research varies in terms of data sources, characteristics, and methods, making traditional systematic reviews for mapping the literature impractical.

2. Materials and methods

2.1. Search strategy

We adhered to Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for scoping reviews (PRISMA-ScR) guidelines [40] and the protocol was registered in Open Science Framework [41]. A comprehensive search for peer reviewed articles was conducted in April 2025 in six electronic databases: PubMed, Web of Science, Scopus, Cochrane, Embase, and EBSCOhost-CINAHL. Search terms were designed in accordance with the Population-Context-Concept (PCC) framework [42], where Population encompassed all studies about vaccination coverage; Concept referred to studies using spatial or spatial-statistical modelling methods; and Context to studies in LLMICs.

Supplementary File 1 Table S1 shows how search terms were designed on the PCC framework.

2.2. Screening and selection criteria

Article screening was conducted in two phases (title and abstract screening and full-text review) by two reviewers (AMN and MMM), to minimize bias in article selection. Disagreements regarding exclusion or inclusion of articles were resolved by a third reviewer (PMM). We included studies published in English up to April 2025, that were conducted in LLMICs and used or explicitly described the use of spatial data to map or model ZD children or routine childhood immunisation coverage. We also included studies using geospatial methods to predict, visualize, or analyse coverage of routine childhood vaccinations such as DTP1, and measles-containing vaccines (MCV). Since national immunisation schedules vary across countries [43], the specific vaccines assessed differed between studies, reflecting the routine childhood immunisation programmes and data sources available in each setting. Studies were excluded if they were conducted outside LLMICs, focused on immunisation coverage without specific attention to childhood vaccination, or addressed only clinical aspects of vaccine efficacy or safety without examining coverage. We also excluded literature reviews and studies that examined determinants, barriers, or correlates of immunisation uptake without incorporating a spatial component. The inclusion and exclusion criteria are detailed in **Supplementary File 1 Table S2**.

Search terms were first piloted on PubMed and adapted to the other databases. Grey literature from unpublished reports conference proceedings websites dissertations and snowballing of eligible studies was eligible if it was cited in the included papers. Supplementary Box 1 illustrates the search terms used PubMed database and adapted in other databases.

2.3. Data extraction

From each study, we extracted: (i) bibliographic information, including title, authors, Digital Object Identifier (DOI), year of publication, and study objective, (ii) study characteristics such as the geographical setting and study period, (iii) vaccine-related details, including vaccine type, source of vaccination data and how ZD was defined in the study, where applicable, (iv) types and sources of covariates, (v) modelling approaches, including model type, software used, and whether modelling code was available, (vi) results, such as spatial and temporal resolution of estimates and spatial aggregation units, and (vii) limitations and recommendations reported by the authors. A summary of the variables we extracted from the articles is presented in **Supplementary File 1 Table S3**.

2.4. Data synthesis

Data synthesis was performed independently by two reviewers (AMN and PMM) using integrated narrative and thematic approaches to synthesize the extracted data, as these methods are well suited to integrate diverse findings from scoping reviews.

As there is no standardized framework for classifying geospatial approaches for ZD prevalence and RI coverage modelling, we adopted a bespoke taxonomy, informed by the objectives of the review and the common analytical structure of included studies. We summarised the studies by their geographical distribution, year of publication, whether they provided spatial modelling methods, spatial data or both, the type of vaccines they assessed, the target age groups used to compute coverage and how ZD was defined. Thematic summarisation involved inductively identifying recurring themes related to geospatial data and modelling approaches. Modelling methods were hierarchically organized into bespoke or ad-hoc themes and sub-themes based on the core concepts and relative methodological complexity. Covariates identified from the studies were thematically classified into broad categories (such as demographic, and health system) and specific sub-categories like household characteristics factors. This classification was informed primarily by the contextual usage of the covariates in the studies. Modelled estimates were summarised based on the aggregation units (for example, by administrative region or by pixel), spatial and temporal resolution, while tools, packages, reported limitations and recommendations were presented narratively. In addition, we identified limitations beyond those explicitly reported in the studies and proposed recommendations to address these gaps, with the aim of strengthening future ZD prevalence and RI coverage modelling.

3. Results

3.1. Article search and screening

Of 15,587 initially retrieved articles (15,586 from databases and one peer-reviewed paper from snowballing of studies), 7,871 duplicates were removed. The remaining 7,716 articles underwent title and abstract screening, resulting in the exclusion of 7,445 articles that were either literature reviews, focused on immunisation other than routine childhood vaccination (e.g., COVID-19) or did not include or describe spatial data or methods (Figure 1).

Of the 271 articles selected for full-text review, the full text of one article could not be found. We further excluded 169 articles that did not use geospatial methods (n = 151), did not focus on childhood vaccination (n=7) or vaccination coverage (n=5), or focused on disease modelling without addressing vaccination coverage (n=5).

3.2. Study characteristics

Studies either focused exclusively on ZD (n=20; 19.6%) or on RI (n=82; 80.4%). Thus, in this review, we refer to studies focused on ZD only as *"ZD studies"* and those focused on broad RI as "*RI studies*". RI studies are presented in **Supplementary File 2 Table S1** and ZD studies in **Supplementary File 2 Tables S2.**

Among all 76 LLMICs [30], 68 (89.5%) countries had at least one included study (Fig. 2). Of the 102 studies, 18 (17.6%) were conducted across multiple countries as detailed in **Supplementary File 1 Table S4,** while 84 (82.4%) focused on a single country **Supplementary File 1 Table S5** shows studies focused on a single country**.** Ethiopia (38%), Nigeria (30%), and India (19%) accounted for the largest portion of studies, together representing 87% of all included studies. Of the 84 single-country studies, 90% covered the entire country, while the remainder focused on specific subnational areas, including states, provinces, districts, counties and cities as outlined in **Supplementary File 1 Table S5**.

The included studies were published between 2010 and 2025, with the majority (70%) published between 2021 and 2024 (**Figure 3**). Among the ZD studies, 90% (n = 18/20) were published between 2022 and 2024, while most RI studies (n=19/82; 23%) were published in 2024. Most studies (n=86/102; 84.3%) provided both geospatial data and methodological approaches for modelling vaccination coverage. The rest (n=16/86;15.7%) only examined associations or correlations between covariates and vaccination outcomes without spatially predicting vaccination coverage. Among these 16 studies, four were ZD studies.

Seven of the 20 ZD studies were conducted in multiple countries: one spanned the whole of SSA [44], two covered all low- and middle-income countries (LMICs) [45,46] and the remaining four were conducted in various combinations of individual countries. The rest of the studies (n=13) spanned individual countries, with Nigeria accounting for the majority (n=4) (Supplementary File 2 Table S2). Eleven of the 82 RI studies spanned multiple countries. The same pattern as in all studies was observed, where Ethiopia (n=25), Nigeria (n=13), and India (n=12) had the most RI studies.

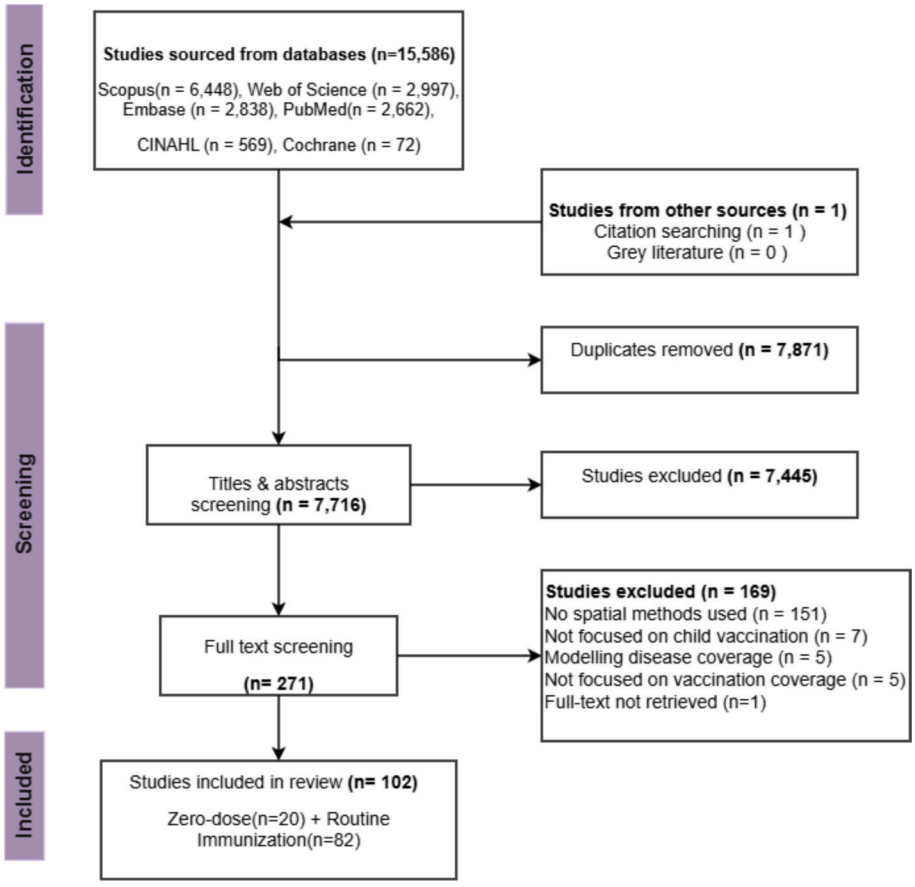

Fig. 1. The PRISMA flow diagram showing the different phases of the scoping review from literature search, article screening and exclusion.

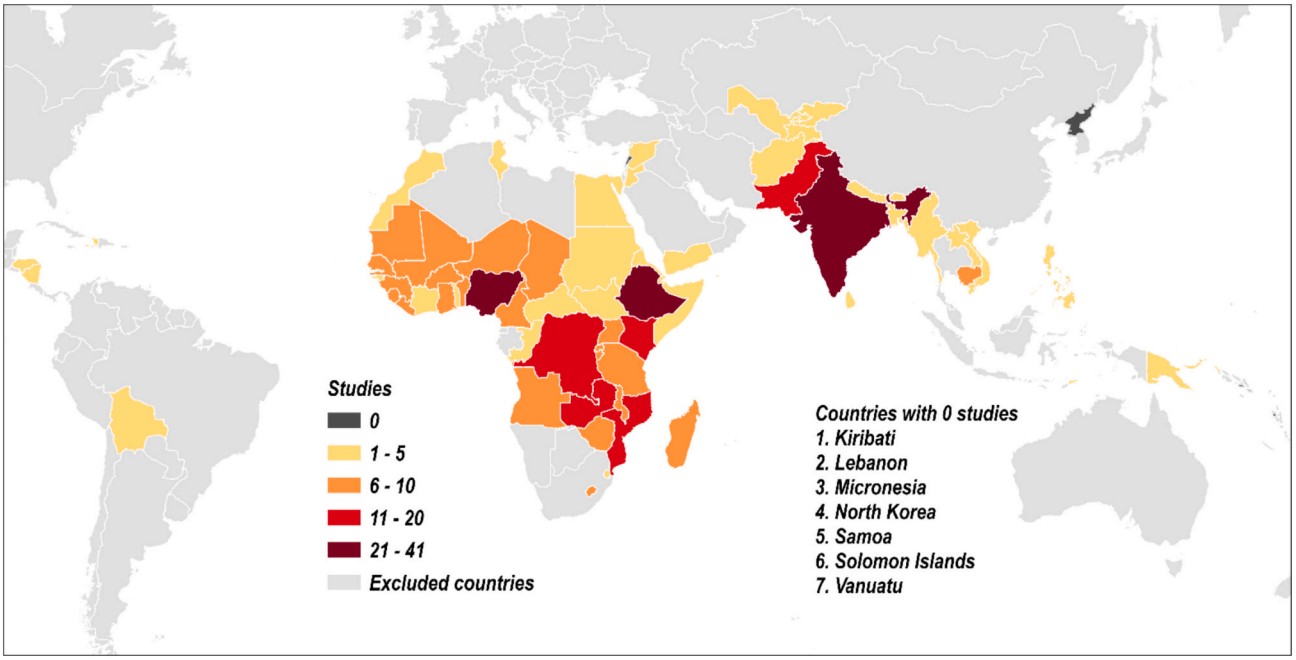

Fig. 2. Number of included studies by country. Light grey colour shows countries that were excluded from the study because they were not LLMICs.

3.3. Vaccination

3.3.1. Vaccines studied

Most studies (71.6%; n=73/102) examined multiple vaccines, resulting in 29 unique vaccine combinations as summarised in **Supplementary File 1 Table S6**. Overall, MCV1 (n=68), DPT1 (n=55) and DPT3 (n=55) were the most frequently studied vaccines, and this pattern remained consistent across stratified ZD and RI studies. 95% (n

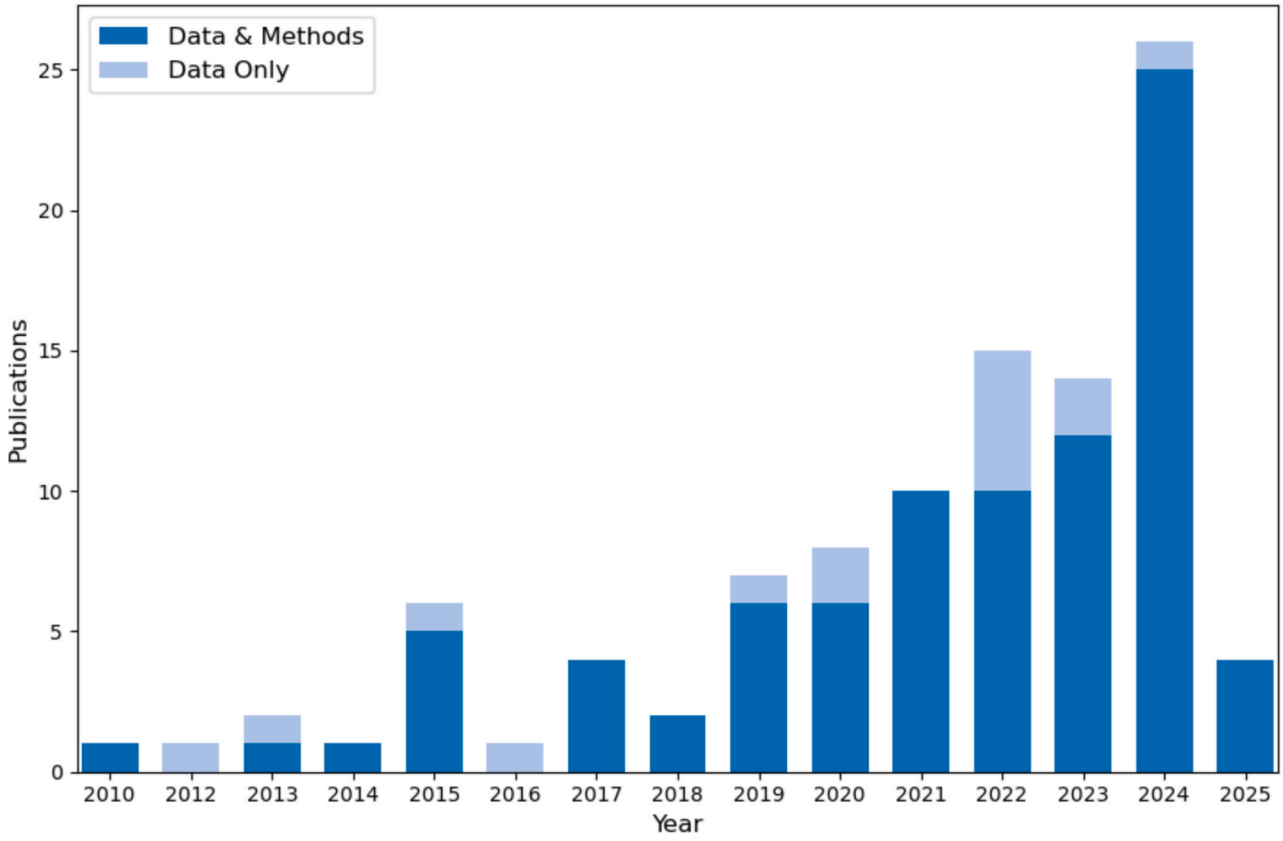

Fig. 3. Distribution of studies by year of publication and information provided: (a) both geospatial data and methodological approaches for modelling ZD children and (b) only geospatial data on factors associated with immunisation coverage. Not all publications from 2025 were included in the review as the search was conducted in April 2025.

= 19/20) of ZD studies assessed DPT1, either in combination with other vaccines (n = 14), yielding five distinct vaccine combinations, or as the only vaccine (n=5). One ZD study did not specify the vaccine assessed. Notably, no ZD study assessed MCV2. A detailed tabulation of vaccines and the corresponding number of studies is presented in **Supplementary File 1 Table S7**. Across all studies, 24 different age groups were used to report coverage of 21 vaccines as illustrated in **Supplementary File 1 Table S23.** The number of target age groups used for the same vaccine also varied, going up to 21 for MCV1, with the most common age group being children aged 12–23 months (n=32 studies). Similarly, the most common age group for DTP1 and DTP3 was children aged 12–23 months See **Supplementary File 1 Table S23** for a detailed tabulation of the age groups and the corresponding vaccines.

3.3.2. ZD definition

Across the 20 ZD studies, ZD was operationalized inconsistently, using two definitions and four target age-groups. Specifically, a ZD child was defined as: one who had not received DTP1 in 17 studies [17,44,45,47–59] or one missing a single dose in the routine vaccination schedule in three studies [60–62]. In addition, five age groups were used to define the target population for evaluating ZD children, including <1 year (n=2), 0–23 months (n=1), 12–23 months (n=12), 12–35 months (n=3) and <5 years(n=1). One study did not specify the target age groups used to define ZD. A summary of the target age-groups used is presented in **Supplementary File 1 Table S8**.

3.4. Data characteristics and sources

3.4.1. Vaccination data

3.4.1.1. Survey data only. Of the 102 studies, 90 (18 ZD studies and 72 RI studies) obtained vaccination status data from survey-based sources. Of these, seven ZD studies and 49 RI studies relied on DHS data only while 13 studies (7 RI studies and 6 ZD studies) combined DHS data with other household survey data like Multiple Indicator Cluster Surveys (MICS) (n=13). Other studies (n=12) used field survey data collected after Supplementary Immunisation Activities (SIA), clinical trials and community demonstration projects. Additionally, three studies (2 ZD and 1 RI) used pre-modelled vaccination estimates from the Institute for Health Metrics and Evaluation (IHME)'s local burden of disease project [45,46,63] which were derived using data from multiple household surveys.

3.4.1.2. Routine data only. Overall, only seven of all included studies (6.9%) relied on vaccination data from routine health information systems only. Two of these were ZD studies conducted in Cameroon and Pakistan, while the remaining five were RI studies conducted in Zambia, Mozambique, Pakistan (2 studies) and Nigeria.

3.4.1.3. Studies combining survey and routine data. Only five studies used both routine and survey data to assess vaccine coverage. These included two studies in Ethiopia integrating DHIS2 and DHS data, one study in Zambia combining HMIS records with data from 20 household surveys, a study in Pakistan linking health facility records with post-SIA survey data, and another study in Madagascar using EPI records and longitudinal cohort study data. Notably, none of these studies focused on ZD children. Further details on vaccination data sources for RI and ZD studies, respectively, are provided in **Supplementary File 1 Tables S9 & S10.**

3.4.2. Covariates

We extracted details on covariate data immunisation from 81 of the

Table 1
Summary of covariates and data inputs across all included studies. The numbers in brackets represent the number of covariate instances within each category. Under data sources, values indicate how many covariate types within each category were derived from that specific source.

Broad category	Subcategory	Specific covariates	Data source
Demographic (n=461, 49.3%)	Population (n=32)	Density (n=22), subset of the population (n=5) and other characteristics (n=5)	Empirically modelled (n=1), National population Census (n=4), NGO, HMIS, Global mapping projects (n=24), Existing survey (n=1), Global health organization (n=1)
	Urbanicity (n=51)	Urban/rural dichotomy (n=40), urban continuum (n=7) and settlements (n=4)	Global mapping projects (n=11), Global health organization (n=1), Existing survey (n=31), Satellite-based (n=2), University research unit (n=1), Primary data collection (n=1), Electronic Immunisation Registry (n=1)
	Age (n=44)	Age of the care giver (n=13) and the child (n=31)	Existing survey (n=37), Primary data collection (n=6)
	Socio-economic (n=77)	Household wealth/assets (n=37), occupation (n=15), poverty (n=15), economic environment (n=7) and bank account (n=3)	Empirically modelled (n=2), Existing survey (n=59), University research unit (n=1), Primary data collection (n=3), Global health organization (n=2), Global mapping projects (n=8)
	Education and awareness (n=91)	Maternal education (n=42), literacy (n=12), Media and internet (n=23), knowledge of disease (n=4) and other aspects of education (n=10)	Existing survey (n=73), Global mapping projects (n=4), Primary data collection (n=8), Electronic Immunisation Registry (n=1), HMIS (n=1), Empirically modelled (n=1)
	Culture and beliefs (n=34)	Ethnicity (n=10), religion (n=19) and social group (n=5)	Existing survey (n=27), University research unit (n=3), Primary data collection (n=3), HMIS (n=1)
	Child characteristics (n=53)	Child's gender (n=28), birth order (n=17) and birth interval (n=2) and others (n=6)	Existing survey (n=45), Primary data collection (n=5), Electronic Immunisation Registry (n=1), HMIS (n=2)
	Household characteristics (n=54)	Household head (n=17), size (n=11), marital status (n=13), number of children (n=10), and others (n=3)	Existing survey (n=46), Primary data collection (n=7), Empirically modelled (n=1)
	Fertility and reproduction (n=14)	Fertility (n=3), parity (n=6), pregnancy (n=4) and desire for last child (n=1)	Existing survey (n=11), Global mapping projects (n=1), Primary data collection (n=2)
	Nutrition and hygiene (n=11)	Water (n=3), sanitation (n=3), breast feeding and diet (n=5)	Existing survey (n=9), Empirically modelled (n=2)
	Disease & morbidity (n=12)	Childhood diarrhoea (n=1), respiratory infections (n=1), malnutrition (n=2), malaria (n=4), Polio (n=2) and others (n=2)	Global mapping projects (n=6), Existing survey (n=1), Empirically modelled (n=2), Primary data collection (n=1)
	Health care utilization (n=91)	Antenatal care (n=30), postnatal care (n=12), place of delivery (n=23), mode of delivery (n=3), skilled birth attendance (n=6), autonomy in decision making (n=8) and possession of a health card or document (n=9)	Existing survey (n=83), Primary data collection (n=3), Global mapping projects (n=1), Electronic Immunisation Registry (n=1)
Health system (n=179, 19.1%)	Health intervention (n=20)	Bed nets (n=3), family planning (n=2) and other vaccinations (n=15)	Existing survey (n=12), Primary data collection (n=1), Electronic Immunisation Registry (n=1), Empirically modelled (n=1)
	Access to health care services (n=46)	Proximity to healthcare (n=32), availability of healthcare facilities and workers (n=14)	Global mapping projects (n=13), Primary data collection (n=9), Existing survey (n=2), Empirically modelled (n=13), HMIS (n=2), Crowdsourced (n=1), census (n=1), Satellite-based (n=1), Global health organization (n=2), Electronic Immunisation Registry (n=1)
	Health financing (n=10)	Health insurance (n=6) and expenditure (n=4)	Existing survey (n=9), Global mapping projects (n=1)
Infrastructural (n=36, 3.8%)	Access to infrastructure (n=36)	Transport infrastructures (n=18), electricity (n=3) and night-time lights as a proxy (n=15)	Crowdsourced (n=8), Global mapping projects (n=6), Empirically modelled (n=3), Existing survey (n=2), Satellite-based (n=12), Global climate database (n=1), Other global databases (roads, boundaries, water bodies) (n=2)
	Conflict (n=12)	Conflict areas and proximity to such areas	University research unit (n=1), Global mapping projects (n=9)
Hard to reach (n=74, 7.9%)	Remoteness (n=57)	Access to cities (n=20) and settlements (n=16) proximity to cultivated areas (n=6), protected areas (n=4) and water bodies (n=10)	Crowdsourced (n=9), Satellite-based (n=9), Empirically modelled, Global mapping projects (n=27), Other global databases (roads, boundaries, water bodies) (n=4), Regional mapping agency (n=1)
	Migration (n=3)	Migration status (n=3)	Existing survey (n=1), Primary data collection (n=1), HMIS (n=1)
	Slums (n=2)	Slum areas (n=2)	Global health organization (n=1), Existing survey (n=1)
Physical and environmental (n=148, 15.8%)	Topographical (n=21)	Elevation (n=16) and slope (n=5)	Satellite-based (n=14), Regional mapping agency (n=1), National mapping agency (n=3), Global mapping projects (n=1)
	Hydrological (n=41)	Precipitation (n=21), evapotranspiration (n=8), aridity (n=5) and soil/vegetation moisture (n=7)	Global research partnership (n=7), University research unit (n=14), Global climate database (n=9), Satellite-based (n=7), Empirically modelled (n=1)
	Atmospheric conditions (n=45)	Temperature (n=37), cloud cover percentage (n=3), frost day frequency (n=3) and mean vapour pressure (n=2)	University research unit (n=17), Satellite-based (n=16), Global climate database (n=7)
	Vegetation conditions (n=21)	Enhanced vegetation index (n=13), normalized difference vegetation index (n=5) and other indices (n=3)	Satellite-based (n=20)
	Agricultural (n=20)	Livestock density (n=13), irrigation (n=3) and the growing season and suitability (n=4)	Global mapping projects (n=10), Primary data collection (n=1), Global health organization (n=7), University research unit (n=2)
Others (n=38, 4.1%)	Geographical location (n=38)	Representation of space through coordinates (n=2), subnational (n=23) or national regions (n=13).	Satellite-based (n=1), Other global databases (roads, boundaries, water bodies) (n=7), Existing survey (n=21), HMIS (n=1), Crowdsourced (n=1), Global health organization (n=1), Primary data collection (n=1), Empirically modelled (n=1)

102 studies, comprising 17 ZD studies and 64 RI studies. The remaining 21 studies were excluded from covariate extraction either because they did not use covariates in modelling (n=5) or they performed exploratory spatial analysis without predicting vaccine coverage [45,57,64–66]. **Supplementary File 1 Table S11** shows the 21 the studies.

The following section reports covariates extracted from all included studies, as differences between ZD and RI studies were minimal. Where there were notable differences, findings specific to either group are highlighted. Also, since individual studies included multiple covariates, percentages reported in this section reflect the total number of covariate instances extracted across all studies (n=936) rather than the number of studies.

3.4.3. Types of covariates

We identified six general categories of covariates (Table 1). Demographic factors, accounted for nearly half (n=460/936; 49.4%) of all the covariates used, while health system factors and physical and environmental factors represented 19.1% (n=179/936) and 15.8% (n=148/936) of all covariates, respectively. Factors representing hard-to-reach contexts, such as exposure to conflict, and remoteness comprised only 7.9%. Infrastructural factors such as access to electricity and covariates representing spatial characteristics such as the region where the child resided (classified as "others" in Table 1) were also less frequently used. The distribution of covariates was largely consistent between ZD and RI studies, with ZD studies showing slightly greater use of variables related to hard-to-reach populations at 9.1% (n=23/253) (Figure 4). **Supplementary File 1 Table S13** provides more details of covariates and data inputs across ZD studies only.

A comprehensive breakdown of all covariates (n=936) beyond the six classes (Table 1) shows that the most frequently used variables are those linked to healthcare access and utilization, education and awareness, socio-economic status, characteristics of the child and the household and environmental factors. Details on the covariate data extracted from RI studies are presented in **Supplementary File 1 Figure S1** and **Table S12**.

3.4.3.1. Sources of data on covariates. Covariate data were drawn from a wide range of sources, including secondary household surveys for 51% (n=477) of all 936 extracted covariates. Other major sources were university-led global mapping initiatives (n=149/936; 15.9%), mapping agencies and global organizations (n=80/936; 8.5%), and satellite-derived products (n=73/936; 7.8%). Other sources included primary data collection, national population censuses, crowd-sourced data, model-derived outputs, and HMIS. For 69 covariates, studies triangulated multiple data sources and data sources were not reported for 39 covariates.

Covariates obtained from secondary surveys were mostly from DHS (n=420/477; 88%) and MICS (n=48/477;10%). Global mapping projects led by universities or independent research groups also provided substantial sources of covariates: Worldpop, University of Southampton (33%) and Malaria Atlas Project, Kids Research Institute Australia and Curtin University (19%), among other similar projects. A summary of the sources of covariates across all 81 studies is provided in Table 1, and a breakdown of the number of covariates by source is provided in **Supplementary File 1 Table S14** for all studies and **Supplementary File 1 Table S14b** for ZD studies.

3.5. Modelling vaccination coverage

Studies clustered around ten broad themes. Most focused on geospatial mapping of vaccination coverage, hotspot analysis, ZD and under-immunisation, and determinants of immunisation inequity such as wealth and maternal education. Other themes included vaccine timeliness and dropout, geographic accessibility, vaccine delivery strategies, spatial integration of immunisation within broader health programmes and use of advanced spatial-statistical methods and machine learning to address challenges in data quality and coverage estimation. A summary of these themes is presented in **Supplementary File 2 Table S3**.

3.5.1. Modelling methods

Several modelling approaches were used across the 86 modelling studies, spanning from exploratory spatial clustering methods to advanced geostatistical and machine learning techniques. These approaches were either spatial (67.4%) or spatiotemporal (32.6%) and were summarised into five categories: i) spatial autocorrelation and clustering approaches, ii) small area estimation (SAE) methods, iii) spatial interpolation techniques, iv) machine learning methods and v) other methods such as disaggregation and multi-criteria decision analysis as shown in Table 2. Most studies (n=51) applied multiple methods, either sequentially or in combination to address different analytical objectives, including spatial pattern detection, variable selection, and prediction.

3.5.1.1. Spatial autocorrelation & clustering. Over half of the methodological studies (n=46/86; 53.5%) analysed spatial autocorrelation and clustering of immunisation status either as standalone analysis (n=15; 32.6%) or in combination with other statistical methods (n=31; 67.4%) such as time series and logistic regression analysis. Methods used included global and local Moran's I, hotspot analysis using the Getis-Ord Gi* statistic, and Kulldorff's spatial scan statistic, as shown in Table 2.

3.5.1.2. Small area estimation. SAE modelling frameworks were used in 14% (n=12/86) of studies to estimate vaccination coverage in small geographic areas where there were limited sample sizes. SAE approaches varied, depending on whether they accounted for spatial autocorrelation only or incorporated both spatial and temporal dependencies and whether they included covariates or not.

3.5.1.3. Spatial interpolation. Spatial interpolation methods ranged from simpler approaches like inverse distance weighting and kriging to more complex Bayesian geostatistical modelling (Table 2). Kriging was implemented in three forms – ordinary, universal, and empirical Bayesian – predominantly in ArcGIS (Esri, Redlands, CA, USA, without covariates, and mostly in Ethiopia (83.3%).

Bayesian MBG studies produced gridded estimates at 1 km or 5 km resolution, incorporated covariates (n=21), and were implemented primarily using R-INLA (n=20). Out of the studies that used MBG, 16 reported uncertainty estimates via 95% credible intervals, standard deviations, or non-exceedance probabilities. In contrast to kriging studies, the majority of MBG analyses were conducted in Nigeria (n=14) and only three in Ethiopia.

3.5.1.4. Machine learning. Only seven studies (~8%) as shown in Table 2 used machine learning algorithms to estimate vaccination coverage, spanning tree-based models (random forests, decision trees, gradient boosting), regularization models (LASSO, ridge regression), additive models, neural networks (multi-layer perceptron), and instance-based models (nearest neighbour).

Methods used in RI studies were broadly consistent with those used across all included studies. For ZD studies Bayesian MBG was the most used method (n=9, 45%), and local spatial autocorrelation analyses exclusively applied Getis-Ord Gi* statistic, with no use of Local Moran's I. **Supplementary File 1 Table S15** shows the methods used in ZD studies.

3.5.2. Tools and reproducibility

To model or map vaccination coverage, R [131] and STATA [132] were the two dominant statistical software used in 49 (11 ZD, 38 RI) and 39 (7 ZD, 32 RI) studies, respectively. Specialized mapping tools which

were mostly used for interpolation, data management and visualization of vaccination data included ArcGIS (Esri, Redlands, CA, USA) (n=38) and QGIS (n=6) [133]. **Supplementary File 1 Table S16** shows a summary of the tools and software used in the studies. In terms of reproducibility, only seven (three ZD, four RI) of the 86 studies shared their analytical code publicly.

3.6. Modelled outputs, gaps and recommendations

3.6.1. Aggregation units, spatial and temporal resolution

3.6.1.1. ZD studies. Of the 16 ZD studies that estimated ZD prevalence, spatial outputs were presented as gridded surfaces only (n=1), at administrative units only (n=5), or as both (n=8); two studies did not report the spatial resolution of their outputs. Among studies producing gridded outputs, spatial resolutions of 1 km (n=5), 5 km (n=2), and both 1 km and 5 km (n=1) were used. Notably, majority of these studies (n=8) used geostatistical approaches. Studies reporting estimates at administrative units did so at the first administrative level (n=1), second administrative level (n=2), or health area level (n=2). Spatial resolution and aggregation units for ZD studies are summarised in **Supplementary File 1 Tables S18 and S19.**

3.6.1.2. RI studies. Out of 82 RI studies, 70 (85.4%) modelled vaccine coverage. Spatial resolution of coverage estimates was presented as gridded surfaces only (n=6), aggregated at administrative units only (n=26) or as both gridded surfaces and administrative units (n=15). The remaining 23 studies used exploratory spatial autocorrelation and clustering methods and did not produce coverage estimates. Studies providing estimates as gridded surfaces used spatial resolutions of 1km (n=10), 5km (n=6), and 10km (n=1), both 1km and 5km (n=2), and two studies did not report the spatial resolution used. Spatial resolution and aggregation units for ZD studies are summarised in **Supplementary File 1 Tables S20 and S21.**

Across all modelling studies (ZD and RI combined; n=86), 27 produced annual estimates at the country level (n=19) or multi-country level (n=8), while the remaining 59 reported estimates for a single time point.

3.6.2. Evidence gaps and recommendations

We synthesised gaps and limitations in the vaccination data, covariates, and modelling methods used, as reported in **Supplementary File 1 Table S22** and drawing on both the limitations and recommendations reported by authors and our own critical appraisal, proposed recommendations to address them, as detailed in **Supplementary File 3** and summarised in **Supplementary File 1 Figure S2.**

Data limitations centred on the overreliance on DHS and other household survey data, with no triangulation with routine administrative sources such as DHIS2. Data scarcity in marginalized areas and systematic underrepresentation of populations in these areas led to critical blind spots in coverage estimates. Other limitations included inaccurate population denominators, low spatial and temporal resolution of survey data, and exclusion of key covariates such as conflict exposure and vaccine stocks.

Methodological limitations included reliance on single cross-sectional survey rounds, masking of subnational heterogeneities due to reliance on exploratory analyses, inconsistent reporting of uncertainty in modelled estimates, and method-specific weaknesses such as poor kriging performance in unsampled areas. Broader gaps encompassed limited use of spatio-temporal modelling, low reproducibility of the studies, and poor model transferability to other contexts.

To address these gaps, we proposed several recommendations, as shown in **Supplementary File 3**, such as formally integrating survey and routine data through data fusion frameworks; investing in community-based data collection and proxy indicators (e.g., satellite-derived settlement density, travel time to facilities) to improve coverage of marginalised populations; adopting spatio-temporal models

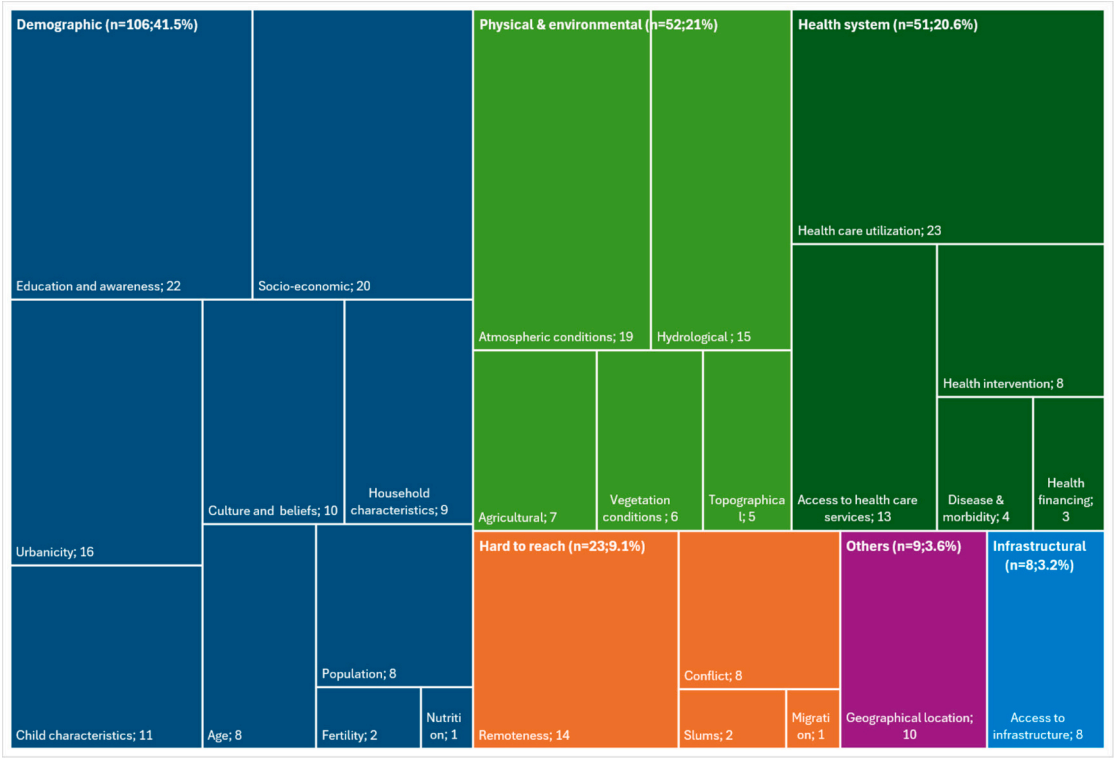

Fig. 4. Distribution of covariate categories and sub-categories across ZD studies. Since studies had multiple covariates, the tree diagram displays the relative frequency of covariate instances within each category and sub-category, with tile size proportional to the number of instances. Percentages are based on the total number of covariate instances extracted across all studies (n=253).

Table 2
Spatial and spatiotemporal methods used to model or map vaccination coverage. Values indicate the number of studies employing each method. As some studies applied multiple methods, percentages do not sum to 100%.

General category	Sub-category	Method	Reference
Spatial autocorrelation, hot spot analysis and cluster detection (n=46; 53.5%)	Global spatial autocorrelation	Global Moran's I (n=37)	[52,60,62,65,67–99]
	Local spatial autocorrelation	Local Moran's I (n=15)	[67,69,71,72,76,78–80,82,90,96,97,100–103]
		Subtype not specified (n=2)	[65,94]
		Getis-Ord Gi* statistic (n=21)	[52,60,67,70,74–77,82,84–88,91,95,103–105]
	Cluster detection	Kulldorff's spatial scan (n=21)	[56,60,62,67,68,70–72,74,76,77,81,82,85,86,88,91,95,98,103,106,107]
Small area estimation (n=12; 14%)	Spatial model	Various SAE spatial specifications (n=6)	[17,57,92,101,108,109]
	Spatiotemporal model	Various spatiotemporal SAE model specifications (n=6)	[110–115]
	Other	Inverse distance weighting (n=1)	[52]
		Exact method not stated	[99]
Spatial Interpolation (n=39; 45.3%)	Kriging	Universal kriging (n=2)	[76,85]
		Empirical Bayesian kriging (n=3)	[72,76,82]
		Ordinary kriging (n=10)	[62,67,70,71,76,77,82,86,88,103]
		Type not specified (n=6)	[60,81,83,89,91,95]
	Geostatistical models	Bayesian model-based geostatistics (MBG) (n=21)	[15,17,18,44,47,51,54,58,59,61,66,116–126]
		Reused outputs derived from a geostatistical model (n=1)	[45]
	Additive	Generalized Additive Models (GAMs) (n=5)	[44,54,116,127,128]
Artificial Intelligence (Machine learning (n=7; 8.1%))	Tree-based models	Gradient Boosting Model (GBM), and Boosted regression trees (BRT), Random forests (RF), Decision Tree (DT), (n=6)	[44,54,63,83,116,128]
	Regularization-linear models	Least Absolute Shrinkage and Selection Operator (LASSO), Ridge classifier (n=3)	[44,54,63]
	Neural Networks	Multi-Layer Perceptron (MLP) (n=1)	[48]
	Instance-based	Nearest Neighbour (n=1)	[48]
Others (n=4; 4.7%)	Disaggregation	Spatial regression (n=1)	[129]
	Multi-criteria decision analysis	Vulnerability index (n=2)	[53,58]
		Adjusted numerator (routine) and denominator (population) (n=2)	[64,130]

to capture trends between survey rounds; and promoting open sharing of code and data to improve reproducibility.

4. Discussion

This scoping review mapped the geospatial approaches used to estimate RI coverage and ZD prevalence across LLMICs and their associated gaps. Across 102 studies in 68 LLMICs, we found that while this domain has grown substantially over the recent years, evidence remains geographically concentrated in Ethiopia, Nigeria and India, and dominated by a narrow set of data sources – household survey data. Routine administrative data remains largely underused despite its potential for continuous, granular monitoring. Most RI studies rely on simpler exploratory methods that do not estimate coverage in unsampled areas. Critical gaps persist in data triangulation, spatio-temporal modelling limiting the capacity to track vaccination trends, and analytical focus on the most marginalised populations that have high ZD burden. Yet even in these high-burden settings, most studies mapped overall RI coverage rather than ZD prevalence. Addressing these gaps is crucial for geospatial approaches and tools to meaningfully inform immunisation programming. Below, we discuss each point and its implications for the identification of ZD children and mapping RI coverage in LLMICs.

The geographic concentration of studies in just three countries – Ethiopia, Nigeria, and India – reflects greater research attention due to high ZD burden in these countries [2]. However, research investment is still limited in conflict-affected and fragile countries, such as Yemen and South Sudan that have high ZD burden [2]. Further, the surge in publications between 2022 and 2024 signals growing recognition of geospatial approaches as essential for immunisation programming, likely driven by global initiatives like the Immunisation Agenda 2030 [134] and the Big Catch-Up aimed at recovering from COVID-19-related decline in childhood immunization [135]. Still, there is need to expand the geographic scope of geospatial immunisation research through targeted funding and capacity building in underrepresented settings.

Regardless of the growing recognition of the value of geospatial approaches for immunisation programming [39], mapping of ZD children is limited in scope and uptake relative to their demonstrated utility for identifying pockets of ZD children [17,44]. This reflects technical and structural barriers; generating high-resolution ZD estimates requires high resolution spatial data, advanced modelling, and cross-sector collaboration, which remain unevenly available in many LLMICs [15]. Thus, RI and ZD modelling studies are led by a handful of well-resourced academic groups, e.g., IHME local burden of disease and Worldpop's VaxPop project [136,137]. In addition, limited translation of ZD estimates in routine country planning, where administrative unit averages still dominate further discourages adoption of geospatial approaches [20,138].

The small proportion of ZD studies identified (~20%) is compounded by inconsistent operationalisation of the ZD concept: studies defined ZD as not receiving any routine vaccine [60–62], or missing DTP1 [17,44,45,47–59] and used different target age groups to assess prevalence. These definitions capture distinct populations and can substantially distort prevalence estimates and undermine comparability across settings. For example, globally, DTP1-ZD (14.2%) is nearly double that of completely unvaccinated children (7.5%) [139]. Subsequently, this has important consequences on policy and programmatic actions for reaching the most disadvantaged children [130]. Standardising the ZD definition and target age groups, guided by context, is therefore essential. Where routine administrative data are reliable, the DTP1-based definition is operationally justified as it enables continuous facility-level monitoring [139,140]. In marginalized settings where even partial immunisation is rare, the broader no-vaccine definition may better capture the most marginalised children [140]. Regardless of the

definition adopted, consistent application and transparent reporting of any deviations are prerequisite for comparable evidence.

The diversity of vaccine combinations (**Supplementary File 1 Table S6)** and age groups **(Supplementary File 1 Table S23)** used across studies reflects the absence of standardised reporting practices. While the dominance of MCV1, DTP1, and DTP3 aligns with their programmatic importance in tracking immunisation system performance [2], the use of up to 21 different age groups for a single vaccine, as observed for MCV1, further undermines cross-study comparability. These further cements the need for standardized reporting even for broader RI.

The main source of vaccination and covariate data in both RI and ZD studies was DHS (**Supplementary File 1 Table S8**). These surveys are nationally representative, standardized, and are less vulnerable to reporting incompleteness or treatment-seeking biases. They have accurate population denominators and detailed socio-demographic indicators. However, they are cross-sectional and fail to capture subnational heterogeneities [133]. The recent defunding of DHS further threatens tracking of health indicators in LLMICs, including ZD [25]. In contrast, there was limited use of routine vaccination data despite its continuously increasing availability through DHIS2 [28]. Routine health facility data is timely, has high spatial granularity and it can enable continuous ZD and RI monitoring. However, it is prone to incompleteness, outliers, and inaccurate population denominators since estimating health facility catchment areas is challenging [141]. Hence, leveraging routine data requires advanced methods, which may explain why studies used survey data [108]. This highlights a need to address systemic and structural gaps to improve collection and reporting of routine data [142], for instance, using rapid and targeted assessment tools such as lot quality assurance sampling and micro-planning to pinpoint low coverage areas [143], and triangulation of survey and routine data to leverage their differing strengths [141].

There was no triangulation of routine and survey data – the five RI studies combining both datasets treated them separately (e.g., using DHS coverage to adjust DHIS2 denominators) rather than jointly modelling them [130]. Joint modelling of routine and survey data is crucial, to maximise the complementary strengths of both data types. Such integrated frameworks have proven superior in other applications, for instance in mapping malaria incidence [141], by improving estimation accuracy and revealing hidden inequities that single-source models miss; for example, in Madagascar, integrating routine malaria surveillance and survey data revealed fine-scale spatial heterogeneity that was less apparent from either data source alone [141]. Integrated routine-survey modelling pipelines represents a high-impact priority for ZD mapping, enabling frequent monitoring and robust estimation in data-sparse areas.

Demographic, and health-system factors were the most applied, consistent with evidence identifying these as key barriers to vaccination uptake [144]. Still, there is a significant gap in the covariates used to capture marginalized or hard-to-reach populations, mainly due to data unavailability or scarcity in these settings [44,46]. There is higher prevalence of ZD and under-immunisation in marginalized settings [46], therefore, limited use of covariates capturing these contexts constrains the ability of models to identify populations at greatest risk of ZD. Future ZD studies should prioritize covariates capturing marginalization such as conflict exposure, displacement, and remoteness. Collaborative efforts by data agencies, local health authorities and international partners such as the International Organization for Migration (IOM) and United Nations High Commissioner for Refugees (UNHCR) are needed to expand covariate data in marginalized areas.

Most RI studies relied on exploratory autocorrelation and clustering approaches which do not interpolate estimates for unsampled locations and cannot generate high-resolution gridded estimates. Gridded estimates are valuable because they can be directly overlaid with high resolution population estimates (typically derived from national population censuses [145]), to estimate ZD population, or with other spatially resolved health indicators to identify overlapping dual or triple burdens [46,58]. They can also be aggregated to subnational administrative units that align with the scales at which immunisation programmes are planned and evaluated [116,127]. Dominance of exploratory methods reflects limited technical capacity, as these methods require less expertise and computational resources than advanced modelling approaches.

Capacity building in LLMICs, especially in SAE, geostatistical and machine learning approaches is essential to move beyond descriptive spatial analysis to predictive modelling. These advanced modelling approaches are better suited to estimate ZD, as they incorporate covariates, generate uncertainty and produce outputs at operationally meaningful scales [146,147]. Alternative user-friendly web tools such as Maplaria [148], MBGapp [149], and sae4health [150] that apply these models can also be used as they can host computations remotely and require no coding or advanced statistical knowledge. Yet, most studies using SAE, MBG or machine learning generated estimates at 1–10 km resolution, insufficient for precise identification of localised ZD clusters. Higher resolution outputs (such as 100 m) would enable more accurate targeting but achieving this requires fine-scale input data that remain largely unavailable across LLMICs [145].

Uptake of machine learning remains limited, partly due to the evidence that geostatistical models slightly outperform machine learning in estimating vaccine coverage [19] and the substantial technical and computational capacity required to use these models. However, with increasing availability of geospatial big data and satellite-derived covariates, it is crucial to explore the full potential of AI in this domain. AI models can handle large, multidimensional datasets, such as DHS and routine HMIS data, enabling integration of different variables and recognition of non-linear patterns in data [47]. They can also improve the efficiency of analytical tasks, for instance, using Large Language Models (LLMs) to automate feature extraction or multimodal foundation models that integrate multiple types of data including text, video, images and audio [151,152].

Only 31% of the studies incorporated a spatiotemporal framework, reflecting the complexity of spatiotemporal modelling and the scarcity of longitudinal data. Temporal estimates are critical for understanding vaccination trends over time and linking fluctuations to events or seasonal factors. Where longitudinal routine data are available, spatiotemporal approaches should be employed to bridge microplanning needs and dynamic monitoring of immunisation performance. Promoting the availability and use of longitudinal routine data, alongside advancing spatiotemporal modelling approaches is essential to enhance temporal analysis and prediction of ZD prevalence.

Overall, our review characterises the landscape of spatial ZD and RI coverage modelling in LLMICs, highlighting persistent data and methodological limitations that constrain the accuracy, equity, and comparability of estimates. Hard-to-reach populations are systematically excluded from analysis due to the lack of both reliable vaccination data and covariates capturing marginalized contexts. This leads to model misspecification in the settings where ZD burden is highest. Further, heavy reliance on household surveys, with limited triangulation with DHIS2 data, restricts the effective use of routine data. Addressing these challenges requires standardization of RI and ZD reporting, improved integration of survey and routine data through joint modelling, and the incorporation of non-traditional data sources such as satellite imagery, mobility data, and conflict databases. Strengthening data collection in underserved settings through approaches such as community health worker enumeration and rapid assessments is equally crucial. We present a synthesis of identified gaps and proposed recommendations in **Supplementary File 1 Figure S2** and **Supplementary File 3**.

5. Strengths and limitations

This review synthesizes evidence from a broad range of geospatial studies focused on assessing childhood vaccination coverage, providing

a consolidated understanding the gaps in data and sources, methods, and structural limitations of studies already available in the literature. To our knowledge, it is the first review to examine ZD prevalence and RI coverage through a geospatial lens, offering a unique contribution to the field and helping clarify a potential roadmap on how spatial data and methods can be applied to map vaccination coverage.

This review has several limitations. First, the included articles were published in English, potentially excluding other relevant studies published in other languages, especially French language studies from West Africa. Second, the included studies varied in ZD definitions, target age groups, spatial scales, and modelling approaches, limiting direct comparability of estimates across settings. Third, consistent with scoping-review methodology, we did not formally assess the quality or bias of studies. In addition, our search was limited to peer-reviewed, indexed literature published up to April 2025, potentially excluding relevant programme reports, and more recent studies in the field. Fourth, we acknowledge a minor deviation from the registered protocol [41]. We included articles from LLMICs, rather than LMICs as originally proposed. This refinement was made because the majority of the global ZD burden is concentrated in LLMICs and the evidence examined in this review are predominantly used in these settings. However, this decision excluded upper-middle-income countries that have persistent ZD children and under-immunisation, potentially limiting the applicability of the findings in these contexts. Finally, some aspects of the synthesis, including the classification of covariates and modelling approaches, involved interpretive judgement, and the reported limitations may under-represent issues not identified by the original study authors.

6. Policy implications

This review has several implications for policy and practice. Immunization programmes should move beyond administrative-unit averages and adopt spatially disaggregated estimates to identify and reach localised ZD pockets. Realising this requires three enabling conditions: sustained investment in local analytical capacity; institutional integration of spatial estimation into routine programme planning and budgeting; and stronger data foundations, including a harmonised ZD definition and routine data systems that can be triangulated with survey data. Without these, geospatial tools will remain technically advanced but concentrated in a few well-resourced settings, failing to translate into equitable immunization gains.

7. Conclusion

Our review emphasizes the critical role that geospatial data and methods play in modelling and mapping ZD prevalence and RI coverage, and highlights substantial gaps in the data and methods used, offering insights into where improvements are needed to better estimate immunisation coverage. Future research should prioritize triangulating routine and household survey data while placing greater emphasis on understudied populations such as nomadic groups, refugees, urban slum residents, and conflict-prone areas.

In addition, studies should move beyond describing spatial patterns through clustering and similar exploratory methods and progress towards generating monitoring tools (e.g., dashboards) and using spatiotemporal statistical and machine learning models that integrate survey, routine, and geospatial data to predict ZD prevalence and RI coverage at detailed spatiotemporal scales. Overall, this review provides a foundational reference for future ZD and RI surveillance and modelling work as well as for policymakers seeking to integrate geospatial evidence into programming and monitoring. The covariates and methodological approaches identified across studies offer a practical starting point for researchers, while the documented gaps and recommendations can guide efforts to strengthen and streamline geospatial modelling of ZD populations and RI coverage.

CRediT authorship contribution statement

Ann M. Njogu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Moses M. Musau:** Writing – review & editing, Writing – original draft, Software, Formal analysis, Data curation. **Swati Srivastava:** Writing – review & editing, Funding acquisition. **Francesco Menegale:** Writing – review & editing. **Emma Clarke:** Writing – review & editing, Funding acquisition. **Caroline Mudereri:** Writing – review & editing. **Felix R. Kitema:** Writing – review & editing. **Yvonne Opanga:** Writing – review & editing, Funding acquisition. **Arnold Mmbando:** Writing – review & editing. **Absolomon Gashaija:** Writing – review & editing. **Hassan Sibomana:** Writing – review & editing. **Jeanine Condo:** Writing – review & editing, Resources, Funding acquisition. **Frank Osei:** Writing – review & editing. **Lenka Beňová:** Writing – review & editing. **Justine I. Blanford:** Writing – review & editing. **Piero Poletti:** Writing – review & editing, Resources, Funding acquisition. **Aleksandra Torbica:** Writing – review & editing, Funding acquisition. **Alessia Melegaro:** Writing – review & editing, Funding acquisition. **Carlo Federici:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Peter M. Macharia:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Ethical approval

Not applicable.

Declaration of generative AI and AI-assisted technologies in the writing process

ChatGPT- text editing

Funding

The work was funded by the European Union under The Global Health EDCTP3 Joint Undertaking (GH EDCTP3 JU) – Grant Agreement number 101159477. Views and opinions expressed are however, those of the authors only and do not necessarily reflect those of the European Union or GH EDCTP3. Neither the European Union nor the granting authority can be held responsible for them. PMM is supported by Fonds voor Wetenschappelijk Onderzoek (FWO) under a Senior Postdoctoral Fellowship (Grant number: 1201925N).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank Rehema Ouko (Department of Public Health, Institute of Tropical Medicine (ITM), Antwerp, Belgium) and Dr. Aliki Christou (Department of Public Health, Institute of Tropical Medicine (ITM), Antwerp, Belgium) for their assistance in obtaining access to relevant articles used in this review.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.vaccine.2026.128904.

Data availability

No data was used for the research described in the article.

References

[1] World Health Organization.. Immunization [Internet] [cited 2025 Nov 25]. Available from: https://www.afro.who.int/health-topics/immunization; 2026.

[2] World Health Organization,. United Nations International Children's Emergency Fund. WUENIC Trends [Internet] [cited 2026 Jan 27]. Available from: https://worldhealthorg.shinyapps.io/wuenic-trends/; 2026.

[3] Gavi the Vaccine Alliance.. The zero-dose child: explained [Internet] [cited 2025 Nov 25]. Available from: https://www.gavi.org/vaccineswork/zero-dose-child-explained; 2026.

[4] Gavi the Vaccine Alliance.. Zero-dose children and missed communities [Internet] [cited 2025 Nov 25]. Available from: https://www.gavi.org/our-alliance/strategy/phase-5-2021-2025/equity-goal/zero-dose-children-missed-communities; 2026.

[5] IA2030 IG 2.1: Number of zero dose children [Internet] [cited 2026 Jun 1]. Available from: https://www.who.int/data/gho/indicator-metadata-registry/imr-details/7792.

[6] Corrêa GC, Uddin MJ, Wahed T, Oliveras E, Morgan C, Kamya MR, et al. Measuring zero-dose children: reflections on age cohort flexibilities for targeted immunization surveys at the local level. Vaccines (Basel) 2024;12(2). https://doi.org/10.3390/vaccines12020195.

[7] Gavi the Vaccine Alliance.. Turning the corner: Immunization Agenda 2030 Global Report 2023. 2023.

[8] Federal Ministry of Health and Social Welfare of Nigeria, National Population Commission, ICF International. Nigeria Demographic and Health Survey [Internet]. 2025 Oct [cited 2025 Nov 25]. Available from: https://dhsprogram.com/publications/publication-FR395-DHS-Final-Reports.cfm; 2024.

[9] Rainey JJ, Watkins M, Ryman TK, Sandhu P, Bo A, Banerjee K. Reasons related to non-vaccination and under-vaccination of children in low and middle income countries: findings from a systematic review of the published literature, 1999–2009. Vaccine 2011:8215–21. https://doi.org/10.1016/j.vaccine.2011.08.096. PubMed PMID: 21893149.

[10] Jani JV, De Schacht C, Jani IV, Bjune G. Risk factors for incomplete vaccination and missed opportunity for immunization in rural Mozambique. BMC Public Health. 2008:8. https://doi.org/10.1186/1471-2458-8-161. PubMed PMID: 18485194.

[11] Murhekar MV, Kumar MS. Reaching zero-dose children in India: progress and challenges ahead. The Lancet Global Health. Elsevier Ltd 2021:e1630–1. https://doi.org/10.1016/S2214-109X(21)00406-X. PubMed PMID: 34798011.

[12] Gavi the Vaccine Alliance.. Immunization Agenda 2030: A Global Strategy to Leave No One Behind [Internet] [cited 2025 Aug 22]. Available from: https://www.who.int/teams/immunization-vaccines-and-biologicals/strategies/ia2030; 2020.

[13] Gavi the Vaccine Alliance.. Phase 5 (2021–2025) [Internet] [cited 2025 Nov 20]. Available from: https://www.gavi.org/our-alliance/strategy/phase-5-2021-2025.

[14] Gavi the Vaccine Alliance. Phase 6 (2026–2030) [Internet] [cited 2025 Nov 24]. Available from: https://www.gavi.org/our-alliance/strategy/phase-6-2026-2030#vision.

[15] Utazi CE, Thorley J, Alegana VA, Ferrari MJ, Takahashi S, Metcalf CJE, et al. High resolution age-structured mapping of childhood vaccination coverage in low and middle income countries. Vaccine 2018;36(12):1583–91. https://doi.org/10.1016/j.vaccine.2018.02.020. PubMed PMID: 29454519.

[16] Gavi the Vaccine Alliance.. Improving Immunisation Coverage and Equity through the Effective Use of Geospatial Technologies and Data [Internet] [cited 2025 Nov 28]. Available from: https://www.gavi.org/our-impact/evaluation-studies/using-geospatial-technologies-improve-immunisation-coverage-equity; 2020.

[17] Baptiste AEJ, Wagai J, Hahné S, Adeniran A, Koko RI, de Vos S, et al. High-Resolution Geospatial Mapping of Zero-Dose and Underimmunized Children Following Nigeria's 2021 Multiple Indicator Cluster Survey/National Immunization Coverage Survey. Journal of Infectious Diseases. 2024;230(1):e131–8. https://doi.org/10.1093/infdis/jiad476. PubMed PMID: 39052714.

[18] Arambepola R, Yang Y, Hutchinson K, Mwansa FD, Doherty JA, Bwalya F, et al. Using geospatial models to map zero-dose children: Factors associated with zero-dose vaccination status before and after a mass measles and rubella vaccination campaign in Southern province, Zambia. BMJ Glob. Health. 2021;6(12). https://doi.org/10.1136/bmjgh-2021-007479.

[19] Utazi CE, Yankey O, Chaudhuri S, Olowe ID, Danovaro-Holliday MC, Lazar AN, et al. Geostatistical and machine learning approaches for high-resolution mapping of vaccination coverage. Spat Spatiotemporal Epidemiol. 2025;54:100744. https://doi.org/10.1016/J.SSTE.2025.100744. PubMed PMID: 40935503.

[20] ReliefWeb.. Reaching the unreached with life-saving vaccines through data science and geospatial technologies - World | ReliefWeb [Internet] [cited 2026 Mar 18]. Available from: https://reliefweb.int/report/world/reaching-unreached-life-saving-vaccines-through-data-science-and-geospatial-technologies.

[21] Kirby RS, Delmelle E, Eberth JM. Advances in spatial epidemiology and geographic information systems. Ann Epidemiol. 2017:27(1). https://doi.org/10.1016/j.annepidem.2016.12.001.

[22] Delmelle EM, Desjardins MR, Jung P, Owusu C, Lan Y, Hohl A, et al. Uncertainty in geospatial health: challenges and opportunities ahead. Ann. Epidemiol. 2022. https://doi.org/10.1016/j.annepidem.2021.10.002.

[23] Morrison CN, Mair CF, Bates L, Duncan DT, Branas CC, Bushover BR, et al. Defining spatial epidemiology: a systematic review and re-orientation. Epidemiology 2024. https://doi.org/10.1097/EDE.0000000000001738.

[24] Corsi DJ, Neuman M, Finlay JE, Subramanian SV. Demographic and health surveys: a profile. Int J Epidemiol. 2012;41(6):1602–13. https://doi.org/10.1093/ije/dys184. PubMed PMID: 23148108.

[25] Khaki JJ, Molenaar J, Karki S, Olal E, Straneo M, Mosuse MA, et al. When health data go dark: the importance of the DHS Program and imagining its future. BMC Med. 2025;23(1). https://doi.org/10.1186/s12916-025-04062-6. PubMed PMID: 40275318.

[26] Macharia PM, Beňová L, Ray N, Semaan A, Musau MM, Kipterer JK, et al. Putting health facilities on the map: a renewed call to create geolocated, comprehensive, updated, openly licensed dataset of health facilities in sub-Saharan African countries. BMC Med. 2025;23(1):211. https://doi.org/10.1186/S12916-025-04023-Z. PubMed PMID: 40197252.

[27] Tatem AJ. Innovation to impact in spatial epidemiology sally blower; gerardo chowell. BMC Med. 2018;16(1). https://doi.org/10.1186/s12916-018-1205-5. PubMed PMID: 30424754.

[28] University of Oslo.. District Health Information Software 2 (DHIS2) In Action [Internet] [cited 2025 Nov 25]. Available from: https://dhis2.org/in-action/#map.

[29] Population Reference Bureau.. The DHS Program - Evolution of The DHS Program [Internet] [cited 2025 Nov 25]. Available from: https://dhsprogram.com/data/visualizations/Evolution-of-The-DHS-Program.cfm.

[30] World Bank. Country and Lending Groups,. World Bank Data Help Desk [Internet] [cited 2026 Feb 3]. Available from: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

[31] Favin M, Steinglass R, Fields R, Banerjee K, Sawhney M. Why children are not vaccinated: a review of the grey literature. International Health. 2012:229–38. https://doi.org/10.1016/j.inhe.2012.07.004. PubMed PMID: 24029668.

[32] Tauil M de C, Sato APS, Waldman EA. Factors associated with incomplete or delayed vaccination across countries: a systematic review. Vaccine. Elsevier Ltd; 2016. p. 2635–43. doi:https://doi.org/10.1016/j.vaccine.2016.04.016 PubMed PMID: 27109562.

[33] Galadima AN, Zulkefli NAM, Said SM, Ahmad N. Factors influencing childhood immunisation uptake in Africa: a systematic review. BMC Public Health. 2021;21(1). https://doi.org/10.1186/s12889-021-11466-5. PubMed PMID: 34320942.

[34] Bangura JB, Xiao S, Qiu D, Ouyang F, Chen L. Barriers to childhood immunization in sub-Saharan Africa: a systematic review. BMC Public Health. BioMed Central; 2020. doi:https://doi.org/10.1186/s12889-020-09169-4 PubMed PMID: 32664849.

[35] Guzman-Holst A, DeAntonio R, Prado-Cohrs D, Juliao P. Barriers to vaccination in Latin America: a systematic literature review. Vaccine. Elsevier Ltd; 2020. p. 470–81. https://doi.org/10.1016/j.vaccine.2019.10.088. PubMed PMID: 31767469.

[36] Belt RV, Abdullah S, Mounier-Jack S, Sodha SV, Danielson N, Dadari I, et al. Improving equity in urban immunization in low- and middle-income Countries: a qualitative document review. Vaccines. Multidisciplinary Digital Publishing Institute (MDPI) 2023. https://doi.org/10.3390/vaccines11071200.

[37] Lyons C, Nambiar D, Johns NE, Allorant A, Bergen N, Hosseinpoor AR. Inequality in childhood immunization coverage: a scoping review of data sources, analyses, and reporting methods. Vaccines. Multidisciplinary Digital Publishing Institute (MDPI) 2024. https://doi.org/10.3390/vaccines12080850.

[38] Crocker-Buque T, Mindra G, Duncan R, Mounier-Jack S. Immunization, urbanization and slums - A systematic review of factors and interventions. BMC Public Health. 2017;17(1). https://doi.org/10.1186/s12889-017-4473-7. PubMed PMID: 28595624.

[39] Musuka G, Umar-Al Umra, Dadari I, Moyo E, Mano O, Iradukunda PG, et al. Bridging immunization gaps in Sub-Saharan Africa: a narrative review of microplanning, geospatial, and machine learning approaches to reach zero-dose children and under-immunised children. Vaccine 2026;79:128413. https://doi.org/10.1016/j.vaccine.2026.128413. PubMed PMID: 41806761.

[40] Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Ann Intern Med. 2018;169(7):467–73. https://doi.org/10.7326/M18-0850. PubMed PMID: 30178033.

[41] Njogu A, Mutinda M, Macharia P. Geospatial data and methods for mapping zero-dose children in low- and middle-income countries: a scoping literature review protocol [Internet]. 2025. https://doi.org/10.17605/OSF.IO/2Z3XV.

[42] Peters MD, Godfrey CM, Mclnerney P, Soares CB, Khalil H, Parker D. The Joanna Briggs Institute Reviewers' Manual 2015. Methodology for JBI Scoping Reviews. 2015.

[43] World Health Organization. World Health Organization Immunization Data portal - All Data [Internet] [cited 2026 Jun 21]. Available from: https://immunizationdata.who.int/global?topic=Vaccination-schedule&location; 2026.

[44] Mosser JF, Gagne-Maynard W, Rao PC, Osgood-Zimmerman A, Fullman N, Graetz N, et al. Mapping diphtheria-pertussis-tetanus vaccine coverage in Africa, 2000–2016: a spatial and temporal modelling study. The Lancet. 2019;393(10183):1843–55. https://doi.org/10.1016/S0140-6736(19)30226-0. PubMed PMID: 30961907.

[45] Fullman N, Correa GC, Ikilezi G, Phillips DE, Reynolds HW. Assessing potential exemplars in reducing zero-dose children: a novel approach for identifying positive outliers in decreasing national levels and geographic inequalities in

unvaccinated children. Vaccines (Basel) 2023;11(3). https://doi.org/10.3390/vaccines11030647.
[46] Wigley A, Lorin J, Hogan D, Utazi CE, Hagedorn B, Dansereau E, et al. Estimates of the number and distribution of zero-dose and under-immunised children across remote-rural, urban, and conflict-affected settings in low and middle-income countries. PLOS. Global Public Health. 2022;2(10 October). https://doi.org/10.1371/journal.pgph.0001126.
[47] Alegana VA, Ticha JM, Mwenda JM, Katsande R, Gacic-Dobo M, Danovaro-Holliday MC, et al. Modelling the spatial variability and uncertainty for under-vaccination and zero-dose children in fragile settings. Sci Rep. 2024;14(1). https://doi.org/10.1038/s41598-024-74982-5. PubMed PMID: 39420047.
[48] Biswas A, Tucker J, Bauhoff S. Performance of predictive algorithms in estimating the risk of being a zero-dose child in India, Mali and Nigeria. BMJ Glob Health. 2023;8(10). https://doi.org/10.1136/bmjgh-2023-012836.
[49] Edson Utazi C, Pannell O, Aheto JMK, Wigley A, Tejedor-Garavito N, Wunderlich J, et al. Assessing the characteristics of un- and under-vaccinated children in low- and middle-income countries: a multi-level cross-sectional study. PLOS. Global Public Health. 2022;2(4 April). https://doi.org/10.1371/journal.pgph.0000244.
[50] Mbunga BK, Liu PY, Bangelesa F, Mafuta E, Dalau NM, Egbende L, et al. Zero-dose childhood vaccination status in rural democratic republic of congo: quantifying the relative impact of geographic accessibility and attitudes toward vaccination. Vaccines (Basel) 2024;12(6). https://doi.org/10.3390/vaccines12060617.
[51] Aheto JMK, Olowe ID, Chan HMT, Ekeh A, Dieng B, Fafunmi B, et al. Geospatial Analyses of Recent Household Surveys to Assess Changes in the Distribution of Zero-Dose Children and Their Associated Factors before and during the COVID-19 Pandemic in Nigeria. Vaccines (Basel) 2023;11(12). https://doi.org/10.3390/vaccines11121830.
[52] Shiferie F, Gebremedhin S, Andargie G, DelPizzo F, Belete K, Fenta TG. Spatial distribution of zero-dose children in Ethiopia: evidence for a targeted intervention from a large-scale cross-sectional evaluation survey. Front Pediatr. 2024:12. https://doi.org/10.3389/fped.2024.1337922.
[53] Saidu Y, Agbor VN, Di Mattei P, Nchinjoh SC, Edwidge NN, Njoh AA, et al. Development of a composite scoring system to rank communities at high risk of zero-dose children in Cameroon: a geospatial analysis. J Glob Health. 2023:13. https://doi.org/10.7189/jogh.13.04136. PubMed PMID: 37971948.
[54] Haeuser E, Nguyen JQ, Rolfe S, Nesbit O, Fullman N, Mosser JF. Assessing Geographic Overlap between Zero-Dose Diphtheria–Tetanus–Pertussis Vaccination Prevalence and Other Health Indicators. Vaccines (Basel) 2023;11(4). https://doi.org/10.3390/vaccines11040802.
[55] Mehmood M, Setayesh H, Siddiqi DA, Siddique M, Iftikhar S, Soundardjee R, et al. Prevalence, geographical distribution and factors associated with pentavalent vaccine zero dose status among children in Sindh, Pakistan: analysis of data from the 2017 and 2018 birth cohorts enrolled in the provincial electronic immunisation registry. BMJ Open. 2022;12(5). https://doi.org/10.1136/bmjopen-2021-058985. PubMed PMID: 35584879.
[56] Mutwadi AM, Madinga JN, Vanlerberghe V, Mbala PK, van der Sande MAB. Geospatial and multilevel clustering of zerodose children in Kikwit, Democratic Republic of the Congo in 2022. PLOS. Global Public Health. 2024;4(2). https://doi.org/10.1371/journal.pgph.0002617.
[57] Johri M, Rajpal S, Kim R, Subramanian SV. Small-area variation in child under-vaccination in India: a multilevel analysis of cross-sectional data from 36 states and Union Territories, 707 districts, and 22,349 small-area clusters. The Lancet Regional Health - Southeast Asia. 2025:32. https://doi.org/10.1016/j.lansea.2024.100504.
[58] Utazi CE, Chan HMT, Olowe I, Wigley A, Tejedor-Garavito N, Cunningham A, et al. A zero-dose vulnerability index for equity assessment and spatial prioritization in low- and middle-income countries. Spatial Statistics. Elsevier B. V.; 2023. https://doi.org/10.1016/j.spasta.2023.100772.
[59] Utazi CE, Aheto JMK, Wigley A, Tejedor-Garavito N, Bonnie A, Nnanatu CC, et al. Mapping the distribution of zero-dose children to assess the performance of vaccine delivery strategies and their relationships with measles incidence in Nigeria. Vaccine 2023;41(1):170–81. https://doi.org/10.1016/j.vaccine.2022.11.026. PubMed PMID: 36414476.
[60] Tamir TT, Zegeye AF, Mekonen EG, Tekeba B, Ali MS, Gonete AT, et al. Prevalence, spatial variation and determinants of zero-dose children in Ethiopia: spatial and multilevel analyses. Public Health. 2024;236:365–72. https://doi.org/10.1016/j.puhe.2024.09.011. PubMed PMID: 39303624.
[61] Utazi CE, Aheto JMK, Chan HMT, Tatem AJ, Sahu SK. Conditional probability and ratio-based approaches for mapping the coverage of multi-dose vaccines. Stat Med. 2022;41(29):5662–78. https://doi.org/10.1002/sim.9586. PubMed PMID: 36129171.
[62] Agimas MC, Asmamaw M, Hailu MK, Kidie T, Abuhay HW, Yismaw GA, et al. Geospatial mapping to assess the distribution and determinants of zero dose vaccination status hot spots among children in Ethiopia using EDHS 2019: spatial and geographical weighted regression. PLoS One. 2024;19(12). https://doi.org/10.1371/journal.pone.0312610. PubMed PMID: 39739825.
[63] Ikilezi G, Augusto OJ, Sbarra A, Sherr K, Dieleman JL, Lim SS. Determinants of geographical inequalities for DTP3 vaccine coverage in sub-Saharan Africa. Vaccine 2020;38(18):3447–54. https://doi.org/10.1016/j.vaccine.2020.03.005. PubMed PMID: 32204938.
[64] Nilsen K, Tejedor-Garavito N, Leasure DR, Utazi CE, Ruktanonchai CW, Wigley AS, et al. A review of geospatial methods for population estimation and their use in constructing reproductive, maternal, newborn, child and adolescent health service indicators. BMC Health Serv Res. 2021;21. https://doi.org/10.1186/s12913-021-06370-y. PubMed PMID: 34511089.
[65] Ilesanmi MM, Adeyinka DA, Olakunde BO. Sustainable Development Goals and childhood measles vaccination in Ekiti State, Nigeria: results from spatial and interrupted time series analyses. Vaccine 2022;40(28):3861–8. https://doi.org/10.1016/j.vaccine.2022.05.037. PubMed PMID: 35644673.
[66] Singh R, Agarwal S, De Figueiredo A, Mishra M, Agarwal D. Quantifying the role of maternal recall in estimates of routine immunisation rates in India: a large-scale sub-national Bayesian modelling study. In: COMPASS 2024 - Proceedings of the ACM SIGCAS/SIGCHI Conference on Computing and Sustainable Societies. Association for Computing Machinery, Inc; 2024. p. 74–84. https://doi.org/10.1145/3674829.3675062.
[67] Gamachu M, Mussa I, Deressa A, Tolera M, Birhanu A, Getachew T, et al. Patterns of basic pneumococcal conjugated vaccine coverage in Ethiopia from 2015 to 2018; further analysis of Ethiopian DHS (2016–2019). Vol. 17. Elsevier Ltd. 2024. https://doi.org/10.1016/j.jvacx.2024.100428.
[68] Tesfa GA, Yehualashet DE, Getnet A, Bimer KB, Seboka BT. Spatial distribution of complete basic childhood vaccination and associated factors among children aged 12–23 months in Ethiopia. A spatial and multilevel analysis. PLoS One. 2023;18(1 January). https://doi.org/10.1371/journal.pone.0279399. PubMed PMID: 36608032.
[69] Muloliwa AM, Camacho LAB, Verani JFS, Simões TC, do Dgedge MC. Impact of vaccination on the incidence of measles in Mozambique in the period 2000 to 2011. Cad Saude Publica. 2013. doi:https://doi.org/10.1590/s0102-311x2013000200013.
[70] Agimas MC, Asmamaw M, Mekonen N, Mamo F, Shewaye DA. Spatial pattern and associated factors of timely vaccination in Ethiopia using EDHS-2016 data: a multilevel and spatial analysis. PLoS One. 2024;19(2 February). https://doi.org/10.1371/journal.pone.0296123. PubMed PMID: 38324535.
[71] Melaku MS, Nigatu AM, Mewosha WZ. Spatial distribution of incomplete immunization among under-five children in Ethiopia: evidence from 2005, 2011, and 2016 Ethiopian Demographic and health survey data. BMC Public Health. 2020;20(1). https://doi.org/10.1186/s12889-020-09461-3. PubMed PMID: 32891120.
[72] Awol M, Alemu ZA, Moges NA, Jemal K. Geographical variations and associated factors of defaulting from immunization among children aged 12 to 23 months in Ethiopia: using spatial and multilevel analysis of 2016 Ethiopian Demographic and Health Survey. Environ Health. Prev Med. 2021;26(1). https://doi.org/10.1186/s12199-021-00984-8. PubMed PMID: 34118886.
[73] Bantie GM, Tadege M, Nigussie TZ, Woya AA, Tekile AK, Melese AA, et al. Regional disparities of full pentavalent vaccine uptake and the determinants in Ethiopia: mapping and spatial analysis using the EDHS data. PLoS One. 2025;20(1 January). https://doi.org/10.1371/journal.pone.0312514. PubMed PMID: 39787194.
[74] Tesfa GA, Demeke AD, Hailegebreal S, Amede ES, Ngusie HS, Kasie MN, et al. Spatial distribution and associated factors of measles vaccination among children aged 12–23 months in Ethiopia. A spatial and multilevel analysis. Hum Vaccin Immunother. 2022;18(1). https://doi.org/10.1080/21645515.2022.2035558. PubMed PMID: 35148252.
[75] Shiferie F, Gebremedhin S, Andargie G, Tsegaye DA, Alemayehu WA, Fenta TG. Low Measles Vaccination Coverage and Spatial Analysis of High Measles Vaccination Dropout in Ethiopia's Underprivileged Areas. Vaccines (Basel) 2024;12(3). https://doi.org/10.3390/vaccines12030328.
[76] Agegnehu CD, Alem AZ. Exploring spatial variation in BCG vaccination among children 0-35 months in Ethiopia: spatial analysis of Ethiopian Demographic and Health Survey 2016. BMJ Open. BMJ Publishing Group; 2021. https://doi.org/10.1136/bmjopen-2020-043565. PubMed PMID: 33910946.
[77] Hailegebireal AH, Hailegebreal S, Tirore LL, Wolde BB. Spatial variation and predictors of incomplete pneumococcal conjugate vaccine (PCV) uptake among children aged 12–35 months in Ethiopia: spatial and multilevel analyses. Front. Public Health. 2024:12. https://doi.org/10.3389/fpubh.2024.1344089. PubMed PMID: 38864011.
[78] Akinyemi YC. Geospatial Analysis of Vaccination Coverage and Predictors of Non- and Under-Vaccination of Children Aged 12–23 Months in Nigeria. Papers in Applied Geography. 2021;7(1):1–33. https://doi.org/10.1080/23754931.2020.1809009.
[79] Khan J, Shil A, Prakash R. Exploring the spatial heterogeneity in different doses of vaccination coverage in India. PLoS One. 2018;13(11). https://doi.org/10.1371/journal.pone.0207209. PubMed PMID: 30485291.
[80] Dhalaria P, Kumar P, Verma A, Priyadarshini P, Kumar Singh A, Tripathi B, et al. Exploring landscape of measles vaccination coverage: a step towards measles elimination goal in India. Vaccine 2024;42(17):3637–46. https://doi.org/10.1016/j.vaccine.2024.04.075. PubMed PMID: 38704248.
[81] Tamir TT, Terefe B, Wassie M, Workneh BS, Zegeye AF. Prevalence, spatial distribution and determinants of complete childhood pneumococcal conjugate vaccination in Ethiopia: spatial and multilevel analyses. BMC Public Health. 2024;24(1). https://doi.org/10.1186/s12889-024-19926-4. PubMed PMID: 39243021.
[82] Kamal A, Waseem A, Siddiqa M, Ijaz M, Shakeel A, Iftikhar S. Contextual factors influencing incomplete immunization and investigation of its geospatial heterogeneity in Pakistan: a cross-sectional study based on PDHS (2017–18). BMC Public Health. 2023;23(1). https://doi.org/10.1186/s12889-023-16508-8. PubMed PMID: 37620868.
[83] Forzy T, Tesfaye L, Getnet F, Misganew A, Lamma SW, Worku A, et al. Assessing the geographic and socioeconomic determinants of vaccine coverage in Ethiopia: a spatial and multistage analysis at the district level. Vaccine 2025;53. https://doi.org/10.1016/j.vaccine.2025.126834. PubMed PMID: 40056895.

[84] Diress F, Negesse Y, Worede DT, Bekele Ketema D, Geitaneh W, Temesgen H. Multilevel and geographically weighted regression analysis of factors associated with full immunization among children aged 12–23 months in Ethiopia. Sci Rep.; 14(1). doi:https://doi.org/10.1038/s41598-024-74189-8 PubMed PMID: 39349770.
[85] Tamir TT, Workneh BS, Mekonen EG, Zegeye AF. Coverage, spatial distribution and determinants of childhood inactivated poliovirus vaccine immunization in Ethiopia. PLoS One. 2024;19(5 May). https://doi.org/10.1371/journal.pone.0301933. PubMed PMID: 38820454.
[86] Zegeye AF, Mekonen EG, Tekeba B, Alemu TG, Ali MS, Gonete AT, et al. Spatial distribution and determinants of measles vaccination dropout among under-five children in Ethiopia: a spatial and multilevel analysis of 2019 Ethiopian demographic and health survey. PLoS One. 2024;19(7 July). https://doi.org/10.1371/journal.pone.0305393. PubMed PMID: 38976660.
[87] Defar A, Okwaraji YB, Tigabu Z, Persson LÅ, Alemu K. Geographic differences in maternal and child health care utilization in four Ethiopian regions; A cross-sectional study. Int J Equity Health. 2019;18(1). https://doi.org/10.1186/s12939-019-1079-y. PubMed PMID: 31718658.
[88] Agimas MC, Belew AK, Sisay M, Baffa LD, Gashaw M, Abriham ZY, et al. Spatial variations and determinants of timely completion of vaccination in Ethiopia using further analysis of EDHS 2019 data: spatial and multilevel analysis. PLoS One. 2024;19(4 April). https://doi.org/10.1371/journal.pone.0301409. PubMed PMID: 38578785.
[89] Root ED, Lucero M, Nohynek H, Anthamatten P, Thomas DSK, Tallo V, et al. Distance to health services affects local-level vaccine efficacy for pneumococcal conjugate vaccine (PCV) among rural Filipino children. Proc Natl Acad Sci U S A. 2014;111(9):3520–5. https://doi.org/10.1073/pnas.1313748111. PubMed PMID: 24550454.
[90] Puri P, Khan J, Shil A, Ali M. A cross-sectional study on selected child health outcomes in India: quantifying the spatial variations and identification of the parental risk factors. Sci Rep. 2020;10(1). https://doi.org/10.1038/s41598-020-63210-5. PubMed PMID: 32313048.
[91] Teshale AB, Amare T. Exploring spatial variations and the individual and contextual factors of uptake of measles-containing second dose vaccine among children aged 24 to 35 months in Ethiopia. PLoS One. 2023;18(1 January). https://doi.org/10.1371/journal.pone.0280083. PubMed PMID: 36598928.
[92] Khan J, Shil A, Puri P. Population and sub-national (district) level diversity in missed and dropout of different doses of hepatitis-B vaccine among Indian children aged 12–59 months. PLOS. Global Public Health. 2022;2(5). https://doi.org/10.1371/journal.pgph.0000243.
[93] Kumar G, R.S. R.. Availability of public health facilities and utilization of maternal and child health services in districts of India. Clin Epidemiol Glob Health. 2022;15. https://doi.org/10.1016/j.cegh.2022.101070.
[94] Panda BK, Kumar G, Mishra S. Understanding the full-immunization gap in districts of India: a geospatial approach. Clin Epidemiol Glob Health. 2020;8(2):536–43. https://doi.org/10.1016/j.cegh.2019.11.010.
[95] Tegegne KT, Tegegne ET, Tessema MK, Wudu TK, Chalachew AA, Workneh AZ. Spatial Distribution and Associated Factors of Measles Vaccination Among Children Aged 12–23 Months in Mozambique 2022–2023: a Spatial and Multilevel Analysis. Bratislava Medical Journal. 2025;126(2):181–95. https://doi.org/10.1007/s44411-024-00008-1.
[96] Das T. Unveiling Spatial Heterogeneity: a Study of Diverse Child Immunization Indicators Across Indian Districts. Child Indic Res. 2024;17(4):1615–59. https://doi.org/10.1007/s12187-024-10135-4.
[97] Singh SK, Vishwakarma D. Spatial heterogeneity in the coverage of full immunization among children in India: exploring the contribution of immunization card. Child Youth Serv Rev. 2021:121. https://doi.org/10.1016/j.childyouth.2020.105701.
[98] Geremew TT, Gezie LD, Abejie AN. Geographical variation and associated factors of childhood measles vaccination in Ethiopia: a spatial and multilevel analysis. BMC Public Health. 2019;19(1). https://doi.org/10.1186/s12889-019-7529-z. PubMed PMID: 31470822.
[99] Chauhadry IA, Soofi SB, Sajid M, Ali R, Khan A, Naqvi SK, et al. Bridging the Vaccination Equity Gap: a Community-Driven Approach to Reduce Vaccine Inequities in Polio High-Risk Areas of Pakistan. Vaccines (Basel). 2024;12(12). https://doi.org/10.3390/vaccines12121340.
[100] Khan J, Shil A, Mohanty SK. Hepatitis B vaccination coverage across India: exploring the spatial heterogeneity and contextual determinants. BMC Public Health. 2019;19(1). https://doi.org/10.1186/s12889-019-7534-2. PubMed PMID: 31510967.
[101] Uthman OA, Adedokun ST, Olukade T, Watson S, Adetokunboh O, Adeniran A, et al. Children who have received no routine polio vaccines in Nigeria: who are they and where do they live? Hum Vaccin Immunother. 2017;13(9):2111–22. https://doi.org/10.1080/21645515.2017.1336590. PubMed PMID: 28665749.
[102] Brownwright TK, Dodson ZM, Van Panhuis WG. Spatial clustering of measles vaccination coverage among children in sub-Saharan Africa. BMC Public Health. 2017;17(1). https://doi.org/10.1186/s12889-017-4961-9. PubMed PMID: 29246217.
[103] Bantie B, Atnafu Gebeyehu N, Adella GA, Ambaw Kassie G, Mengstie MA, Abebe EC, et al. Mapping geographical inequalities of incomplete immunization in Ethiopia: a spatial with multilevel analysis. Front Public Health. 2024:12. https://doi.org/10.3389/fpubh.2024.1339539. PubMed PMID: 38912271.
[104] Dimitrova A, Carrasco-Escobar G, Richardson R, Benmarhnia T. Essential childhood immunization in 43 low- and middle-income countries: analysis of spatial trends and socioeconomic inequalities in vaccine coverage. PLoS Med. 2023;20(1). https://doi.org/10.1371/journal.pmed.1004166. PubMed PMID: 36649359.
[105] Rerolle F, Dey AK, Benmarhnia T, Arnold BF. Spatial targeting and integration across vaccination, vitamin A and deworming programs throughout India 2019–21. Int J Epidemiol. 2024;53(6). https://doi.org/10.1093/ije/dyae160. PubMed PMID: 39657980.
[106] Umer MF, Zofeen S, Hu W, Qi X, Zhuang G. Spatiotemporal clustering analysis of Expanded Program on Immunization (EPI) vaccination coverage in Pakistan. Sci Rep. 2020;10(1). https://doi.org/10.1038/s41598-020-67839-0. PubMed PMID: 32620798.
[107] Ketsela A, Gebreyesus SH, Deressa W. Spatial distribution of under immunization among children 12–23 months old in Butajira HDSS, southern Ethiopia. BMC Pediatr. 2021;21(1). https://doi.org/10.1186/s12887-021-02690-4. PubMed PMID: 33971837.
[108] Utazi CE, Nilsen K, Pannell O, Dotse-Gborgbortsi W, Tatem AJ. District-level estimation of vaccination coverage: discrete vs continuous spatial models. Stat Med. 2021;40(9):2197–211. https://doi.org/10.1002/sim.8897. PubMed PMID: 33540473.
[109] Alegana VA, Atkinson PM, Pezzulo C, Sorichetta A, Weiss D, Bird T, et al. Fine resolution mapping of population age-structures for health and development applications. J R Soc Interface 2015;12(105). https://doi.org/10.1098/rsif.2015.0073. PubMed PMID: 25788540.
[110] Colson KE, Dwyer-Lindgren L, Achoki T, Fullman N, Schneider M, Mulenga P, et al. 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(1). https://doi.org/10.1186/s12916-015-0308-5. PubMed PMID: 25889124.
[111] Pramanik S, Muthusamy N, Gera R, Laxminarayan R. Vaccination coverage in India: a small area estimation approach. Vaccine 2015;33(14):1731–8. https://doi.org/10.1016/j.vaccine.2015.01.083. PubMed PMID: 25681661.
[112] Roberts DA, Ng M, Ikilezi G, Gasasira A, Dwyer-Lindgren L, Fullman N, et al. Benchmarking health system performance across regions in Uganda: a systematic analysis of levels and trends in key maternal and child health interventions, 1990-2011. BMC Med. 2015;13(1). https://doi.org/10.1186/s12916-015-0518-x. PubMed PMID: 26631048.
[113] Wollum A, Burstein R, Fullman N, Dwyer-Lindgren L, Gakidou E. Benchmarking health system performance across states in Nigeria: a systematic analysis of levels and trends in key maternal and child health interventions and outcomes, 2000-2013. BMC Med. 2015;13(1). https://doi.org/10.1186/s12916-015-0438-9. PubMed PMID: 26329607.
[114] Dong TQ, Wakefield J. Space-time smoothing models for subnational measles routine immunization coverage estimation with complex survey data. Annals of Applied Statistics. 2021;15(4):1959–79. https://doi.org/10.1214/21-AOAS1474.
[115] Mercer LD, Safdar RM, Ahmed J, Mahamud A, Khan MM, Gerber S, et al. Spatial model for risk prediction and sub-national prioritization to aid poliovirus eradication in Pakistan. BMC Med. 2017;15(1). https://doi.org/10.1186/s12916-017-0941-2. PubMed PMID: 29017491.
[116] Sbarra AN, Rolfe S, Nguyen JQ, Earl L, Galles NC, Marks A, et al. Mapping routine measles vaccination in low- and middle-income countries. Nature 2021;589(7842):415–9. https://doi.org/10.1038/s41586-020-03043-4.
[117] Atalell KA, Alemayehu MA, Teshager NW, Belay GM, Alemu TG, Anlay DZ, et al. Mapping BCG vaccination coverage in Ethiopia between 2000 and 2019. BMC Infect Dis. 2022;22(1). https://doi.org/10.1186/s12879-022-07547-4. PubMed PMID: 35739462.
[118] Utazi CE, Thorley J, Alegana VA, Ferrari MJ, Takahashi S, Metcalf CJE, et al. Mapping vaccination coverage to explore the effects of delivery mechanisms and inform vaccination strategies. Nat Commun. 2019;10(1). https://doi.org/10.1038/s41467-019-09611-1. PubMed PMID: 30967543.
[119] Wariri O, Utazi CE, Okomo U, Metcalf CJE, Sogur M, Fofana S, et al. Mapping the timeliness of routine childhood vaccination in The Gambia: a spatial modelling study. Vaccine 2023;41(39):5696–705. https://doi.org/10.1016/j.vaccine.2023.08.004. PubMed PMID: 37563051.
[120] Atalell KA, Liyew AM, Alene KA. Spatial distribution of rotavirus immunization coverage in Ethiopia: a geospatial analysis using the Bayesian approach. BMC Infect Dis. 2022;22(1). https://doi.org/10.1186/s12879-022-07825-1. PubMed PMID: 36352357.
[121] Sbarra AN, Rolfe S, Haeuser E, Nguyen JQ, Adamu A, Adeyinka D, et al. Estimating vaccine coverage in conflict settings using geospatial methods: a case study in Borno state, Nigeria. Sci Rep. 2023;13(1). https://doi.org/10.1038/s41598-023-37947-8. PubMed PMID: 37422502.
[122] Wolde HF, Clements ACA, Gilmour B, Alene KA. Spatial co-distribution of tuberculosis prevalence and low BCG vaccination coverage in Ethiopia. Sci Rep. 2024;14(1). https://doi.org/10.1038/s41598-024-68549-7. PubMed PMID: 39738221.
[123] Utazi CE, Wagai J, Pannell O, Cutts FT, Rhoda DA, Ferrari MJ, et al. Geospatial variation in measles vaccine coverage through routine and campaign strategies in Nigeria: analysis of recent household surveys. Vaccine 2020;38(14):3062–71. https://doi.org/10.1016/j.vaccine.2020.02.070. PubMed PMID: 32122718.
[124] Utazi CE, Olowe ID, Chan HMT, Dotse-Gborgbortsi W, Wagai J, Umar JA, et al. Geospatial Variation in Vaccination Coverage and Zero-Dose Prevalence at the District, Ward and Health Facility Levels Before and After a Measles Vaccination Campaign in Nigeria. Vaccines (Basel). 2024;12(12). https://doi.org/10.3390/vaccines12121299.
[125] Ferreira LZ, Utazi CE, Huicho L, Nilsen K, Hartwig FP, Tatem AJ, et al. Geographic inequalities in health intervention coverage – mapping the composite coverage

index in Peru using geospatial modelling. BMC Public Health. 2022;22(1). https://doi.org/10.1186/s12889-022-14371-7. PubMed PMID: 36397019.
[126] Dong TQ, Wakefield J. Modeling and presentation of vaccination coverage estimates using data from household surveys. Vaccine 2021;39(18):2584–94. https://doi.org/10.1016/j.vaccine.2021.03.007. PubMed PMID: 33824039.
[127] Takahashi S, Metcalf CJE, Ferrari MJ, Tatem AJ, Lessler J. The geography of measles vaccination in the African Great Lakes region. Nat Commun. 2017;8. https://doi.org/10.1038/ncomms15585. PubMed PMID: 28541287.
[128] Kawakatsu Y, Mosser JF, Adolph C, Baffoe P, Cheshi F, Aiga H, et al. High-resolution mapping of essential maternal and child health service coverage in Nigeria: a machine learning approach. BMJ Open. 2024;14(6). https://doi.org/10.1136/bmjopen-2023-080135. PubMed PMID: 38858137.
[129] Utazi CE, Thorley J, Alegana VA, Ferrari MJ, Nilsen K, Takahashi S, et al. A spatial regression model for the disaggregation of areal unit based data to high-resolution grids with application to vaccination coverage mapping. Stat Methods Med Res. 2019;28(10–11):3226–41. https://doi.org/10.1177/0962280218797362. PubMed PMID: 30229698.
[130] Tesfaye L, Forzy T, Getnet F, Misganaw A, Woldekidan MA, Wolde AA, et al. Estimating immunization coverage at the district level: a case study of measles and diphtheria-pertussis-tetanus-Hib-HepB vaccines in Ethiopia. PLOS. Global Public Health. 2024;4(7). https://doi.org/10.1371/journal.pgph.0003404.
[131] R: The R Project for Statistical Computing [Internet]. [cited. Available from: https://www.r-project.org/; 2026.
[132] Statistical software for data science | Stata [Internet]. [cited 2026 Mar 18]. Available from: https://www.stata.com/
[133] The DHS Program. The DHS Program- Quality information to plan, monitor and improve population, health, and nutrition programs [Internet]. [cited 2025 Nov 28]. Available from: https://www.dhsprogram.com/
[134] World Health Organisation. Immunization Agenda 2030 [Internet]. [cited 2026 Jun 22]. Available from: https://www.who.int/teams/immunization-vaccines-and-biologicals/strategies/ia2030.
[135] World Health Organisation. The Big Catch-Up: An Essential Immunization Recovery Plan for 2023 and Beyond [Internet]. [cited 2026 Jun 27]. Available from: https://www.who.int/publications/i/item/9789240075511.
[136] Homepage | Institute for Health Metrics and Evaluation [Internet]. [cited 2025 Nov 28]. Available from: https://www.healthdata.org/.
[137] WorldPop. Mapping zero-dose populations: conflict, remote rural, urban poor (Phase II amendment)- Nigeria VaxPop II [Internet]. [cited 2025 Nov 28]. Available from: https://www.worldpop.org/current-projects/completed-projects/nigeria-vaxpop-ii/.
[138] Ngo-Bebe D, Mechael P, Kwilu FN, Bukele TK, Langwana F, Lobukulu GL, et al. Assessing the use of geospatial data for immunization program implementation and associated effects on coverage and equity in the Democratic Republic of Congo. BMC Public Health. 2025;25(1). https://doi.org/10.1186/s12889-025-21578-x. PubMed PMID: 39856652.
[139] Wonodi C, Farrenkopf BA. Defining the zero dose child: a comparative analysis of two approaches and their impact on assessing the zero dose burden and vulnerability profiles across 82 low- and middle-income countries. Vaccines (Basel). 2023;11(10). https://doi.org/10.3390/vaccines11101543.
[140] Hogan D, Gupta A. Why Reaching Zero-Dose Children Holds the Key to Achieving the Sustainable Development Goals. Vaccines (Basel). 2023;11(4). https://doi.org/10.3390/vaccines11040781.
[141] Arambepola R, Keddie SH, Collins EL, Twohig KA, Amratia P, Bertozzi-Villa A, et al. Spatiotemporal mapping of malaria prevalence in Madagascar using routine surveillance and health survey data. Sci Rep. 2020;10(1). https://doi.org/10.1038/s41598-020-75189-0. PubMed PMID: 33093622.
[142] Molenaar J, Kikula A, van Olmen J, Pembe A, Beňová L. Getting the numbers right: power, creativity and 'good' routine maternal and neonatal health data in Southern Tanzania. Soc Sci Med. 2025;366. https://doi.org/10.1016/j.socscimed.2024.117668. PubMed PMID: 39787826.
[143] Bharti N, Djibo A, Tatem AJ, Grenfell BT, Ferrari MJ. Measuring populations to improve vaccination coverage. Sci Rep. 2016:5. https://doi.org/10.1038/srep34541.
[144] Beaulieu A, Ducharme J, Thibeault C, Akani BC, Ziegler D, Hogan D, et al. The Immunization Agenda 2030 Strategy to reach zero-dose children in low-income and middle-income countries: a scoping review. BMJ Glob Health. 2025;10(8): e018293. https://doi.org/10.1136/BMJGH-2024-018293. PubMed PMID: 40763981.
[145] Stevens FR, Gaughan AE, Linard C, Tatem AJ. Disaggregating Census Data for Population Mapping Using Random Forests with Remotely-Sensed and Ancillary Data. PLoS One. 2015;10(2):e0107042. https://doi.org/10.1371/JOURNAL.PONE.0107042. PubMed PMID: 25689585.
[146] Diggle PJ, Tawn JA, Moyeed RA. Model-Based Geostatistics. J R Stat Soc Ser C Appl Stat. 1998;47(3):299–350. https://doi.org/10.1111/1467-9876.00113.
[147] Giorgi E, Fronterrè C, Macharia PM, Alegana VA, Snow RW, Diggle PJ. Model building and assessment of the impact of covariates for disease prevalence mapping in low-resource settings: to explain and to predict. J R Soc Interface. 2021;18(179):20210104. https://doi.org/10.1098/rsif.2021.0104.
[148] Giorgi E, Macharia PM, Woodmansey J, Snow RW, Rowlingson B. Maplaria: a user friendly web-application for spatio-temporal malaria prevalence mapping. Malaria Journal 2021;20(1):471. https://doi.org/10.1186/S12936-021-04011-7. PubMed PMID: 34930265.
[149] Johnson O, Fronterre C, Diggle PJ, Amoah B, Giorgi E. MBGapp: a Shiny application for teaching model-based geostatistics to population health scientists. PLoS One. 2021;16(12):e0262145. https://doi.org/10.1371/JOURNAL.PONE.0262145. PubMed PMID: 34972193.
[150] Wu Y, Dong Q, Xu J, Li ZR, Wakefield J. sae4health: An R Shiny Application for Small Area Estimation in Low- and Middle-Income Countries. ArXiv [Internet]. 2025 May 2 [cited 2025 Nov 28]. Available from: https://arxiv.org/pdf/2505.01467; 2026.
[151] Espinosa L, Salathé M. Use of large language models as a scalable approach to understanding public health discourse. PLOS Digital Health. 2024;3(10): e0000631. https://doi.org/10.1371/JOURNAL.PDIG.0000631.
[152] Burstein R, Mafuta E, Proctor JL. Large language models for analyzing open text in global health surveys: why children are not accessing vaccine services in the Democratic Republic of the Congo. Int Health. 2025;17(5):843–52. https://doi.org/10.1093/INTHEALTH/IHAF015. PubMed PMID: 40052518.