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Mapping the timeliness of routine childhood vaccination in The Gambia: A spatial modelling study

Oghenebrume Wariri [a,b,c,*], Chigozie Edson Utazi [d,e], Uduak Okomo [a,f], C. Jessica E. Metcalf [g], Malick Sogur [h], Sidat Fofana [h], Kris A. Murray [i,1], Chris Grundy [b,1], Beate Kampmann [a,c,j,1]

[a] Vaccines and Immunity Theme, MRC Unit The Gambia a London School of Hygiene and Tropical Medicine, Fajara, Gambia
[b] Department of Infectious Disease Epidemiology, London School of Hygiene and Tropical Medicine, London, United Kingdom
[c] Vaccine Centre, London School of Hygiene and Tropical Medicine, London, United Kingdom
[d] WorldPop, School of Geography and Environmental Science, University of Southampton, Southampton, United Kingdom
[e] Southampton Statistical Sciences Research Institute, University of Southampton, Southampton, United Kingdom
[f] MARCH Centre, London School of Hygiene and Tropical Medicine, London, United Kingdom
[g] Department of Ecology & Evolutionary Biology, Princeton University, Princeton, NJ, USA
[h] Expanded Programme on Immunization, Ministry of Health and Social Welfare, The Gambia, Banjul, Gambia
[i] Centre on Climate Change and Planetary Health, MRC Unit The Gambia at The London School of Hygiene and Tropical Medicine, Fajara, Gambia
[j] Centre for Global Health, Charité Universitatsmedizin, Berlin, Germany

A B S T R A C T

Introduction: Timeliness of routine vaccination shapes childhood infection risk and thus is an important public health metric. Estimates of indicators of the timeliness of vaccination are usually produced at the national or regional level, which may conceal epidemiologically relevant local heterogeneities and make it difficult to identify pockets of vulnerabilities that could benefit from targeted interventions. Here, we demonstrate the utility of geospatial modelling techniques in generating high-resolution maps of the prevalence of delayed childhood vaccination in The Gambia. To guide local immunisation policy and prioritize key interventions, we also identified the districts with a combination of high estimated prevalence and a significant population of affected infants.

Methods: We used the birth dose of the hepatitis-B vaccine (HepB0), third-dose of the pentavalent vaccine (PENTA3), and the first dose of measles-containing vaccine (MCV1) as examples to map delayed vaccination nationally at a resolution of 1×1-km^2 pixel. We utilized cluster-level childhood vaccination data from The Gambia 2019–20 Demographic and Health Survey. We adopted a fully Bayesian geostatistical model incorporating publicly available geospatial covariates to aid predictive accuracy. The model was implemented using the integrated nested Laplace approximation—stochastic partial differential equation (INLA-SPDE) approach.

Results: We found significant subnational heterogeneity in delayed HepB0, PENTA3 and MCV1 vaccinations. Specific districts in the central and eastern regions of The Gambia consistently exhibited the highest prevalence of delayed vaccination, while the coastal districts showed a lower prevalence for all three vaccines. We also found that districts in the eastern, central, as well as in coastal parts of The Gambia had a combination of high estimated prevalence of delayed HepB0, PENTA3 and MCV1 and a significant population of affected infants.

Conclusions: Our approach provides decision-makers with a valuable tool to better understand local patterns of untimely childhood vaccination and identify districts where strengthening vaccine delivery systems could have the greatest impact.

1. Introduction

Immunisation is a highly effective and cost-efficient means of controlling infectious diseases [1]. Studies estimate that every dollar spent on immunisation yields a return on investment (ROI) of more than 16 dollars. If the broader benefits of immunisation are considered, the ROI rises to 48 dollars [2]. Since its establishment, the expanded programme on immunisation (EPI) has significantly reduced the incidence of and mortality from childhood vaccine-preventable diseases (VPDs) [3]. Between 2000 and 2019, vaccination programs in low- and middle-income countries (LMICs) prevented 36 million deaths among children aged under five [4]. Despite these hard-won successes, the COVID-19 pandemic caused the biggest setback in routine childhood vaccinations in 30 years. In 2021 alone, 18.2 million children globally did not receive the first dose of the diphtheria-tetanus-pertussis (DTP) containing vaccine, and an additional 6.8 million children were under-vaccinated [5]. Thus, a more holistic approach, considering different aspects of the routine vaccination system, needs to be adopted to

* Corresponding author at: Vaccines and Immunity Theme, MRC Unit The Gambia at London School of Hygiene and Tropical Medicine, Fajara, Gambia.
E-mail address: Oghenebrume.Wariri@lshtm.ac.uk (O. Wariri).
[1] Co-senior authors.

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facilitate speedy recovery from the drastic disruptions caused by the pandemic.

The success of EPI programs has traditionally been evaluated by measuring vaccination coverage rates [6,7]. This indicator assumes uptake and overlooks whether doses are received within the recommended window, are too early or delayed [8,9]. Yet, several factors, including local VPD epidemiology, maternal antibodies, and the earliest safe age for a vaccination with optimal efficacy and minimal risks, determine an ideal age window for vaccination [10]. High coverage and timely delivery are crucial to achieve the full benefits of vaccines [6]. Timely vaccination, that is, vaccination received within the recommended window in an age-appropriate manner [11], is an essential quality dimension of immunisation programs for various reasons. At the programmatic level, too early or delayed vaccination could alert program managers to potential issues with vaccine delivery [7]. At the individual level, vaccines received too early could lead to suboptimal immune response due to interference with maternal antibodies [12,13]. Conversely, delayed vaccination could increase children's exposure to VPDs, such as pertussis and measles, whose peaks occur during the first year of life [10,14]. Because of its high infectivity rate, measles requires at least 95 % vaccination coverage and population immunity to prevent outbreaks [15]. However, evidence from high-income countries suggests that measles outbreaks have occurred in the past due to suboptimal population immunity associated with delayed measles vaccination, even in the presence of a high overall coverage [16]. It is therefore imperative that countries like The Gambia [17,18], which have attained a persistently high vaccination coverage, must now explore the quality dimension – i.e., ensuring that children across all subpopulations receive vaccination in a timely, age-appropriate manner.

Regardless of source or strength of evidence of vaccination, survey-based estimates of vaccination coverage are typically produced at the national level or at the scale of large regions. This approach is often due to administrative convenience, operational limitations, or high cost of data collection to produce more spatially detailed estimates. Such large-area estimates mask epidemiologically important heterogeneities in local vaccine coverage and limit the identification of low coverage areas capable of sustaining pockets of disease transmission and which could benefit from targeted efforts [19]. Consequently, geospatial modelling approaches, utilizing geolocated household survey data have gained traction as a vital tool for creating high-resolution estimates and maps of vaccination coverage [20–24]. Recently, studies exploring the timeliness of childhood vaccination in LMICs have also gained significant momentum [25,26]. Nevertheless, to date, no studies have produced high-resolution maps showing the spatial patterns of the timeliness of routine childhood vaccination. The Immunization Agenda 2030 (IA2030) is an ambitious global strategy that aims to halve the number of under- or unvaccinated children and eliminate measles transmission globally [3]. This requires new data and methodological approaches to precisely locate and target these subpopulations to ensure no one is left behind. Maps are a powerful tool that can help identify vulnerable subpopulations and their programmatic relevance in vaccination is well recognised by the WHO IA2030 [3], UNICEF, and Gavi, the Vaccine Alliance [27].

In this paper, we show the utility of geospatial modelling techniques for high-resolution mapping of the timeliness of routine vaccination in The Gambia. We mapped the prevalence of delayed vaccination nationally at 1 × 1-km^2 resolution, second (District), and third (Wards) health administrative levels among children aged 12–35 months in The Gambia. To guide immunisation micro-planning, we also identified the specific districts and wards where there was a combination of high estimated prevalence and a significant population of affected infants. We focused our spatial analysis on delayed vaccination because we have previously shown that it is significantly more prevalent in The Gambia than other dimensions of vaccination timeliness [28]. We used the birth-dose of hepatitis-B vaccine (HepB0), the third dose of pentavalent vaccine (PENTA3) and the first-dose of the measles-containing vaccine (MCV1) as case studies for three reasons. First, several studies have shown that delayed HepB0 is a key marker of incomplete or delayed subsequent doses of routinely recommended childhood vaccines [29,30]. Second, the coverage of PENTA3 (formerly coverage of DPT3) is commonly used as a performance indicator for routine vaccine delivery in The Gambia and globally [7]. Third, a single valid dose of a measles-containing vaccine is approximately 93 % effective in providing lifelong protection against measles [31]. Yet, despite achieving consistently high coverage of MCV1, The Gambia experienced a significant six-fold increase in measles cases by mid-2022 compared to the numbers reported in 2020 [32]. Postponed measles campaigns and stagnating MCV1 coverage since 2017, along with the potential impact of delayed MCV1 resulting in the accumulation of susceptible sub-populations, might explain the recent trend. The high-resolution geospatial mapping of delayed HepB0, PENTA3 and MCV1 may therefore offer critical insights on the pattern of vaccination timeliness that could guide targeted programmatic actions in The Gambia and serve as an example for other immunisation programs.

2. Methods

2.1. Study setting and context

The Gambia, situated in West Africa, has a population of 2.5 million and a yearly birth cohort of about 90,000 children who are added to the routine childhood immunisation program [33]. In May 1967, The Gambia achieved the distinction of being the first country in the world to interrupt the transmission of measles virus successfully [34]. The Gambian EPI was established in 1979 with six vaccines targeting tuberculosis (BCG vaccine), diphtheria, pertussis, tetanus (combined DTP vaccine), measles, polio, and yellow fever. The current vaccination schedule includes several additional vaccines recommended at birth, two, three, four, nine, twelve and eighteen months of age [35].

2.2. Data collection

We obtained cluster-level routine vaccination data for HepB0, PENTA3 and MCV1 for children aged 12–35 months from the 2019–20 Gambia Demographic and Health Survey (GDHS) [36]. The GDHS used a stratified, two-stage sampling design to produce estimates of health and demographic indicators, including vaccination coverage at the national and Local Government Area (LGA) levels and for urban and rural areas. Stratification was achieved by separating each of the eight LGAs (i.e., Banjul, Basse, Brikama, Janjanbureh, Kanifing, Kerewan, Kuntaur and Mansakonko) into urban and rural areas [36]. Samples were drawn from within each stratum in two stages. In the first stage, survey clusters were selected using a probability proportional to their size within each sampling stratum from a national sampling frame. In the second stage, households were randomly selected from household lists within the chosen clusters. The survey was implemented in a total of 281 clusters and 7,025 selected households between 21 November 2019 to 30 March 2020 [36].

The 2019–20 GDHS collected childhood immunization data from 5,148 children aged 0–35 months who received vaccines at any time before the survey. The data was collected based on the mother's recall of vaccination or parent-held vaccination cards. However, to determine the timeliness of vaccination, we require a child's date of birth and vaccination dates [6], information only available from their home-based vaccination records (HBR). We therefore restricted our analysis to the 3,248 children (93 % of 12–35-month-olds) with complete birth and vaccination dates from their home-based vaccination records. For each child, we also extracted the geographical locations, i.e., latitude and longitude of the cluster from which their household was selected.

2.3. Defining and computing vaccination timeliness

We used the accepted childhood vaccination window for The Gambia [35], converting age recommendations from months to days. For consistency, we considered a month to be 30 days. Delayed HepB0, PENTA3 or MCV1 was defined as being vaccinated after the latest recommended window according to the national vaccination schedule in The Gambia (i.e., >1 day for HepB0 [37], >150 days for PENTA3, and >300 days for MCV1) [35]. We determined the age at vaccination (in days) for each vaccine by calculating the difference between vaccination dates and birth dates at the individual child level. Afterward, we aggregated the individual data from each survey cluster to generate observed cluster-level delayed HepB0, PENTA3 and MCV1 prevalence (Fig. 1a, b, and c).

2.4. Geospatial covariate data and selection

Geospatial covariates play a crucial role in geostatistical modelling by explaining and predicting the outcome variable(s) [38]. In our specific modelling approach, the inclusion of covariates aimed to improve the accuracy of outcome predictions, rather than serving an explanatory purpose to identify which covariates are driving the outcome [38]. We assembled a suite of socio-economic, environmental, and physical geospatial covariates from WorldPop which have been previously used in predictive modelling of vaccination coverage (Supplementary Table S1) [39]. These covariates were processed to generate 1 × 1-km^2 raster layers using ESRI ArcGIS v10.6. Subsequently, cluster-level data values were extracted from each standardised gridded layer using geographical coordinates from the 2019–20 GDHS, as previously described [20,22,23]. To accommodate DHS's confidentiality measures involving random cluster location displacement [40], we extracted mean covariate values from a 2 km and 5 km buffer around urban and rural clusters, respectively. We note that this covariate data extraction process can be further refined by using a population density layer to calculate weighted means within the buffers.

To determine the optimal set of covariates to be included for the predictive modelling of each outcome, we followed previous work by conducting a covariate selection process [21,23]. The selection process involved checking the relationship between the covariates and vaccination timeliness indicators and applying the log transformation where necessary to improve relationship; fitting single covariate models and ranking the covariates based on their predictive ability using predictive R^2 values; checking for multicollinearity and selecting between highly correlated covariates (correlation > 0.8 or variance inflation factor [VIF] > 4.0) using their ranks. Subsequently, the best model/combination of covariates for modelling the indicator was chosen using stepwise regression, with backward elimination based on Akaike Information Criterion (AIC) in a nonspatial framework using binomial regression models. For all the modelled indicators, we included urbanicity (i.e., urban or rural) as a covariate even if it was not chosen during the covariate selection process, as a way of accounting for the urban/rural stratification used in the survey design [41]. The covariates chosen for each vaccine are displayed as Supplementary Table S1 and Fig. S1.

To evaluate the need for accounting for spatial autocorrelation when modelling the indicators, we fitted binomial regression models with independent and identically distributed (iid) random effects, including the selected covariates for each indicator. Using the estimates of the iid random effect, we fitted a variogram in each case to assess the presence of residual spatial autocorrelation in the models (Supplementary Fig. S2). To enable the modelling of the prevalence of delayed vaccination at district level, we obtained relevant population estimates corresponding to the survey years for children one year and below in The Gambia from WorldPop [42]. The data were also used to generate the estimated population of infants affected with delayed HepB0, PENTA3 and MCV1 in all districts.

2.5. Geospatial modelling and validation

The general model we used to create 1x1-km^2 prevalence maps of

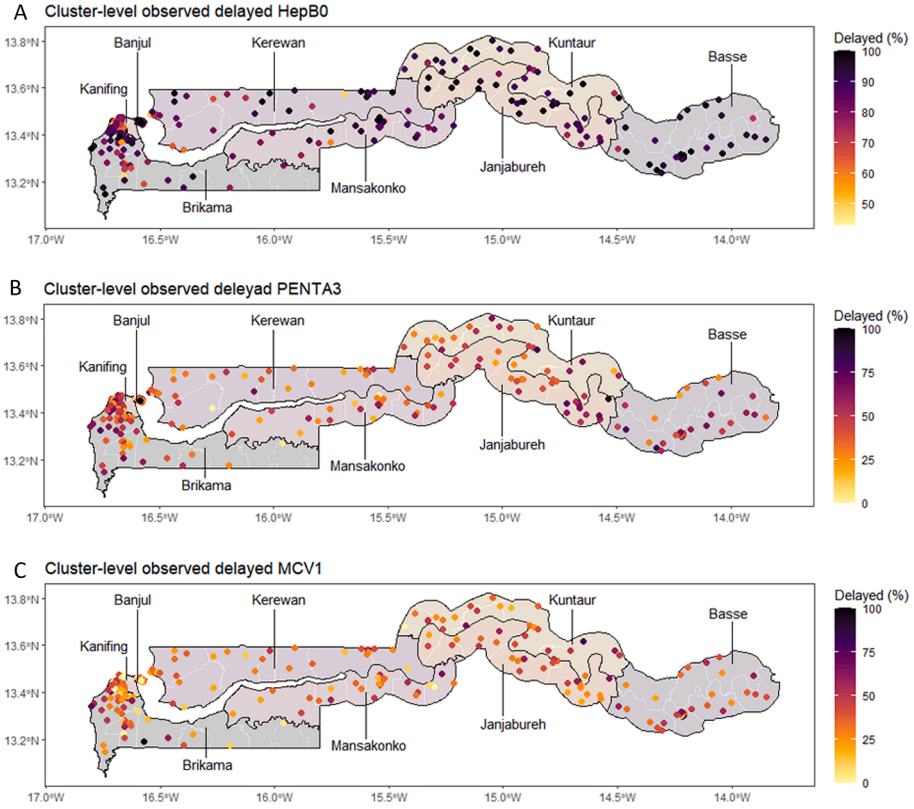

Fig. 1. Spatial distribution of the observed delayed HepB0, PENTA3, and MCV1 among children aged 12–35 months as recorded at the 2019–20 GDHS cluster level. Note. The cluster-level observed delayed vaccination was computed as the proportion of children sampled in a survey cluster who were vaccinated after the recommended national window, based on evidence from vaccination cards. *The names on the cluster-level observed maps indicate the eight Local Government Areas (LGAs) in The Gambia.*

delayed HepB0, PENTA3 and MCV1 is a fully Bayesian geostatistical technique with a binomial likelihood (see Supplementary material for details). The model was implemented using the integrated nested Laplace approximation—stochastic partial differential equation (INLA-SPDE) approach [43]. The INLA approach is a faster alternative to the traditional Markov chain Monte Carlo (MCMC) technique for performing approximate Bayesian inference. The approach uses numerical techniques to approximate the marginal posterior distributions of each of the unknown quantities in the model. The SPDE approach facilitates the estimation of the Gaussian spatial random effect by reducing the computational burden involved in the estimation of Σ_ω through a Gaussian Markov random field (GMRF) representation [43]. Further details on the implementation of the INLA-SPDE approach are provided in Utazi et al. [21,44].

To ensure consistency in the modelled prevalence (p) estimates for indicators of timeliness across each vaccine [i.e. p(early vaccination) + p (timely vaccination) + p(delayed vaccination) = 1 for each prediction location], we independently modelled p(timely vaccination) and p (delayed vaccination), and then derived p(early vaccination) as 1 - p (timely vaccination) - p(delayed vaccination) using the corresponding posterior samples. Where necessary, we adjusted the modelled estimates to ensure consistency across all indicators for each vaccine and prediction location. We chose to model p(timely vaccination) and p(delayed vaccination) because there were more observed cases of both events for the included vaccines compared to early vaccination, which increased the likelihood of obtaining more accurate estimates.

We summarised the calibrated draws for each predicted outcome as mean estimates and 95 % credible interval width (CIs). The predicted estimates at 1x1-km^2 were then aggregated to policy-relevant administrative areas (i.e., district- and ward-levels) as population-weighted means taken over all the grid cells falling within each areas in The Gambia by use of administrative boundaries from the Global Administrative Area (GADM) database [45]. We conducted a bivariate analyses and then created maps to visualize areas with a combination of high prevalence of delayed vaccination and a significant number of affected children.

In-sample model validation was done by comparing the model predictions at the first-administrative level (LGA) to the actual observed design-based direct survey estimates computed using the survey package (Supplementary Fig. S4) [46]. To evaluate the performance of our model on out-of-sample predictions, we used a 5-fold cross-validation approach. We quantified predictive performance using percentage bias, mean absolute error (MAE), and root mean squared error (RMSE). All of these metrics are described in the Supplementary Table S2. All analyses were performed using the R-INLA package in R (R Development Core Team, 2023) [47]. To ensure easy understanding of the main findings, the results section primarily presents cluster-level, 1x1-km^2 pixel, and district-level estimates (including uncertainty estimate) for each vaccine. Additional ward-level estimates (third-administrative level) are provided in the Supplementary material, but will be referenced throughout the results section.

3. Results

Table 1 below shows the design-based estimates of vaccination coverage and delayed vaccination at the national and LGA level in The Gambia. Overall, the vaccination coverage rates for all three vaccines was high, both at the national level and across all the eight LGAs (first-administrative level) in The Gambia. However, the prevalence of delayed vaccination is also high, particularly for HepB0.

3.1. Predicted delayed HepB0, PENTA3 and MCV1 vaccination at district and ward-level

The predicted prevalence of delayed HepB0 vaccination surpassed that of the other vaccines, indicating a higher degree of delay for this particular vaccine. At the 1 × 1-km^2 pixel-level, there were significant subnational disparities in the predicted prevalence of delayed vaccination throughout The Gambia. The highest pockets of predicted delayed vaccination were located in the central and eastern end of the country, while the coastal areas generally exhibited the lowest pockets of delays (Fig. 2a, b, and c). This pattern was consistent for all three vaccines studied, i.e., delayed HepB0, PENTA3, and MCV1 vaccinations.

The predicted prevalence of delayed HepB0 vaccination at the district level exhibited significant variation, ranging from 66.4 % to 95.0 %, representing a difference of over 25 % (Fig. 3a). Among the 49 districts in the country, 17 (34.7 %) had a HepB0 vaccination delay of ≥ 90 %, surpassing the national average. Notably, Basse LGA accounted for 41 % (7/17) of these districts, while Janjanbureh and Kuntaur LGAs each had 23.5 % (4/17) (Fig. 3a). A similar pattern emerged at the ward level, where the predicted prevalence of delayed HepB0 vaccination ranged from 63.5 % to 95.6 %. Janjanbureh, Kuntaur, and Basse LGAs, located

Table 1
Design-based Direct Survey Estimates of Vaccination Coverage and Delayed Vaccination Among 12–23 Months Old Children at the First-Administrative Level in The Gambia.

Administrative level	Coverage (95 % CI)			Delayed vaccination (95 % CI)*		
	HepB0	PENTA3	MCV1	HepB0	PENTA3	MCV1
National-level	98.9 (98.3, 99.5)	93.8 (92.2, 95.6)	90.6 (88.3, 92.8)	89.4 (81.9, 87.9)	42.8 (39.5, 46.1)	31.6 (28.5, 34.6)
Banjul	96.7 (93.4, 99.5)	90.1 (83.0, 97.1)	86.1 (77.1, 95.1)	89.1 (81.8, 96.4)	48.5 (34.3, 62.7)	26.9 (14.0, 39.9)
Basse	97.1 (95.3, 98.9)	92.3 (87.2, 97.4)	89.8 (85.2, 94.3)	95.9 (93.4, 98.4)	49.4 (43.5, 55.3)	39.6 (31.2, 48.1)
Brikama	98.5 (97.1, 99.9)	95.4 (92.8, 97.9)	89.6 (85.5, 93.7)	80.4 (74.4, 86.4)	42.4 (36.7, 48.7)	27.6 (22.5, 32.7)
Janjabureh	98.9 (97.5, 99.8)	92.5 (88.9, 96.1)	93.8 (90.3, 97.3)	95.3 (92.0, 98.7)	52.2 (44.9, 59.6)	40.6 (31.8, 49.4)
Kanifing	97.4 (95.0, 99.9)	86.7 (80.2, 93.2)	85.7 (78.1, 93.2)	80.8 (73.6, 87.9)	40.1 (31.5, 48.7)	30.3 (21.5, 39.1)
Kerewan	99.5 (98.7, 99.9)	98.7 (97.2, 99.8)	95.4 (92.2, 98.5)	84.2 (77.7, 90.7)	37.9 (30.7, 45.1)	30.7 (24.5, 36.8)
Kuntaur	98.0 (96.0, 99.7)	95.7 (92.8, 98.6)	94.4 (91.1, 97.7)	92.5 (88.4, 96.6)	44.8 (37.2, 52.5)	36.1 (28.9, 43.3)
Mansakonko	96.8 (94.1, 99.6)	97.0 (94.4, 99.6)	97.3 (94.4, 99.9)	88.0 (82.1, 93.9)	35.6 (26.4, 44.8)	34.8 (27.8, 41.8)

Note: The administrative levels mentioned in this table include the national level and the Local Government Area level (first administrative level). The direct-survey estimates from the 2019–20 The Gambia Demographic Survey are only representative at these specific levels, as well as at the urban and rural levels. *This indicates the prevalence of delayed vaccination among children who received vaccination and had documented dates of birth and vaccination. CI = Confidence Interval.

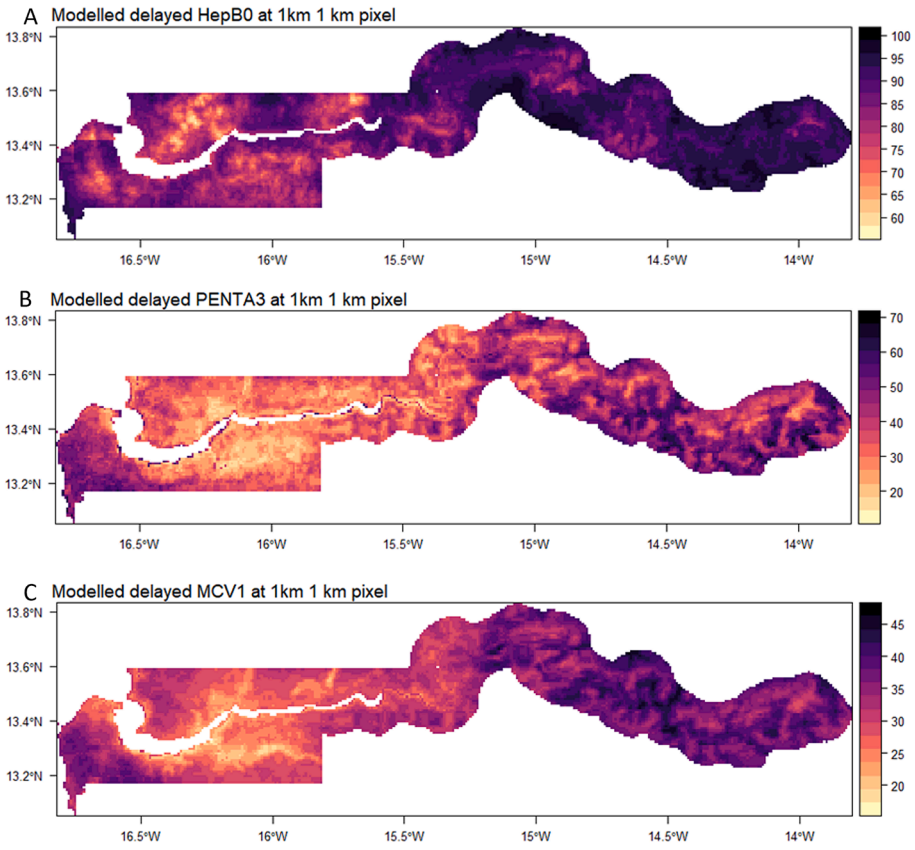

Fig. 2. (A) Predicted delayed birth-dose of hepatitis B vaccine (HepB0) at 1 × 1 km^2 pixel; (B) predicted delayed third-dose of pentavalent vaccine (PENTA3) at 1 × 1 km^2 pixel; (C) predicted delayed first-dose of the measles-containing vaccine (MCV1) at 1 × 1 km^2 pixel among 12–35 months children in The Gambia.

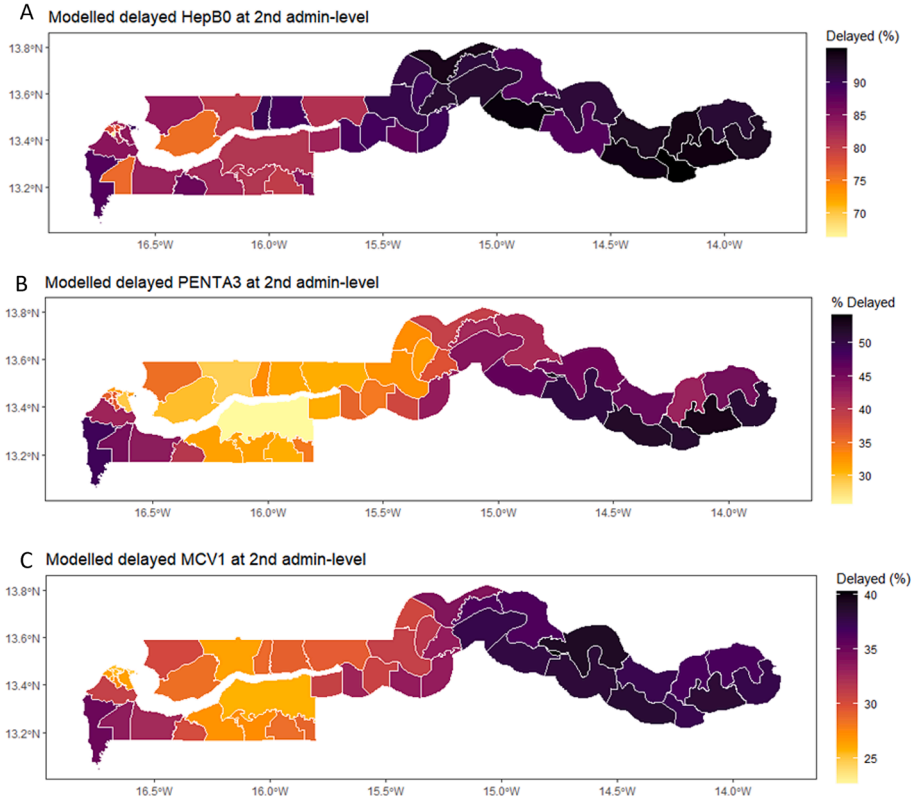

Fig. 3. (A) Predicted delayed birth-dose of hepatitis B vaccine (HepB0) at the district level; (B) predicted delayed third-dose of pentavalent vaccine (PENTA3) at the district level; (C) predicted delayed first-dose of the measles-containing vaccine (MCV1) at the district level among 12–35 months children in The Gambia.

in the central and eastern parts of the country had a higher concentration of wards with a delay of ≥ 90 % (Supplementary Fig. S5 and Table S3). It is worth noting that even in the coastal areas of Mansokonko, Banjul, Kerewan, and Kanifing LGAs, which generally had the lowest prevalence of delayed HepB0 vaccination, a few wards still experienced delays of ≥ 90 %.

The predicted prevalence of delayed PENTA3 vaccination at the district level ranged from 25.7 % to 54.1 %. Among the seven districts with a delay of 50 % or more in PENTA3 vaccination, four were located in Basse LGA, two in Janjanbureh LGA, and one in Banjul LGA (Fig. 3b). Similarly, at the ward level, the prevalence of delayed PENTA3 vaccination ranged from 24.2 % to 54.5 %. Basse LGA accounted for the majority (57 % or 8/14) of wards with a delay of 50 % or more (see Supplementary Fig. S6 and Table S4). The districts and wards with the lowest predicted prevalence of delayed PENTA3 vaccinations were primarily situated in coastal areas of The Gambia.

The predicted prevalence of delayed MCV1 vaccination at the district level ranged from 22.7 % to 40.2 %, as shown in Fig. 3c. Of the top 10 districts with delayed MCV1 vaccinations (i.e., delay of 37 % or more), five (50 %) were located in Basse LGA in the eastern part of The Gambia, while four (40 %) were in Janjanbureh LGA, and one (10 %) was in Kuntaur LGA in central parts (Fig. 3c and Supplementary Table S5). Similarly, the top 10 wards with the highest delayed MCV1 vaccinations (i.e., delay of 38 % or more) were also located in Basse, Janjanbureh, and Kuntaur LGAs (Supplementary Table S7).

Fig. 4 presents the summary of the pattern of delayed vaccination, categorized as tertiles, for all vaccines in all the wards in The Gambia. In the Basse LGA, all the districts, except one, fell within the highest tertile of delayed vaccination for the three vaccines.

The 95 % credible interval width around the modelled estimates, which reflects the uncertainty in the estimates, was generally narrow (i.e., <15 %) for the three vaccines and outcomes examined (Fig. 4a, b, and c). This indicates that the modelled estimates are relatively robust and precise. However, it is worth noting that the uncertainty was generally highest for districts and wards located in Brikama LGA, which is situated in the coastal area of the country (Fig. 5).

3.2. Districts with a combination of high estimated prevalence and a significant population of affected infants

Overall, there was some similarity in the spatial pattern of districts where there was a combination of high estimated prevalence and a significant population of affected infants by delayed HepB0, PENTA3 and MCV1 (Fig. 5). Our findings revealed that certain districts in Basse and Janjabureh LGAs in the eastern and central Gambia, as well as in Brikama LGA in coastal Gambia, had a spatial overlap of high estimated prevalence and a significant population of affected infants (Fig. 6 and Supplementary Table S6). In particular, there was a consistent spatial overlap of high delayed vaccination and a significant number of affected children across four districts in Basse LGA. These districts include Kantora, Jimara, Basse, and Tumana, and this pattern was observed for all the vaccines studied.

4. Discussion

The routine childhood vaccination program in The Gambia has achieved remarkable success, maintaining vaccination coverage of at least 90 % for most childhood vaccines for over a decade [18,48]. This accomplishment has positioned the country as a model for vaccine delivery in many sub-Saharan African countries. However, our findings emphasize an important point: relying solely on overall vaccination coverage estimates may not accurately measure immunisation program quality. Significantly, our results offer valuable insights into the performance of the vaccine delivery system in The Gambia applying novel methodology that could be used in other countries.

Previous studies on vaccination timeliness in The Gambia did not incorporate spatial analysis [49–51], thus, missing the opportunity to identify specific areas or "hotspots" of delayed childhood vaccinations. The estimates from these studies serve as an important initial step in exploring vaccination timeliness, but they are insufficient for targeted

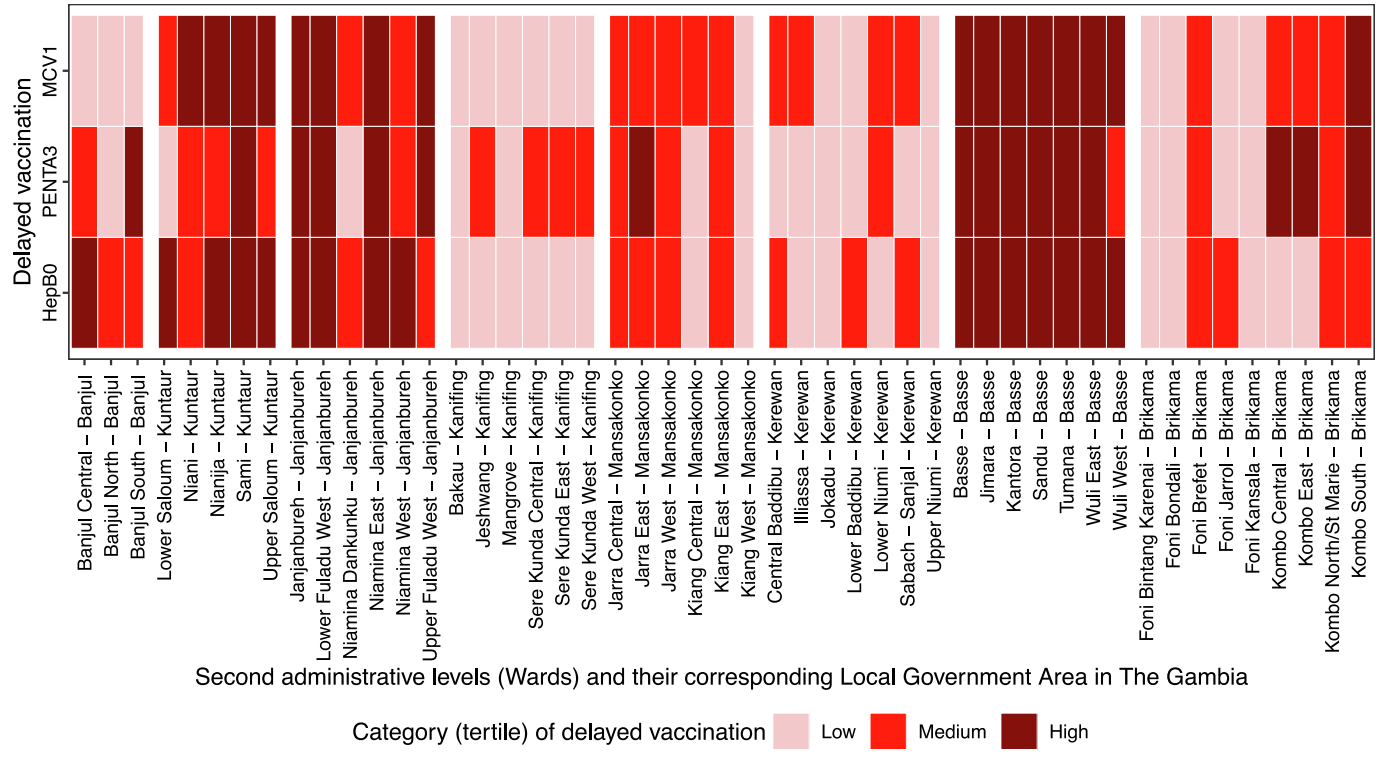

Fig. 4. The summary of the pattern of modelled estimates for delayed vaccination, categorized as tertiles, for the three vaccines (HepB0, PENTA3 and MCV1) in all the 49 districts in The Gambia. Note. Each district (second administrative level) is shown with their corresponding LGA (first administrative level).

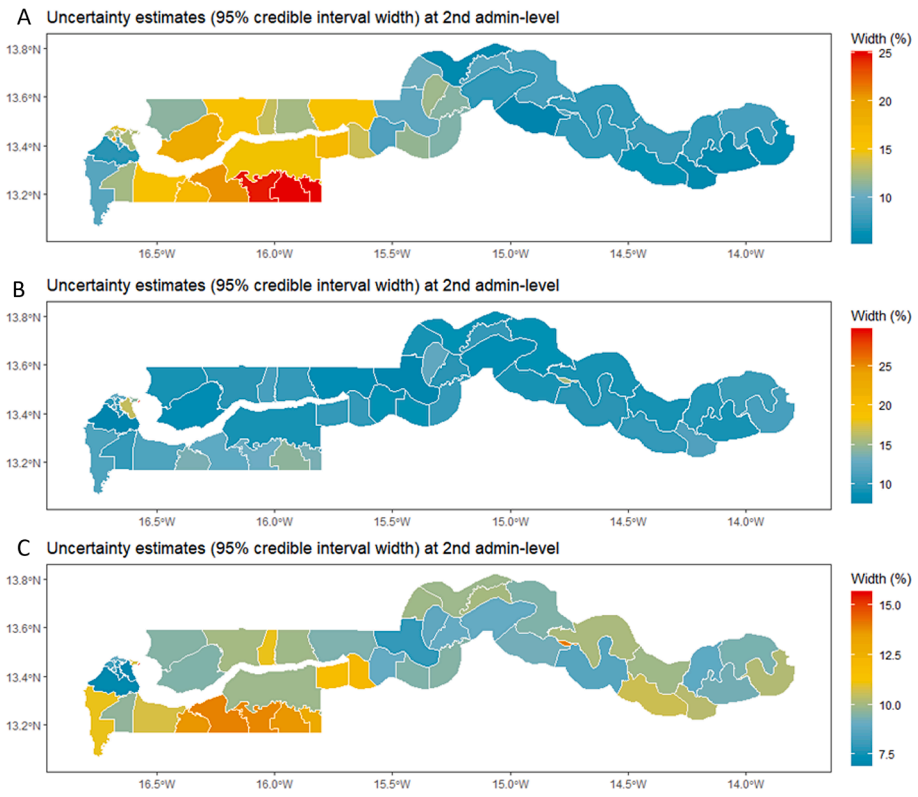

Fig. 5. (A) Uncertainty estimate (95 % credible interval width) around predicted delayed HepB0 at district level in The Gambia; (B) uncertainty estimate (95 % credible interval width) around predicted delayed PENTA3 at district level in The Gambia; (C) uncertainty estimate (95 % credible interval width) around predicted delayed MCV1 at district level among 12–35 months children in The Gambia.

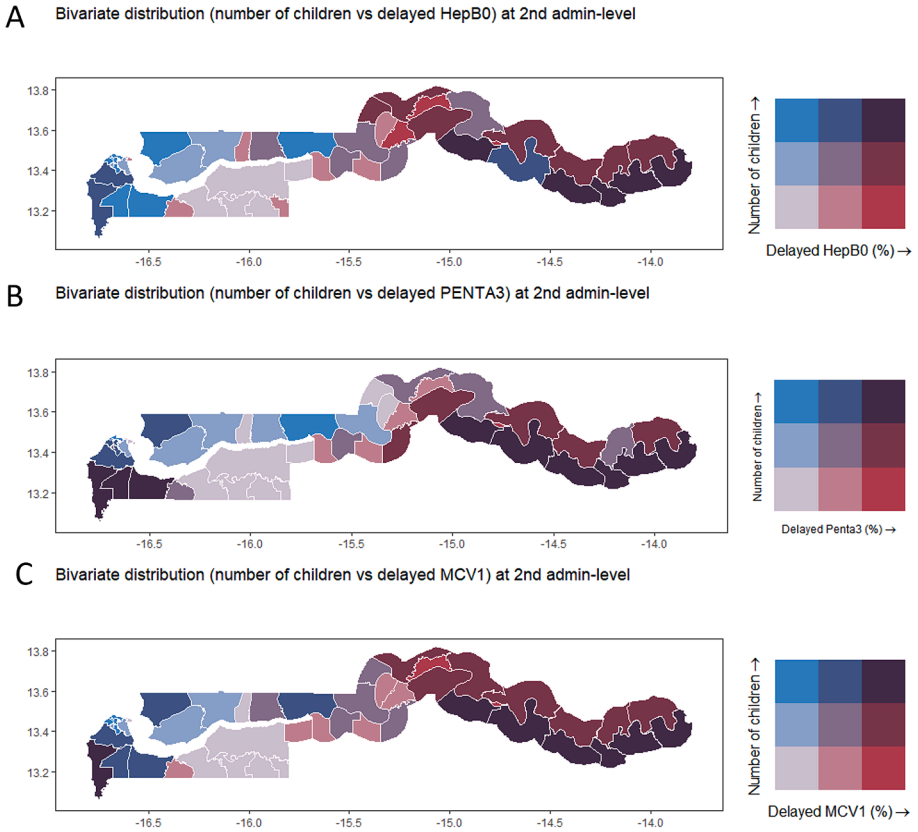

Fig. 6. Bivariate maps showing the spatial relationship between delayed HepB0 (A), PENTA3 (B), MCV1 (C) and the number of affected children across the 49 districts (second administrative level) in The Gambia.

programmatic interventions because they did not identify pockets of vulnerabilities that could benefit from targeted interventions. Our analysis is the first of its kind to provide a country-wide, high-resolution spatial estimation of the timeliness of routine childhood vaccination within the context of an LMIC. Our data reveal significant subnational inequalities in delayed HepB0, PENTA3, and MCV1 vaccinations, primarily concentrated in The Gambia's central and eastern regions which are also the most economically disadvantaged regions [52]. Conversely, children in western coastal areas experienced less vaccination delay, further corroborating findings from a previous large cross-sectional study conducted in The Gambia [51]. National-level estimates of vaccination timeliness mask these subnational pockets of delayed vaccination, thereby potentially exposing children in those areas to the risk of measles and pertussis outbreaks or vertical transmission of hepatitis B virus.

Family sociodemographic barriers, health facility readiness, and physical accessibility of vaccination services, among other factors, have previously been reported to impact vaccine delivery and uptake [53,54], and they may help explain the observed pattern of subnational inequalities in our study. Previous research has established a clear connection between geographical isolation from service delivery channels and the coverage of routine childhood vaccines [55,56]. However, the extent to which these factors affect vaccination timeliness remains largely unexplored. To achieve optimal vaccination coverage, The Gambia currently employs a unique system that combines fixed facilities and outreach sites. Most fixed health facilities are located in coastal areas and provide services at least once a week [57]. Outreach sites, on the other hand, serve remote locations, potentially more prevalent in the eastern region of The Gambia, at least once a month [57]. Travel difficulties between households, fixed facilities and outreach sites may hinder travel and result in delayed uptake and delivery of vaccines to remote communities. This two-tier routine vaccine delivery mechanism may partially explain the spatial pattern of delayed vaccination observed in our study. However, exploring other potential health system or structural drivers contributing to the significant subnational inequalities reported in our data is a crucial next step.

While the majority of districts or wards with the highest prevalence of delays were not located in the coastal areas of The Gambia, we observed that some districts had a combination of high prevalence and a significant absolute number of children with delayed vaccinations in this area. This finding is unsurprising, as it reflects a higher population density in these areas. More children likely live in districts and wards in the country's more urban and coastal regions. These findings demonstrate the usefulness of geospatial analysis in uncovering areas with co-occurrence of high under-vaccination (including delays) and a significant absolute number of children. Clusters or pockets of locations with high population density, under- or delayed vaccination can sustain outbreaks of VPDs such as measles and pertussis. Previous studies have demonstrated the significant impact of clustering or pockets of under-vaccinated subpopulations on the occurrence of disease outbreaks, particularly in countries that have already achieved high overall coverage rates [58,59]. While we have not established a direct link between vaccination timeliness and VPDs outbreaks, improving timeliness potentially plays a role in preventing outbreaks or contributing to achieving disease elimination in the context of high coverage.

Our findings provide valuable insights for immunization program managers and decision-makers, offering a tool to visualize and comprehend local patterns of vaccination timeliness more precisely. This information can play a crucial role in identifying districts where routine vaccine delivery systems require strengthening and prioritizing interventions for maximum impact. It is especially significant considering our data demonstrated that four districts in Basse consistently exhibited high delayed vaccination and a significant number of affected children across all the vaccines studied. This finding suggests that these districts may have peculiar health system or other issues that could benefit from targeted interventions. Our findings underscore the significance of employing fine-scale spatial mapping techniques to investigate timeliness, particularly in countries like The Gambia, where overall vaccination coverage is high. This approach is crucial as it can reveal untimely vaccination patterns at lower administrative levels that may be masked by the aggregated data at higher levels.

In future work, we need to explore the spatiotemporal pattern of untimely vaccination to determine whether the subnational heterogeneities in delayed vaccination identified in our study persist over time or exhibit seasonal or monthly variations. Such analysis could benefit from geocoded longitudinal population survey data. One strength of using such data is the ability to link vaccination data with other epidemiological and disease surveillance data, and the fact that they cover under-documented or often missed communities. There is also a need to investigate whether there is a spatial relationship between areas that report measles outbreaks, low overall MCV1 coverage rates, and high prevalence of delayed MCV1. This can be done by using longitudinal vaccination data linked to measles epidemiological or disease-surveillance data. When triangulated with other datasets to produce additional metrics, such data could potentially shed more light on the impact of untimely vaccination on population immunity and enable the programmatic assessment of EPI performance. In future work, we will also consider developing a methodology for mapping indicators of timeliness of routine childhood vaccination using a combination of geolocated survey data and District Health Information Software (i.e., DHIS2) data. In a multi-temporal analysis, this could have the added benefit of improving the accuracy of the modelled estimates.

Our study provides valuable insights into subnational patterns of vaccine timeliness using a probabilistic spatial modelling framework. However, the dataset analyzed and the methods deployed are subject to some limitations. First, the sampling frames used in the 2019–20 GDHS may have missed hard-to-reach or disadvantaged populations. This could lead to an under- or over-estimation of the prevalence of delayed vaccination in certain areas. To address this, we recommend using more accurate geocoded data from targeted surveys in future analyses to obtain better estimates in such locations. Second, to ensure confidentiality of respondents, the GDHS randomly displaced the geographical coordinates at the cluster level. This displacement is restricted so that the points remain within the country and within the DHS survey region. While we created buffers around the coordinates in rural and urban locations in line with previous approaches [20,22,23], there might have been some residual influence on the modelled estimates, especially at a more granular level. Thirdly, excluding children without HBR may lead to potential under- or overestimation of the timeliness estimates, especially if there is differential availability of records across clusters, districts or wards. Nevertheless, it is worth noting that HBR and vaccination records availability was high (~93 %) in the 2019–20 GDHS, which likely limited such potential bias in our analysis. Lastly, it is important to acknowledge that the 2019–20 GDHS sample was designed to be representative at the national and regional levels, considering urban/rural stratification, and not at the district or ward level. However, the Bayesian spatial modelling approach utilized in this analysis has been well validated and is known to provide robust estimates. Despite these limitations, our analysis provides an important first step in refining interventions to strengthen vaccination programs in a targeted and cost-effective manner. This is especially important in the wake of the COVID-19 pandemic, as we need to ensure that children receive their routine vaccines in a timely manner so they are protected from VPDs. Our findings can also be used to assess the progress made in expanding immunisation and ensuring effective protection for children following the implementation of such interventions.

5. Conclusion

This study identified all districts and wards in The Gambia where there was a combination of a high estimated prevalence of delayed vaccination and a significant population of affected infants. Our

methodological approach enabled us to identify districts and wards with the highest prevalence of delayed vaccination, which would not have been possible using large area estimates. This information is valuable for immunisation programme managers as it allows them to identify the most vulnerable districts that could benefit from targeted immunisation interventions. Our results and existing subnational-level estimates of vaccination coverage provide a more detailed understanding of the overall quality of routine childhood vaccination in The Gambia. This information is valuable for identifying areas that require targeted interventions to improve vaccination timeliness. Additionally, our approach can be applied to other countries, serving as a model to guide immunisation programs and service providers that seek to enhance the overall quality of the immunisation system.

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CRediT authorship contribution statement

Oghenebrume Wariri: Conceptualization, Methodology, Resources, Project administration, Data curation, Writing – original draft. **Chigozie Edson Utazi:** Conceptualization, Methodology, Resources, Supervision, Data curation, Writing – review & editing. **Uduak Okomo:** Conceptualization, Methodology, Supervision, Writing – review & editing. **C. Jessica E. Metcalf:** Conceptualization, Methodology, Writing – review & editing. **Malick Sogur:** Conceptualization, Methodology, Writing – review & editing. **Sidat Fofana:** Conceptualization, Methodology, Writing – review & editing. **Kris A. Murray:** Conceptualization, Methodology, Resources, Writing – review & editing. **Chris Grundy:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Beate Kampmann:** Conceptualization, Resources, Methodology, Writing – review & editing.

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.

Data availability

The 2019–20 GDHS survey data used for this study is publicly available and can be downloaded from the websites of the DHS program after securing approval.

All the R codes developed for the purposes of this analysis are freely available in open repository at: https://github.com/drwariri/Mapping-the-timeliness-of-routine-childhood-vaccination-in-The-Gambia-a-spatial-modelling-study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.vaccine.2023.08.004.

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