Mapping child health: statistical applications for high-resolution estimation of child mortality and healthcare utilization

Roy Burstein

A dissertation
Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

University of Washington
2018

Reading Committee:
Simon I Hay, Chair
Emmanuela Gakidou
Haidong Wang
Robert C Reiner

Program Authorized to Offer Degree:
Global Health
Abstract

Mapping child health: statistical applications for high-resolution estimation of child mortality and healthcare utilization

Chair of the Supervisory Committee:

Professor Simon Iain Hay, DPhil

Global Health

This dissertation is comprised of three distinct chapters which each aim to improve understanding of child health and survival in developing countries through novel applications of statistical modelling. In each case, modelling was used to make estimates at more refined levels than previously existed, either geographically or in age categories, with the goal of improving the evidence base upon which trends and inequalities in child health could be monitored and assessed.

In the first chapter, *Mapping under-5 and neonatal mortality in Africa, a baseline analysis for the Sustainable Development Goals*, a geostatistical model was developed to estimate the child mortality rate for each 5 x 5 kilometer piece of land in 46 countries in Africa, from 2000 to 2015. The study utilized geographically referenced data from 235 household surveys and censuses and a suite of geospatially disaggregated covariates to make high resolution estimates. Resultant estimates on a gridded surface were also aggregated to the district and province level in each country, to provide a full range of estimates at useful spatial resolutions. Despite large declines in mortality rates overall during the study period, there was substantial heterogeneity in both the absolute levels and rates of change in child mortality, both across and within countries. While declines in many areas met or surpassed the 2015 UN Millennium Development Goal for a 4.4% annual reduction, the hard threshold of 25 deaths per 1000 livebirths set for the 2030 Sustainable Development goal would require much of Africa to reduce mortality at unprecedented rate during the coming years.
The second chapter, *Development and validation of a new method for indirect estimation of neonatal, infant, and under-5 mortality using summary birth histories*, dealt with the issue arising in child mortality estimation wherein the dominant source of data, summary birth histories (SBHs), do not on their own provide enough information to estimate age-specific trends in child mortality. To address this, a discrete hazards model was trained on complete birth history data from 243 surveys in 76 countries, representing over 8 million births. A novel approach was developed for prediction at the level of the hypothetical child, each weighted by their probability of birth. Three validation and verification approaches were developed: survey-wise cross validation, comparison against existing indirect methods, and external validation employed through the application of the new method to an addition 243 SBH-only data sources. The new method was found to produce results which are comparable to current best methods for under-5 mortality estimation while additionally producing valid age-specific estimates. Use of this method could allow researchers to utilize a massive amount of SBH data for estimation of trends in neonatal and infant mortality.

The third chapter, *Geographic accessibility and utilization of facility-based care in Zambia: a geostatistical analysis*, explored the predictive ability of geographic factors, including travel time to nearest health facility, to explain healthcare utilization in Zambia, and developed on geostatistical model in order to predict a gridded surface representing treatment seeking rates for diarrhea and febrile illness in children across the country. This analysis overcame a number of important data and methodological limitations present in previous research, including using exact household locations, using flexible splines to represent the decay function over travel time, and using a full probabilistic model and providing uncertainty around all estimates. Results indicate that while at least three quarters of Zambians live within an hour of a health facility, small differences in travel time to healthcare are independently associated with large declines in utilization rates within the first hour. The decision to seek care at a health facility is a complex process that is not easily reduced to geography. As such, a univariate model based solely on geographic accessibility is not sufficient for accurate prediction of utilization across a gridded surface. Improved prediction using a probabilistic model is possible but uncertainty remains high.
Acknowledgements

I am grateful to a lot people who have supported me and my work on this dissertation.

I would like to thank my advisor Simon Hay for your guidance and support over the years. For allowing me independence, and giving me opportunities to explore and grow as a researcher and take on a role of leadership. You have been flexible, open, understanding, and have always kept your door open for me.

I would like to thank my committee members. Haidong Wang, for your guidance, friendship and intellectual support in all things Demography related. Bobby Reiner for being so generous with your time; you are a natural teacher and our conversations helped to solidify many concepts for me. To Emmanuel Gakidou for encouraging me over the years and enabling so many of the opportunities that have formed me into the researcher I have become. For helping me through indecision, and for seeing my potential and giving me the opportunities with which to grow.

I would like to thank my family for being my consistent base of support. You have instilled in me the important values of education and persistence. Thank you to my parents for sacrificing so that it didn’t have to be a hard decision for me to decide to pursue a PhD.

I would like to thank Clare Ortblad for filling my life with love and unconditional support. For being the best listener, best friend, and study buddy. For encouraging me when I’ve been down and for showing me I can be proud of myself.

I would like to thank my peers in the PhD program in Global Health. I'll always cherish our times in the ‘nice office’ and in the ‘cave’. To David Phillips for paving the way, sagely advice, and solid friendship all the way through. To Sarah Wulf Hanson for always insisting on self-care and community. To Grégoire Lurton, I feel lucky to have had you to go through this with me, your thoughtful perspectives have always challenged my thinking. To Gloria, William, Matt, Wisal, Reed, Emily, Hong, Xiaochen, Caroline, Orvalho, and all the others for your support and commiseration.

I would like to thank all the colleagues and collaborators who have contributed to this research. Special thanks to Nick Graetz, Nat Henry, Michael Collison, Molly Biehl, Annie Browne, Josh Longbottom, Laura Dwyer-Lindgren, Chloe Shields, Ian Davis, Chloe Morozoff, Drew Dolgert, Chun-Wei Yuan, Amber Sligar, Bob Thompson, Lucas Earl, and many others. Thank you to Aaron Osgood-Zimmerman: you were the friend and confidant I needed when you joined our team. Thanks for teaching me all that statistics, and for your patience with all my questions. I’ve enjoyed sharing my office space, research questions, and countless laughs with you. Thank you to Nancy Fullman for being such a constant positive source of support and energy, and for helping me with me so much with my writing. Thank you to Felix Masiye for giving me the opportunity to work in Zambia, which was a formative experience for me, and for encouraging me to develop research using the ZHHEUS data. Thank you to Nick Golding for your valued collaboration on mapping child mortality. Thanks to Mike Hanlon for being there from the start as a source of candid advice and continued mentorship. Thank you to Jon Wakefield for taking an interest in me and my work and lending so much of your time and intellectual support; I have greatly appreciated your friendship and mentorship.

I would like to thank IHME, and in particular Kelsey Bannon, Michael MacIntyre, and Chris Murray for giving me a place to grow professionally and giving me the institutional support that every PhD student deserves.

I would like to thank the Bill and Melinda Gates Foundation for funding and for giving me the opportunity as an intern to experience how my research can have value on practical grounds.

I would like to thank Dane Boog and Céline Abell for doing all the hard program management work to make this whole thing happen.

I would like to thank Ralphie, you are a wonderful companion.

Thanks to all my dear friends for all the inspiration, and all the love and fun times we’ve shared.
**Table of Contents**


Chapter 3: Geographic accessibility and utilization of facility-based care in Zambia: a geostatistical analysis ...................................................................................................................................................... 134
Chapter 1: Mapping under-5 and neonatal mortality in Africa, 2000-2015: a baseline analysis for the Sustainable Development Goals

(Reprinted from https://doi.org/10.1016/S0140-6736(17)31758-0)

Abstract

During the Millennium Development Goal (MDG) era, many countries in Africa achieved marked reductions in under-5 and neonatal mortality. Yet the pace of progress toward these goals substantially varied at the national level, demonstrating an essential need for tracking even more local trends in child mortality. With the adoption of the Sustainable Development Goals (SDGs) in 2015, which established ambitious targets for improving child survival by 2030, optimal intervention planning and targeting will require understanding of trends and rates of progress at a higher spatial resolution. In this study, we aimed to generate high-resolution estimates of under-5 and neonatal all-cause mortality across 46 countries in Africa.

We assembled 235 geographically resolved household survey and census data sources on child deaths to produce estimates of under-5 and neonatal mortality at a resolution of 5 × 5 km grid cells across 46 African countries for 2000, 2005, 2010, and 2015. We used a Bayesian geostatistical analytical framework to generate these estimates, and implemented predictive validity tests. In addition to reporting 5 × 5 km estimates, we also aggregated results obtained from these estimates into three different levels—national, and subnational administrative levels 1 and 2—to provide the full range of geospatial resolution that local, national, and global decision makers might require.

Amid improving child survival in Africa, there was substantial heterogeneity in absolute levels of under-5 and neonatal mortality in 2015, as well as the annualised rates of decline achieved from 2000 to 2015. Subnational areas in countries such as Botswana, Rwanda, and Ethiopia recorded some of the largest decreases in child mortality rates since 2000, positioning them well to achieve SDG targets by 2030 or earlier. Yet these places were the exception for Africa, since many areas, particularly in central and western Africa, must reduce under-5 mortality rates by at least 8.8% per year, between 2015 and 2030, to achieve the SDG 3.2 target for under-5 mortality by 2030.

In the absence of unprecedented political commitment, financial support, and medical advances, the viability of SDG 3.2 achievement in Africa is precarious at best. By producing under-5 and neonatal mortality rates at multiple levels of geospatial resolution over time, this study provides key information for decision makers to target interventions at populations in the greatest need. In an era when precision public health increasingly has the potential to transform the design, implementation, and impact of health programmes, our 5 × 5 km estimates of child mortality in Africa provide a baseline against which local, national, and global stakeholders can map the pathways for ending preventable child deaths by 2030.

Introduction

Improvement of child survival is a long-standing international priority [1-3], and as shown in the last few decades, substantial progress has been accomplished in reducing child mortality and absolute inequalities in rates of child death across countries worldwide [4,5]. Yet by the conclusion of the Millennium Development Goals (MDGs), which aimed to reduce under-5 mortality by two-thirds from 1990 to 2015, only 57 of 195
countries and territories worldwide met or exceeded the pace of progress required to achieve MDG 4 (ie, a 4.4% annualised rate of decline) during that period [5]. Additionally, despite narrowing disparities over time, geographic inequalities persisted among countries with the lowest and highest child mortality rates. In sub-Saharan Africa, for example, this divergence in 2015 spanned from 15.6 deaths per 1000 livebirths in Botswana to 135.0 deaths per 1000 livebirths in the Central African Republic [5]. National mortality rates, although useful for macro-level comparisons [4,6,7], obscure variations in child survival at lower administrative units (eg, districts), the levels at which most health programme planning and implementation occur. Without advancing the aims of precision public health, which includes robust subnational monitoring of child mortality levels and trends, health authorities face sizeable challenges to optimally funding and targeting interventions for the populations who most need them [8-11]. Ending all preventable child deaths by 2030 is the bold aim set forth by the Sustainable Development Goals (SDGs) [3], and an ambition that requires a much better understanding of where exactly the largest gaps remain in improving child survival.

Advances in both data availability and statistical methods have facilitated subnational assessments of under-5 mortality in several sub-Saharan African countries, including provinces in South Africa [4], regions in Tanzania [12], states in Nigeria [13], counties in Kenya [4], and districts in Ghana, Mozambique, Uganda, and Zambia [14-16]. Such work has unveiled the initial magnitude of subnational disparities in all-cause child deaths, but it is likely that much more heterogeneity remains within formal administrative units. In an ideal setting, national vital registration or health information systems would routinely capture local data on deaths and births, and estimates of child survival could be generated at a similar resolution on the basis of vital registration data. However, few countries in sub-Saharan Africa have complete or high-quality vital registration systems [17-19], and thus often rely on household surveys and periodic censuses to assess their demographic and health profiles [20]. These data sources often include geolocated cluster-level or administrative-area-level identification. They can therefore be analysed with spatially explicit methods such as model-based geostatistics, which quantify spatial differences in variables from geolocated data. Use of model-based geostatistics allows for the synthesis of disparate geographical data into gridded maps and thus yields comparable high-resolution estimates over larger study areas [21,22]. Previous studies have used model-based geostatistics methods to produce gridded estimates of infant mortality and child mortality in Mali [23], and advancements in computational statistics now allow for high-resolution estimation of health outcomes and related indicators at the continental scale [24-27].

Recent analyses [28,29] have sought to quantify under-5 mortality with greater geospatial resolution in sub-Saharan Africa, including one study that produced 10 × 10 kilometre (km) estimates of all-cause under-5 mortality in 28 countries [29]. However, these studies feature several data and methodological shortcomings. First, previous studies exclusively drew from the Demographic and Health Survey (DHS) series for their data sources [28,29], constraining their analyses to a limited subset of surveys with both complete birth histories and GPS-identified survey clusters. Second, popular spatial interpolation methods such as kernel-density estimation can be overly sensitive to data variations that result from small numbers found at the survey cluster rather than true subnational differences in child survival. Without a more stable estimation approach that accounts for spatial and temporal correlations in the data, misleading or implausible results can arise (eg, localities experiencing increases in under-5 mortality that exceeded an average of 10% per year from the 1980s to 2000s) [29]. Third, recent analyses do not have the temporal specificity or timeliness that is of greatest demand from policy makers; for instance, a study that presented decade-wise estimates for the 1980s, 1990s, and 2000s [29] could not detail the potential effects of the MDGs on under-5 mortality trends. Last, previous studies have not calibrated the aggregation of geospatial estimates to externally validated national estimates [4,5,30], a key step to ensuring the internal consistency of subnational results. Since high-resolution estimates of child mortality could serve as a crucial input for local health programme funding and deployment, it is of equally high importance to address these outstanding data and analytic challenges.
In this study, we aimed to advance geospatial analysis of child mortality in Africa by using a larger set of data sources and types than previously published, as well as applying advanced modelling techniques [22,24,27,31] in order to generate high-resolution estimates of under-5 and neonatal all-cause mortality in 46 countries in Africa in 2000, 2005, 2010, and 2015.

Methods

Overview

Our analysis provides estimates of under-5 mortality (the probability of death before age 5 years per 1000 livebirths) and neonatal mortality (probability of death within first month of life per 1000 livebirths) for each 5 x 5 km cell in 46 countries in Africa. These countries accounted for 54% of global under-5 deaths in 2015 [5], and they fully overlap with the African countries included in the EQUitable Impact Sensitive Tool (EQUIST), a UNICEF-supported initiative that aims to maximise the effect of health policies for children who reside in low-income countries. Analytical steps are described below and in the appendix. Our study follows the Guidelines for Accurate and Transparent Health Estimates Reporting (GATHER). The GATHER checklist appears in the appendix.

Data

We extracted data on child mortality and geographical locations from censuses and several household survey series, including the DHS, UNICEF Multiple Indicator Cluster Surveys, and other country-specific surveys. We included data sources if they had summary or complete birth history modules and subnational geographical information. When available at the cluster level (ie, a group of neighbouring households or a village associated with a set of geolocated data), data were extracted together with cluster GPS or located on the basis of precise location names (n=59 279). In the absence of geographic coordinates, we extracted names of the smallest available administrative area units (n= 6111). The appendix lists all data sources (pp 7–22).
Figure 1. Data availability by type and country, 2000–15. All data are mapped (A), and shown by country and year of survey (B). Surveys can contribute mortality data up to 17 years before the time of the survey. (A) Complete birth history data are displayed in preference to summary birth histories when both have been used in that location. Cluster locations are mapped as points, and polygon data as shapes where available. (B) Data on summary birth histories are green and complete birth histories data are blue.

We estimated child mortality rates in 5-year periods, such that mortality rates for each period of time represented probabilities of death for a synthetic cohort. Thus, mortality rates at each point in time
reflected average mortality rates over the corresponding years. For the estimates, we refer to 1998–2002 as 2000, 2003–07 as 2005, 2008–12 as 2010, and 2013–17 as 2015. These estimates were disaggregated by monthly probabilities of death for the age groups of first month of life, 1–11 months, 12–35 months, and 36–59 months. As such, exposures and deaths could fall into one of 16 age-group–time period bins. A month counted as an exposure if the child was alive at the beginning of the month. Probability of death before reaching age 5 years for a given period can then be calculated directly as 1 minus the product of age-bin-specific survival probabilities (see appendix) [32]. Only livebirths were captured and we did not estimate stillbirths.

We extracted two types of child mortality data, namely complete birth histories and summary birth histories. Data availability by type and country is shown in figure 1, and is further detailed in the appendix. Records of complete birth histories contain dates of birth and death, as applicable, of all children of sampled women. We summed the total exposure months and death events within each age group and time period at the most precise available geographic level (ie, either cluster points or administrative polygons). Summary birth history records provide considerably less information than complete birth histories. They only include mothers’ reports of the total number of children ever born and those who died, and do not include children’s age or date of death. However, summary birth history data are relatively easy to collect and are widely available in Multiple Indicator Cluster Surveys and censuses. After we extended methodological advancements in model-based approaches to adjust data on summary birth histories [33], we developed a model using data in which both complete and summary birth histories were available, to partition summary birth history data into age-specific and period-specific mortality probabilities, and applied this relationship to datasets in which summary birth history data were available. Additional detail on our summary birth histories-adjustment model is in the appendix. Finally, bias ratios calculated for GBD 2016 [5], which are specific to data type, source, and year, were applied to both complete birth histories and summary birth histories data (see appendix).

When cluster-level geographic coordinates were not available for a given country, we matched reported administrative units with first-level, second-level, or third-level administrative divisions from the Global Administrative Unit Layers database or the Database of Global Administrative Areas. We refer to the geographical data that only contained administrative boundaries as polygons. If data could not be mapped to administrative units (polygons) from these sources, we matched them using other sources or modified available polygons on the basis of the available information about polygon boundaries. In several cases, for example, we disaggregated an administrative unit into city boundaries and the surrounding rural area to match the disaggregation of the available mortality data. We resampled polygon data into geographically dispersed points and weighted them on the basis of population. In terms of sample size, polygons contributed 41% of the total data (see appendix).

To inform our model, we compiled several layers of sociodemographic and health-related covariates at the 5×5 km pixel level (value estimates for each 5×5 km grid cell in the study area), all of which have shown some relationship with child survival or overall child health outcomes. The covariates were average years of educational attainment of women aged 15–49 years [34,35], prevalence of wasting and stunting in children younger than 5 years [36], *Plasmodium falciparum* parasite rate [24], a proxy index of fertility (based on the ratio of women aged 15–49 years and children under 5 years) per pixel [37,38], and total population [39]. Additionally, we included several covariate layers that were reflective of potential environmental and infrastructural factors related to overall development and thus child survival (ie, an enhanced vegetation index [40], daytime land-surface temperature [40], proportion of land under irrigation [41], urban-rural distinction [42], brightness of night-time light from the Defense Meteorological Satellite Program [43,44], and accessibility to cities with populations greater than 50 000) [45]. When several years’ worth of data were available, we either took the synoptic mean from available years in each estimation period or used the mid-period-year estimate. Two covariate layers, irrigation and accessibility, were only available for
the year 2000, and therefore did not vary over time in our analysis. The appendix contains more information on our spatial covariates, including plots of all covariates.

We then used an ensemble method, stacked generalisation, to select covariates, capture possible non-linear effects, and to account for the complex interactions between them [31]. For each age group and year, we fit four sub-models, namely generalised additive models, boosted regression trees, lasso regression, and ridge regression, and predicted for each cluster in the data using five-fold cross-validation. The four sub-model predictions were included as covariates when fitting the full geostatistical model described below. This approach removes covariates that are not predictive and identifies optimal combinations of covariates that are predictive, and thus is expected to improve overall predictive performance over a singular model [31]. Because of their heightened predictive validity, ensemble modelling approaches are increasingly used in population health measurement [46], as well as other fields [47,48]. More details on this approach are in the appendix.

Analysis

We fitted four separate Bayesian model-based geostatistics models (ie, one for each age group) to estimate the monthly probability of mortality in any given pixel. We modelled covariate effects using the ensemble approach discussed above, and the model explicitly accounted for spatiotemporal autocorrelation by modelling the covariance of data residuals in space and time. This allowed us to leverage the correlation structure of the data to more accurately predict mortality within locations where data on child death were absent. Pixel-level uncertainty intervals (UIs) were generated from 1000 draws (ie, candidate maps) [22] that were created from the posterior distributions of modelled parameters. The appendix includes additional detail of our model and estimation process.

We then aggregated pixel-level estimates from the 1000 candidate maps up to two subnational administrative units and national levels [49]. Such aggregation allowed us to further calibrate estimates of under-5 and neonatal mortality to national GBD estimates for the 2000, 2005, 2010, and 2015 periods. [5] We achieved this by calculating the ratio of the population-weighted posterior mean national-level estimate from our analysis to mean national estimates for the same time period from GBD, [5] and then multiplying each cell in the posterior sample by this ratio. The median for these ratios was 1.01 (IQR 0.95–1.07), indicating generally close agreement with GBD estimates. The appendix includes scatterplots comparing our national-level estimates from this analysis with GBD estimates.

For reported results, we masked all final model outputs for which land cover was classified as barren or sparsely vegetated, on the basis of MODIS satellite data in 2013 [50], the most recent year of available data, as well as areas in which total population density was less than ten individuals per 1 × 1 km pixel in 2015 [39].

We validated our models using spatially stratified five-fold out-of-sample cross validation and report bias (mean error), total variance (root-mean-square error), and 95% cluster-level data coverage within prediction intervals. We stratified space either by the first or second subnational administrative unit. By aggregating predictions and observations to administrative units, we could increase sample sizes to a level high enough for better determining model fit; this was not feasible at the cluster level because of data noisiness due to very small sample sizes. Generally, across our four models and at both levels of aggregation, we found out-of-sample mean error to be very close to zero, indicating no systematic bias. Correlations between aggregated out-of-sample model fit and aggregated holdout data ranged from 0.81 to 0.94 for administrative level 1, and from 0.62 to 0.87 for administrative level 2. Root-mean-square error relative to mean estimated probability ranged from 17.7% to 33.3% for administrative level 1 and 32.7% to 50.0% for administrative level 2. These metrics indicate relatively good model fits; however, these metrics are sensitive
to sample sizes at aggregation and average probabilities at different age groups, and thus should be interpreted within that context. The 95% prediction interval at the cluster level covered 94% of the out-of-sample data points, indicating that our models' fit could reproduce out-of-sample data within the specified level of uncertainty. Detail on validation procedures and full results is in the appendix.

Data sharing

Data are available at http://ghdx.healthdata.org/.

Results

Although under-5 mortality rates decreased throughout Africa between 2000 and 2015 (figure 2), stark disparities endured across the continent and within national borders. On the basis of pixel-level estimates, we found that in 2000, most of sub-Saharan Africa recorded under-5 mortality rates exceeding 138 deaths per 1000 livebirths, while large swathes of Nigeria, Niger, Sierra Leone, and Mali, along with other countries in western and central Africa, surpassed 200 deaths per 1000 livebirths. By 2015, half of sub-Saharan Africa had under-5 mortality rates below 72 deaths per 1000 livebirths, and increasingly more places in Africa neared or had fewer than 25 deaths per 1000 livebirths, the SDG3.2 target for 2030. Nonetheless, 118 locations at the second administrative level in Chad, Mali, Burkina Faso, the Central African Republic, and Nigeria still faced average under-5 mortality rates higher than 170 per 1000 livebirths in 2015. Further, sizeable within-country inequalities remained. For instance, Nigeria had a national under-5 mortality rate of 115.4 deaths (95% uncertainty interval [UI] 99.6–132.2) per 1000 livebirths in 2015 [5], yet at the local government area level (administrative level 2), under-5 mortality rates ranged from 54.8 (48.2–62.9) deaths per 1000 livebirths in the Osun local governmental area of Osogbo to 214.6 (190.2–240.6) deaths per 1000 livebirths in the Bauchi local governmental area of Ningi.
Figure 2. Under-5 mortality rates at the 5 × 5 km resolution in 2000, 2005, 2010, and 2015. Data are at 5 × 5 km resolution. All pixels with an under-5 mortality rate equal to or fewer than 25 deaths per 1000 livebirths (the Sustainable Development Goal 3.2 target for under-5 mortality) are coloured purple. Pixels with fewer than ten people and classified as barren or sparsely vegetated are coloured in grey. Grey areas with diagonal lines are not included in this analysis. km=kilometre.
Somewhat similar geographic patterns emerged for neonatal mortality as were found for under-5 mortality (appendix), with Botswana and Egypt having large areas meeting the SDG target (ie, 12 deaths per 1000 livebirths). In 2015, Côte d’Ivoire had one of the widest gaps between districts, ranging from 29.6 (95% UI 23.9–35.7) neonatal deaths per 1000 livebirths in Cavally in Montagnes district to 52.9 (43.2–64.1) neonatal
deaths per 1000 livebirths in Bagoue in Savanes district. Côte d'Ivoire, Mali, and Nigeria all had second administrative units with mean neonatal mortality rates greater than 50 deaths per 1000 livebirths. More information on neonatal mortality can be found in the appendix.

Figure 3 illustrates the effects of disaggregating under-5 mortality estimates across levels of geospatial granularity (national, first and second administrative levels, and the 5 × 5 km grid), and how inequalities in child survival can be masked by geographic aggregation. In 2015, Egypt and Morocco achieved the SDG3.2 target for under-5 mortality, at 20.6 deaths per 1000 livebirths in Egypt and 22.9 deaths per 1000 livebirths in Morocco [5]. Still, approximately 25% of each country’s population lived in areas with mortality rates higher than the SDG threshold. Botswana was the only other African nation that met the SDG 3.2 target by 2015, with an under-5 mortality rate of 15.6 deaths per 1000 livebirths [5]. The appendix includes full geographical disaggregation of neonatal mortality rates by administrative level.

Figure 4 compares dimensions of under-5 mortality, from low to high, against relative uncertainty, as measured by the ratio of the 95% UI range to the mean, in 2015. Senegal, Gambia, Ghana, Kenya, Rwanda, Tanzania, and Zimbabwe had large areas with relatively low under-5 mortality and low uncertainty, whereas most of the Central African Republic and Somalia had both relatively high under-5 mortality and uncertainty. There were geographical areas of high mortality and low uncertainty in northern and eastern Nigeria, Mali, Burkina Faso, northern Cameroon, and southwestern Chad. By contrast, most of Botswana, Namibia, eastern Ethiopia, eastern Angola, and South Africa had relatively low under-5 mortality rates, but these estimates were accompanied by relatively high uncertainty. More plots of uncertainty in predictions are available in the appendix.

In many countries, under-5 mortality decreased by more than 4.4% per year from 2000 to 2015 (figure 5) [5], a rate that exceeded the pace of progress established under MDG 4 (ie, a two-thirds reduction by 2015). Further, average annualised rates of decline in Botswana, Ethiopia, Liberia, Rwanda, and Angola exceeded 6.0%. Many other countries, including Burundi, Malawi, Togo, Uganda, and Tanzania, had second-level administrative areas that had a mixture of annualised rates of decline between 2.0% and 4.4%, as well as those that exceeded a 4.4% decrease each year; results for administrative levels 1 and 2 are in the appendix. By contrast, areas throughout 17 countries, including the Central African Republic, South Sudan, Lesotho, and Madagascar, had no second-level administrative areas that achieved an average annualised rate of decline exceeding 4.4% from 2000 to 2015. Nigeria had wide disparities in terms of progress, with annualised rates of change spanning from 0.7% annual decline (95% UI 0.2% to −1.6%) to a 5.0% annual decline (−4.1 to −5.9%). On the basis of pixel-level annualised rates of decline achieved from 2000 to 2015, and projections of these rates through 2030 (figure 5), several countries could have localities achieving SDG 3.2 if past rates of decline in under-5 mortality are sustained over the next 15 years. These locations were primarily in northern, southern, and eastern Africa, but also included areas in Senegal, Liberia, and Ghana. 20 of the 46 countries had second-level administrative areas that, on the basis of average current trajectories, could reduce under-5 mortality rates to 25 deaths per 1000 livebirths. However, only 26.1% of second administrative-level areas had an annualised rate of decline from 2000 to 2015 that was faster than the MDG 4 target of 4.4% per year. At least 60% of these locations need to match or surpass the rates of progress achieved from 2000 to 2015 to meet the SDG3.2 target for under-5 mortality by 2030 (figure 5). For instance, within the Central African Republic, Mali, Sierra Leone, Niger, Chad, and Burkina Faso, the majority of populations live in areas where annual declines of 8.8% or more are needed to achieve SDG 3.2.
Figure 4. Overlapping population-weighted quartiles of under-5 mortality and relative uncertainty in 2015. Under-5 mortality rate quartile cutoff points were 56, 80, and 102 deaths per 1000 livebirths. Relative uncertainty was computed as the ratio of the 95% uncertainty intervals and under-5 mortality rate for each pixel. Cutoff points for uncertainty were 29%, 35%, and 41%. The lowest quartile of mortality is white, and the highest is dark pink. The lowest quartile for uncertainty is white and the highest is blue. These colours overlap such that areas coloured purple have both high under-5 mortality rates and high relative uncertainty. Pixels with fewer than ten people and classified as barren or sparsely vegetated are coloured in grey. Grey areas with diagonal lines are not included in this analysis.
Figure 5. Annualised rates of decline in under-5 mortality during the MDG era, with projections to 2030, and needed rates of decline to reach the SDG target. 4.4% is the annualised rate of decline that was equivalent to the pace of progress required to meet Millennium Development Goal 4. (A) Annualised rates of decline for under-5 mortality from 2000 to 2015. Pixels coloured blue exceeded the annualised rate of decline between 2000 and 2015, whereas pixels coloured green to yellow had a slower rate of annualised decline during this time. (B) Predicted under-5 mortality rates in 2030, based on annualised rates of decline achieved between 2000 and 2015. Pixel-level under-5 mortality rates were predicted for 2030 on the basis of annualised rates of decline achieved from 2000 to 2015. Based on this prediction, pixels for which under-5 mortality rates equalled or were less than 25 deaths per 1000 livebirths in 2030 are coloured purple. (C) Rates of decline required to reach the SDG 3.2 target for under-5 mortality by 2030 (25 deaths per 1000 livebirths). Pixels coloured blue will need to achieve a 4.4% or greater decline per year from 2015 to 2030 to achieve the SDG 3.2 target for under-5 mortality. Pixels coloured green to yellow can meet the SDG 3.2 target by 2030 at a pace slower than a 4.4% reduction per year from 2015 to 2030. Pixels with fewer than ten people and classified as barren or sparsely vegetated are coloured in grey. SDG=Sustainable Development Goal.

Discussion

To the best of our knowledge, our study offers the first quantification of 5 × 5 km estimates of under-5 and neonatal mortality in 46 African countries, highlighting a mixture of impressive gains and enduring disparities in child survival across the continent. By 2015, nearly all locations had a reduction in under-5 mortality rates from 2000, with many areas of Ethiopia, Botswana, and Rwanda recording particularly large reductions. Yet in Chad, Mali, the Central African Republic, and Sierra Leone, more than half of populations live in places where under-5 mortality rates still exceeded 120 deaths per 1000 livebirths in 2015. Despite achieving notable rates of decline between 2000 and 2015, most of Africa must substantially accelerate reductions in under-5 mortality to meet the SDG 3.2 target of 25 deaths per 1000 livebirths by 2030. These results underscore the crucial importance of tracking geospatially granular patterns in child survival, particularly if all countries aim to end all preventable child deaths by 2030.

Charting 5 × 5 km trends in child mortality from 2000 to 2015 provides the foundation from which local achievements and challenges during the MDG era can be better understood. Although the duration of MDG assessment spanned from 1990 to 2015, its greatest catalytic effects on political, social, and financial commitments to improving child health in Africa mainly occurred from 2000—when the MDGs were established—to 2015. Nationally, 19 countries in Africa met or exceeded the MDG4 rate of reduction (4.4% each year) between 2000 and 2015 [5]. Although several factors probably influenced this progress during the 2000s, the confluence of escalated development assistance focused on child health [51], the rapid scale-up of multiple interventions that target childhood illnesses (eg, vaccination, malaria control, and HIV prevention) [25,52-56], and heightened overall socioeconomic development undoubtedly contributed to improving child survival in many African countries. By contrast, it is an unlikely coincidence that many places with slower gains (ie, much of the Central African Republic, Chad, and Somalia) also received less international funding for newborn and child health [26] and had some of Africa’s lowest levels of overall coverage for key maternal and child health interventions [55]. In Nigeria, for example, where annualised declines in under-5 mortality ranged from 0.7% each year to 5.0% per year since 2000, large differences in
state-level trends for various maternal and child health interventions also occurred during that time [13]. National case studies have explored drivers of MDG 4 progress in sub-Saharan Africa [54,57-60], but few delve into more local factors and their association with changes in under-5 and neonatal survival at a high geographic resolution. In-depth analyses that link our 5 × 5 km estimates of child mortality to more granular measures of intervention coverage and other indicators, akin to a recent study on the effects of malaria control in Africa [25], could strengthen inputs into local health policy and resource allocation planning.

In the transition from MDG 4 to SDG 3.2, child survival targets changed from achieving relative rates of progress to attaining absolute levels by 2030. This shift is heralded by many [61-63], because setting specific thresholds could encourage a greater focus on the places which bear the highest toll of child deaths. Effectively directing such attention might be a challenge in Africa, however, especially since more than 75% of the continent’s children live in areas where annual declines in under-5 mortality must exceed the pace of reductions they achieved from 2000 to 2015 to meet the SDG 3.2 target by 2030. From 2000 to 2015, only 26.1% of second administrative level areas recorded an annualised rate exceeding the MDG target of 4.4%, whereas at least 60% of these locations will need to at least match their current pace to make the SDG 3.2 target for under-5 mortality a reality. Of particular concern are the areas encompassing nearly 27% of Africa’s population that must at least double the MDG 4 rate to achieve the SDG 3.2 target by 2030, a pace that is unprecedented in the last few decades. Envisaging such a feat is difficult without the occurrence of substantial medical breakthroughs, such as a fully effective malaria vaccine [64], or considerably extending access to high-quality health care, eliminating risk factors that account for a large proportion of child deaths [36], and bolstering socioeconomic factors that directly affect child survival [7], or all of the above. That is not to say achieving SDG3.2 is impossible in Africa, since there have been several instances in which the introduction and scale-up of cost-effective interventions swiftly reduced child mortality in many countries [45], such as the expansion of measles immunisation, screening and treatment of maternal syphilis during antenatal care, and the provision of oral rehydration therapy for severe diarrhoea. At a time when precision public health could offer transformative power for local intervention design and implementation [9,10], these results and initiatives, such as EQUIST, which account for subnational variations in health, intervention effectiveness, and costs, are vital going forward in the SDG era. However, staying the current course and failing to address more systemic barriers to improving child survival will not be sufficient to meet the SDG 3.2 target for most of Africa.

This study offers the analytical framework from which we aim to extend geospatial modelling of child mortality to an increased number of locations, with a heightened focus on estimating specific causes with greater temporal resolution. By expanding our high-resolution estimation of child mortality to additional high-burden countries outside of Africa, we aim to generate estimates in locations that represent 95% of under-5 deaths globally [5]. We also intend to disaggregate estimates by year rather than by 5-year intervals. Ultimately, our goal is to generate cause-specific mortality estimates at the 5 × 5 km resolution globally, but this undertaking necessitates improved encoding or identification of specific causes of death by precise locations. A recent analysis [24] produced 5 × 5 km estimates of malaria mortality in Africa by age group [24], including children younger than 5 years, which served as an initial foray into this kind of high-resolution, cause-specific mortality mapping. Generating pixel-level estimates of mortality for children younger than 5 years from other causes that disproportionately affect children, such as diarrhoeal diseases and lower respiratory infections, are also future analytical priorities.

The production of more geospatially granular estimates of key child health outcomes hinges upon heightened accessibility to and collection of geo-referenced data. Increased data availability would both facilitate cause-specific mortality estimation and reduce uncertainty in all-cause estimates, which particularly affect locations with substantive geographical or temporal data gaps. In an ideal setting, agencies involved in local data collection and management would work with the array of data users to identify best practices for sharing geo-referenced data and thus creating global goods, while maintaining
privacy and respecting data use agreements. Increasing the availability of geolocated data, from surveys to censuses to facility records, would greatly strengthen the precision of local monitoring of child health needs. By highlighting geographical areas where data gaps are most strikingly pronounced, we hope to encourage more collaboration between data users and providers.

Although household survey and census data offer good information on child deaths, they are inferior substitutes to high-quality, fully representative vital registration systems for providing timely, continuous, and complete subnational information on births and deaths. Vital registration systems should remain the gold standard for routine monitoring of national and local child mortality, and in recent years both political and financial investments in improving vital registration have increased [65-67]. Moreover, SDG indicator 17.19.2 explicitly outlines targets for birth and death registration completeness [3], and efforts such as the Bloomberg Data for Health Initiative seek to swiftly strengthen existing vital registration systems and to help build vital statistics infrastructure in places where they are inadequate or non-existent. Nonetheless, massive disparities persist in birth and death registration levels, and Africa has some of the largest gaps in the establishment, coverage, and quality of vital registration [68]. Using household survey and census data to inform child mortality estimation is likely to be a necessity in many parts of the world for the immediate future, but as vital registration systems continue to improve, future analyses should involve developing methods to integrate vital registration data with survey and census data within the model-based geostatistics framework.

Our findings should be interpreted within the context of some methodological limitations. First, we assumed no migration, which implied that all recorded births, deaths, and exposures were assumed to occur in the survey location. The ability to properly measure and incorporate indices of migration has been an enduring challenge for large-scale demographic and epidemiological studies [4,5,69,70], and though innovative efforts such as the WorldPop project [71] are improving the quantification of population movement, they do not yet provide the temporal and geographical resolution necessary for our analysis. Continued data collation and methodological advances are required to appropriately account for migration in mortality estimation. Second, we modelled death probabilities in age groups separately, because of software and computation limitations. This allowed us to avoid potential age-composition bias in small clusters, but ultimately meant ignoring a high level of correlation in these data. Future work is needed to develop methods that enable computationally efficient estimation of the under-5 survival curve simultaneously rather than approximating survival in a piece-wise manner. Third, the included set of spatial covariates does not represent the full universe of potential correlates for drivers of under-5 mortality (eg, exposure to unsafe water and sanitation) because of an absence of high-resolution spatial data or layers for these particular indicators. As these measures become available, future studies should incorporate them into modelling approaches. Fourth, to include a massive amount of polygon data in our spatially continuous model, we re-sampled polygon data to points. It is possible that this procedure introduced over-smoothing, although these effects are probably minimal given their agreement with other subnational mortality models (see appendix). Future research will need to develop computational methods for scaling up geostatistical integration of point and polygon data to continental-scale mapping studies [72]. Last, the potential effects of urban slums on child mortality were not explicitly quantified. Although our study offers the highest geospatial resolution of child mortality to date, the 5 × 5 km pixel-level remains too coarse to fully account for intra-city slums and disparities.

Amid impressive overall gains in decreasing under-5 mortality rates in Africa, sizeable populations within the continent have yet to experience such improvements in child survival. The SDG 3.2 targets for under-5 and neonatal mortality demand extraordinary progress in child health for Africa—and without substantial, sustained commitments to financing better access to improved health care and targeting interventions to high-burden areas, we are likely to fall short of these aims. Monitoring high-resolution trends in child mortality is a vital tool for swiftly recognising local child health needs and prioritising resources accordingly. With continued and expanded mapping efforts, collectively we can garner greater recognition of and attention to communities in which child survival remains tenuous.
References


### GATHER Checklist

<table>
<thead>
<tr>
<th>Item #</th>
<th>Checklist item</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Objectives and funding</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Define the indicator(s), populations (including age, sex, and geographic entities), and time period(s) for which estimates were made.</td>
<td>Main text (Methods)</td>
</tr>
<tr>
<td>2</td>
<td>List the funding sources for the work.</td>
<td>Bill and Melinda Gates Foundation</td>
</tr>
<tr>
<td><strong>Data Inputs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>For all data inputs from multiple sources that are synthesized as part of the study:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Describe how the data were identified and how the data were accessed.</td>
<td>Main text (Methods)</td>
</tr>
<tr>
<td>4</td>
<td>Specify the inclusion and exclusion criteria. Identify all ad-hoc exclusions.</td>
<td>Main text (Methods); Methods appendix (Sections 2 and 4)</td>
</tr>
<tr>
<td>5</td>
<td>Provide information on all included data sources and their main characteristics. For each data source used, report reference information or contact name/institution, population represented, data collection method, year(s) of data collection, sex and age range, diagnostic criteria or measurement method, and sample size, as relevant.</td>
<td>Methods appendix (Supplementary Table 1) and available through ghdx.healthdata.org/</td>
</tr>
<tr>
<td>6</td>
<td>Identify and describe any categories of input data that have potentially important biases (e.g., based on characteristics listed in item 5).</td>
<td>Main text (Methods); Methods appendix (Section 6)</td>
</tr>
<tr>
<td><strong>For data inputs that contribute to the analysis but were not synthesized as part of the study:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Describe and give sources for any other data inputs.</td>
<td>Methods appendix (Section 10.1)</td>
</tr>
<tr>
<td><strong>For all data inputs:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Provide all data inputs in a file format from which data can be efficiently extracted (e.g., a spreadsheet rather than a PDF), including all relevant meta-data listed in item 5. For any data inputs that cannot be shared because of ethical or legal reasons, such as third-party ownership, provide a contact name or the name of the institution that retains the right to the data.</td>
<td>Available through ghdx.healthdata.org/ or on request</td>
</tr>
<tr>
<td><strong>Data analysis</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Provide a conceptual overview of the data analysis method. A diagram may be helpful.</td>
<td>Main text (Methods);</td>
</tr>
<tr>
<td>10</td>
<td>Provide a detailed description of all steps of the analysis, including mathematical formulae. This description should cover, as relevant, data cleaning, data pre-processing, data adjustments and weighting of data sources, and mathematical or statistical model(s).</td>
<td>Main text (Methods); methods appendix</td>
</tr>
<tr>
<td>11</td>
<td>Describe how candidate models were evaluated and how the final model(s) were selected.</td>
<td>Main text (Analysis); methods appendix section 11.6)</td>
</tr>
<tr>
<td>12</td>
<td>Provide the results of an evaluation of model performance, if done, as well as the results of any relevant sensitivity analysis.</td>
<td>Main text (Analysis); methods appendix (Supplementary tables)</td>
</tr>
</tbody>
</table>
Describe methods for calculating uncertainty of the estimates. State which sources of uncertainty were, and were not, accounted for in the uncertainty analysis.

State how analytic or statistical source code used to generate estimates can be accessed.

Provide published estimates in a file format from which data can be efficiently extracted.

Report a quantitative measure of the uncertainty of the estimates (e.g. uncertainty intervals).

Interpret results in light of existing evidence. If updating a previous set of estimates, describe the reasons for changes in estimates.

Discuss limitations of the estimates. Include a discussion of any modelling assumptions or data limitations that affect interpretation of the estimates.

2. Geographic Inclusion

This analysis aimed to provide high-resolution under-5 and neonatal mortality rate maps across 46 countries in Africa considered among priority countries for monitoring child mortality by the Countdown to 2015 for Maternal, Newborn, and Child Survival. To this list we added Namibia so that the resulting maps also had continuous coverage of sub-Saharan Africa, a region over which mortality rates and other development metrics are often aggregated.

It was not possible to extend the analysis to include Algeria, Tunisia, Libya, or Western Sahara due to a lack of subnational mortality data from these countries. Cape Verde, Comoros, Mauritius, and São Tomé and Príncipe are each geographically isolated from included countries and cover very small geographic areas, so including these countries in the analysis would provide little advance over existing national estimates. The map of 46 included countries is shown in Supplementary Figure 1.

*Supplementary Figure 6. Countries included in mapping under-5 and neonatal mortality rates.*
3. Mortality data sources

Supplementary Table 1. Sources of mortality data used in the model. The datasets and reports from which complete birth history (CBH) and summary birth history (SBH) were extracted for each country are detailed under Citation, and the institutions that provided these data are given under Source. Further details are given marked for those sources labelled † as follows: ICF International. 2004-2012. Demographic Health Surveys (various). Calverton, Maryland: ICF International, 2012. CBH surveys marked with * included both CBH and SBH data and were used in the SBH adjustment model described in section 6. Admin = Administrative level

<table>
<thead>
<tr>
<th>Country</th>
<th>Year</th>
<th>Data Type</th>
<th>Source</th>
<th>Geographic level</th>
<th>Citation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>-------------</td>
<td>-------</td>
<td>-----------</td>
<td>-------------------------------------</td>
<td>------------------</td>
<td>---------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Benin</td>
<td>2006</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Admin 1</td>
<td>Institut National de la Statistique et de l'Analyse Economique &amp; Macro International Inc. Enquête Démographique et de Santé (EDSBIII) - Bénin 2000 [Dataset] BJBR61DT. (ICF International [Distributor], Calverton, Maryland, USA, 2007).</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>-------------------------</td>
<td>------</td>
<td>-----------</td>
<td>---------------------------------------------</td>
<td>------------------</td>
<td>----------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Cameroon</td>
<td>2011</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Institut National de la Statistique &amp; ICF International. Enquête Démographique et de Santé et à Indicateurs Multiples du Cameroun 2011 [Dataset] CMBR60DT. (ICF International [Distributor], Calverton, Maryland, USA, 2012).</td>
</tr>
<tr>
<td>Cameroon</td>
<td>2004</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Institut National de la Statistique &amp; ORC Macro. Enquête Démographique et de Santé du Cameroun 2004 [Dataset] CMBR44DT. (ICF International [Distributor], Calverton, Maryland, USA, 2004).</td>
</tr>
<tr>
<td>Chad</td>
<td>2015</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>National Institute of Statistical Economic and Demographic Studies (Chad) &amp; ICF International. Chad Demographic and Health Survey 2014-2015 [Dataset] TDBR71DT. (ICF International [Distributor], Fairfax, USA, 2016).</td>
</tr>
<tr>
<td>Chad</td>
<td>2010</td>
<td>SBH</td>
<td>UNICEF</td>
<td>Admin 2</td>
<td>Institut national de la statistique des études économiques et démographiques. Enquête par grappes à indicateurs multiples Tchad 2010 [Dataset], 364pp (Chad, 2011).</td>
</tr>
<tr>
<td>Chad</td>
<td>2004</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Admin 1</td>
<td>Ouagadjo, B. et al. Enquête Démographique et de Santé Tchad 2004 [Dataset] TDBR41DT. (ICF International [Distributor], Calverton, Maryland, USA, 2004).</td>
</tr>
<tr>
<td>Congo</td>
<td>2009</td>
<td>SBH</td>
<td>DHS Program†</td>
<td>Admin 1</td>
<td>Centre National de la Statistique et des Études Economiques &amp; ICF Macro. Enquête de Séroprévalence et sur les Indicateurs du Sida – Congo 2009 [Dataset] CGBR61DT. (ICF Macro [Distributor], Calverton, Maryland, USA, 2009).</td>
</tr>
<tr>
<td>Cote d'Ivoire</td>
<td>2005</td>
<td>CBH</td>
<td>DHS Program†</td>
<td>&gt; Admin 1</td>
<td>Institut National de la Statistique, Ministère de la Lutte contre le Sida (Côte d’Ivoire) &amp; Macro, O. Enquête sur les Indicateurs du Sida, Côte d’Ivoire 2005 [Dataset] CIBR50DT. 283pp (ICF International [Distributor], Calverton, Maryland, USA, 2006).</td>
</tr>
<tr>
<td>Cote d'Ivoire</td>
<td>1999</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Institut National de la Statistique (Côte d'Ivoire) &amp; ORC Macro. Enquête Démographique et de Santé, Côte d'Ivoire 1998-1999 [Dataset] CIBR3ADT. (ICF International [Distributor], Calverton, Maryland, USA, 2001).</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>----------------</td>
<td>-------</td>
<td>-----------</td>
<td>------------------------------------------------------------------------</td>
<td>------------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Djibouti</td>
<td>2012</td>
<td>CBH</td>
<td>Pan Arab Project for Family Health (PAPFAM)</td>
<td>Admin 1</td>
<td>Department of Statistics and Demographic Studies (Djibouti), League of Arab States, Ministry of Health (Djibouti), Pan Arab Project for Family Health (PAPFAM). Djibouti Family Health Survey 2012 [Dataset]. (2002).</td>
</tr>
<tr>
<td>Egypt</td>
<td>2014</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Ministry of Health and Population (Egypt), El-Zanaty and Associates (Egypt) &amp; ICF International. Egypt Demographic and Health Survey 2014 [Dataset] EGBR61DT. (ICF International [Distributor], Cairo, Egypt and Rockville, Maryland, USA, 2015).</td>
</tr>
<tr>
<td>Egypt</td>
<td>2008</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>El-Zanaty, F. &amp; Way, A. Egypt Demographic and Health Survey 2008 [Dataset] EGBR51DT. (ICF International [Distributor], Cairo, Egypt, 2008).</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>---------</td>
<td>------</td>
<td>-----------</td>
<td>--------</td>
<td>------------------</td>
<td>----------</td>
</tr>
<tr>
<td>Ghana</td>
<td>1999</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Ghana Statistical Service &amp; Macro International Inc. Ghana Demographic and Health Survey 1998 [Dataset] GHBR41DT. (ICF International [Distributor], Calverton, Maryland, USA, 1999).</td>
</tr>
<tr>
<td>Guinea</td>
<td>2012</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Institut National de la Statistique (Guinée) &amp; ICF International. Enquête Démographique et de Santé et à Indicateurs Multiples (EDS-MICS) [Dataset] GNBR61DT. (ICF International [Distributor], Calverton, Maryland, USA, 2013).</td>
</tr>
<tr>
<td>Guinea</td>
<td>2005</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Direction Nationale de la Statistique (Guinée) &amp; ORC Macro. Enquête Démographique et de Santé, Guinée 2005 [Dataset] GNBR52DT. (ICF International [Distributor], Calverton, Maryland, USA, 2006).</td>
</tr>
<tr>
<td>Guinea</td>
<td>1999</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Direction Nationale de la Statistique (Guinée) &amp; Macro International Inc. Enquête Démographique et de Santé, Guinée 1999 [Dataset] GNBR41DT. (ICF International [Distributor], Calverton, Maryland, USA, 2000).</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-----------</td>
<td>------------------------------------------------------------------------</td>
<td>------------------</td>
<td>-------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>---------------</td>
<td>--------</td>
<td>-----------</td>
<td>-------------------------------</td>
<td>-----------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Lesotho</td>
<td>2010</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Ministry of Health and Social Welfare (Lesotho) &amp; ICF Macro. Lesotho Demographic and Health Survey 2009 [Dataset] LSBBr60DT. (ICF International [Distributor], Maseru, Lesotho, 2010).</td>
</tr>
<tr>
<td>Lesotho</td>
<td>2005</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Ministry of Health and Social Welfare (Lesotho), Bureau of Statistics (Lesotho) &amp; ORC Macro. Lesotho Demographic and Health Survey 2004 [Dataset] LBBN41DT. (ICF International [Distributor], Calverton, Maryland, USA, 2005).</td>
</tr>
</tbody>
</table>

32
<table>
<thead>
<tr>
<th>Country</th>
<th>Year</th>
<th>Data Type</th>
<th>Source</th>
<th>Geographic level</th>
<th>Citation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malawi</td>
<td>2010</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>National Statistical Office &amp; ICF Macro. Malawi Demographic and Health Survey 2010 [Dataset] MWBR41DT. (ICF International [Distributor], Zomba, Malawi, and Calverton, Maryland, USA, 2011).</td>
</tr>
<tr>
<td>Malawi</td>
<td>2005</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>National Statistical Office (Malawi) &amp; ORC Macro. Malawi Demographic and Health Survey 2004 [Dataset] MWBR4DDT. (ICF International [Distributor], Calverton, Maryland, USA, 2005).</td>
</tr>
<tr>
<td>Malawi</td>
<td>2000</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>National Statistical Office (Malawi) &amp; ORC Macro. Malawi Demographic and Health Survey 2000 [Dataset] MWBR41DT. (ICF International [Distributor], Zomba, Malawi and Calverton, Maryland, USA, 2001).</td>
</tr>
<tr>
<td>Mali</td>
<td>2001</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Cellule de Planification et de Statistique du Ministère de la Santé, Direction Nationale de la Statistique et de l’Informatique &amp; ORC Macro. Enquête Démographique et de Santé au Mali 2001 [Dataset] MLBR41DT. (ICF International [Distributor], Calverton, Maryland, USA, 2002).</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>------------</td>
<td>------</td>
<td>-----------</td>
<td>-----------------------------</td>
<td>------------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Namibia</td>
<td>2013</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>The Namibia Ministry of Health and Social Services &amp; ICF International. The Namibia Demographic and Health Survey 2013 [Dataset]. NMBR61DT. (ICF International Distributors). Windhoek, Namibia, and Rockville, Maryland, USA, 2014.</td>
</tr>
<tr>
<td>Namibia</td>
<td>2007</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Ministry of Health and Social Services (Namibia) &amp; Macro International Inc. Namibia Demographic and Health Survey 2006-07 [Dataset]. NMBR51DT. (ICF International Distributors). Windhoek, Namibia, and Calverton, Maryland, USA, 2008.</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>---------</td>
<td>------</td>
<td>-----------</td>
<td>--------</td>
<td>------------------</td>
<td>----------</td>
</tr>
<tr>
<td>Rwanda</td>
<td>2013</td>
<td>SBH</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Malaria and Other Parasitic Diseases Division (MAL &amp; OPD Division-RBC) [Rwanda] &amp; ICF International. Rwanda Malaria Indicator Survey 2013 [Dataset] RWBR52DT. 103pp (ICF International [Distributor], 2014, Rockville, Maryland, USA, 2014).</td>
</tr>
<tr>
<td>Rwanda</td>
<td>2005</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Institut National de la Statistique du Rwanda &amp; ORC Macro. Rwanda Demographic and Health Survey 2005 [Dataset] RWBR63DT. (ICF International [Distributor], Calverton, Maryland, USA, 2006).</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>-----------</td>
<td>------</td>
<td>-----------</td>
<td>--------</td>
<td>------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Senegal</td>
<td>2015</td>
<td>CBH* DHS Program†</td>
<td>Admin 1</td>
<td>Cheikh Anta Diop University, ICF International, National Agency of Statistics and Demography (Senegal). Senegal Continuous Demographic and Health Survey 2015 [Dataset]. (ICF International [Distributor], Fairfax, USA, 2016).</td>
<td></td>
</tr>
<tr>
<td>Senegal</td>
<td>2006</td>
<td>SBH DHS Program†</td>
<td>Admin 1</td>
<td>Statistics Sierra Leone &amp; ICF International. Sierra Leone Demographic and Health Survey 2008 [Dataset] SLBR51DT. (ICF International [Distributor], Freetown, Sierra Leone and Rockville, Maryland, USA, 2014).</td>
<td></td>
</tr>
<tr>
<td>Sierra Leone</td>
<td>2008</td>
<td>CBH* DHS Program†</td>
<td>Point</td>
<td>Statistics Sierra Leone &amp; ICF Macro. Sierra Leone Demographic and Health Survey 2008 [Dataset] SLBRS1DT. (ICF International [Distributor], Calverton, Maryland, USA, 2009).</td>
<td></td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>-----------------</td>
<td>------</td>
<td>-----------</td>
<td>---------------------------------------------</td>
<td>------------------</td>
<td>--------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Sudan</td>
<td>2006</td>
<td>CBH</td>
<td>Pan Arab Project for Family Health (PAPFAM)</td>
<td>Admin 1</td>
<td>Ministry of Health (Southern Sudan), Federal Ministry of Health (Sudan), Southern Sudan Centre for Census, Statistics and Evaluation (SSCS). Central Bureau of Statistics (Sudan). Sudan Family Health Survey 2006 [Dataset].</td>
</tr>
<tr>
<td>Swaziland</td>
<td>2007</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Central Statistical Office (Swaziland) &amp; Macro International Inc. Swaziland Demographic and Health Survey 2006-07 [Dataset] SZBR51DT. 13pp (IFC International [Distributor], Mbabane, Swaziland, 2008).</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-----------</td>
<td>--------</td>
<td>------------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Tanzania</td>
<td>1999</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>National Bureau of Statistics (Tanzania) &amp; Macro International Inc. Tanzania Reproductive and Child Health Survey 1999 [Dataset] TZBR41DT. (ICF International [Distributor], Calverton, Maryland, USA, 2000).</td>
</tr>
<tr>
<td>Uganda</td>
<td>2011</td>
<td>SBH</td>
<td>World Bank</td>
<td>Point</td>
<td>Uganda Bureau of Statistics. The Uganda National Panel Survey 2010/11 [Dataset], (Kampala, Uganda, 2013)</td>
</tr>
<tr>
<td>Uganda</td>
<td>2006</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Uganda Bureau of Statistics &amp; Macro International Inc. Uganda Demographic and Health Survey 2006 [Dataset] UGBR52DT. (ICF International [Distributor], Calverton, Maryland, USA, 2007).</td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Data Type</td>
<td>Source</td>
<td>Geographic level</td>
<td>Citation</td>
</tr>
<tr>
<td>-----------</td>
<td>------</td>
<td>-----------</td>
<td>--------------------</td>
<td>------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Zambia</td>
<td>2007</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Central Statistical Office, Ministry of Health, Tropical Diseases Research Centre, University of Zambia &amp; Macro International Inc. Zambia Demographic and Health Survey 2007 [Dataset] ZMBR51DT. (ICF International [Distributor], Calverton, Maryland, USA, 2009).</td>
</tr>
<tr>
<td>Zimbabwe</td>
<td>2006</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Zimbabwe National Statistics Agency &amp; Macro International Inc. Zimbabwe Demographic and Health Survey 2005-06 [Dataset] ZWBK51DT. (ICF International [Distributor], Calverton, Maryland, USA, 2007).</td>
</tr>
<tr>
<td>Zimbabwe</td>
<td>1999</td>
<td>CBH*</td>
<td>DHS Program†</td>
<td>Point</td>
<td>Central Statistical Office (Zimbabwe) &amp; Macro International Inc. Zimbabwe Demographic and Health Survey 1999 [Dataset] ZWBK42DT. (ICF International [Distributor], Calverton, Maryland, USA, 2000).</td>
</tr>
</tbody>
</table>

4. Data outliers

Several surveys were identified for inclusion but were ultimately excluded from the final analysis for concerns about data quality. The 2007 Ethiopia census was dropped due to 80% missingness in SBH data and unrealistic geographic distribution of mortality risk. A CBH dataset was dropped if the percent of children who died missing either birth or death date exceeded 10%, or exceeded 5% and had reported data quality issues. Such surveys were South Africa NIDS 2011, subnational MICS surveys from Kenyan counties Bungoma, Turkana, Kakamega (2013-2014), and Somalia NE Zone (2011), and the Djibouti PAPFAM survey 2012. Finally, we dropped data points from Diffa region (2012 Niger DHS) and Jonglei and Unity states (South Sudan 2010 MICS) as they were highly discordant with data points from the same surveys in nearby regions with similar sociodemographic profiles.
5. Tabulating CBH data

For each survey cluster we tabulated monthly exposures and deaths for each of four age bins over four separate five-year periods, as illustrated in Supplementary Figure 2. This tabulation process is similar to that used to compute under-5 mortality estimates for GBD 2016. The exception to this is that we use four component bins: month 0, months 1-11, months 12-35, and months 36-59, whereas GBD uses six bins: 0 months, 1–11 months, 12–23 months, 24–36 months, 36–47 months, and 48–59 months. For areas larger than survey clusters, survey weights were used in the tabulation step to make weighted mortality rates for each of the component bins, which were then applied to the observed tabulated exposure months to estimate an equivalent number of deaths. Estimates for the 2015 period may be slightly overestimated due to the relatively smaller amount of data in the later years of the period.

Supplementary Figure 7: Lexis diagram illustrating periods and age bins within which CBH data were tabulated. For each month (grey parallelograms) within each age bin/period pair, (rectangles bounded by solid black lines) we tabulated the number of exposures (number of children alive and entering the month of life within the given period) and number of deaths (exposures who died during that month) for each survey cluster, or geographic area comprising multiple clusters, where cluster-specific data were unavailable. For example, if we observed a living child who was 3.5 years old in a January 2004 survey, their life history would be represented with the red line in the figure, extending back to midway through 2001 when they were born. This child would have contributed exposure months in the cells (month/period combinations) crossed by their life history: (age bin 4/period 2005: 6 months; 3/2005: 18 months; 3/2000: 6 months, 2/2000: 12 months; and 1/2000, 1 month). If the same child had died at age 3.5 in January 2004, they would have contributed the same number of exposure months, but also a death event in age bin 4/period 2005.
6. Adjustment of summary birth history data

In a summary birth history (SBH) survey module, a woman is asked a minimum of two questions: the number of children ever born (CEB) to them and the number of those who have died (CD). While providing much less information than the full account of life histories available in CBH data, SBH is widely available. Of the 235 surveys for which we had microdata, 104 contained only summary birth histories, most notably in many Unicef MICS and census datasets.

To be usable for child mortality estimation, SBH needs to be adjusted such that they are representative of age- and time-specific mortality. This involves an adjustment of the rate as well as localizing the mortality rates in time. Recent model-based improvements have been made on classical indirect methods by relating the CBH- and SBH-derived rates from surveys where both are available, along with information on parity and maternal age.

SBH and CBH survey modules capture different information on child births and deaths. For CBH data we can tabulate information for each child to directly estimate deaths and exposure months for any desired age bin and time period, while in SBH, the only mortality data available is the CD/CEB ratio for each mother interviewed. Ultimately, for this analysis, we wish to approximate CBH-style binomial samples from available information in SBH. The strong linear relationship between the logit of the CD/CEB ratio and the logit under-5 probability of death (5q0) has been noted in the past and used as motivation for a model-based approach to adjusting SBH to match CBH data. In this analysis, we had the added challenge of dealing with data that need to be child-age disaggregated, which has not been well explored in the literature. Using surveys with both SBH and CBH modules, we found evidence that logit of CD/CEB had a strong relationship with the monthly probabilities of death tabulated in our analytical age groups from CBH data. The plots in Supplementary Figure 3 show the bivariate relationships across ages and lag-times between in surveys that collect both CBH and SBH data. These plots give strong motivation that a modelling approach should work for smaller age bins as well.
Supplementary Figure 8: Comparison of SBH and CBH mortality. Using surveys that collect both SBH and CBH mortality data, we find a strong relationship between the logit of the monthly probability of death for all of our analytical age bins, as well as with the full under-5 bin, with the logit of CD/CEB for each survey. The logit of CD/CEB is highly predictive of CBH tabulated age-specific monthly mortality probability going back up to 19 years before the survey. Lines drawn show a linear regression line, with a beta coefficient and R-squared provided. SBH = Summary birth history; CBH = Complete birth history; CD = Children died; CEB = Children ever born.
6.1 Data preparation

First, we collated data on over four million children from 119 datasets (mostly DHS) collected since 1998 (the beginning of our study period) that contain both SBH and CBH data, these are marked with an asterisk on Supplementary table 1. We tabulated the CBH deaths and exposure months at the age-period level as described in the section above. Thus, each survey produced up to 16 rows of data, one for each child age bin (month 0, months 1–11, months 12–35, and months 36–59) and time period bin (centred at 2000, 2005, 2010, 2015), each with the number of CBH-tabulated deaths and exposures and SBH-tabulated CD and CEB for the cluster.

We will refer to the CBH-SBH combined dataset as the training set, and the SBH-only data which we aim to adjust as the prediction dataset. The prediction dataset will be aggregated to the level of the smallest possible geography – either survey cluster or some identifiable administrative unit. We will refer from now on to this smallest geography simply as cluster.

In order to use a logit transformation of the CD/CEB ratio in the modelling step (described in the following subsection), we had to ensure the CD data did not include zeroes since the logit of 0 is negative infinity. To do so, we fitted the following Bayesian hierarchical shrinkage model to adjust death counts in surveys that contained clusters with no deaths recorded:

\[
CD_i \sim \text{Binomial}(q_i, CEB_i) \\
\text{logit}(q_i) = \alpha + \gamma_i \\
\gamma_i \sim N(0, \sigma^2)
\]

where \(i\) is cluster and \(\gamma\) is a normal independent random effect by cluster. Models were fit separately for each survey. A minimally informative prior, \(\log \left( \frac{1}{\sigma^2} \right) \sim \text{loggamma}(1,0.00005)\), was placed on \(\sigma\). The effect of this adjustment was extremely small, correlation between original CD and adjusted was greater than 0.9999. We then used \(\hat{q}_i\) in place of the CD/CEB ratio in the full SBH adjustment model, described in the next section.

6.2 SBH adjustment models

We developed a two-stage regression model for cross-walking SBH data into age and period bin approximate binomial samples to match the CBH input data. In the first model we estimate \(\hat{p}\), the bin specific monthly probability of death. In the second model we estimate \(\hat{N}\), the number of exposure months in that bin. From these two quantities we then simulate bin-specific deaths \(\hat{N}^+\). \(\hat{N}\) and \(\hat{N}^+\) are used as training data at SBH clusters in the geostatistical model described in detail later in this document. 10,000 \(\hat{N}^+\) draws are simulated from draws taken from the predictive posterior distributions of \(\hat{N}\) and \(\hat{p}\) and the resulting variance is used to down-weight these observations when fitting the geostatistical model. We describe these models in detail below.

The \(\hat{p}\) model was fit to the training set at the survey, age bin, period, and level, and then used to predict to SBH-only data at the smallest identifiable geography.

We fit the following Bayesian hierarchical logistic regression model to the training data:
\( N_{s,a,p} \sim \text{Binomial}(p_{s,a,p}, N_{s,a,p}) \)

\[
\log(p_{s,a,p}/(1-p_{s,a,p})) = \beta_0 + \logit(\tilde{\alpha}_i) (\beta_1 + \text{Age}\beta_2 + \text{Lag}\text{Age}\beta_4) + X_{s,a,p}\beta_{fe} + \gamma_s + \gamma_{country}
\]

\( \gamma_s \sim N(0, \sigma_s^2) \)

\( \gamma_{country} \sim N(0, \sigma_{country}^2) \)

where \( N_{s,a,p} \) are the number of monthly exposures recorded in a survey \( s \), age bin \( a \), and time period \( p \), and \( N_{s,a,p}^+ \) are the number of deaths resulting from all monthly exposures. \( N_{s,a,p} \) and \( N_{s,a,p}^+ \) both come from direct tabulations of the CBH data. \( \alpha_0 \) is a global intercept term. \( \tilde{\alpha}_i \) is the zero-adjusted CD/CEB ratio described above in equation (1). The logit of CD/CEB is modified by interactions with child age bin, lag, and the interaction of child age bin and lag. Lag represents the number of periods between the survey to time of mortality risk. We further included fixed effects for all individual terms from the interactions as well as for mean maternal age, year, parity ratios between 15-19 and 20-24 year olds, parity ratios between 20-24 and 25-29 year olds, the proportions of mothers in the survey in various maternal age bins (15-19, 20-24, and 25-39), and the number of years of coverage the survey had in the period bin. We represent the values of these fixed effect covariates with the bolded matrix element \( X_{s,a,p} \) and their associated coefficients in the vector \( \beta_{fe} \). Survey weights were used to make estimates of the independent variables at areas larger than clusters in the prediction data set.

We fit another model to estimate \( \tilde{N} \), the expected number of exposure months of life in each child age, period bin. For this second model, the target of inference was a number and not a ratio, so we chose to fit the model on the training set aggregated to the survey-admin1 level, and thus more similar to numbers seen in the prediction dataset. This model was very similar to the model for \( \hat{p} \) described in equation (2) but with several key differences: 1) we fit to \( N_{i,a,p} \) using a Poisson likelihood; 2) we used log(CEB) instead of logit(CD/CEB) as the main effect driving the adjustment; 3) we added a fixed effects term for log(CD) and a random effect on survey-admin1; and 4) we replaced the interaction with lag with an interaction with number of years in the period covered by the survey.

In addition, two prediction set censuses (Zimbabwe 2002, and Zimbabwe 2012) were only available in tabulated form. As such, for these three surveys we trained and predicted slightly modified \( \hat{p} \) and \( \tilde{N} \) models, using proportion of women instead of proportion of mothers fixed effects.

All models were fitted using R-INLA. The following minimally informative priors (http://www.r-inla.org/models/latent-models) were used: \( \beta \sim N(0, 1000) \), \( \log\left(\frac{1}{\alpha_i}\right) \sim \text{loggamma}(1, 0.00005) \).

6.2.1 Model fits of SBH adjustment models

Supplementary Table 2: SBH Adjustment model results for the \( p \) model. SBH=Summary birth history. Reference levels for factor variables lag and child age bin are lag 0 and child age bin 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean coef. estimate</th>
<th>2.5% UI</th>
<th>97.5% UI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-4.3226</td>
<td>-5.629</td>
<td>-3.0253</td>
</tr>
<tr>
<td>CD/CEB</td>
<td>0.1168</td>
<td>0.026</td>
<td>0.2071</td>
</tr>
<tr>
<td>lag 1</td>
<td>0.2435</td>
<td>-0.0841</td>
<td>0.5709</td>
</tr>
<tr>
<td>lag 2</td>
<td>0.5205</td>
<td>0.1469</td>
<td>0.8936</td>
</tr>
</tbody>
</table>
Supplementary Table 3: SBH Adjustment model results for the N model. SBH=Summary birth history.
Reference levels for factor variables lag and child age bin are lag 0 and child age bin 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean coef. estimate</th>
<th>2.5% UI</th>
<th>97.5% UI</th>
</tr>
</thead>
<tbody>
<tr>
<td>lag 3</td>
<td>0.1055</td>
<td>-0.4127</td>
<td>0.6232</td>
</tr>
<tr>
<td>child age bin 2</td>
<td>-1.6537</td>
<td>-1.7677</td>
<td>-1.5399</td>
</tr>
<tr>
<td>child age bin 3</td>
<td>-1.5178</td>
<td>-1.6369</td>
<td>-1.3987</td>
</tr>
<tr>
<td>child age bin 4</td>
<td>-2.2989</td>
<td>-2.4504</td>
<td>-2.1474</td>
</tr>
<tr>
<td>mean maternal age</td>
<td>-0.0075</td>
<td>-0.0322</td>
<td>0.0173</td>
</tr>
<tr>
<td>period</td>
<td>0.123</td>
<td>0.0991</td>
<td>0.1465</td>
</tr>
<tr>
<td>proportion mothers 15-19</td>
<td>3.5498</td>
<td>1.1685</td>
<td>5.909</td>
</tr>
<tr>
<td>proportion mothers 20-24</td>
<td>1.5733</td>
<td>0.1497</td>
<td>2.9987</td>
</tr>
<tr>
<td>proportion mothers 25-39</td>
<td>0.9012</td>
<td>-0.3119</td>
<td>2.1217</td>
</tr>
<tr>
<td>P(15-19)/P(20-24)</td>
<td>-1.3741</td>
<td>-2.079</td>
<td>-0.6674</td>
</tr>
<tr>
<td>P(20-24)/P(25-25)</td>
<td>0.6768</td>
<td>0.0632</td>
<td>1.2865</td>
</tr>
<tr>
<td>years in period</td>
<td>-0.041</td>
<td>-0.051</td>
<td>-0.0309</td>
</tr>
<tr>
<td>CD/CEB * lag 1</td>
<td>0.1887</td>
<td>0.1317</td>
<td>0.2456</td>
</tr>
<tr>
<td>CD/CEB * lag 2</td>
<td>0.3763</td>
<td>0.3123</td>
<td>0.4403</td>
</tr>
<tr>
<td>CD/CEB * lag 3</td>
<td>0.3049</td>
<td>0.2217</td>
<td>0.388</td>
</tr>
<tr>
<td>CD/CEB * child age bin 2</td>
<td>0.414</td>
<td>0.3499</td>
<td>0.4781</td>
</tr>
<tr>
<td>CD/CEB * child age bin 3</td>
<td>0.9688</td>
<td>0.9002</td>
<td>1.0374</td>
</tr>
<tr>
<td>CD/CEB * child age bin 4</td>
<td>0.9449</td>
<td>0.8569</td>
<td>1.0331</td>
</tr>
<tr>
<td>lag 1 * child age bin 2</td>
<td>-0.1006</td>
<td>-0.2422</td>
<td>0.0409</td>
</tr>
<tr>
<td>lag 2 * child age bin 2</td>
<td>-0.0961</td>
<td>-0.2549</td>
<td>0.0625</td>
</tr>
<tr>
<td>lag 3 * child age bin 2</td>
<td>0.3137</td>
<td>0.1049</td>
<td>0.5224</td>
</tr>
<tr>
<td>lag 1 * child age bin 3</td>
<td>0.0649</td>
<td>-0.0832</td>
<td>0.2128</td>
</tr>
<tr>
<td>lag 2 * child age bin 3</td>
<td>-0.081</td>
<td>-0.2488</td>
<td>0.0866</td>
</tr>
<tr>
<td>lag 3 * child age bin 3</td>
<td>-0.2431</td>
<td>-0.4618</td>
<td>-0.0245</td>
</tr>
<tr>
<td>lag 1 * child age bin 4</td>
<td>-0.2064</td>
<td>-0.4000</td>
<td>-0.0129</td>
</tr>
<tr>
<td>lag 2 * child age bin 4</td>
<td>-0.4383</td>
<td>-0.6594</td>
<td>-0.2174</td>
</tr>
<tr>
<td>lag 3 * child age bin 4</td>
<td>-0.4778</td>
<td>-0.7686</td>
<td>-0.1871</td>
</tr>
<tr>
<td>lag 1 * mean maternal age</td>
<td>0.0086</td>
<td>-0.0017</td>
<td>0.0189</td>
</tr>
<tr>
<td>lag 2 * mean maternal age</td>
<td>0.0123</td>
<td>0.0000</td>
<td>0.0238</td>
</tr>
<tr>
<td>lag 3 * mean maternal age</td>
<td>0.0203</td>
<td>0.0041</td>
<td>0.0365</td>
</tr>
<tr>
<td>CD/CEB * lag 1 * child age bin 2</td>
<td>-0.076</td>
<td>-0.155</td>
<td>0.003</td>
</tr>
<tr>
<td>CD/CEB * lag 2 * child age bin 2</td>
<td>-0.1101</td>
<td>-0.1971</td>
<td>-0.0232</td>
</tr>
<tr>
<td>CD/CEB * lag 3 * child age bin 2</td>
<td>0.0212</td>
<td>-0.0885</td>
<td>0.1308</td>
</tr>
<tr>
<td>CD/CEB * lag 1 * child age bin 3</td>
<td>0.003</td>
<td>-0.0817</td>
<td>0.0876</td>
</tr>
<tr>
<td>CD/CEB * lag 2 * child age bin 3</td>
<td>-0.1392</td>
<td>-0.233</td>
<td>-0.0455</td>
</tr>
<tr>
<td>CD/CEB * lag 3 * child age bin 3</td>
<td>-0.3275</td>
<td>-0.4439</td>
<td>-0.2111</td>
</tr>
<tr>
<td>CD/CEB * lag 1 * child age bin 4</td>
<td>-0.0792</td>
<td>-0.1908</td>
<td>0.0323</td>
</tr>
<tr>
<td>CD/CEB * lag 2 * child age bin 4</td>
<td>-0.2944</td>
<td>-0.4183</td>
<td>-0.1706</td>
</tr>
<tr>
<td>CD/CEB * lag 3 * child age bin 4</td>
<td>-0.4218</td>
<td>-0.5768</td>
<td>-0.2667</td>
</tr>
<tr>
<td>Variance of country random effect</td>
<td>0.0101</td>
<td>0.0052</td>
<td>0.0212</td>
</tr>
<tr>
<td>Variance of survey random effect</td>
<td>0.0056</td>
<td>0.0037</td>
<td>0.0090</td>
</tr>
</tbody>
</table>
### 6.3 Out of sample validation of SBH Adjustment Model

We used five-fold cross validation to test how well these models predicted $p$ and $N$ out-of-sample. Using the two training datasets, we fit each of the models five times, each time holding out the response variable from a random subset of one-fifth of the surveys. The plot below shows the out-of-sample fits by child age bin, and the table below shows summary predictive validity metrics for the two models for each child age-year bin.

<table>
<thead>
<tr>
<th>Term</th>
<th>Coefficient 1</th>
<th>Coefficient 2</th>
<th>Coefficient 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.6750</td>
<td>3.5904</td>
<td>5.7556</td>
</tr>
<tr>
<td>log(CEB)</td>
<td>0.9499</td>
<td>0.9069</td>
<td>0.9928</td>
</tr>
<tr>
<td>lag 1</td>
<td>-0.8378</td>
<td>-0.9235</td>
<td>-0.7523</td>
</tr>
<tr>
<td>lag 2</td>
<td>-1.7154</td>
<td>-1.8859</td>
<td>-1.5452</td>
</tr>
<tr>
<td>lag 3</td>
<td>-2.7182</td>
<td>-2.9740</td>
<td>-2.4630</td>
</tr>
<tr>
<td>child age bin 2</td>
<td>2.5561</td>
<td>2.5188</td>
<td>2.5933</td>
</tr>
<tr>
<td>child age bin 3</td>
<td>3.3709</td>
<td>3.3344</td>
<td>3.4074</td>
</tr>
<tr>
<td>child age bin 4</td>
<td>3.3548</td>
<td>3.3182</td>
<td>3.3913</td>
</tr>
<tr>
<td>mean maternal age</td>
<td>-0.1140</td>
<td>-0.1255</td>
<td>-0.1026</td>
</tr>
<tr>
<td>period</td>
<td>-0.1662</td>
<td>-0.2511</td>
<td>-0.0813</td>
</tr>
<tr>
<td>proportion mothers 15-19</td>
<td>-2.2269</td>
<td>-2.8797</td>
<td>-1.5749</td>
</tr>
<tr>
<td>proportion mothers 20-24</td>
<td>-1.5814</td>
<td>-2.0317</td>
<td>-1.1316</td>
</tr>
<tr>
<td>proportion mothers 25-39</td>
<td>-0.8190</td>
<td>-1.1570</td>
<td>-0.4815</td>
</tr>
<tr>
<td>P(15-19)/P(20-24)</td>
<td>-1.2373</td>
<td>-3.6473</td>
<td>1.1637</td>
</tr>
<tr>
<td>P(20-24)/P(25-25)</td>
<td>-3.4624</td>
<td>-5.8158</td>
<td>-1.1069</td>
</tr>
<tr>
<td>years in period</td>
<td>0.5652</td>
<td>0.5573</td>
<td>0.5730</td>
</tr>
<tr>
<td>log(CD)</td>
<td>-0.0578</td>
<td>-0.0955</td>
<td>-0.0201</td>
</tr>
<tr>
<td>log(CEB) * years in period</td>
<td>-0.0039</td>
<td>-0.0049</td>
<td>-0.0029</td>
</tr>
<tr>
<td>log(CEB) * child age bin 2</td>
<td>-0.0154</td>
<td>-0.0203</td>
<td>-0.0105</td>
</tr>
<tr>
<td>log(CEB) * child age bin 3</td>
<td>-0.0302</td>
<td>-0.0350</td>
<td>-0.0254</td>
</tr>
<tr>
<td>log(CEB) * child age bin 4</td>
<td>-0.0279</td>
<td>-0.0327</td>
<td>-0.0231</td>
</tr>
<tr>
<td>child age bin 2 * years in period</td>
<td>-0.0476</td>
<td>-0.0558</td>
<td>-0.0394</td>
</tr>
<tr>
<td>child age bin 3 * years in period</td>
<td>-0.0744</td>
<td>-0.0824</td>
<td>-0.0664</td>
</tr>
<tr>
<td>child age bin 4 * years in period</td>
<td>-0.0923</td>
<td>-0.1003</td>
<td>-0.0842</td>
</tr>
<tr>
<td>log(CEB) * child age bin 2 * years in period</td>
<td>0.0032</td>
<td>0.0022</td>
<td>0.0043</td>
</tr>
<tr>
<td>log(CEB) * child age bin 3 * years in period</td>
<td>0.0063</td>
<td>0.0053</td>
<td>0.0074</td>
</tr>
<tr>
<td>log(CEB) * child age bin 4 * years in period</td>
<td>0.0054</td>
<td>0.0044</td>
<td>0.0065</td>
</tr>
<tr>
<td>log(CEB) * child age bin 2 * years in period</td>
<td>0.0096</td>
<td>0.0092</td>
<td>0.0099</td>
</tr>
<tr>
<td>log(CEB) * child age bin 3 * years in period</td>
<td>0.0363</td>
<td>0.0359</td>
<td>0.0367</td>
</tr>
<tr>
<td>log(CEB) * child age bin 4 * years in period</td>
<td>0.0621</td>
<td>0.0615</td>
<td>0.0627</td>
</tr>
<tr>
<td>lag 1 * mean maternal age</td>
<td>0.0355</td>
<td>0.0110</td>
<td>0.1446</td>
</tr>
<tr>
<td>lag 2 * mean maternal age</td>
<td>0.1501</td>
<td>0.1408</td>
<td>0.1600</td>
</tr>
<tr>
<td>lag 3 * mean maternal age</td>
<td>0.1942</td>
<td>0.1407</td>
<td>0.2760</td>
</tr>
</tbody>
</table>

Variance for country random effect: 0.0355, 0.0110, 0.1446
Variance for admin1 random effect: 0.1501, 0.1408, 0.1600
Variance for survey: 0.1942, 0.1407, 0.2760
Supplementary Figure 9. Out of sample fits for SBH adjustment models. SBH = summary birth history. X axis: Out of sample data at from the SBH adjustment model. Y axis: observed truth from CBH tabulations. 4A shows out of sample predictions from the $p$ model for monthly probability of death. 4B shows the out of sample predictions from the $N$ model for monthly exposures. Plotted in modelled logit and log scales, respectively. Colours indicate child-age groups. Red line indicates unity. SBH=Summary birth history.

Supplementary Table 4. Out-of-sample predictive validity metrics for SBH adjustment models in probability and exposure month space, respectively. Calculated using five holdout folds.

<table>
<thead>
<tr>
<th>Age Bin</th>
<th>Year</th>
<th>Mean $\hat{p}$ (observed)</th>
<th>mean $\hat{p}$</th>
<th>RMSE</th>
<th>ME</th>
<th>Mean $\hat{N}$ (observed)</th>
<th>Mean $\hat{N}$</th>
<th>RMSE</th>
<th>ME</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2015</td>
<td>0.02534</td>
<td>0.02446</td>
<td>0.0096</td>
<td>-0.00089</td>
<td>181.5</td>
<td>188.6</td>
<td>66.5</td>
<td>7.1</td>
</tr>
<tr>
<td>2</td>
<td>2015</td>
<td>0.00166</td>
<td>0.00204</td>
<td>0.0075</td>
<td>0.00038</td>
<td>2068.0</td>
<td>2104.4</td>
<td>685.5</td>
<td>36.4</td>
</tr>
<tr>
<td>3</td>
<td>2015</td>
<td>0.00067</td>
<td>0.00077</td>
<td>0.00028</td>
<td>0.00010</td>
<td>4299.3</td>
<td>4247.1</td>
<td>1428.4</td>
<td>-52.2</td>
</tr>
<tr>
<td>4</td>
<td>2015</td>
<td>0.00041</td>
<td>0.00037</td>
<td>0.00020</td>
<td>-0.00004</td>
<td>4138.4</td>
<td>4128.8</td>
<td>1347.0</td>
<td>-9.6</td>
</tr>
<tr>
<td>1</td>
<td>2010</td>
<td>0.02866</td>
<td>0.02670</td>
<td>0.00716</td>
<td>-0.00196</td>
<td>407.5</td>
<td>433.8</td>
<td>94.4</td>
<td>26.3</td>
</tr>
<tr>
<td>2</td>
<td>2010</td>
<td>0.00236</td>
<td>0.00239</td>
<td>0.00075</td>
<td>0.00004</td>
<td>4279.0</td>
<td>4469.9</td>
<td>756.3</td>
<td>190.9</td>
</tr>
<tr>
<td>3</td>
<td>2010</td>
<td>0.00095</td>
<td>0.00096</td>
<td>0.00036</td>
<td>0.00002</td>
<td>8843.8</td>
<td>8934.3</td>
<td>1152.2</td>
<td>90.5</td>
</tr>
<tr>
<td>4</td>
<td>2010</td>
<td>0.00044</td>
<td>0.00044</td>
<td>0.00020</td>
<td>0.00000</td>
<td>8354.2</td>
<td>8123.0</td>
<td>1156.8</td>
<td>-231.2</td>
</tr>
<tr>
<td>1</td>
<td>2005</td>
<td>0.03120</td>
<td>0.03126</td>
<td>0.00723</td>
<td>0.00006</td>
<td>421.9</td>
<td>418.1</td>
<td>95.4</td>
<td>-3.8</td>
</tr>
<tr>
<td>2</td>
<td>2005</td>
<td>0.00324</td>
<td>0.00302</td>
<td>0.00090</td>
<td>-0.00022</td>
<td>4346.7</td>
<td>4307.7</td>
<td>815.6</td>
<td>-39.0</td>
</tr>
<tr>
<td>3</td>
<td>2005</td>
<td>0.00132</td>
<td>0.00133</td>
<td>0.00040</td>
<td>0.00001</td>
<td>8572.6</td>
<td>8559.1</td>
<td>1313.4</td>
<td>-13.5</td>
</tr>
<tr>
<td>4</td>
<td>2005</td>
<td>0.00059</td>
<td>0.00060</td>
<td>0.00020</td>
<td>0.00001</td>
<td>7691.9</td>
<td>7659.0</td>
<td>1108.8</td>
<td>-33.0</td>
</tr>
<tr>
<td></td>
<td>Year</td>
<td>Value1</td>
<td>Value2</td>
<td>Value3</td>
<td>Value4</td>
<td>Value5</td>
<td>Value6</td>
<td>Value7</td>
<td>Value8</td>
</tr>
<tr>
<td>---</td>
<td>------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td>1</td>
<td>2000</td>
<td>0.03482</td>
<td>0.03633</td>
<td>0.00795</td>
<td>0.00152</td>
<td>386.6</td>
<td>373.9</td>
<td>73.5</td>
<td>-12.7</td>
</tr>
<tr>
<td>2</td>
<td>2000</td>
<td>0.00399</td>
<td>0.00379</td>
<td>0.00110</td>
<td>-0.00020</td>
<td>3915.9</td>
<td>3835.7</td>
<td>609.8</td>
<td>-80.2</td>
</tr>
<tr>
<td>3</td>
<td>2000</td>
<td>0.00174</td>
<td>0.00178</td>
<td>0.00049</td>
<td>0.00005</td>
<td>7637.5</td>
<td>7608.4</td>
<td>1157.5</td>
<td>-29.1</td>
</tr>
<tr>
<td>4</td>
<td>2000</td>
<td>0.00080</td>
<td>0.00079</td>
<td>0.00030</td>
<td>-0.00001</td>
<td>6592.9</td>
<td>6750.3</td>
<td>1424.1</td>
<td>157.3</td>
</tr>
</tbody>
</table>

6.4 Inverse-variance weighting of SBH observations

To account for the fact that the adjusted SBH approximated binomial data points were modelled, we chose to weight SBH observations in the prediction proportionally to the uncertainty in each prediction from the two-stage model. These weights are then used when fitting the full geostatistical model.

For each observation of SBH-only data, we took 10,000 draws from the predictive posterior distributions of $\hat{p}$ and $\hat{N}$. For each draw $m$ we then simulated $\hat{N}^{\pm}_m$ from a binomial distribution with parameters $\hat{p}_m$ and $\hat{N}_m$, giving us 10,000 corresponding draws of $\hat{N}^{\pm}$. We then took the weights as the inverse of the ratio of the simulated variance of $\hat{N}^{\pm}$ and the expected binomial variance $E[\hat{N}]E[\hat{p}] (1 - E[\hat{p}])$. As defined, the weights represent the proportion of excess variance in these observations induced by the two-stages of $N$ and $p$ modelling.

In 7.2% of our predicted SBH observations, weights exceeded 1 because small $N$ and small monthly death probabilities resulted in 10,000 draws of nearly all zeros. This caused very low variance of observed deaths across the draws (lower than expected) and inflated weights. We view this as a computational issue in managing to capture low binomial variance via simulation in situations where we have high confidence that the outcome should be 0. Taking more draws from the predictive posterior distributions of $\hat{p}$ and $\hat{N}$ is computationally expensive and for these observations we set the weight to 1. Weights ranged from 0.00013 to 1.0, with 25% falling below 0.36, a median weight of 0.75, and a 75th quantile of 0.91.

7. Applying GBD bias correction

Prior to geostatistical modelling, we adjusted mortality data by applying the bias correction ratios used by Wang and colleagues for GBD 2016. Briefly, raw under-5 mortality data may differ due to various source-specific biases, sampling-related or non-sampling, and it is thus desirable to account for them when possible in order to generate a consistent time series of under-5 mortality. To adjust for this, a non-linear mixed effects model with source-type specific fixed effects and source-specific random effects nested within a location was fit by Wang and colleagues. In addition, one high-quality reference source is chosen as the reference based on expert opinion and general data quality from specific survey series for each country. In the case of Africa, this is typically complete birth histories from DHS. For all non-reference sources, data are adjusted based on the difference between the combination of source-type fixed effects and source specific random effects between the source of interest and the reference source. The ratio of the unadjusted mortality to the adjusted from the model are thus country-source-year specific. We converted these to monthly ratios and multiplied the number of deaths in each bin-period-cluster by them for all matching records from non-reference data sources.

8. Spatial integration over polygon records

Supplementary Figure 5, shown below, illustrates the k-means clustering method used to generate spatial integration points for areal mortality estimates. For each geographic area, we extracted a raster layer of population counts with cell area of approximately 5x5 km from an Africa-wide population raster for 2010 from the WorldPop project (panel A). We then sampled 10,000 point locations with replacement from each
area, with sampling probability proportional to cell population, to simulate a random sample of the population of the area (panel B). Finally, we applied k-means clustering to the latitudes and longitudes of these locations, with J clusters, such that there was one cluster per 100 raster cells within each polygon area. For each of the J cluster centres, we computed the integration weight as the proportion of the representative points falling within this cluster (being geographically closer to that cluster centre than any other cluster centre) (panel C). These weighted points (pseudo-clusters, representing areal estimates) are then combined with true geographically referenced clusters to create the dataset to train the geostatistical model.

Supplementary Figure 10: Illustration of k-means clustering for selecting spatial integration points and weights for polygon mortality data, applied to the district of Makonde, Zimbabwe. A) Spatial raster of cell-level population counts (blue cells indicating larger populations), B) locations of 10,000 population-representative point locations (with added spatial jitter for illustrative purposes), C) 11 spatial integration points selected by k-means clustering, with the size of each point proportional to its integration weight.

9. Raw data plots
The plots in Supplementary Figures 6 through 10 show the model input data for the four age bins over time. Monthly probabilities of death are plotted over a 48 x 48 pixel lattice over Africa. Pixels represent average mortality probabilities from points falling within each pixel. Plots are unweighted by sample size and are meant only to give a general idea of data coverage and values.
Supplementary Figure 11: Model input data for age bin 1 (neonatal), values indicate the mean monthly probability of death among clusters in each grid cell.
Supplementary Figure 12: Model input data for age bin 2 (1 – 11 months), values indicate the mean monthly probability of death among clusters in each grid cell.
Supplementary Figure 13: Model input data for age bin 3 (12 – 35 months), values indicate the mean monthly probability of death among clusters in each grid cell.
Supplementary Figure 14: Model input data for age bin 4 (36 – 59 months), values indicate the mean monthly probability of death among clusters in each grid cell.
Supplementary Figure 15: Combined input data for age bins1-4, approximating under-5 mortality.
10. Covariates and covariate transformation

10.1 Covariates

Supplementary Table 5. Description of covariate layers used and their sources. For years, if multiple years were provided (included in parentheses), we took a synoptic mean.

<table>
<thead>
<tr>
<th>Plot</th>
<th>Covariate</th>
<th>Years</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Travel time (in seconds) to nearest population centre (of at least 50,000 population)</td>
<td>2000</td>
<td>Uchida &amp; Nelson, 2008: Agglomeration Index: Towards a New Measure of Urban Concentration</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td><a href="https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html">https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html</a></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td><a href="http://www.worldpop.org.uk/data/get_data/">http://www.worldpop.org.uk/data/get_data/</a></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td><a href="http://www.worldpop.org.uk/data/get_data/">http://www.worldpop.org.uk/data/get_data/</a></td>
</tr>
<tr>
<td>E</td>
<td>Irrigation (area irrigated per pixel)</td>
<td>2000</td>
<td>Siebert at al 2005: Development and validation of the global map of irrigation areas</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td><a href="https://www.uni-frankfurt.de/45218039/Global_Irrigation_Map">https://www.uni-frankfurt.de/45218039/Global_Irrigation_Map</a></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td><a href="https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod13a1">https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod13a1</a></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td><a href="http://www.map.ox.ac.uk/">http://www.map.ox.ac.uk/</a></td>
</tr>
</tbody>
</table>
10.2 Covariate selection and transformation with stacking

Stacked generalization/regression, or stacking, is a method of combining (ie, ensembling) multiple predictive models in order to enhance predictive validity relative to a single approach or model and has been shown to be effective for geostatistical exercises. In short, a suite of child models are fit using different modelling approaches and then combined, or stacked, by using a secondary learner, or stacker. Our implementation of stacking largely follows the approach described in Bhatt and colleagues.

Our stacking hierarchy features two levels: a collection of ‘child’ models and a stacker model. Although there are possible other configurations, this direct, two-stage approach was taken because of its simplicity, computational tractability, and previous success. The child models used for this study include a generalized additive model, a gradient boost machine (also known as boosted regression trees), and penalized regressions (ridge, lasso, and elastic net). All analyses were performed in R, using the mgcv, dismo, and glmnet packages.

Each child model was fit 5+1 times, where five is the number of folds for out-of-sample cross validation, plus one full data model. Data are divided into five folds and for each fold a given model is fit while leaving out one fold of data and training on the remaining data. The left-out fold subsequently serves as out-of-sample test dataset for prediction. Once the out-of-sample cross-validation process is complete for every fold the child model is then trained on the entire dataset. By the end of this process, each observation has an out-of-sample cross-validated prediction and full-fit prediction for each child model. Both the cross-validated predictions and the full-fit predictions are preserved for the subsequent stacking.
The final stacker model (the geostatistical model described in the next section) is fit using the cross-validated predictions of the child models as covariates. By fitting on the cross-validated predictions we incorporate the generalization capabilities of each child model and otherwise reduce overfitting. If correlations in predictions from a pair of child models exceeded 0.99 we dropped one of the models. In all cases, elastic net and lasso regressions met this threshold of correlation and thus we dropped elastic net. Model correlations are reported in supplementary table 6. Final predictions from the geostatistical model were produced using the full-fit predictions from the constituent child models. Supplementary figure 12 illustrates child model full-fit predictions for each child model for age bin 1 in 2000. Child models were fit separately for each age bin and time period.

Supplementary Figure 17. Plots illustrating child model estimates of mortality for one age bin and year (age bin 1 in 2000). Each of these estimated surfaces is then used as a covariate in the geostatistical model. A. Generalized Additive Model (GAM); B. Boosted Regression Trees (BRT); C. Ridge regression; and D. Lasso regression.
**Supplementary Table 6.** Pairwise correlations between stacking model fits. Elastic Net was dropped due to high correlation with lasso. * = correlation exceeding 0.99.

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
<th>Age Bin 1</th>
<th>Age Bin 2</th>
<th>Age Bin 3</th>
<th>Age Bin 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAM</td>
<td>BRT</td>
<td>0.928</td>
<td>0.947</td>
<td>0.947</td>
<td>0.939</td>
</tr>
<tr>
<td>GAM</td>
<td>Ridge</td>
<td>0.850</td>
<td>0.956</td>
<td>0.961</td>
<td>0.954</td>
</tr>
<tr>
<td>GAM</td>
<td>Elastic Net</td>
<td>0.831</td>
<td>0.941</td>
<td>0.945</td>
<td>0.935</td>
</tr>
<tr>
<td>GAM</td>
<td>Lasso</td>
<td>0.824</td>
<td>0.940</td>
<td>0.940</td>
<td>0.933</td>
</tr>
<tr>
<td>BRT</td>
<td>Ridge</td>
<td>0.820</td>
<td>0.934</td>
<td>0.931</td>
<td>0.922</td>
</tr>
<tr>
<td>BRT</td>
<td>Elastic Net</td>
<td>0.828</td>
<td>0.938</td>
<td>0.938</td>
<td>0.937</td>
</tr>
<tr>
<td>BRT</td>
<td>Lasso</td>
<td>0.822</td>
<td>0.938</td>
<td>0.938</td>
<td>0.938</td>
</tr>
<tr>
<td>Ridge</td>
<td>Elastic Net</td>
<td>0.953</td>
<td>0.978</td>
<td>0.986</td>
<td>0.979</td>
</tr>
<tr>
<td>Ridge</td>
<td>Lasso</td>
<td>0.953</td>
<td>0.974</td>
<td>0.982</td>
<td>0.977</td>
</tr>
<tr>
<td>Elastic Net</td>
<td>Lasso</td>
<td>0.991*</td>
<td>0.997*</td>
<td>0.997*</td>
<td>0.995*</td>
</tr>
</tbody>
</table>

11. Geostatistical model

11.1 Model Geographies
In total, we ran four geostatistical models, one for each age bin.

11.2 Model description
The underlying statistical model, fitted separately for each of the four age bins was a spatially and temporally explicit hierarchical generalised linear regression model for binomial data, using the logit link function:

\[
N_i^+ \sim Binomial(p_i, N_i)
\]

\[
\text{logit}(p_i) = \alpha + X_i \beta + \epsilon_{GP i}
\]

\[
\epsilon_{GP} \sim GP\left(0, K_{space} \otimes K_{time}\right)
\]

\[
K_{space} = \left(\tau 2^{\nu - 1} \Gamma(\nu)\right)^{-1} (\kappa D)^\nu K_0(\kappa D)
\]

\[
K_{time_{k,l}} = \rho |t_k - t_l|
\]

where \(N_i\) are the number of monthly exposures recorded in survey cluster/period \(i\), \(N_i^+\) are the number of deaths resulting from all monthly exposures, \(p_i\) is the estimated cluster-level 5-year period mortality probability of death, modelled as a logit-linear function of the global intercept \(\alpha\), cluster-level covariate values \(X_i\) and vector of regression coefficients \(\beta\). One fixed effect was included for each of the predictions from the cross-validated ‘child’ stacking models. Spatiotemporally correlated residuals \(\epsilon_{GP}\) are drawn from a three-dimensional, zero-mean Gaussian process (GP) with covariance matrix constructed as the Kronecker product of a spatial covariance matrix \(K_{space}\) and temporal covariance.
matrix $K_{time}$. $K_{space}$ was defined by a stationary Matérn covariance function over the Euclidean distance matrix $D$ between all survey cluster locations, with spatial decay parameter $\kappa$, spatial smoothness/complexity parameter $\nu$, precision parameter $\tau$, modified Bessel function of the second kind $K_{\nu}$, and Gamma function $\Gamma(.)$. Since this Matérn covariance function is the stationary solution of a stochastic partial differential equation (SPDE), it enables the use of efficient statistical machinery for modelling with SPDEs, as described below. We set the complexity parameter $\nu$ to be fixed at 2. $K_{time}$ was defined by the covariance function corresponding to the discrete-time autoregressive stochastic process of the first order (AR1). The AR1 process is typically defined over a nominal random variable: $x_t = \rho x_{t-1} + N(0, \sigma^2)$ where $t$ indexes time (in our case the period) and $\rho$ (which is constrained such that $|\rho| < 1$) and $\sigma^2$ are parameters. When convolving the space and time correlation structures with this definition of the AR1 process, the spatial variance $1/\tau$ and the temporal variance $\sigma^2$ would be non-identifiable. We therefore omit $\sigma^2$ from our definition above, and represent overall space-time variance via the parameter $1/\tau$.

11.3 Priors
The following minimally informative priors were specified over parameters in all four age bin models: $\alpha \sim N(0, 1000)$, $\beta \sim N(0, 1000)$, $\log((1 + \rho)/(1 - \rho)) \sim N(0, 0.15)$. INLA sets an uncorrelated multivariate normal prior on log-transformations of $\kappa$ and $\tau$, and by default it determines priors based on the characteristics of the finite elements mesh (described in the section below). We use the default minimally informative priors that INLA suggests which, in our setting, yielded $\theta_1 = \log(\tau) \sim N(0.378, 10)$ and $\theta_2 = \log(\kappa) \sim N(-1.64, 10)$.

11.4 Model fitting
Models were fitted by integrated nested Laplace approximations (INLA) and a stochastic partial differential equation (SPDE) representation of the Gaussian-Markov random field (GMRF) approximation to the GP model, using the INLA R package. The INLA-SPDE approach makes use of the close correspondence between a GMRF defined on a sufficiently dense lattice and a GP, the efficient numerical routines enabled by representing GMRFs as SPDEs, and efficient inference over the parameters of these models using the INLA method. These approximations enable us to carry out full Bayesian inference over the model for a very large dataset, where other inference methods (such as MCMC) would be computationally prohibitive. While the result is an approximation to the model posterior, this approach has been shown to have extremely high accuracy when compared with MCMC in both theoretical and real-world mapping problems. We defined the GMRF on a lattice constructed by constrained, refined Delaunay triangulation within a convex hull no closer than five decimal degrees from the coastline of Africa (including Madagascar). Over land this lattice was constrained to have edge length no greater than 0.35 decimal degrees and over sea no greater than five decimal degrees. This was the densest possible lattice we were able to use over the study area at this time before running into computational issues. These fitted models were then used to generate 1,000 posterior samples each of mapped monthly mortality probability estimates for each of the four age groups by random sampling from the numerical approximation to the joint posterior density of the model parameters. These estimates were combined to estimate the pixel-level (marginal) predictive posterior mean neonatal and under-5 mortality probabilities and prediction uncertainty intervals (0.025% and 0.975%).
11.5 Model Results
Geostatistical model results are presented in the Supplementary Table 7. Spatial Matérn covariance parameters $\kappa$ and $\tau$ have been transformed (as have their lower and upper 95% uncertainty intervals) to be more interpretable. Range represents the distance in decimal degrees at which point approximately 90% of correlation has decayed, and is taken to be $\sqrt{8/\kappa}$. Nominal variance can be interpreted as the variance at each data point, in logit space, it is calculated as: $4\pi \kappa^2 \tau^2$. The auto-regressive correlation coefficient for time, $\rho$, has not been transformed. Fixed effects include an intercept and the cross-validated predictions from the four included ‘child’ stacking models.

**Supplementary Table 7: Model fits for each age-specific model.**

<table>
<thead>
<tr>
<th></th>
<th>0 – 1 month</th>
<th>1 – 11 months</th>
<th>12 – 35 months</th>
<th>36 – 59 months</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>median</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>2.5%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>97.5%</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>intercept</td>
<td>-0.291</td>
<td>-0.669</td>
<td>0.074</td>
<td>-0.931</td>
</tr>
<tr>
<td>child model: lasso</td>
<td>0.521</td>
<td>0.229</td>
<td>0.812</td>
<td>0.291</td>
</tr>
<tr>
<td>child model: ridge</td>
<td>-0.077</td>
<td>-0.356</td>
<td>0.203</td>
<td>0.119</td>
</tr>
<tr>
<td>child model: BRT</td>
<td>0.360</td>
<td>0.238</td>
<td>0.481</td>
<td>0.345</td>
</tr>
<tr>
<td>child model: GAM</td>
<td>0.132</td>
<td>-0.020</td>
<td>0.283</td>
<td>0.138</td>
</tr>
<tr>
<td>GP: Range (Decimal Degrees)</td>
<td>4.914</td>
<td>4.097</td>
<td>5.869</td>
<td>3.058</td>
</tr>
<tr>
<td>GP: Nominal Variance</td>
<td>0.058</td>
<td>0.046</td>
<td>0.073</td>
<td>0.099</td>
</tr>
<tr>
<td>GP: AR1 correlation coefficient $\rho$</td>
<td>0.940</td>
<td>0.911</td>
<td>0.961</td>
<td>0.941</td>
</tr>
</tbody>
</table>

The figures below show model prediction surfaces for neonatal and under-5 mortality for the four study periods, as well as surfaces representing the lower (2.5%) and upper (97.5%) uncertainty bounds for each pixel.
Supplementary Figure 18. Mean, lower, and upper uncertainty interval predictions for under-5 mortality (5q0) in 2000, 2005, 2010, and 2015. Uncertainty intervals were taken as the 2.5% and 97.5% quantiles of 1,000 predictive draws for each pixel.
Supplementary Figure 19. Mean, lower, and upper uncertainty interval predictions for neonatal mortality in 2000, 2005, 2010, and 2015. Uncertainty intervals were taken as the 2.5% and 97.5% quantiles of 1,000 predictive draws for each pixel.
Supplementary Table 8 shows the posterior expectation of the deviance $D(\theta) = -2\log(p(y|\theta))$ for each model. In addition to the full models (described above), we ran a ‘null’ model, which only included an intercept and the spatiotemporal random effect. The relative differences of these deviances show how much additional information, at minimum, was gained by including covariates. Across all models the percent difference in deviance between the full and null model ranged from 0.99% to 1.32%.

**Supplementary Table 8. Posterior expectation of the deviance for each model, both full and null, and their relative differences.**

<table>
<thead>
<tr>
<th>Age bin</th>
<th>Deviance</th>
<th></th>
<th></th>
<th></th>
<th>Percent difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full model</td>
<td>Null model</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 – 1 month</td>
<td>296222.6</td>
<td>300147.3</td>
<td></td>
<td></td>
<td>1.32%</td>
</tr>
<tr>
<td>1 – 11 months</td>
<td>339985.2</td>
<td>344045.8</td>
<td></td>
<td></td>
<td>1.19%</td>
</tr>
<tr>
<td>12 – 35 month</td>
<td>322265.1</td>
<td>325793.8</td>
<td></td>
<td></td>
<td>1.09%</td>
</tr>
<tr>
<td>36 – 59 months</td>
<td>242887.9</td>
<td>245299.5</td>
<td></td>
<td></td>
<td>0.99%</td>
</tr>
</tbody>
</table>

### 11.6 Model validation

In order to understand how well our model predicts mortality in locations where there are no data, we wish to estimate metrics of out-of-sample predictive validity. These are typically mean error (ME, to indicate level of bias), root-mean-squared error (RMSE, to indicate total variation in errors), correlation, and 95% coverage of the predictive intervals.

Model validation with these particular data presents a unique challenge. For relatively rare binomial data with small sample sizes, there is too much variance in the raw data to accurately assess model fit. In Supplementary Figure 15, we illustrate this using simulated data. Here we show that the empirical estimate taken as the ratio of events to observations in simulated binomial data with small $p$ and relatively small $N$ cannot reliably retrieve the probability (true $p$) they were simulated from. This means that even if we modelled mortality perfectly, we may not know it because many of our sample sizes are so small relative to the mortality proportion we are trying to estimate. The plot on the left shows this experiment done with $N=100$ (plus or minus some noise) and the plot on the right shows the same done with $N=500$ (plus or minus some noise). Adding sample size decreases variance in the empirical estimates, allowing for validation to be done. Many of our clusters are small, with median CBH clusters at 15, 150, 298, and 268 months for age bins 1 through 4, respectively. Furthermore, the monthly mortality probabilities which we estimate, particularly for age bins 3 and 4 are typically well below 0.001.
11.6.1 Spatial aggregation
We chose to aggregate spatially proximal data points within administrative 1 and 2 areas to stabilize estimates of model predictive validity. This offers several benefits: 1) points close to each other should be more similar, and thus if we hold out points randomly in space we will likely inflate metrics of predictive validity because we would have predicted them well based on neighboring points; and 2) by aggregating points and thus creating areas of data sparseness in the model fitting, we more closely reflect true data missingness patterns over un-sampled administrative areas. At the same time it is important to note that choice of aggregation level can be somewhat arbitrary and model fit will generally improve with larger sample sizes at larger areas of aggregation, and different administrative levels will have varying sample sizes.

To predict out of sample, stacking and geostatistical models are run five times for each age bin, each time holding out data assigned to each respective fold. All data points were assigned identified membership within a given administrative unit area. Each administrative area was then randomly assigned a fold. This was done for both level 1 and 2 administrative areas. Once each model had run, we calculated ME, RMSE, correlation, and 95% coverage for the data we held out. We aggregated predictions and data estimates at each administrative unit by taking weighted aggregates based on sample size adjusted for integration and SBH-adjustment weights. RMSE, ME, and correlation were calculated by comparing mean aggregated estimates and predictions across administrative units, weighted on the aggregated sample size at each unit. Coverage was calculated by simulating predictions of child deaths from posterior draws of probability of death and observed sample sizes at each cluster location, thus representing our ability to reproduce hold out data within the specified level of certainty.

11.6.2 Metrics of predictive validity
The tables below show how each model performed based on the metrics of bias, total variance, and coverage. Tables are shown for first administrative unit-level predictions (Supplementary Table 9), and second administrative unit-level predictions (Supplementary Table 10). The number of data points and

Supplementary Figure 20. Illustration of sample size impact on the ability to retrieve true probability from empirical binomial estimates.
exposure months in a given holdout area could vary greatly, and validation metrics will be sensitive to this.

*Supplementary Table 9. Out-of-sample predictive validity for first administrative-level holdout predictions*

<table>
<thead>
<tr>
<th>Age Bin</th>
<th>Avg estimated monthly probability</th>
<th>Mean Exposure months</th>
<th>Mean Error</th>
<th>RMSE</th>
<th>Correlation</th>
<th>95% Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1 month</td>
<td>0.0328</td>
<td>783</td>
<td>-0.0003</td>
<td>0.0058</td>
<td>0.8111</td>
<td>95.0%</td>
</tr>
<tr>
<td>1-11 months</td>
<td>0.0031</td>
<td>8134</td>
<td>0.0000</td>
<td>0.0006</td>
<td>0.9043</td>
<td>95.3%</td>
</tr>
<tr>
<td>12-35 month</td>
<td>0.0013</td>
<td>16640</td>
<td>0.0000</td>
<td>0.0003</td>
<td>0.9432</td>
<td>92.7%</td>
</tr>
<tr>
<td>36-59 months</td>
<td>0.0006</td>
<td>17180</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.8989</td>
<td>93.8%</td>
</tr>
</tbody>
</table>

*Supplementary Table 10. Out-of-sample predictive validity for second administrative-level holdout predictions*

<table>
<thead>
<tr>
<th>Age Bin</th>
<th>Avg estimated monthly probability</th>
<th>Mean Exposure months</th>
<th>Mean Error</th>
<th>RMSE</th>
<th>Correlation</th>
<th>95% Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-1 month</td>
<td>0.0327</td>
<td>104</td>
<td>-0.0002</td>
<td>0.0107</td>
<td>0.6236</td>
<td>95.1%</td>
</tr>
<tr>
<td>1-11 months</td>
<td>0.0031</td>
<td>1110</td>
<td>0.0000</td>
<td>0.0011</td>
<td>0.8017</td>
<td>95.5%</td>
</tr>
<tr>
<td>12-35 month</td>
<td>0.0013</td>
<td>2342</td>
<td>0.0000</td>
<td>0.0005</td>
<td>0.8670</td>
<td>93.5%</td>
</tr>
<tr>
<td>36-59 months</td>
<td>0.0006</td>
<td>2446</td>
<td>0.0000</td>
<td>0.0003</td>
<td>0.7766</td>
<td>94.4%</td>
</tr>
</tbody>
</table>
Supplementary Figure 21. Data estimates for aggregated administrative 1 level holdouts versus mean out of sample predictions for the same locations. Estimates are taken at each point where there was data in a holdout area and then aggregated weighted by data sample size. Red lines indicate equivalence.

A. Age bin 1

B. Age bin 2

C. Age bin 3

D. Age bin 4
Supplementary Figure 22. Data estimates for aggregated administrative 1 level holdouts versus mean out of sample predictions for the same locations. Estimates are taken at each point where there was data in a holdout area and then aggregated weighted by data sample size. Red lines indicate equivalence.

Predictive agreement in the most recent time period was more difficult to assess because all survey data from this time period (2012-2017) included only data with partial period coverage, and thus smaller sample sizes than the previous time periods. As more data become available for future iterations of this work, we expect these predictions to improve.

12. Calibration to national estimates

As described in the main methods, we calibrated our mapped mortality rate estimates to match at the national level (or first administrative level where available) with mortality estimates from GBD 2016. GBD estimates aggregate a wider pool of mortality data that are only available at a national level, including vital registration data. Supplementary figure 17 shows differences in population-weighted national-level estimates of mortality rates from the uncalibrated maps produced by our geostatistical modelling framework and GBD 2016 estimates for all countries and all four time periods. For each period, the average GBD estimate across the 5-years was used, with exception of the more recent period, for which GBD only makes estimates up to 2016 and thus 2017 was excluded. Maps were scaled to GBD by multiplying each pixel-draw by the ratio of national level GBD estimate to national level geostatistical estimate. National level geospatial estimates generally agreed well with GBD estimates as the median under-5 ratio was 1.01 and neonatal was 1.00 with 95% range of 0.81 and 1.22 and 0.76 and 1.19 respectively. There were some extreme outliers with Botswana in 2015 on the low end (0.33 for child and 0.32 for neonatal), and Madagascar 2015 (1.48 for child) and Central African Republic 2010 (1.40 for neonatal) at the high end.

Supplementary Figure 23. Comparison of nationally aggregated population-weighted geospatial estimates, and GBD estimates for the same years. A) Under-5 mortality estimates. B) Neonatal mortality estimates. Red lines indicate unity. The median ratio between GBD and this study’s estimates for under-5 mortality was 1.01 [inter-quartile range (IQR): 0.95, 1.14] and for neonatal mortality 1.00 [IQR 0.93, 1.05]. Red lines indicate equivalence.
13. Verification and comparison against other subnational child mortality models

13.1 Gavi Full Country Evaluation small area estimates

As part of the Gavi Full Country Evaluation (Gavi FCE), evaluation teams produced under-5 mortality estimates for Mozambique, Zambia, Uganda, Chad, and Cameroon. Supplementary Figure 18 (A, B, C, D, and E) shows agreement between aggregated population-weighted estimates from this study with the district level small area estimates of that one.

*Supplementary Figure 24 Comparison of district- and county-level aggregated population-weighted geospatial estimates, and Gavi-FCE estimates of under-5 mortality for the same years. A) Mozambique. B) Zambia, C) Uganda, D) Chad, and E) Cameroon. Red lines indicate equivalence.*
13.2 GBD 2015 subnational estimates in Kenya and South Africa

GBD 2016 included subnational estimates for Kenyan counties and South African regions. Comparisons are shown in Supplementary Figure 19 (A and B) below.

*Supplementary Figure 25. Comparison of subnational aggregated population-weighted geospatial estimates, and GBD estimates of under-5 mortality for the same years. A) Kenyan Counties. B) South African Regions. Red lines indicate equivalence.*
14. Source code

Source code is available through http://ghdx.healthdata.org/

References


(Reprinted from https://doi.org/10.1371/journal.pmed.1002687)

Abstract

The addition of neonatal (NN) mortality targets in the Sustainable Development Goals highlights the increased need for age-specific quantification of mortality trends, detail that is not provided by summary birth histories (SBHs). Several methods exist to indirectly estimate trends in under-5 mortality from SBHs; however, efforts to monitor mortality trends in important age groups such as the first month and first year of life have yet to utilize the vast amount of SBH data available from household surveys and censuses.

We analyzed 243 Demographic and Health Surveys (DHS) from 76 countries, which collected both complete and SBHs from 8.5 million children from 2.3 million mothers to develop a new empirically based method to indirectly estimate time trends in age-specific mortality. We used complete birth history (CBH) data to train a discrete hazards generalized additive model in order to predict individual hazard functions for children based on individual-, mother-, and country-year-level covariates. Individual-level predictions were aggregated over time by assigning probability weights to potential birth years from mothers from SBH data. Age-specific estimates were evaluated in three ways: using cross-validation, using an external database of an additional 243 non-DHS census and survey data sources, and comparing overall under-5 mortality to existing indirect methods.

Our model was able to closely approximate trends in age-specific child mortality. Depending on age, the model was able to explain between 80% and 95% of the variation in the validation data. Bias was close to zero in every age, with median relative errors spanning from 0.96 to 1.09. For trends in all under-5s, performance was comparable to the methods used for the Global Burden of Disease (GBD) study and significantly better than the standard indirect (Brass) method, especially in the 5 years preceding a survey. For the 15 years preceding surveys, the new method and GBD methods could explain more than 95% of the variation in the validation data for under-5s, whereas the standard indirect variants tested could only explain up to 88%. External validation using census and survey data found close agreement with concurrent direct estimates of mortality in the NN and infant age groups. As a predictive method based on empirical data, one limitation is that potential issues in these training data could be reflected in the resulting application of the method out of sample.

This new method for estimating child mortality produces results that are comparable to current best methods for indirect estimation of under-5 mortality while additionally producing age-specific estimates. Use of such methods allows researchers to utilize a massive amount of SBH data for estimation of trends in NN and infant mortality. Systematic application of these methods could further improve the evidence base for monitoring of trends and inequalities in age-specific child mortality.
Introduction

Monitoring levels and trends of child mortality is a key component to understanding progress in child survival and for targeting additional policy and financial assistance to accelerate gains [1]. A complete, prospective, and continuous registration of births and deaths is the preferred source of information on child mortality [2], but in countries where child mortality is highest, deaths often go unrecorded because of poor or nonexistent vital registration (VR) systems [3]. In the absence of quality VR data, trends in under-5 mortality are typically estimated using retrospectively collected household sample survey and census data that ask mothers about births and deaths of their children [4,5].

Age-specific under-5 mortality varies widely both by and within country [4,6], and thus, it is critical to estimate levels and trends by age group with as much data as possible. The implications have high national and global relevance, particularly as the UN Sustainable Development Goals explicitly emphasized neonatal (NN) mortality in addition to under-5 mortality [7].

Household survey- and census-based child mortality questionnaires are available as either complete birth histories (CBHs), also sometimes known as full birth histories, or summary birth histories (SBHs). CBHs are preferred over SBHs because they capture detailed vital event histories on each child born to the surveyed mothers. Information on dates of birth and ages at death can thus be tabulated directly by age group and for specific years. In contrast, SBH surveys only ask each mother how many children she has birthed (children ever born [CEB]), how many of her children have died to date (children died [CD]), her age, and sometimes information about the time since first birth (TSFB) and/or marriage. Nevertheless, SBHs are widely available in many censuses and other sample surveys, in part because of the relative simplicity of collecting them. To utilize this vast source of data, several methods have been developed to indirectly estimate trends in under-5 mortality (5q0) from SBHs [8–11]. However, such methods have yet to be specifically adapted for wider application to estimate age-specific mortality among under-5s from SBHs; subsequently, past assessments of NN and infant mortality have been informed by comparably fewer data, especially outside of VR settings.

The Demographic and Health Surveys (DHS) have been widely collected in low- and middle-income countries (LMICs) since 1984 and provide a major source of CBH data. DHS surveys also collect SBH information, and the linked SBH–CBH serves as the basis for the method we describe in this paper. Other large survey families, such as the Multiple Indicator Cluster Surveys (MICS), collect SBHs in some settings and CBHs in others. Censuses are the largest global source of SBH data, representing data on many millions more children than are available in CBH surveys and often offering high sample sizes within small spatial areas. The DHS program takes steps to ensure high-quality and consistent data collection, including probing to ensure that CBH and SBH tabulations are aligned. Censuses have much more variation in collection methods and quality. For example, SBH modules are sometimes collected not from mothers but from household informants who are often male heads of household. Indirect trends in child mortality from SBHs are currently estimated using either the standard indirect method [8,11–15], a version of which is used by the UN Inter-Agency Groups for Child Mortality Estimation (IGME), or the combination of two methods outlined by Rajaratnam and colleagues [9], used in the Global Burden of Disease (GBD) study. For detailed review on these methods, see S1 Text. In brief, the standard indirect method uses simulated coefficients applied to the ratio of CD to CEB, aggregated at different maternal age (or TSFB) cohorts to estimate mortality rates and locate them in time. The GBD methods use pooled DHS survey data to inform two types of indirect estimation models, which are then combined to produce final estimates. The maternal age cohort (MAC)-based method is fundamentally
similar to the standard indirect method. The maternal age period (MAP) method uses empirical distributions, tabulated from DHS CBH data, describing the proportion of children born as well as the proportion of CD to mothers of specific ages in each year preceding the survey. Separate MAP distributions are produced by maternal age, CEB, and region. The period-specific aggregations of expected CD and children born derived from these distributions are used to locate mortality risk in time in SBH data.

Other methods such as cohort change and birth history imputation have been proposed [10,16], but in general, the development of new methods for indirect estimation of age-specific mortality has been understudied. Furthermore, none of the major existing methods have explored the use of predictive covariates measured at the individual mother or child level. The continued investment in collection of DHS surveys over the past 30 years has provided a massive dataset in which both SBHs and CBHs are available and thus the opportunity to empirically train and test new methods.

In this paper, we describe and test a novel method for indirect estimation of age-specific mortality using SBHs, based on a discrete hazards survival analysis model. This approach differs from existing popular indirect methods in two main respects: it produces a cohesive set of age-specific trend estimates without reliance on model life tables, thus allowing for the flexibility to estimate mortality rates for younger age groups such as neonates, and it is fit and predicted at the individual level, utilizing time-varying individual covariates.

Methods
Data

We analyzed 243 DHS (https://dhsprogram.com/) surveys from 76 countries, collecting CBHs and SBHs on 8,504,688 children from 2,346,538 mothers. We included DHS surveys and related Macro Malaria Indicator Surveys conducted since 1988 and available by October 2017. A full listing of the surveys used with summary information can be found in the S1 Table.

Birth history data in DHS surveys are recorded as follows: women are asked a series of questions about how many sons and daughters they have given live births to, including how many live with them now and how many have died. Certain probing questions are included to get more accurate responses. These data are aggregated to CEB and CD, forming the SBH component of the data. CBHs are also collected for each child born to the mother. Month and year of birth are recorded, as is age if the child is still alive. If the child reporting on had died, age at death is recorded in days if the child was under 1 month at death, in months if the child was under 2 years at death, and in years if the child was 2 years or older at death.

We further analyzed an additional 243 censuses and household surveys from 93 LMICs in order to demonstrate how the method can be applied in datasets in which only SBH was collected and to validate our results against concurrent CBH data. Of the SBH-only sources used, 71 were census, 81 were UNICEF Multiple Indicator Cluster Surveys (MICS), and the rest were from other household survey families such as Living Standards Measurement Surveys and other country-specific household surveys. The DHS datasets, as well as an additional 99 other CBH data sources, were used for comparison.

To identify data sources, we searched the Global Health Data Exchange (GHDx, http://ghdx.healthdata.org/) for national census and survey data in LMICs with the following key words: complete birth history, summary birth history, child mortality, and infant mortality. This was
further supplemented by bespoke searches on national statistics agency websites. We used only data sources for which individual-level data were available. A full listing of these data sources can be found in the S1 Table and S2 Table, along with their GHDx record identification number, where links to data distributors are provided.

Statistical model

Our goal was to develop a model that could be used to predict age-specific trends in mortality using SBH data only. We used CBH data to train the model, since it allowed us to identify mortality risk in time and age. For independent variables, we only used attributes that were available from SBHs, since we ultimately wanted to use this model to estimate mortality trends in datasets in which only SBHs are available.

We treated data from CBH as time to event, or survival data [17,18]. The goal of survival modeling is to estimate the underlying hazard or survival functions that describe the risk of event over exposure time. Special care is taken for data that are right censored, for which event status is unobserved after a certain period. In the context of child mortality data, the “event” of interest is a death, “exposure time” is age since birth, and right censoring occurs when a child is reported alive.

Most survival models can be expressed in the general form 

\[ h(\text{age}|\beta X) = h_0\text{age}e^{\beta X} \]

where \( h_0 \) represents the baseline hazard function over age, which is shifted by weighted effects of covariates \( X \). The baseline hazard function can be fit either parametrically to a variety of smooth functions defined either by probability distributions or as flexible splines [19] or discretely, either using arbitrary age bins or in data-defined age bins, as in the widely used Cox proportional hazards model. Covariates will generally shift the hazard function and as such have a proportional effect across ages. This proportionality can be relaxed using age-varying covariates.

For this analysis, we adopted a discrete time survival analysis (DTSA) [20] approach to modeling the baseline hazard function. In a DTSA model, age is split into discrete bins, which conforms well to the discrete nature of age reporting in CBH data. The baseline hazard function is flexibly parameterized using fixed effects dummies, \( I \), for chosen discrete age bins. This is achieved by reshaping input data such that every row in the new dataset is associated with each age bin, \( a \), entered into by each child, \( i \), in the data. Censored age bins for any child are not included in the reshaped data. An indicator variable \( Y_{i,a} \) is included for each row and recorded as 1 if the child died in that age bin and 0 if they survived it. A no-covariate baseline hazard could then be determined by fitting the following logistic regression model:

\[ Y_{i,a} \sim \text{Bernoulli}(q_a) \]

\[ \text{logit}(q_a) = \sum_{a=1}^{A} I_{i,a} \beta_a \]

Note that fixed effects are estimated for each age bin without an intercept term, so that each \( \beta_a \) is in reference to zero, and thus each \( e^{\beta_a} \) are interpretable as the probability of mortality in age group \( a \), conditional on survival to age group \( a \), or \((q_a)\). In the discrete case we thus refer to \( q_a \) as the probability
of death within age bin \( a \), though ‘mortality rate’ is commonly used interchangeably to describe the same quantity. This basic model can be extended to include individual-level covariates, random effects to account for hierarchical data, transformations or smoothing splines on covariates to improve prediction, and interactions with age-bin dummies in order to allow for non-proportional effects of covariates.

For this application, we used the following seven age bins for this analysis: live birth to 29 days (NN), 30 days to 5 months inclusive (post-neonatal 1 [PNN1]), 6 to 11 months inclusive (post-neonatal 2 [PNN2]), 12 to 23 months inclusive (1yr), 24 to 35 months inclusive (2yr), 36 to 47 months inclusive (3yr), and 48 to 59 months inclusive (4yr). These bins were chosen to align with the way in which age information is collected in DHS such that each age bin would have identifiable data on children entering and dying within it. We separated the first year of life further into three age bins because there is a high and quickly changing mortality hazard during this period. The NN period during the first month of life is further split because it is often of separate public health interest because of the unique epidemiology of causes of death during this period. Fig 1 shows this simple baseline hazard function fit to the 2011 Burundi DHS dataset for illustration purposes.

\[ S_{\text{age}} = \prod_{a=1}^{7} (1 - q_a) \]

**Fig 1.** Illustrating the estimated pooled baseline discrete hazard and survival functions from the 2011 Burundi DHS dataset, fit using the seven age bins \( a \in \{1 = \text{NN}, 2 = \text{PNN1}, 3 = \text{PNN2}, 4 = \text{1yr}, 5 = \text{2yr}, 6 = \text{3yr}, 7 = \text{4yr}\} \). Note that we are estimating discrete hazards, and thus, hazards (shown in panel B) are interpreted as a conditional probability rather than a conditional rate. The survival function (shown in panel A), showing estimated survival at the end of each age bin, is calculated directly from estimated hazards as \( S_{\text{age}} = \prod_{a=1}^{7} (1 - q_a) \). DHS, Demographic and Health Surveys; NN, neonatal; PNN1, post-neonatal 1; PNN2, post-neonatal 2.
We trained the model on the pooled CBH database with the purpose of making predictions in situations for which only SBHs are available, as in census data. As such, we were limited to using covariates from the training data, which were also available in SBH-only datasets. Certain covariates, such as year of birth and mother’s age at birth, were found to be highly predictive of mortality but could not be ascertained directly from SBH data. In order to account for them, we approach predicting from the perspective of a hypothetical child. Specifically, for any given woman in the target SBH data, we wished to predict hazard functions for all hypothetical children she could have had over the course of her childbearing years. For example, if a 30-year-old woman was observed in a dataset collected in 2010, we could predict a separate hazard function for a potential child born to her each year going back until she was 12 in 1992. Hazard functions for these hypothetical children could be differentiated by covariate values that vary over the mother’s life.

We specified the following generalized additive DTSA model for the conditional probability of death for every age bin \( a \) of each child \( i \) to each mother \( m \):

\[
Y_{m,i,a} \sim \text{Bernoulli}(q_{m,i,a})
\]

\[
\logit(q_{m,i,a}) = \sum_{a=1}^{7} [I_{i,a}\beta_a] + \sum_{a=1}^{7} [g_1, \text{yr}, SDI_{c,\text{yr},i}]l_{i,a} + g_2 \left( \frac{CD_{m,\text{yr}}}{CEB_{m,\text{yr}}}, \text{MothAge}_{m,\text{yr}} \right) + \nu_{\text{yr}} + \eta_{\text{country},a}
\]

\[
\nu \sim \text{Normal}(0, \sigma^2_{\nu})
\]

\[
\eta \sim \text{Normal}(0, \sigma^2_{\eta})
\]

where \( g_1(\cdot) \) represents thin plate regression spline smooths, with \( g_1(\cdot) \) having separate smooths for each age bin \( a \), operationalized by the age bin dummy variable \( I_{i,a} \). \( \text{yr}_{\text{r}} \) represents the year of birth for child \( i \). This is directly observed in the training data but for prediction is assigned for each hypothetical child. \( SDI_{c,\text{yr},i} \) represents the Socio-demographic Index (SDI) [21] for the country \( c \) that child \( i \) was born in at their year of birth \( \text{yr} \). \( SDI \) is a composite average, expressed on a scale of 0 to 1, of income per capita, average educational attainment, and fertility rates and has been found to be a strong predictor of child mortality [21]. The interaction of \( SDI \) and year of birth allows the secular trend in mortality for each age bin to vary by the level of development in each country, thus allowing for prediction in countries without training data.

The variables in the second smooth represent child- and mother-level covariates. \( \frac{CD_{m}}{CEB_{m}} \) is the ratio of children died to children born to each mother \( m \) at the time of the survey. \( \text{MothAge}_{m,i,\text{yr}} \) is the mother’s age at the year of birth. This is observed in the training data and assigned for prediction of hypothetical children in the same way as \( \text{yr} \). Finally, \( CEB_{m,\text{yr}} \) is the number of children born to the mother at the time of birth \( \text{yr} \) of child \( i \). This is directly observed in the training data. For prediction, we use empirical probability of birth distributions [9] to impute this value for each hypothetical child. Much in the same way that the standard indirect method interacts \( \frac{CD}{CEB} \) with fertility ratios, this interaction is
included to address the fact that the relationship between \( \frac{CD}{CEB} \) and \( q \) is mediated by the fertility experiences of the women reporting \( \frac{CD}{CEB} \) [15]. This differs from previous approaches, which used aggregate levels of fertility, and instead depends on individual women’s fertility experiences.

Finally, \( \nu \) and \( \eta \) are independent normal random intercepts for each survey and each age bin within country.

All covariates were centered and scaled by their standard deviations for model fitting. Models were fit separately by the same regions used by Rajaratnam and colleagues [9]. Uncertainty in predictions was ascertained by taking 1,000 multivariate normal draws from the variance–covariance matrix of fitted model parameters, including fitted random effects values [22]. In cases for which prediction data had random effects levels not used in the training data (for a new survey or a new country), estimated variances \( \sigma^2_\nu \) and \( \sigma^2_\eta \) were used to simulate 1,000 independent normal draws. Models were fit using restricted maximum likelihood with the bam command from the mgcv package in the R Statistical Computing Language Version 3.4.3 [23,24].

Conversion to trends

Using the model described above, we estimated age-specific mortality hazards for individual hypothetical children to mothers responding to SBH questionnaires. These hazard functions of hypothetical children must then be converted into trends in age-specific mortality. To do so, we aggregated estimates of mortality among hypothetical children born in the period using weights that indicated the likelihood that each hypothetical child actually existed. This process is illustrated in Fig 2.
Fig 2. Illustration of procedure to convert discrete hazard functions for hypothetical children to population-level age-specific trends.
(A) Discrete hazard functions are estimated for each hypothetical child from each mother in the target SBH dataset. Here, we color all children born in the same year with the same color. Only 3 years are shown for simplicity in this example. In real data, the years of birth of hypothetical children would vary by mother based on her age, such that there would be one hypothetical child for each year going back in time from the survey until the mother was 12 years old. (B) Probability of birth distributions is applied to each hypothetical birth from each mother. These are derived from the empirical map distributions from Rajaratnam and colleagues [9], in which a different probability is available by woman’s age, CEB, region of residence, and year prior to the survey. These probabilities are multiplied by each mother’s CEB and carried through to subsequent age bins to estimate the expected number of children entering each age bin (EEB) using estimated survival probabilities. As such, line thicknesses get slightly smaller with each subsequent age bin. The EEB value for each hypothetical child’s age bin represents the number of children entering that age bin that the hypothetical child represents for their given mother. (C) All hypothetical children to mothers are grouped by year of birth. The estimated mortality probabilities for each age bin from all hypothetical children born in the same year are pooled, and EEB is used to calculate a weighted mean. Trends are drawn across \( q_{\alpha} \) for each year, indicated here by a trend in the third age bin. This aggregation procedure can be done for any grouping of women to make estimates for a survey cluster, a district, or a whole country. CEB, children ever born; EEB, expected entering bin; NN, neonatal; PNN1, post-neonatal 1; PNN2, post-neonatal 2; SBH, summary birth history.

From the model, we obtained estimates of \( \hat{q}_{m,a,y,r} \): the probability of death in age bin \( a \) for a hypothetical child born in yr \( y \) to mother \( m \). To obtain estimates of \( \hat{q}_{m,y,r} \): age-bin and period-specific hazards representative of the population surveyed, we weighted each child based on their probability of birth. Each hypothetical child was assigned a probability of birth \( \text{POB}_{m,y,r} \) using the birth distributions used for the GBD-MAP method. Probability of birth distributions are compiled from empirical distributions that describe, for each year preceding a survey, the probability of birth based on mothers’ age and CEB and by region. Distributions were matched based on geographical region, mothers’ age, CEB, and yr to each hypothetical child.

We then assigned a weight to each age bin of each hypothetical child. We defined the expected number of children entering each age bin (expected entering bin [EEB]) \( a \) for child born in year \( y \) from mother \( m \) as the following:

\[
EEB_{m,a,y,r} = \text{POB}_{m,y,r} \times \text{CEB}_{m} \times \hat{S}_{m,a,y,r}
\]

where \( \hat{S}_{m,a,y} \) is the estimated survival until age bin \( a \), and EEB is the estimate of the number of children entering each age bin for the hypothetical child born to mother \( m \) in year \( y \), given each mother’s overall fertility and the estimated mortality experiences of her children over time.

We aggregated our estimates across \( \hat{q}_{a,y,r} \) by taking a weighted mean such that

\[
\hat{q}_{a,y,r} = \frac{\sum_{m=1}^{M} \hat{q}_{m,a,y,r} EEB_{m,a,y,r}}{\sum_{m=1}^{M} EEB_{m,a,y,r}} = \frac{\text{Expected Deaths}_{a,y,r}}{\text{Expected Children Entering}_{a,y,r}}
\]

The benefit of predicting at the individual level is that weighted means can be aggregated for any population desired. Also, this procedure conveniently provides not only estimates of \( \hat{q}_{a,y,r} \) and expected children entering each bin but also the numbers of expected deaths. For nationally representative estimates, survey weights can also be included into this procedure by multiplying weights into the summands. Finally, age bins can be combined as independent conditional probabilities to produce trends in wider age bins that may be of interest, such as \( 1q0 \) or \( 5q0 \).
Uncertainty in aggregate estimates of all quantities are calculated by repeating the aggregation procedure 1,000 times based on the predictive draws of $\hat{q}_{m,a,yr}$. We report the 2.5% and 97.5% quantiles.

Validation and verification

We developed three approaches to model validation. We first used cross-validation on the DHS data in order to assess how well age-specific mortality trends estimated from our method could reproduce those directly estimated from CBH data. We then compared our indirect $5q0$ estimates to those produced using existing methods. Finally, we applied the method to nationally representative non-DHS surveys that only collected SBHs and compared those results to contemporaneous direct estimates.

We developed the first model validation framework to assess out-of-sample predictive validity, holding out entire DHS surveys from the database, fitting the predictive model in their absence, and using their SBH variables to produce indirect age-specific time trends. We then used direct estimates from the CBHs of these held surveys to reproduce age-specific trends to serve as a basis for validation.

For each country in the DHS database, we held out the most recent DHS. We fit the model, used the fitted parameters to make indirect estimates from SBHs, and compared to direct estimates from CBHs. This was repeated for each country. Using the most recent survey represents a particularly difficult test because doing so requires several years of out-of-sample projection from the time since the penultimate survey in that country.

Our aim was to minimize the bias and magnitude of errors (the difference between estimates and validation data). We used the following five metrics to assess out-of-sample predictive performance: (1) Mean error (ME) to capture systematic bias. An ME of zero indicates a perfectly unbiased estimate. ME is an absolute (as opposed to relative) metric and thus cannot be compared across age bins. (2) Standard deviation of the errors (SDE) to capture how much variation there is in out-of-sample errors across countries and years. The smaller the SDE, the more precise the errors are. Again, SDE is an absolute metric. (3) Median relative error (MRE) to capture relative bias. MRE is simply the ratio of estimate to validation data, and as such, an MRE close to one indicates no bias. MRE allows us to compare bias on a relative scale across age bins. (4) Median absolute percentage error (MAPE) to capture the relative scale of errors. This is calculated as the ratio of the absolute error to the direct validation estimate multiplied by 100. The MAPE represents overall relative accuracy of the estimates, with a value close to zero indicating high accuracy. (5) The coefficient of determination ($R^2$) represents the proportion of total variance in the directly tabulated hazards explained by the modeled estimates. Each of the metrics were assessed for each age bin as well as for $5q0$.

Single-year age-specific direct tabulations of CBHs have relatively small sample sizes and can produce somewhat noisy estimates of a “truth” for comparison. Since we are interested in modeling the actual underlying trend and not the noisy observed values, very good predictive performance in this case could actually signal overfitting. Furthermore, mean-based metrics are sensitive to large outliers in errors, which could emerge spuriously when validation data are noisy. In other words, validation data with a larger sample size are expected to produce a precise approximation of the true underlying mortality hazard. We dealt with this in two ways. First, following Rajaratnam and colleagues [9], we smoothed the noisy validation trends using loess (with $\alpha$ set to 0.85). Second, we weighted all of our metrics of
predictive performance by the sample sizes (number entering each age bin) as tabulated from the raw validation data.

We also used this same validation approach to evaluate our estimates of the numbers of children expected to enter each age bin, or $E_{EB}$. This is done by comparing $E_{EB}$ with the direct tabulations of numbers of children entering each bin, in each year, from the validation data.

With increasing interest in subnational child mortality estimation [6,25–28], it is also critical to assess the validity of these results at subnational levels of aggregation. Most SBH data are geographically identifiable to the first administrative level—typically referred to as states or regions in most countries [6]. We aggregated to the first administrative unit, defined using the Global Administrative Unit Layers (GAUL) shape file made available by the FAO (http://www.fao.org/geonetwork/srv/en/metadata.show?id=12691). In order to obtain large enough sample sizes for stable comparison in the validation, we also aggregated data into 5-year bins preceding each survey. As such, each administrative area only supplied three estimates, and thus, we did not smooth them.

We also compared how well the proposed method estimated trends in 5$q_0$ relative to existing methods, since a well-behaving method for age-specific trends should also be able to accurately reproduce trends in 5$q_0$. We thus compared out-of-sample trends in 5$q_0$ estimated from our test data to those produced by the GBD methods, as well as the standard indirect method. GBD-combined indirect estimates for each available survey were taken from the GBD mortality database (Available online: https://vizhub.healthdata.org/mortality/) and were produced by combining MAP and MAC estimates. For the standard indirect method, we matched model life tables to countries as used by IGME. We included two variants of the standard indirect method: one based on MACs and one based on TSFB (see [11]).

We also used this cross-validation framework to compare our model to several other model specifications. These results are presented in the S1 Fig.

Finally, in order to better establish external validity of this method, we also sought to understand its performance on non-DHS data. By nature of joint data collection, CBH and SBH data from DHS are presumed to be highly consistent. For this reason, SBHs from DHS could be different enough from data for which only SBHs are collected—for example, in censuses—that a cross-validation based on DHS alone may not be sufficient evidence that method performs well for these sources. Thus, for a more practical perspective on the performance of this method in settings where it is intended to be used (i.e., in data for which only SBHs were collected), we compared estimates from these data to directly estimated mortality for which concurrent CBH data were available. First, we applied our method to 243 nationally representative SBH surveys and censuses in order to estimate trends in NN, infant, and under-5 mortality. We then directly estimated these same trends from CBH surveys in the same countries, as described above for the DHS cross-validation, which served as a basis for comparison. We then identified CBH–SBH estimate pairs from the same country-years. Looking at the differences in these pairs of estimates, we used the same set of predictive validity metrics described for the cross-validation assessment in order to assess how similar the age-specific indirect estimates were to contemporaneous direct estimates. Furthermore, in order to understand how our model performed across different data source types, we stratified this comparison across MICS, censuses, and other survey sources.
Data and code availability

All datasets used for this analysis are listed in the Supporting information (S1 Table for the DHS and S2 Table for additional surveys and censuses used for external validation). Each source in the tables is supplied with an ID number associated with a record in the GHDx (http://ghdx.healthdata.org/). Each GHDx record links to data providers for each survey.

All code for the analyses in this manuscript is available at https://github.com/royburst/sbh_agespecific_indirect_paper_code. In the near future, we plan to release a package for R that allows users to apply this indirect method to any SBH dataset.

Results

Table 1 shows summary statistics from our cross-validation. The table shows the mean estimates of age-specific mortalities, $q_a$, across all countries and age bins, along with aggregated out-of-sample predictive validity metrics for estimates of $q_a$. We find little bias across all ages, as indicated by very small MEs and MREs close to one. The bias that does exist tends to be slightly over in the younger age bins and slightly under in the older age bins. We also see relatively small SDE across all age bins, indicating that, on average, there is a not large variation in out-of-sample errors across countries and years. Relative variance in errors, measured by MAPE, increases as $q_a$ decreases as a function of age.

<table>
<thead>
<tr>
<th>Age-bin</th>
<th>$q_a$</th>
<th>ME</th>
<th>SDE</th>
<th>MRE</th>
<th>MAPE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NN</td>
<td>0.031</td>
<td>0.0022</td>
<td>0.005</td>
<td>1.05</td>
<td>9.5%</td>
<td>0.82</td>
</tr>
<tr>
<td>PNN1</td>
<td>0.015</td>
<td>0.0010</td>
<td>0.004</td>
<td>1.09</td>
<td>15.9%</td>
<td>0.80</td>
</tr>
<tr>
<td>PNN2</td>
<td>0.013</td>
<td>0.0004</td>
<td>0.004</td>
<td>1.08</td>
<td>17.3%</td>
<td>0.82</td>
</tr>
<tr>
<td>1yr</td>
<td>0.013</td>
<td>0.0002</td>
<td>0.004</td>
<td>1.02</td>
<td>18.2%</td>
<td>0.88</td>
</tr>
<tr>
<td>2yr</td>
<td>0.009</td>
<td>-0.0001</td>
<td>0.002</td>
<td>1.00</td>
<td>16.2%</td>
<td>0.93</td>
</tr>
<tr>
<td>3yr</td>
<td>0.006</td>
<td>-0.0002</td>
<td>0.002</td>
<td>0.96</td>
<td>20.7%</td>
<td>0.88</td>
</tr>
<tr>
<td>4yr</td>
<td>0.003</td>
<td>-0.0001</td>
<td>0.001</td>
<td>0.97</td>
<td>20.6%</td>
<td>0.81</td>
</tr>
<tr>
<td>5q0</td>
<td>0.083</td>
<td>0.0033</td>
<td>0.010</td>
<td>1.05</td>
<td>8.8%</td>
<td>0.95</td>
</tr>
</tbody>
</table>

**Table 1:** Overall out of sample predictive validity metrics for each age bin and mean direct estimates of $q_a$ across all country years in the Demographic and Health Surveys database, for the 15 years prior to the survey being taken. Abbreviations: NN = livebirth to 29 days (Neonatal); PNN1 = 30 days to 5 months inclusive (Post Neonatal 1); PNN2 = 6 to 11 months inclusive; 1yr = 12 to 23 months inclusive; 2yr = 24 to 35 months inclusive; 3yr = 36 to 47 months inclusive; 4yr = 48 to 59 months inclusive; ($\bar{q}_a$ = average estimated mortality probability; ME = mean error; SDE = standard deviation of the errors; MRE = median relative error; MAPE = median absolute percentage error; $R^2$ = coefficient of determination.}
Fig 3 plots the agreement between age-specific mortality rates from the validation data compared to out-of-sample estimates. We also see a relatively high proportion of variance explained as measure by $R^2$, with all age bins above 0.80. Predictive validity metrics for the combined 5q0 age bin perform better than for the smaller age bins, as the model can explain 95% of the variance in input data. This is likely because of several reasons: errors are averaged over when collapsing across ages; relative metrics are less sensitive with a larger overall $q_a$; age bins with larger relative errors tend to have lower hazards, which contribute less overall mortality and thus impact metrics in the combined group less; and larger sample sizes lead to more stable estimates.

Fig 3. Out-of-sample predictions of mortality probability compared against loess-smoothed validation data. Each point represents a country–age mortality estimate ($q_{a,\text{yr}}$) for each held-out survey from the DHS database. Red line indicates unity. DHS, Demographic and Health Surveys; loess, local regression; PNN1, post-neonatal 1; PNN2, post-neonatal 2.

Fig 4 compares $EEB$ with the observed number of children entering each age bin from the validation data. There was high agreement across age groups, with MRE ranging from 1.015 to 1.032 and MAPE ranging from 6.8% to 11.0%, indicating small errors and potentially a very slight upward bias in the $EEB$ estimates. There is no clear difference in $EEB$ performance across age bins. Overall, $R^2$ was 0.97. This indicates that empirical probability of birth distributions can be reliably used to approximate sample sizes for indirect estimates. This also adds support to the favorable validation results shown above, as $EEB$ weights are an important component of aggregating trends to the national level and because empirical probability of birth distributions are used to impute $CEB$ at birth for prediction.
Fig 4. Comparison of EEB and observed children entering each age bin from CBH validation data. Each point represents a survey year age bin; both axes are on log 10 scale. $R^2 = 0.97$. CBH, complete birth history; EEB, expected entering bin; PNN1, post-neonatal 1; PNN2, post-neonatal 2.

At the subnational level, model performance was somewhat weaker. There was a similar pattern in direction of bias across the ages, though bias remained minimal overall. There was more variability in the errors, with MAPE ranging from 20.0% in the NN group to 38.0% in 4-year-olds. The percentage of variance explained was also somewhat lower than at the national level. $R^2$ of the subnational $5q0$ estimates was 0.91. Some of this difference was likely due to smaller sample sizes in the subnational data compared to the national validation. Our validation data, which were based on direct estimates from CBH, represent realizations of the underlying probability, and thus, the empirical probability from the validation is measured with noise. Despite aggregating to 5-year bins, the average number of children born in each 5-year aggregated subnational observation was 520, compared to 1,769 in each annual national observation, and 4,148 (27%) of each survey-administrative area-age bin observation had no observed deaths. S2 Fig and S3 Table replicate Fig 3 and Table 1, respectively, at the first administrative subnational level.
Fig 5 shows the out-of-sample estimated trends in age-specific mortality rates estimated using the 2013 Nigeria DHS and compared to the directly estimated validation data. In the S4 Fig, we provide similar plots for each country with extended discussion on those results. Overall, the model was able to reproduce trends in the validation data in Nigeria and in most other countries. Performance was suboptimal in cases for which test and train data differed significantly (for example, in Benin) and when trends were unique to a given country (for example, in Lesotho).

![Out of Sample Predictions and Validation Data for Nigeria 2013](image)

**Fig 5.** Trends in mortality for each age bin from the 2013 Nigeria DHS. Thick blue lines are validation data; hatched lines are the 95% uncertainty bounds on the out-of-sample predictions. Sampling variation is evident in the blue line through year-on-year spikes. The target of prediction was the overall time trend, leading to a smoother prediction. Axis scales are fixed except for $5q_0$, which is the combination of the mortality rates from the seven age bins. Similar plots for each country in the validation data are available in the S4 Fig. DHS, Demographic and Health Surveys; PNN1, post-neonatal 1; PNN2, post-neonatal 2.

We compared predictive validity in our out-of-sample estimates to indirect estimates of trends in $5q_0$ made from the same SBH holdout data, using the GBD-combined method and the standard indirect method. Fig 6 compares predictive validity metrics for the three methods over the 15 years preceding the survey. Confirming results from Rajaratnam and colleagues [9], we find unstable estimates from the standard indirect method in the most recent 5 years preceding surveys. Near overlap in the MRE and MAPE over time indicates that the new method and the GBD-combined methods generally produce similarly performing results. Overall, we estimated a MAPE of 8.8% for the new method, 6.1% for the GBD-combined method, and 25.6% and 36.5% for the MAC and TSFB variants of the standard indirect method, respectively. The new method and GBD-combined methods each had an MRE of 1.05 and 1.02, whereas the MAC and TSFB variants of the standard indirect method each had an MRE of 1.25 and 1.36. Finally, the $R^2$ for the new method was 0.95, whereas it was 0.98 for the GBD-combined method and 0.80 for the MAC variant and 0.88 for the TSFB variance of the standard indirect method. If we excluded
the most recent 5 years, MRE and MAP remained largely the same, but the $R^2$ for the MAC and TSFB variants rose to 0.92 and 0.88, respectively. S3 Fig shows trends for each survey in the testing data. We note that for certain surveys with no GBD-combined estimates, such as the Malawi DHS 2016, we are able to produce accurate trends using the new method. It is possible that the non-GBD methods would have performed even better by comparison if these were included. Furthermore, several of the surveys in the testing set were used to train the GBD-combined models while remaining out of sample for the new method and the standard indirect method, potentially giving the GBD-combined method a slight advantage in this comparison.

For external validation, we identified 243 censuses and surveys from 93 countries, in which only SBH was collected. As a basis for comparison, we identified 316 CBH datasets. Applying our method, we estimated trends from each SBH-only data source and identified 16,527 estimate pairs for which we had contemporaneous SBH- and CBH-derived estimates in a single country-year. Estimates for any year after 1990 and within 15 years of the survey data were kept. We further identified 2,694 country-year–age pairs of data from 524 unique country-years for which only SBH data were available. For comparison, we also identified 10,655 country-year–age pairs for which two concurrent CBH direct estimates were available.

Full trend plots for each country with available data are in S6 Fig. In the majority of cases, trends from SBH-only data closely match contemporaneous trends from CBH data. There were several SBH-only surveys that exhibit overall source-level bias relative to concurrent trends.
Table 2 summarizes our findings for these paired comparisons for NN, infant (under-1), and under-5 mortality. We find close agreement across validation metrics. Overall variance was slightly higher and unadjusted $R^2$ was slightly lower than in the cross-validation assessment. Much of this additional variance could be explained by survey; by simply controlling for data source using survey-level fixed effects, we find large improvements in $R^2$, with each age bin around 0.96. We further found these results to be robust across SBH data type (census, MICS, and other surveys).

<table>
<thead>
<tr>
<th>Age-bin</th>
<th>SBH SOURCE</th>
<th>$\bar{q}_{a,c,bh}$</th>
<th>$\bar{q}_{a,asbh}$</th>
<th>ME</th>
<th>SDE</th>
<th>MRE</th>
<th>MAPE</th>
<th>$R^2$</th>
<th>$R^2_{corr}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neonatal</td>
<td>ALL</td>
<td>0.030</td>
<td>0.033</td>
<td>0.0026</td>
<td>0.010</td>
<td>1.06</td>
<td>17.7%</td>
<td>0.52</td>
<td>0.96</td>
</tr>
<tr>
<td>Infant</td>
<td>ALL</td>
<td>0.061</td>
<td>0.064</td>
<td>0.0030</td>
<td>0.018</td>
<td>1.05</td>
<td>16.4%</td>
<td>0.64</td>
<td>0.96</td>
</tr>
<tr>
<td>Under-5</td>
<td>ALL</td>
<td>0.093</td>
<td>0.096</td>
<td>0.0029</td>
<td>0.028</td>
<td>1.04</td>
<td>16.4%</td>
<td>0.74</td>
<td>0.97</td>
</tr>
<tr>
<td>Neonatal</td>
<td>MICS</td>
<td>0.038</td>
<td>0.041</td>
<td>0.0030</td>
<td>0.009</td>
<td>1.09</td>
<td>17.9%</td>
<td>0.5</td>
<td>0.96</td>
</tr>
<tr>
<td>Infant</td>
<td>MICS</td>
<td>0.075</td>
<td>0.080</td>
<td>0.0047</td>
<td>0.019</td>
<td>1.05</td>
<td>16.1%</td>
<td>0.67</td>
<td>0.97</td>
</tr>
<tr>
<td>Under-5</td>
<td>MICS</td>
<td>0.123</td>
<td>0.129</td>
<td>0.0055</td>
<td>0.029</td>
<td>1.05</td>
<td>16.3%</td>
<td>0.79</td>
<td>0.98</td>
</tr>
<tr>
<td>Neonatal</td>
<td>CENSUS</td>
<td>0.030</td>
<td>0.032</td>
<td>0.0019</td>
<td>0.010</td>
<td>1.02</td>
<td>18.4%</td>
<td>0.55</td>
<td>0.96</td>
</tr>
<tr>
<td>Infant</td>
<td>CENSUS</td>
<td>0.062</td>
<td>0.063</td>
<td>0.0013</td>
<td>0.019</td>
<td>1.00</td>
<td>17.2%</td>
<td>0.68</td>
<td>0.97</td>
</tr>
<tr>
<td>Under-5</td>
<td>CENSUS</td>
<td>0.097</td>
<td>0.096</td>
<td>-0.0005</td>
<td>0.026</td>
<td>0.98</td>
<td>17.0%</td>
<td>0.79</td>
<td>0.98</td>
</tr>
<tr>
<td>Neonatal</td>
<td>OTHER</td>
<td>0.029</td>
<td>0.032</td>
<td>0.0029</td>
<td>0.010</td>
<td>1.07</td>
<td>17.5%</td>
<td>0.48</td>
<td>0.96</td>
</tr>
<tr>
<td>Infant</td>
<td>OTHER</td>
<td>0.056</td>
<td>0.059</td>
<td>0.0034</td>
<td>0.017</td>
<td>1.07</td>
<td>15.8%</td>
<td>0.57</td>
<td>0.95</td>
</tr>
<tr>
<td>Under-5</td>
<td>OTHER</td>
<td>0.083</td>
<td>0.087</td>
<td>0.0037</td>
<td>0.028</td>
<td>1.06</td>
<td>16.2%</td>
<td>0.62</td>
<td>0.96</td>
</tr>
</tbody>
</table>

Table 2. Summary results for the external validation comparisons across 16,527 country-year data pairs for which a CBH and SBH estimate were both available. We also show a sub-analysis by data source, indicating good robustness of results across source type. $\bar{q}$, average estimated mortality probability; ME, mean error; SDE, standard deviation of the errors; MRE, median relative error; MAPE, median absolute percentage error; $R^2$, coefficient of determination.

Fig 7 shows a scatterplot of each country-year concurrent estimate. We also plot the same comparison for country-year pairs for which two direct CBH estimates are available. The comparison of CBH to CBH estimates represents a theoretical baseline difference we would expect to see in concurrent estimates. The similarity between the two sets of scatterplots highlights that much, though not all, of the variation we see between indirect and direct also exists between direct estimates and would be expected even given the best available survey data from which direct estimates could be made.
Discussion

Our new method for indirect estimation produces age-specific mortality trends consistent with those produced using CBH data in most cases at the country- and first administrative unit–level, as well as producing 5q0 estimates that improve on the standard indirect method and are closely comparable in performance with the current best-performing method [9]. We applied the method to external SBH data and found considerable agreement when comparisons could be made to contemporaneous estimates from CBHs. This new method greatly expands the potential utility of SBH data and fills a critical gap in the literature on indirect methods, extending indirect mortality estimation toward specific age bins of interest.

There are two main methodological innovations introduced by this new approach: using hierarchical survival analysis to model individual-level hazard functions and developing a hybrid approach to locating mortality risk in time. By viewing CBHs as time-to-event data, we were able to directly model the quantity of interest, the conditional probability of death $q$ at various ages from birth until age 5. Leveraging existing data from millions of CBHs, we inferred hazard functions that vary across countries, surveys, mothers, and their individual children using only covariates that were available in SBHs. These hazard functions, built up from flexibly chosen discrete age bins, then allowed us to produce indirect age-specific estimates for children born at various times. Since these estimates are made at the
individual level, they could then be aggregated to any population. Furthermore, accompanying model uncertainty is included in all predictions.

All indirect methods must rely on some approximation in order to locate mortality risk in time, since SBH does not provide explicit information on time of birth or death. MAC methods such as GBD-MAC and the standard indirect approach rely on observed fertility patterns to locate the mean time of risk for each maternal age group. They typically assume unchanging fertility and furthermore ignore recent mortality experiences to children from older mothers. The GBD-MAP method relies on empirical distributions of births and deaths to distribute risks in terms of years prior to survey. This allows older mothers to contribute information from more recent births but also runs the danger of overgeneralizing trends to the level at which data were pooled. Our new method utilizes several sources of information in order to locate mortality risk and to overcome some of the limitations with previous methods. First, secular trends over time are incorporated in the model but are allowed to vary by country-SDI to avoid overgeneralization and allow for prediction in countries not in the training data. Second, individual-level time-varying covariates allow us to predict hazard functions for hypothetical children born throughout different times in each mother’s life so that all potential children, including recent births to older women, are incorporated. In order to aggregate trends, we use weights derived for the GBD-MAP method, which put more weight on hypothetical children that were more likely to have existed.

In applying our method to a variety of SBH-only data sources, we found that performance varied across specific sources, and validation metrics in the external data were slightly worse than in the DHS cross-validation assessment. It could be argued that the utility of any indirect method will depend on the quality of SBH data collected [15]. Though to the contrary, indirect methods such as ours, which have been validated externally as well as against high-quality DHS data, can also serve as a tool to assess the quality of these data sources. For example, by comparing trends from multiple available sources within a country, as we show in supplementary Fig 5, certain sources stand out as problematic. See, for example, the upward trend apparent in the Ghana 2000 census or the downward shift seen in the 2008 Cambodia census. These two censuses suffer from different data quality issues, and a future research should focus on understanding the topology of potential issues in SBH data. Modeling groups such as IGME and GBD regularly exclude data sources because of quality concerns that arise in vetting. Furthermore, we found that much of the variation in the external validation could be explained using source-specific effects. In practice, the data-synthesizing models used by groups such as IGME and GBD can account for source-level biases using fixed or random effects.

As global child mortality has declined rapidly in recent years, it has become clear that improvements have not been equal across all ages in early childhood [21]. The Sustainable Development Goals now have an explicit target of reducing NN mortality to 12 deaths per 1,000 live births [7]. Until now, estimates of NN mortality have depended mostly on CBH data or VR, when it is available. If no data are available, estimates are completely modeled based on external information. Until complete and reliable VR data are available from all countries, SBH data should be considered an “inexpensive” alternative to costlier CBH surveys. As we have demonstrated through extensive and systematic external validation, this new method now opens the possibility of leveraging a huge amount of SBH data available from surveys and censuses for monitoring progress toward the NN mortality Sustainable Development Goal.
Limitations and directions for future research

These results should be interpreted within the context of several limitations. First, despite being widely seen as high quality, and thus the basis for many child mortality estimates, DHS CBH data can suffer from certain issues such as selection biases [29] and misplacement of births [30]. By serving as the empirical basis upon which our model was trained, potential issues in these data could be reflected in the resulting application of it. Future research should focus on quantifying such issues and adjusting empirically based indirect methods to accommodate them. Second, the method presented here relies on formalizing existing relationships between covariates in the data to drive predictions. As such, when these relationships do not hold, predictions can suffer. Given the lack of period-based information in any one given SBH survey, it is expected that indirect estimates will poorly capture rapid changes in mortality [9]. This is partially mitigated in our approach by incorporating individual-level covariates, in which case mortality experiences from younger mothers will be more heavily weighted in recent periods. Third, by using GBD-MAP probability of birth distributions, we assume that fertility experiences are relatively stable over time among women in the same region, age, and number of CEB. Our preliminary analyses indicate this is generally true (see S7 Fig). Future research should focus on modeling these distributions at the individual level as well, potentially jointly fit within one model. Fourth, subnational predictions could likely be improved in the future by using subnational-level covariates rather than national-level covariates like SDI, as well as by implementing models that account for spatial autocorrelation in residuals. Fifth, by relying on concurrent SBH and CBH estimates as the basis for external validation, we could not ascertain the performance of this method in locations where only SBH exists, and thus, our sample may be somewhat biased toward higher-quality data. Finally, we validated the new model on one specific set of age bins, chosen to align with data collection and the typically used age breakdowns in previous research on child mortality. Future research can further validate other age bins and consider further distinguishing trends by sex.

Conclusions

This new method introduces a novel approach to indirect estimation of child mortality. It produces results comparable to current best methods for indirect estimation of under-5 mortality while additionally producing age-specific estimates at both national and subnational levels, supplying researchers a tool with which to utilize a massive amount of SBH data for estimation of trends in NN and infant mortality at various geographic levels. Systematic application of these methods could further improve the evidence base for monitoring of trends and inequalities in age-specific child mortality.

References


Supporting Information for Chapter 2

S1 Table:

Input data sources for development and cross-validation of the method. This table lists each of the surveys used for training and testing the model. All were either Demographic and Health Surveys or related Malaria Indicator Surveys. Raw sample sizes for number women and number of children are also given. More information on each survey, including download links, can be found by searching the GHDx ID at http://ghdx.healthdata.org/. The most recent survey for each country was used for validation, and marked with an "X" in the table.

Abbreviations: GHDx = Global Health Data Exchange.

<table>
<thead>
<tr>
<th>Model Region</th>
<th>Country</th>
<th>GHDx ID</th>
<th>Survey</th>
<th>Year</th>
<th># Mothers</th>
<th># Children</th>
<th>Test Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>North Africa / Middle East</td>
<td>Afghanistan</td>
<td>157018</td>
<td>MACRO_DHS</td>
<td>2016</td>
<td>26,598</td>
<td>125,715</td>
<td>X</td>
</tr>
<tr>
<td>Asia</td>
<td>Albania</td>
<td>18834</td>
<td>MACRO_DHS</td>
<td>2009</td>
<td>4,817</td>
<td>12,766</td>
<td>X</td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Angola</td>
<td>56169</td>
<td>MACRO_MIS</td>
<td>2011</td>
<td>6,517</td>
<td>22,925</td>
<td>X</td>
</tr>
<tr>
<td>Asia</td>
<td>Armenia</td>
<td>31750</td>
<td>MACRO_DHS</td>
<td>2010</td>
<td>3,780</td>
<td>8,424</td>
<td>X</td>
</tr>
<tr>
<td>Asia</td>
<td>Armenia</td>
<td>18854</td>
<td>MACRO_DHS</td>
<td>2005</td>
<td>4,276</td>
<td>10,297</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Armenia</td>
<td>18843</td>
<td>MACRO_DHS</td>
<td>2000</td>
<td>4,372</td>
<td>11,286</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Bangladesh</td>
<td>157021</td>
<td>MACRO_DHS</td>
<td>2014</td>
<td>16,079</td>
<td>43,772</td>
<td>X</td>
</tr>
<tr>
<td>Asia</td>
<td>Bangladesh</td>
<td>55956</td>
<td>MACRO_DHS</td>
<td>2012</td>
<td>16,014</td>
<td>45,834</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Bangladesh</td>
<td>18913</td>
<td>MACRO_DHS</td>
<td>2007</td>
<td>9,849</td>
<td>30,527</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Bangladesh</td>
<td>18902</td>
<td>MACRO_DHS</td>
<td>2004</td>
<td>10,138</td>
<td>35,979</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Bangladesh</td>
<td>18982</td>
<td>MACRO_DHS</td>
<td>2000</td>
<td>9,353</td>
<td>31,906</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Bangladesh</td>
<td>18878</td>
<td>MACRO_DHS</td>
<td>1997</td>
<td>8,081</td>
<td>29,344</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Bangladesh</td>
<td>18889</td>
<td>MACRO_DHS</td>
<td>1994</td>
<td>8,541</td>
<td>32,581</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Benin</td>
<td>79839</td>
<td>MACRO_DHS</td>
<td>2012</td>
<td>12,522</td>
<td>47,152</td>
<td>X</td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Benin</td>
<td>18959</td>
<td>MACRO_DHS</td>
<td>2006</td>
<td>13,814</td>
<td>57,232</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Benin</td>
<td>18950</td>
<td>MACRO_DHS</td>
<td>2001</td>
<td>4,612</td>
<td>19,398</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Benin</td>
<td>18938</td>
<td>MACRO_DHS</td>
<td>1996</td>
<td>1,804</td>
<td>8,158</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Bolivia</td>
<td>19016</td>
<td>MACRO_DHS</td>
<td>2008</td>
<td>11,720</td>
<td>40,355</td>
<td>X</td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Bolivia</td>
<td>18971</td>
<td>MACRO_DHS</td>
<td>1998</td>
<td>7,634</td>
<td>29,473</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Bolivia</td>
<td>18990</td>
<td>MACRO_DHS</td>
<td>1994</td>
<td>6,053</td>
<td>24,174</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Bolivia</td>
<td>18979</td>
<td>MACRO_DHS</td>
<td>1989</td>
<td>5,542</td>
<td>22,338</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Botswana</td>
<td>19019</td>
<td>MACRO_DHS</td>
<td>1988</td>
<td>3,279</td>
<td>10,670</td>
<td>X</td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Brazil</td>
<td>19046</td>
<td>MACRO_DHS</td>
<td>1996</td>
<td>8,390</td>
<td>25,513</td>
<td>X</td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Burkina Faso</td>
<td>19133</td>
<td>MACRO_DHS</td>
<td>2011</td>
<td>13,247</td>
<td>56,178</td>
<td>X</td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Burkina Faso</td>
<td>19088</td>
<td>MACRO_DHS</td>
<td>2003</td>
<td>9,474</td>
<td>41,520</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Burkina Faso</td>
<td>19076</td>
<td>MACRO_DHS</td>
<td>1999</td>
<td>4,916</td>
<td>22,145</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Burkina Faso</td>
<td>19064</td>
<td>MACRO_DHS</td>
<td>1993</td>
<td>4,778</td>
<td>20,655</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Burundi</td>
<td>30431</td>
<td>MACRO_DHS</td>
<td>2011</td>
<td>5,954</td>
<td>24,520</td>
<td>X</td>
</tr>
<tr>
<td>Region</td>
<td>Country</td>
<td>Macroeconomic Database</td>
<td>Year</td>
<td>Population</td>
<td>Median Income</td>
<td>Notes</td>
<td></td>
</tr>
<tr>
<td>---------------------------------</td>
<td>------------------</td>
<td>-------------------------</td>
<td>------</td>
<td>------------</td>
<td>---------------</td>
<td>-------</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Cambodia</td>
<td>MACRO_DHS</td>
<td>2014</td>
<td>11,723</td>
<td>33,290</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Cambodia</td>
<td>MACRO_DHS</td>
<td>2011</td>
<td>11,856</td>
<td>37,511</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Cambodia</td>
<td>MACRO_DHS</td>
<td>2006</td>
<td>10,791</td>
<td>40,457</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Cambodia</td>
<td>MACRO_DHS</td>
<td>2000</td>
<td>9,930</td>
<td>40,990</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Cameroon</td>
<td>MACRO_DHS</td>
<td>2011</td>
<td>11,023</td>
<td>42,312</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Cameroon</td>
<td>MACRO_DHS</td>
<td>2004</td>
<td>7,557</td>
<td>29,455</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Cameroon</td>
<td>MACRO_DHS</td>
<td>1998</td>
<td>3,847</td>
<td>15,187</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Cameroon</td>
<td>MACRO_DHS</td>
<td>1991</td>
<td>2,839</td>
<td>11,612</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Chad</td>
<td>MACRO_DHS</td>
<td>2015</td>
<td>14,156</td>
<td>68,989</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Chad</td>
<td>MACRO_DHS</td>
<td>2004</td>
<td>4,643</td>
<td>21,448</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Chad</td>
<td>MACRO_DHS</td>
<td>1997</td>
<td>5,865</td>
<td>25,739</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Colombia</td>
<td>MACRO_DHS</td>
<td>2016</td>
<td>25,433</td>
<td>62,580</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Colombia</td>
<td>MACRO_DHS</td>
<td>2005</td>
<td>26,536</td>
<td>71,254</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Colombia</td>
<td>MACRO_DHS</td>
<td>2000</td>
<td>7,830</td>
<td>21,267</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Colombia</td>
<td>MACRO_DHS</td>
<td>1995</td>
<td>7,500</td>
<td>21,830</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Colombia</td>
<td>MACRO_DHS</td>
<td>1990</td>
<td>5,365</td>
<td>15,964</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Comoros</td>
<td>MACRO_DHS</td>
<td>2013</td>
<td>2,934</td>
<td>11,497</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Comoros</td>
<td>MACRO_DHS</td>
<td>1996</td>
<td>1,695</td>
<td>7,913</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Congo</td>
<td>MACRO_DHS</td>
<td>2012</td>
<td>8,787</td>
<td>31,948</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Congo</td>
<td>MACRO_DHS</td>
<td>2005</td>
<td>5,152</td>
<td>16,687</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Cote d'Ivoire</td>
<td>MACRO_DHS</td>
<td>2012</td>
<td>7,498</td>
<td>28,211</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Cote d'Ivoire</td>
<td>MACRO_DHS</td>
<td>1999</td>
<td>2,048</td>
<td>7,575</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Cote d'Ivoire</td>
<td>MACRO_DHS</td>
<td>1994</td>
<td>6,108</td>
<td>24,870</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Democratic Republic of the Congo</td>
<td>MACRO_DHS</td>
<td>2014</td>
<td>14,182</td>
<td>59,276</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Dominican Republic</td>
<td>MACRO_DHS</td>
<td>2007</td>
<td>7,148</td>
<td>29,548</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Dominican Republic</td>
<td>MACRO_DHS</td>
<td>2013</td>
<td>6,687</td>
<td>18,167</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Dominican Republic</td>
<td>MACRO_DHS</td>
<td>2007</td>
<td>19,541</td>
<td>58,037</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Dominican Republic</td>
<td>MACRO_DHS</td>
<td>2002</td>
<td>17,032</td>
<td>53,667</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Dominican Republic</td>
<td>MACRO_DHS</td>
<td>1999</td>
<td>901</td>
<td>2,871</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Dominican Republic</td>
<td>MACRO_DHS</td>
<td>1996</td>
<td>5,942</td>
<td>19,784</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Dominican Republic</td>
<td>MACRO_DHS</td>
<td>1991</td>
<td>4,864</td>
<td>17,163</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Egypt</td>
<td>MACRO_DHS</td>
<td>2014</td>
<td>19,770</td>
<td>59,266</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Egypt</td>
<td>MACRO_DHS</td>
<td>2008</td>
<td>14,778</td>
<td>48,619</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Egypt</td>
<td>MACRO_DHS</td>
<td>2005</td>
<td>17,552</td>
<td>61,455</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Egypt</td>
<td>MACRO_DHS</td>
<td>2003</td>
<td>8,275</td>
<td>30,298</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Egypt</td>
<td>MACRO_DHS</td>
<td>2000</td>
<td>14,164</td>
<td>54,780</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Egypt</td>
<td>MACRO_DHS</td>
<td>1996</td>
<td>13,329</td>
<td>56,390</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Egypt</td>
<td>MACRO_DHS</td>
<td>1993</td>
<td>8,983</td>
<td>38,076</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region</td>
<td>Country</td>
<td>Sample Size</td>
<td>Year</td>
<td>Sample Size</td>
<td>Year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------------------------</td>
<td>---------------</td>
<td>-------------</td>
<td>-------</td>
<td>-------------</td>
<td>-------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Egypt</td>
<td>19472</td>
<td>1989</td>
<td>8,091</td>
<td>35,519</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Eritrea</td>
<td>19539</td>
<td>2002</td>
<td>6,009</td>
<td>24,370</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Ethiopia</td>
<td>218568</td>
<td>2016</td>
<td>10,274</td>
<td>41,392</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Ethiopia</td>
<td>21301</td>
<td>2011</td>
<td>10,896</td>
<td>45,540</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Ethiopia</td>
<td>19557</td>
<td>2005</td>
<td>9,339</td>
<td>39,881</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Ethiopia</td>
<td>19571</td>
<td>2000</td>
<td>10,143</td>
<td>44,174</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Gabon</td>
<td>76706</td>
<td>2012</td>
<td>6,383</td>
<td>23,109</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Gabon</td>
<td>19579</td>
<td>2001</td>
<td>4,499</td>
<td>16,878</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Ghana</td>
<td>157027</td>
<td>2014</td>
<td>6,511</td>
<td>23,118</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Ghana</td>
<td>21188</td>
<td>2008</td>
<td>3,299</td>
<td>11,888</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Ghana</td>
<td>19627</td>
<td>2003</td>
<td>3,992</td>
<td>15,086</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Ghana</td>
<td>19614</td>
<td>1999</td>
<td>3,499</td>
<td>13,188</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Ghana</td>
<td>19604</td>
<td>1994</td>
<td>3,501</td>
<td>13,280</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Guatemala</td>
<td>157031</td>
<td>2015</td>
<td>17,178</td>
<td>55,398</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Guatemala</td>
<td>19656</td>
<td>1999</td>
<td>4,350</td>
<td>18,581</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Guatemala</td>
<td>19637</td>
<td>1995</td>
<td>8,794</td>
<td>38,753</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Guinea</td>
<td>69761</td>
<td>2012</td>
<td>6,950</td>
<td>27,683</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Guinea</td>
<td>19683</td>
<td>2005</td>
<td>6,259</td>
<td>27,115</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Guinea</td>
<td>19670</td>
<td>1999</td>
<td>5,413</td>
<td>22,943</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Guyana</td>
<td>21348</td>
<td>2009</td>
<td>3,484</td>
<td>10,929</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Haiti</td>
<td>65118</td>
<td>2012</td>
<td>8,671</td>
<td>29,013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Haiti</td>
<td>19720</td>
<td>2006</td>
<td>6,547</td>
<td>24,830</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Haiti</td>
<td>19708</td>
<td>2000</td>
<td>6,459</td>
<td>26,437</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Haiti</td>
<td>19695</td>
<td>1995</td>
<td>3,288</td>
<td>12,547</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Honduras</td>
<td>95440</td>
<td>2012</td>
<td>15,854</td>
<td>49,263</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Honduras</td>
<td>19728</td>
<td>2006</td>
<td>13,991</td>
<td>50,093</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>India</td>
<td>19963</td>
<td>2006</td>
<td>84,609</td>
<td>256,782</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>India</td>
<td>19950</td>
<td>2000</td>
<td>80,872</td>
<td>268,879</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>India</td>
<td>19787</td>
<td>1993</td>
<td>79,322</td>
<td>275,143</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Indonesia</td>
<td>76705</td>
<td>2012</td>
<td>32,129</td>
<td>83,650</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Indonesia</td>
<td>20021</td>
<td>2007</td>
<td>30,420</td>
<td>84,726</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Indonesia</td>
<td>20011</td>
<td>2003</td>
<td>27,317</td>
<td>79,791</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Indonesia</td>
<td>19999</td>
<td>1997</td>
<td>26,562</td>
<td>86,276</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Indonesia</td>
<td>19990</td>
<td>1994</td>
<td>26,045</td>
<td>90,326</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Indonesia</td>
<td>19979</td>
<td>1991</td>
<td>21,065</td>
<td>74,329</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Jordan</td>
<td>77517</td>
<td>2012</td>
<td>10,304</td>
<td>42,275</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Jordan</td>
<td>21206</td>
<td>2009</td>
<td>9,124</td>
<td>38,199</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Jordan</td>
<td>20083</td>
<td>2007</td>
<td>9,916</td>
<td>43,460</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Jordan</td>
<td>20073</td>
<td>2002</td>
<td>5,494</td>
<td>25,296</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Jordan</td>
<td>20060</td>
<td>1997</td>
<td>5,038</td>
<td>24,243</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Jordan</td>
<td>20051</td>
<td>1990</td>
<td>5,853</td>
<td>32,812</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Kazakhstan</td>
<td>20103</td>
<td>1999</td>
<td>3,364</td>
<td>8,106</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Kazakhstan</td>
<td>20092</td>
<td>1995</td>
<td>2,649</td>
<td>6,866</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Kenya</td>
<td>157057</td>
<td>2014</td>
<td>23,245</td>
<td>83,591</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region</td>
<td>Country</td>
<td>Code</td>
<td>Year</td>
<td>Sample Size</td>
<td>Population</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>---------</td>
<td>------</td>
<td>------</td>
<td>-------------</td>
<td>------------</td>
<td>-----------</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Kenya</td>
<td>21365</td>
<td>2009</td>
<td>6,102</td>
<td>22,534</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Kenya</td>
<td>20145</td>
<td>2003</td>
<td>5,865</td>
<td>22,074</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Kenya</td>
<td>20132</td>
<td>1998</td>
<td>5,717</td>
<td>23,351</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Kenya</td>
<td>20120</td>
<td>1993</td>
<td>5,415</td>
<td>23,899</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Kenya</td>
<td>20109</td>
<td>1989</td>
<td>5,507</td>
<td>25,173</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Kyrgyzstan</td>
<td>77518</td>
<td>2012</td>
<td>5,601</td>
<td>16,180</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Kyrgyzstan</td>
<td>20154</td>
<td>1997</td>
<td>2,776</td>
<td>8,781</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Lesotho</td>
<td>21382</td>
<td>2010</td>
<td>5,191</td>
<td>14,429</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Lesotho</td>
<td>20167</td>
<td>2005</td>
<td>4,832</td>
<td>14,708</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Liberia</td>
<td>77385</td>
<td>2013</td>
<td>7,559</td>
<td>30,804</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Liberia</td>
<td>34279</td>
<td>2009</td>
<td>3,643</td>
<td>14,872</td>
<td>MACRO_MIS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Liberia</td>
<td>20191</td>
<td>2007</td>
<td>5,701</td>
<td>22,123</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Madagascar</td>
<td>21409</td>
<td>2009</td>
<td>12,970</td>
<td>48,464</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Madagascar</td>
<td>20223</td>
<td>2004</td>
<td>5,845</td>
<td>20,799</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Madagascar</td>
<td>20212</td>
<td>1997</td>
<td>5,233</td>
<td>21,654</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Madagascar</td>
<td>20202</td>
<td>1992</td>
<td>4,369</td>
<td>18,931</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Malawi</td>
<td>218581</td>
<td>2016</td>
<td>18,988</td>
<td>68,074</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Malawi</td>
<td>21393</td>
<td>2010</td>
<td>18,041</td>
<td>72,301</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Malawi</td>
<td>20263</td>
<td>2005</td>
<td>9,298</td>
<td>35,883</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Malawi</td>
<td>20252</td>
<td>2000</td>
<td>10,337</td>
<td>40,421</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Malawi</td>
<td>20235</td>
<td>1995</td>
<td>3,718</td>
<td>16,330</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Maldives</td>
<td>21311</td>
<td>2009</td>
<td>6,106</td>
<td>20,136</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Mali</td>
<td>77388</td>
<td>2013</td>
<td>8,480</td>
<td>33,803</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Mali</td>
<td>20274</td>
<td>2006</td>
<td>11,566</td>
<td>52,140</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Mali</td>
<td>20315</td>
<td>2001</td>
<td>10,379</td>
<td>48,407</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Mali</td>
<td>20301</td>
<td>1996</td>
<td>7,935</td>
<td>37,921</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Mauritania</td>
<td>20322</td>
<td>2001</td>
<td>4,584</td>
<td>19,202</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Morocco</td>
<td>20361</td>
<td>2004</td>
<td>8,660</td>
<td>32,494</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Morocco</td>
<td>20371</td>
<td>1992</td>
<td>4,986</td>
<td>22,657</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Mozambique</td>
<td>55975</td>
<td>2011</td>
<td>10,624</td>
<td>37,984</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Mozambique</td>
<td>20394</td>
<td>2004</td>
<td>9,732</td>
<td>37,443</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Mozambique</td>
<td>20382</td>
<td>1997</td>
<td>6,798</td>
<td>25,752</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Myanmar</td>
<td>157061</td>
<td>2016</td>
<td>7,796</td>
<td>22,898</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Namibia</td>
<td>150382</td>
<td>2013</td>
<td>6,453</td>
<td>18,090</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Namibia</td>
<td>20428</td>
<td>2007</td>
<td>6,636</td>
<td>19,522</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Namibia</td>
<td>20417</td>
<td>2000</td>
<td>4,780</td>
<td>14,946</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Namibia</td>
<td>20404</td>
<td>1992</td>
<td>3,710</td>
<td>13,372</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Nepal</td>
<td>21240</td>
<td>2011</td>
<td>8,800</td>
<td>26,615</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Nepal</td>
<td>20462</td>
<td>2006</td>
<td>7,791</td>
<td>26,394</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Nepal</td>
<td>20450</td>
<td>2001</td>
<td>7,772</td>
<td>28,955</td>
<td>MACRO_DHS</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Nepal</td>
<td>20437</td>
<td>1996</td>
<td>7,479</td>
<td>29,156</td>
<td>NIC/DHS_ENDES</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Nicaragua</td>
<td>126952</td>
<td>2012</td>
<td>11,295</td>
<td>31,244</td>
<td>A</td>
<td></td>
</tr>
<tr>
<td>Region</td>
<td>Country</td>
<td>Sample ID</td>
<td>Study Name</td>
<td>Year</td>
<td>Sample Size</td>
<td>Final Count</td>
<td></td>
</tr>
<tr>
<td>--------------------------------</td>
<td>----------------</td>
<td>-----------</td>
<td>---------------</td>
<td>------</td>
<td>-------------</td>
<td>-------------</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Nicaragua</td>
<td>20487</td>
<td>MACRO_DHS</td>
<td>2001</td>
<td>9,275</td>
<td>34,157</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Nicaragua</td>
<td>20478</td>
<td>MACRO_DHS</td>
<td>1998</td>
<td>9,696</td>
<td>36,820</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Niger</td>
<td>74393</td>
<td>MACRO_DHS</td>
<td>2012</td>
<td>9,209</td>
<td>44,183</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Niger</td>
<td>20499</td>
<td>MACRO_DHS</td>
<td>2006</td>
<td>7,205</td>
<td>34,378</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Niger</td>
<td>20537</td>
<td>MACRO_DHS</td>
<td>1998</td>
<td>5,921</td>
<td>28,888</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Niger</td>
<td>20518</td>
<td>MACRO_DHS</td>
<td>1992</td>
<td>5,068</td>
<td>23,841</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Nigeria</td>
<td>77390</td>
<td>MACRO_DHS</td>
<td>2013</td>
<td>27,451</td>
<td>119,386</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Nigeria</td>
<td>30991</td>
<td>MACRO_MIS</td>
<td>2010</td>
<td>4,632</td>
<td>19,644</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Nigeria</td>
<td>21433</td>
<td>MACRO_DHS</td>
<td>2008</td>
<td>23,751</td>
<td>104,808</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Nigeria</td>
<td>20567</td>
<td>MACRO_DHS</td>
<td>2003</td>
<td>5,111</td>
<td>23,038</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Nigeria</td>
<td>20552</td>
<td>MACRO_DHS</td>
<td>1990</td>
<td>6,477</td>
<td>28,123</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Pakistan</td>
<td>77521</td>
<td>MACRO_DHS</td>
<td>2013</td>
<td>11,965</td>
<td>50,238</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Pakistan</td>
<td>20595</td>
<td>MACRO_DHS</td>
<td>2007</td>
<td>8,798</td>
<td>39,049</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Peru</td>
<td>209930</td>
<td>MACRO_DHS</td>
<td>2014</td>
<td>17,488</td>
<td>47,633</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Peru</td>
<td>270471</td>
<td>MACRO_DHS</td>
<td>2012</td>
<td>16,620</td>
<td>47,261</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Peru</td>
<td>270470</td>
<td>MACRO_DHS</td>
<td>2011</td>
<td>15,636</td>
<td>46,194</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Peru</td>
<td>270469</td>
<td>MACRO_DHS</td>
<td>2010</td>
<td>15,886</td>
<td>46,780</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Peru</td>
<td>270404</td>
<td>MACRO_DHS</td>
<td>2009</td>
<td>16,887</td>
<td>50,084</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Peru</td>
<td>275090</td>
<td>MACRO_DHS</td>
<td>2008</td>
<td>28,613</td>
<td>89,220</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Peru</td>
<td>20649</td>
<td>MACRO_DHS</td>
<td>2000</td>
<td>18,931</td>
<td>65,453</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Peru</td>
<td>20638</td>
<td>MACRO_DHS</td>
<td>1996</td>
<td>19,835</td>
<td>72,390</td>
<td></td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>Peru</td>
<td>20626</td>
<td>MACRO_DHS</td>
<td>1992</td>
<td>10,244</td>
<td>38,783</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Philippines</td>
<td>142943</td>
<td>MACRO_DHS</td>
<td>2013</td>
<td>10,125</td>
<td>31,680</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Philippines</td>
<td>21421</td>
<td>MACRO_DHS</td>
<td>2008</td>
<td>8,639</td>
<td>28,518</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Philippines</td>
<td>20699</td>
<td>MACRO_DHS</td>
<td>2003</td>
<td>8,750</td>
<td>30,443</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Philippines</td>
<td>20683</td>
<td>MACRO_DHS</td>
<td>1998</td>
<td>8,662</td>
<td>32,626</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Philippines</td>
<td>20674</td>
<td>MACRO_DHS</td>
<td>1993</td>
<td>9,197</td>
<td>35,863</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Rwanda</td>
<td>157063</td>
<td>MACRO_DHS</td>
<td>2015</td>
<td>8,736</td>
<td>30,058</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Rwanda</td>
<td>56040</td>
<td>MACRO_DHS</td>
<td>2011</td>
<td>8,501</td>
<td>32,639</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Rwanda</td>
<td>21222</td>
<td>MACRO_DHS</td>
<td>2008</td>
<td>4,686</td>
<td>18,421</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Rwanda</td>
<td>20740</td>
<td>MACRO_DHS</td>
<td>2005</td>
<td>7,045</td>
<td>30,072</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Rwanda</td>
<td>20722</td>
<td>MACRO_DHS</td>
<td>2000</td>
<td>6,539</td>
<td>27,602</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Rwanda</td>
<td>20711</td>
<td>MACRO_DHS</td>
<td>1992</td>
<td>4,292</td>
<td>19,440</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>26866</td>
<td>MACRO_DHS</td>
<td>2009</td>
<td>2,014</td>
<td>7,620</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>286772</td>
<td>MACRO_DHS</td>
<td>2016</td>
<td>8,836</td>
<td>22,740</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>218592</td>
<td>MACRO_DHS</td>
<td>2015</td>
<td>5,906</td>
<td>23,250</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>191270</td>
<td>MACRO_DHS</td>
<td>2014</td>
<td>5,733</td>
<td>22,365</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>111432</td>
<td>MACRO_DHS</td>
<td>2013</td>
<td>5,650</td>
<td>22,563</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>56063</td>
<td>MACRO_DHS</td>
<td>2011</td>
<td>10,652</td>
<td>42,510</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>11540</td>
<td>MACRO_MIS</td>
<td>2009</td>
<td>13,134</td>
<td>53,608</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>26855</td>
<td>MACRO_DHS</td>
<td>2005</td>
<td>9,593</td>
<td>39,895</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>20780</td>
<td>MACRO_DHS</td>
<td>1997</td>
<td>6,097</td>
<td>27,448</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Senegal</td>
<td>20767</td>
<td>MACRO_DHS</td>
<td>1993</td>
<td>4,534</td>
<td>20,815</td>
<td></td>
</tr>
<tr>
<td>Region</td>
<td>Country</td>
<td>Reference</td>
<td>Year</td>
<td>Sample Size</td>
<td>Total Population</td>
<td>Status</td>
<td></td>
</tr>
<tr>
<td>--------------------------------</td>
<td>------------------</td>
<td>-----------</td>
<td>------</td>
<td>-------------</td>
<td>------------------</td>
<td>--------</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Sierra Leone</td>
<td>MACRO_DHS</td>
<td>2013</td>
<td>12,352</td>
<td>47,392</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Sierra Leone</td>
<td>MACRO_DHS</td>
<td>2008</td>
<td>5,876</td>
<td>21,136</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>South Africa</td>
<td>MACRO_DHS</td>
<td>1998</td>
<td>8,223</td>
<td>22,934</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Sudan</td>
<td>MACRO_DHS</td>
<td>1990</td>
<td>5,277</td>
<td>25,805</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Swaziland</td>
<td>MACRO_DHS</td>
<td>2007</td>
<td>3,488</td>
<td>11,410</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Tajikistan</td>
<td>MACRO_DHS</td>
<td>2012</td>
<td>6,172</td>
<td>19,938</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Tanzania</td>
<td>MACRO_DHS</td>
<td>2016</td>
<td>9,721</td>
<td>37,169</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Tanzania</td>
<td>MACRO_DHS</td>
<td>2010</td>
<td>7,326</td>
<td>29,777</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Tanzania</td>
<td>MACRO_DHS</td>
<td>2005</td>
<td>7,573</td>
<td>30,557</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Tanzania</td>
<td>MACRO_DHS</td>
<td>1999</td>
<td>2,935</td>
<td>11,952</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Tanzania</td>
<td>MACRO_DHS</td>
<td>1996</td>
<td>6,083</td>
<td>24,890</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Tanzania</td>
<td>MACRO_DHS</td>
<td>1992</td>
<td>6,913</td>
<td>29,143</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>The Gambia</td>
<td>MACRO_DHS</td>
<td>2013</td>
<td>6,845</td>
<td>26,601</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Timor-Leste</td>
<td>MACRO_DHS</td>
<td>2010</td>
<td>7,969</td>
<td>35,998</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Togo</td>
<td>MACRO_DHS</td>
<td>2014</td>
<td>6,944</td>
<td>26,264</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Togo</td>
<td>MACRO_DHS</td>
<td>1998</td>
<td>6,289</td>
<td>26,269</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, West/Central</td>
<td>Togo</td>
<td>MACRO_DHS</td>
<td>1988</td>
<td>2,536</td>
<td>10,782</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Tunisia</td>
<td>MACRO_DHS</td>
<td>1988</td>
<td>3,856</td>
<td>16,463</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Turkey</td>
<td>MACRO_DHS</td>
<td>2004</td>
<td>7,360</td>
<td>22,443</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Turkey</td>
<td>MACRO_DHS</td>
<td>1998</td>
<td>5,578</td>
<td>17,791</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Turkey</td>
<td>MACRO_DHS</td>
<td>1993</td>
<td>5,923</td>
<td>19,762</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Uganda</td>
<td>MACRO_DHS</td>
<td>2011</td>
<td>6,393</td>
<td>28,609</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Uganda</td>
<td>MACRO_MIS</td>
<td>2010</td>
<td>3,143</td>
<td>13,863</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Uganda</td>
<td>MACRO_DHS</td>
<td>2006</td>
<td>6,417</td>
<td>30,090</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Uganda</td>
<td>MACRO_DHS</td>
<td>2001</td>
<td>5,501</td>
<td>23,410</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Uganda</td>
<td>MACRO_DHS</td>
<td>1995</td>
<td>5,465</td>
<td>22,752</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Uganda</td>
<td>MACRO_DHS</td>
<td>1989</td>
<td>3,563</td>
<td>16,074</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Ukraine</td>
<td>MACRO_DHS</td>
<td>2007</td>
<td>4,811</td>
<td>8,007</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Uzbekistan</td>
<td>MACRO_DHS</td>
<td>1996</td>
<td>3,018</td>
<td>9,650</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Vietnam</td>
<td>MACRO_DHS</td>
<td>2002</td>
<td>5,390</td>
<td>14,383</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Asia</td>
<td>Vietnam</td>
<td>MACRO_DHS</td>
<td>1997</td>
<td>5,352</td>
<td>15,517</td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Yemen</td>
<td>MACRO_DHS</td>
<td>2013</td>
<td>14,688</td>
<td>64,602</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>North Africa / Middle East</td>
<td>Yemen</td>
<td>MACRO_DHS</td>
<td>1992</td>
<td>5,059</td>
<td>27,081</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zambia</td>
<td>MACRO_DHS</td>
<td>2014</td>
<td>12,421</td>
<td>49,207</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zambia</td>
<td>MACRO_DHS</td>
<td>2007</td>
<td>5,410</td>
<td>21,366</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zambia</td>
<td>MACRO_DHS</td>
<td>2002</td>
<td>5,831</td>
<td>23,805</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zambia</td>
<td>MACRO_DHS</td>
<td>1997</td>
<td>5,996</td>
<td>24,799</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zambia</td>
<td>MACRO_DHS</td>
<td>1992</td>
<td>5,186</td>
<td>22,122</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zimbabwe</td>
<td>MACRO_DHS</td>
<td>2015</td>
<td>7,253</td>
<td>20,791</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zimbabwe</td>
<td>MACRO_DHS</td>
<td>2011</td>
<td>6,725</td>
<td>19,279</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zimbabwe</td>
<td>MACRO_DHS</td>
<td>2006</td>
<td>6,281</td>
<td>19,489</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zimbabwe</td>
<td>MACRO_DHS</td>
<td>1999</td>
<td>4,207</td>
<td>14,184</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zimbabwe</td>
<td>MACRO_DHS</td>
<td>1994</td>
<td>4,388</td>
<td>16,777</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Saharan Africa, South/East</td>
<td>Zimbabwe</td>
<td>MACRO_DHS</td>
<td>1989</td>
<td>3,005</td>
<td>12,405</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
**S2 Table:**

External validation data sources. An additional 342 surveys were used for external validation. 243 of these were SBH-only surveys, the rest were additional CBH sources used for comparison but not used in training the model.

Abbreviations: CBH = complete birth history; SBH = summary birth history.

<table>
<thead>
<tr>
<th>Country</th>
<th>GHDx nid</th>
<th>Data Type</th>
<th>Children</th>
<th>Citation</th>
</tr>
</thead>
</table>

103
<table>
<thead>
<tr>
<th>Country</th>
<th>Code</th>
<th>Source Code</th>
<th>Population</th>
<th>Organization(s)</th>
<th>Survey Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Botswana</td>
<td>22125</td>
<td>cbh</td>
<td>10,858</td>
<td>Statistics Botswana, Botswana Family Health Survey 2007-2008</td>
<td></td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>n</td>
<td>Population</td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------------</td>
<td>--------</td>
<td>------</td>
<td>------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>38230</td>
<td>sbh</td>
<td>4,830,714</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>1488</td>
<td>sbh</td>
<td>177,981</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>1489</td>
<td>sbh</td>
<td>174,600</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>1490</td>
<td>sbh</td>
<td>180,887</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>80311</td>
<td>sbh</td>
<td>182,709</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>93528</td>
<td>sbh</td>
<td>179,995</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>93490</td>
<td>sbh</td>
<td>182,709</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>93487</td>
<td>sbh</td>
<td>179,995</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>93522</td>
<td>sbh</td>
<td>182,709</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>105322</td>
<td>sbh</td>
<td>3,915,750</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>106724</td>
<td>sbh</td>
<td>145,313</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>156581</td>
<td>sbh</td>
<td>144,682</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>156583</td>
<td>sbh</td>
<td>144,033</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>238441</td>
<td>sbh</td>
<td>141,577</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brazil</td>
<td>281548</td>
<td>sbh</td>
<td>135,941</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burkina Faso</td>
<td>1927</td>
<td>sbh</td>
<td>25,541</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burkina Faso</td>
<td>105403</td>
<td>sbh</td>
<td>946,618</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burkina Faso</td>
<td>188785</td>
<td>sbh</td>
<td>27,986</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burundi</td>
<td>1970</td>
<td>sbh</td>
<td>20,848</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burundi</td>
<td>1994</td>
<td>sbh</td>
<td>13,864</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Country</td>
<td>Year</td>
<td>Code</td>
<td>Population</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------</td>
<td>------</td>
<td>------</td>
<td>------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burundi</td>
<td>1981</td>
<td>sbh</td>
<td>25,768</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burundi</td>
<td>108080</td>
<td>sbh</td>
<td>13,647</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cambodia</td>
<td>19170</td>
<td>cbh</td>
<td>18,969</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cambodia</td>
<td>35322</td>
<td>sbh</td>
<td>708,771</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cambodia</td>
<td>2002</td>
<td>sbh</td>
<td>58,962</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cambodia</td>
<td>35329</td>
<td>sbh</td>
<td>663,330</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cameroon</td>
<td>2053</td>
<td>sbh</td>
<td>14,980</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cameroon</td>
<td>105800</td>
<td>sbh</td>
<td>1,046,493</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cameroon</td>
<td>244455</td>
<td>cbh</td>
<td>26,201</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cape Verde</td>
<td>27511</td>
<td>cbh</td>
<td>16,772</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central African Republic</td>
<td>2209</td>
<td>sbh</td>
<td>59,424</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central African Republic</td>
<td>2223</td>
<td>sbh</td>
<td>35,974</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central African Republic</td>
<td>82832</td>
<td>sbh</td>
<td>37,331</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chad</td>
<td>2244</td>
<td>sbh</td>
<td>21,938</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chad</td>
<td>76701</td>
<td>sbh</td>
<td>61,128</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chile</td>
<td>2311</td>
<td>sbh</td>
<td>623,140</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Country</th>
<th>Code</th>
<th>Source</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>294255</td>
<td>sbh</td>
<td>4,260,950</td>
</tr>
<tr>
<td>Colombia</td>
<td>3029</td>
<td>sbh</td>
<td>1,771,037</td>
</tr>
<tr>
<td>Colombia</td>
<td>21281</td>
<td>cbh</td>
<td>55,239</td>
</tr>
<tr>
<td>Comoros</td>
<td>3114</td>
<td>sbh</td>
<td>16,560</td>
</tr>
<tr>
<td>Congo</td>
<td>3133</td>
<td>sbh</td>
<td>18,574</td>
</tr>
<tr>
<td>Costa Rica</td>
<td>3243</td>
<td>sbh</td>
<td>189,555</td>
</tr>
<tr>
<td>Cuba</td>
<td>60935</td>
<td>sbh</td>
<td>13,154</td>
</tr>
<tr>
<td>Cuba</td>
<td>169975</td>
<td>sbh</td>
<td>12,553</td>
</tr>
<tr>
<td>Democratic Republic of the Congo</td>
<td>3161</td>
<td>sbh</td>
<td>39,356</td>
</tr>
<tr>
<td>Democratic Republic of the Congo</td>
<td>26998</td>
<td>sbh</td>
<td>40,648</td>
</tr>
<tr>
<td>Djibouti</td>
<td>3392</td>
<td>cbh</td>
<td>10,574</td>
</tr>
<tr>
<td>Djibouti</td>
<td>3404</td>
<td>sbh</td>
<td>10,479</td>
</tr>
<tr>
<td>Dominican Republic</td>
<td>27069</td>
<td>sbh</td>
<td>8,619</td>
</tr>
<tr>
<td>Dominican Republic</td>
<td>151296</td>
<td>sbh</td>
<td>415,435</td>
</tr>
<tr>
<td>Dominican Republic</td>
<td>3455</td>
<td>cbh</td>
<td>18,903</td>
</tr>
<tr>
<td>Dominican Republic</td>
<td>151304</td>
<td>sbh</td>
<td>466,537</td>
</tr>
</tbody>
</table>

*Sources*

- Department of Statistics and Demographic Studies (Djibouti), League of Arab States, Ministry of Health (Djibouti), Pan Arab Project for Family Health (PAPFAM). Djibouti Family Health Survey 2002.
<table>
<thead>
<tr>
<th>Country</th>
<th>Code</th>
<th>Year</th>
<th>Dataset and Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Country</td>
<td>Code</td>
<td>Type</td>
<td>Number</td>
</tr>
<tr>
<td>-----------</td>
<td>--------</td>
<td>------</td>
<td>--------</td>
</tr>
<tr>
<td>Georgia</td>
<td>USA</td>
<td>cbh</td>
<td>27494</td>
</tr>
<tr>
<td>Georgia</td>
<td>USA</td>
<td>cbh</td>
<td>95336</td>
</tr>
<tr>
<td>Guatemala</td>
<td>GUA</td>
<td>cbh</td>
<td>4779</td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Sample Size</td>
<td>Source</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-------------</td>
<td>-------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Honduras</td>
<td>27551</td>
<td>23,535</td>
<td>Honduras Family Planning Association (ASHONPLAFA), Ministry of Health (Honduras), and Division of Reproductive Health-Centers for Disease Control and Prevention (CDC). Honduras Reproductive Health Survey 2001. Tegucigalpa, Honduras: National Institute of Statistics (Honduras).</td>
</tr>
<tr>
<td>Indonesia</td>
<td>6790</td>
<td>438,949</td>
<td>Central Bureau of Statistics (Indonesia), Ministry of Health (Indonesia), World Bank. Indonesia National Socioeconomic Survey 1999.</td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Sbh</td>
<td>Population</td>
</tr>
<tr>
<td>------------------</td>
<td>---------</td>
<td>-----</td>
<td>---------------------------</td>
</tr>
<tr>
<td>Indonesia</td>
<td>56554</td>
<td>sbh</td>
<td>9,961,117</td>
</tr>
<tr>
<td>Indonesia</td>
<td>6842</td>
<td>sbh</td>
<td>458,846</td>
</tr>
<tr>
<td>Indonesia</td>
<td>43510</td>
<td>sbh</td>
<td>432,996</td>
</tr>
<tr>
<td>Indonesia</td>
<td>6874</td>
<td>sbh</td>
<td>449,842</td>
</tr>
<tr>
<td>Indonesia</td>
<td>6904</td>
<td>sbh</td>
<td>501,844</td>
</tr>
<tr>
<td>Indonesia</td>
<td>5376</td>
<td>sbh</td>
<td>510,692</td>
</tr>
<tr>
<td>Indonesia</td>
<td>5401</td>
<td>sbh</td>
<td>545,163</td>
</tr>
<tr>
<td>Indonesia</td>
<td>6970</td>
<td>sbh</td>
<td>582,333</td>
</tr>
<tr>
<td>Indonesia</td>
<td>43526</td>
<td>sbh</td>
<td>131,645</td>
</tr>
<tr>
<td>Indonesia</td>
<td>43552</td>
<td>sbh</td>
<td>129,963</td>
</tr>
<tr>
<td>Indonesia</td>
<td>30235</td>
<td>sbh</td>
<td>125,345</td>
</tr>
<tr>
<td>Indonesia</td>
<td>56558</td>
<td>sbh</td>
<td>10,489,232</td>
</tr>
<tr>
<td>Indonesia</td>
<td>91740</td>
<td>sbh</td>
<td>10,485,859</td>
</tr>
<tr>
<td>Indonesia</td>
<td>85265</td>
<td>sbh</td>
<td>130,728</td>
</tr>
<tr>
<td>Indonesia</td>
<td>150884</td>
<td>sbh</td>
<td>534,256</td>
</tr>
<tr>
<td>Indonesia</td>
<td>151184</td>
<td>sbh</td>
<td>518,178</td>
</tr>
<tr>
<td>Iran</td>
<td>39396</td>
<td>sbh</td>
<td>628,318</td>
</tr>
<tr>
<td>Iraq</td>
<td>7028</td>
<td>cbh</td>
<td>62,359</td>
</tr>
<tr>
<td>Iraq</td>
<td>23429</td>
<td>sbh</td>
<td>34,284</td>
</tr>
<tr>
<td>Iraq</td>
<td>76707</td>
<td>cbh</td>
<td>136,878</td>
</tr>
<tr>
<td>Jamaica</td>
<td>7140</td>
<td>sbh</td>
<td>8,532</td>
</tr>
<tr>
<td>Jamaica</td>
<td>39450</td>
<td>sbh</td>
<td>93,521</td>
</tr>
<tr>
<td>Kazakhstan</td>
<td>7340</td>
<td>sbh</td>
<td>23,329</td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>sbh</td>
<td>Population</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-----</td>
<td>------------</td>
</tr>
<tr>
<td>Kazakhstan</td>
<td>76702</td>
<td>sbh</td>
<td>22,048</td>
</tr>
<tr>
<td>Kazakhstan</td>
<td>260403</td>
<td>sbh</td>
<td>21,482</td>
</tr>
<tr>
<td>Kenya</td>
<td>39481</td>
<td>sbh</td>
<td>964,933</td>
</tr>
<tr>
<td>Kenya</td>
<td>153943</td>
<td>sbh</td>
<td>976,094</td>
</tr>
<tr>
<td>Kenya</td>
<td>7387</td>
<td>sbh</td>
<td>31,278</td>
</tr>
<tr>
<td>Kenya</td>
<td>7375</td>
<td>sbh</td>
<td>37,583</td>
</tr>
<tr>
<td>Kenya</td>
<td>57990</td>
<td>sbh</td>
<td>14,769</td>
</tr>
<tr>
<td>Kenya</td>
<td>133219</td>
<td>sbh</td>
<td>26,155</td>
</tr>
<tr>
<td>Kenya</td>
<td>7427</td>
<td>sbh</td>
<td>2,390,112</td>
</tr>
<tr>
<td>Kenya</td>
<td>106512</td>
<td>sbh</td>
<td>2,388,668</td>
</tr>
<tr>
<td>Kenya</td>
<td>218579</td>
<td>sbh</td>
<td>14,087</td>
</tr>
<tr>
<td>Kyrgyzstan</td>
<td>39466</td>
<td>sbh</td>
<td>256,968</td>
</tr>
<tr>
<td>Kyrgyzstan</td>
<td>7540</td>
<td>sbh</td>
<td>12,820</td>
</tr>
<tr>
<td>Kyrgyzstan</td>
<td>106520</td>
<td>sbh</td>
<td>280,046</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Country</th>
<th>Code</th>
<th>Source</th>
<th>Population</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lebanon</td>
<td>44861</td>
<td>cbh</td>
<td>9,867</td>
<td>Central Administration of Statistics (Lebanon), League of Arab States, Ministry of Social Affairs (Lebanon), Pan Arab Project for Family Health (PAPFAM). Lebanon Family Health Survey 2004.</td>
</tr>
<tr>
<td>Libya</td>
<td>107340</td>
<td>cbh</td>
<td>49,554</td>
<td>League of Arab States, National Center for Disease Control (Libya), Pan Arab Project for Family Health (PAPFAM). Libya Family Health Survey 2007.</td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Sample Size</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td>-------------</td>
<td>--------</td>
<td>-------------</td>
<td>---------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>Mexico</td>
<td>294574</td>
<td>sbh 5,403,100</td>
<td>National Institute of Statistics, Geography and Informatics (INEGI), Minnesota Population Center.  Mexico Intercensal Survey</td>
<td></td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Source Type</td>
<td>Year</td>
<td>Agency(s)</td>
</tr>
<tr>
<td>------------</td>
<td>------</td>
<td>-------------</td>
<td>------</td>
<td>-----------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Object</td>
<td>Year</td>
<td>Title and Details</td>
</tr>
<tr>
<td>---------</td>
<td>------</td>
<td>--------</td>
<td>------</td>
<td>------------------</td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Type</td>
<td>Population</td>
<td>Source</td>
</tr>
<tr>
<td>------------------</td>
<td>-------</td>
<td>------</td>
<td>------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Survey Type</td>
<td>Population</td>
<td></td>
</tr>
<tr>
<td>------------------</td>
<td>------</td>
<td>-------------</td>
<td>------------</td>
<td></td>
</tr>
<tr>
<td>Rwanda</td>
<td>21877</td>
<td>sbh</td>
<td>547,998</td>
<td></td>
</tr>
<tr>
<td>Rwanda</td>
<td>77391</td>
<td>sbh</td>
<td>11,726</td>
<td></td>
</tr>
<tr>
<td>Sao Tome and Principe</td>
<td>27055</td>
<td>sbh</td>
<td>7,765</td>
<td></td>
</tr>
<tr>
<td>Sao Tome and Principe</td>
<td>214640</td>
<td>cbh</td>
<td>7,492</td>
<td></td>
</tr>
<tr>
<td>Senegal</td>
<td>20786</td>
<td>cbh</td>
<td>51,506</td>
<td></td>
</tr>
<tr>
<td>Senegal</td>
<td>43142</td>
<td>sbh</td>
<td>564,269</td>
<td></td>
</tr>
<tr>
<td>Senegal</td>
<td>11516</td>
<td>sbh</td>
<td>18,520</td>
<td></td>
</tr>
<tr>
<td>Sierra Leone</td>
<td>11639</td>
<td>sbh</td>
<td>17,032</td>
<td></td>
</tr>
<tr>
<td>Sierra Leone</td>
<td>11661</td>
<td>sbh</td>
<td>344,320</td>
<td></td>
</tr>
<tr>
<td>Sierra Leone</td>
<td>11649</td>
<td>sbh</td>
<td>28,284</td>
<td></td>
</tr>
<tr>
<td>Sierra Leone</td>
<td>76700</td>
<td>sbh</td>
<td>39,257</td>
<td></td>
</tr>
<tr>
<td>Sierra Leone</td>
<td>286773</td>
<td>sbh</td>
<td>28,463</td>
<td></td>
</tr>
<tr>
<td>Somalia</td>
<td>11774</td>
<td>cbh</td>
<td>20,034</td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>105306</td>
<td>cbh</td>
<td>65,741</td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>106684</td>
<td>cbh</td>
<td>62,706</td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>106686</td>
<td>cbh</td>
<td>104,873</td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>43152</td>
<td>sbh</td>
<td>1,799,625</td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>43158</td>
<td>sbh</td>
<td>469,555</td>
<td></td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Type</td>
<td>Population</td>
<td>Source</td>
</tr>
<tr>
<td>--------------</td>
<td>-------</td>
<td>------</td>
<td>------------</td>
<td>------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Sudan</td>
<td>24143</td>
<td>cbh</td>
<td>77,520</td>
<td>Ministry of Health (Southern Sudan), Federal Ministry of Health (Sudan), Southern Sudan Centre for Census, Statistics and Evaluation (SSCCSE), Central Bureau of Statistics (Sudan). Sudan Family Health Survey 2006.</td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Year</td>
<td>Population</td>
<td></td>
</tr>
<tr>
<td>--------------------</td>
<td>-------</td>
<td>-------</td>
<td>------------</td>
<td></td>
</tr>
<tr>
<td>Tanzania</td>
<td>12630</td>
<td>sbh</td>
<td>33,014</td>
<td></td>
</tr>
<tr>
<td>Tanzania</td>
<td>12644</td>
<td>cbh</td>
<td>27,511</td>
<td></td>
</tr>
<tr>
<td>Tanzania</td>
<td>77395</td>
<td>sbh</td>
<td>32,522</td>
<td></td>
</tr>
<tr>
<td>Tanzania</td>
<td>294725</td>
<td>sbh</td>
<td>3,225,395</td>
<td></td>
</tr>
<tr>
<td>Thailand</td>
<td>43231</td>
<td>sbh</td>
<td>213,031</td>
<td></td>
</tr>
<tr>
<td>Thailand</td>
<td>12732</td>
<td>sbh</td>
<td>48,610</td>
<td></td>
</tr>
<tr>
<td>Thailand</td>
<td>148649</td>
<td>sbh</td>
<td>30,853</td>
<td></td>
</tr>
<tr>
<td>The Gambia</td>
<td>3922</td>
<td>sbh</td>
<td>16,875</td>
<td></td>
</tr>
<tr>
<td>The Gambia</td>
<td>3935</td>
<td>sbh</td>
<td>27,475</td>
<td></td>
</tr>
<tr>
<td>Timor-Leste</td>
<td>20888</td>
<td>cbh</td>
<td>17,889</td>
<td></td>
</tr>
<tr>
<td>Togo</td>
<td>12896</td>
<td>sbh</td>
<td>17,832</td>
<td></td>
</tr>
<tr>
<td>Togo</td>
<td>40021</td>
<td>sbh</td>
<td>18,954</td>
<td></td>
</tr>
<tr>
<td>Trinidad and Tobago</td>
<td>12940</td>
<td>sbh</td>
<td>6,445</td>
<td></td>
</tr>
<tr>
<td>Trinidad and Tobago</td>
<td>12950</td>
<td>sbh</td>
<td>6,551</td>
<td></td>
</tr>
</tbody>
</table>

120
<table>
<thead>
<tr>
<th>Country</th>
<th>Code</th>
<th>Type</th>
<th>Population</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turkey</td>
<td>32421</td>
<td>cbh</td>
<td>19,678</td>
<td>Institute of Population Studies, Hacettepe University, Ministry of Health (Turkey), State Planning Organization (Turkey), Turkish Statistical Institute. Turkey Demographic and Health Survey 2008. Ankara, Turkey: Institute of Population Studies, Hacettepe University, Istanbul University, Ministry of Health (Turkey), Turkish Statistical Institute. Turkey Infant and Under-5 Mortality Survey 2011.</td>
</tr>
<tr>
<td>Ukraine</td>
<td>13218</td>
<td>cbh</td>
<td>8,144</td>
<td>Division of Reproductive Health-Centers for Disease Control and Prevention (CDC) and Kiev International Institute of Sociology. (2001) Ukraine Reproductive Health Survey 1999. Atlanta, United States: Centers for Disease Control and Prevention (CDC).</td>
</tr>
<tr>
<td>Country</td>
<td>Code</td>
<td>Type</td>
<td>Population</td>
<td></td>
</tr>
<tr>
<td>---------------</td>
<td>------</td>
<td>------</td>
<td>------------</td>
<td></td>
</tr>
<tr>
<td>Uzbekistan</td>
<td>21039</td>
<td>cbh</td>
<td>11,607</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13445</td>
<td>sbh</td>
<td>26,751</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13465</td>
<td>sbh</td>
<td>6,316</td>
<td></td>
</tr>
<tr>
<td></td>
<td>43412</td>
<td>sbh</td>
<td>1,161,057</td>
<td></td>
</tr>
<tr>
<td></td>
<td>43718</td>
<td>sbh</td>
<td>1,103,904</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13708</td>
<td>sbh</td>
<td>17,570</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13544</td>
<td>sbh</td>
<td>20,964</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13719</td>
<td>sbh</td>
<td>16,447</td>
<td></td>
</tr>
<tr>
<td></td>
<td>43726</td>
<td>sbh</td>
<td>6,004,427</td>
<td></td>
</tr>
<tr>
<td></td>
<td>57999</td>
<td>sbh</td>
<td>18,127</td>
<td></td>
</tr>
<tr>
<td></td>
<td>152735</td>
<td>cbh</td>
<td>15,479</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13795</td>
<td>sbh</td>
<td>54,378</td>
<td></td>
</tr>
<tr>
<td></td>
<td>13816</td>
<td>cbh</td>
<td>17,213</td>
<td></td>
</tr>
<tr>
<td></td>
<td>151325</td>
<td>sbh</td>
<td>54,378</td>
<td></td>
</tr>
<tr>
<td></td>
<td>151326</td>
<td>sbh</td>
<td>602,546</td>
<td></td>
</tr>
<tr>
<td></td>
<td>35493</td>
<td>cbh</td>
<td>768,988</td>
<td></td>
</tr>
<tr>
<td></td>
<td>35493</td>
<td>cbh</td>
<td>602,546</td>
<td></td>
</tr>
<tr>
<td></td>
<td>152720</td>
<td>cbh</td>
<td>32,285</td>
<td></td>
</tr>
</tbody>
</table>
**S3 Table:**

Overall out of sample predictive validity metrics for each age bin and mean direct estimates of $q_a$ across all first administrative unit years.

$q_\text{a}$ = average estimated mortality probability; ME = mean error; SDE = standard deviation of the errors; MRE = median relative error; MAPE = median absolute percentage error; $R^2$ = coefficient of determination.

<table>
<thead>
<tr>
<th>Age-bin</th>
<th>$q_a$</th>
<th>ME</th>
<th>SDE</th>
<th>MRE</th>
<th>MAPE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NN</td>
<td>0.030</td>
<td>0.002</td>
<td>0.010</td>
<td>1.05</td>
<td>20.0</td>
<td>0.53</td>
</tr>
<tr>
<td>PNN1</td>
<td>0.017</td>
<td>0.000</td>
<td>0.007</td>
<td>1.05</td>
<td>26.5</td>
<td>0.62</td>
</tr>
<tr>
<td>PNN2</td>
<td>0.015</td>
<td>0.000</td>
<td>0.007</td>
<td>1.04</td>
<td>29.0</td>
<td>0.66</td>
</tr>
<tr>
<td>1yr</td>
<td>0.015</td>
<td>0.000</td>
<td>0.008</td>
<td>1.06</td>
<td>30.0</td>
<td>0.72</td>
</tr>
<tr>
<td>2yr</td>
<td>0.011</td>
<td>0.000</td>
<td>0.006</td>
<td>0.98</td>
<td>28.7</td>
<td>0.73</td>
</tr>
<tr>
<td>3yr</td>
<td>0.007</td>
<td>0.000</td>
<td>0.005</td>
<td>0.94</td>
<td>31.5</td>
<td>0.61</td>
</tr>
<tr>
<td>4yr</td>
<td>0.004</td>
<td>0.000</td>
<td>0.004</td>
<td>0.92</td>
<td>38.0</td>
<td>0.43</td>
</tr>
<tr>
<td>5q0</td>
<td>0.094</td>
<td>0.002</td>
<td>0.017</td>
<td>1.04</td>
<td>11.8</td>
<td>0.91</td>
</tr>
</tbody>
</table>

**S1 Fig:**

We used our validation framework to compare several model specifications. We tested and compared the following models: (FULL) The full model specification described in the methods section. (INT) All covariates from the full model specified with no smooths, variable interactions in smooths replaced with interaction terms. (ADD) All covariates from the full model, but specified with no smooths or interactions, all variables included additively and untransformed. (TREND) Only the year-SDI smooth included, with no individual covariates. (INDIV) Only the individual-level covariates used, with no year-SDI trend included.

This figure shows metrics of predictive validity for these different specifications. The full model does reliably best across all metrics, with only a few exceptions. Notably, full specification is outperformed in bias (MRE) for several age groups by the interaction only model. The full model generally outperforms all other models. These findings indicate that the predictive gains from using the more flexible (yet complex) GAM approach was appropriate here. The TREND specification does reliably worst across all metrics, indicating that there was value in including individual level time-varying covariates.

From left: MRE, MAPE, and $R^2$. Dashed red lines are the target values for perfect fit for each metric. Note that if metrics for certain specifications are missing, they are outside of the plotted range and can be considered very poorly performing.

Abbreviations: GAM = generalized additive model; MAPE = median absolute percentage error; MRE = median relative error
S2 Fig:

Out of sample predictions of mortality probability compared against loess-smoothed validation data at the first-administrative level. Each point represents an admin1-age mortality estimate ($q_{a,adm1, yr}$) for each held-out survey. Red line indicates unity.
This figure shows estimated out of sample 5q0 trends for the 15 years preceding each survey in the test data, along with trends estimated via the GBD-combined and MAC and TSFB standard indirect methods. 60 of the surveys had GBD-combined estimates available from the GBD mortality database. Trends begin at the year of the survey and go back 15 years or until 1990. Red lines indicate validation data (smoothed with loess, $\alpha = 0.85$).

Abbreviations: GBD = Global Burden of Disease Study; MAC = maternal age cohort; TSFB = time since first birth.
S4 Fig:

The figures (collectively S4 Fig) show estimated out of sample age-specific mortality trends with uncertainty compared to validation data for each country. Surveys used for out of sample validation are labeled with an ‘X’ in Supplementary Table 1.

https://doi.org/10.6084/m9.figshare.7163300.v1

S5 Fig:

The figures (collectively S5 Fig) show trends for each country from the external validation. Trends estimated using the new indirect method for SBH-only data are in blue, direct estimates from CBH surveys are in red. Citations for censuses and surveys used for external validation additional to the training and testing DHS data are listed in S2 Table. Abbreviations: CBH = complete birth history; DHS = Demographic and Health Surveys; SBH = summary birth history.

https://doi.org/10.6084/m9.figshare.7163321.v1

S6 Fig:

For a test of consistency within the external validation, we looked at the overall ratios of mortality rates across age bins of interest. In this figure, we show scatterplots of the relationships between neonatal and under-5 mortality, infant and under-5 mortality, and neonatal and infant mortality across country-year data pairs from contemporaneous SBH and CBH derived estimates. High overall agreement in these ratios adds further support to the predictive validity of this method. Each point is a contemporaneous country-year estimate. Red line indicates unity. Abbreviations: CBH = complete birth history; SBH = summary birth history.
S7 Fig:

Using probability of birth distributions (POB) from the GBD maternal age period (MAP) method has the limitation of being stationary in time. In other words, birth histories are pooled for all mothers from a region with the same CEB, irrespective of year of birth. If distributions changed significantly over time, this could present concern for this analysis. Using the DHS database, we reproduced POB distributions by region, maternal age, CEB, and year of survey (five-year increments).

This figure shows two examples of empirical POB distributions made to explore changes in POB over time. Overall, we found very little change in POB distributions over time for most maternal age groups. The most change has occurred for low-fertility (1-2 CEB) older women, as the distributions seem to indicate there has been a trend toward delayed fertility in this group in recent years. Overall, this group
represents a very small proportion of the mortality exposure in the data. Noisy distributions in high-fertility women are due to low sample sizes. (a) Sub-Saharan Africa West/Central Region plots for women ages 30-31. (b) Asia region for women ages 46-47. A full set of distributions for all maternal ages and regions can be made available by the authors upon request.

Abbreviations: CEB = children ever born; DHS = Demographic and Health Surveys; GBD = Global Burden of Disease Study; POB = probability of birth.

S1 Text:

A brief review of previous approaches to indirect methods for child mortality estimation using summary birth history data:

Several popular methods have been developed to indirectly estimate $5q_0$ and to locate this mortality risk in time. These methods are referenced in detail in the main manuscript and as such we provide a brief review of them here.

William Brass[1] laid the foundation for the first method to convert summary data on the total number of children born and died into a more conventional life-table measure, $xq_0$, or the probability of death before reaching age $x$. Several refinements[2,3] have since been adopted since Brass's original work, which are widely used and well summarized in the UN’s Manual X: Indirect Techniques for Demographic Estimation[4] and by Preston, Heuveline, and Guillot.[5] We refer to this as the standard indirect method.

Data requirements for the standard indirect method are the counts of number of children ever born (CEB) and the number of children died (CD) to mothers in 5-year age groups, beginning with 15-19 year
olds. The ratio of $CD$ to $CEB$ for each maternal age group ($\frac{CD_i}{CEB_i}$) is converted into a child-age ($x$) and period ($t$) specific mortality probability ($q$) using the following two equations:

\[ xq0 = (a_i + b_i \frac{P_1}{P_2} + c_i \frac{P_2}{P_3}) \frac{CD_i}{CEB_i} \]

\[ t(x) = d_i + e_i \frac{P_1}{P_2} + f_i \frac{P_2}{P_3} \]

where $a_i$ through $f_i$ are maternal age cohort specific coefficients estimated via simulation, and $P_i$ are the average $CEB$ for each 5-year maternal age group. Each equation is used for each maternal age cohort, and each maternal age cohort produces estimates of cumulative mortality since birth, $xq0$, for a child age $x$ which is best identified for that age group of women. These estimates are then localized to a reference period $t(x)$, representing the year in which the estimate of $xq0$ most reliably refers.

Estimates of mortality probabilities at specific ages $xq0$ are then converted to $5q0$ using model life tables. By locating risk from each maternal age cohort to one period in time, estimates of $5q0$ for the most recent periods come from mothers in the youngest age groups. These often do not represent overall mortality in the population because mortality to children of younger mothers is often higher.

The fertility ratios $\frac{p_1}{p_2}$ and $\frac{p_2}{p_3}$ used in the standard indirect method serve as an index for the earliness of fertility in the population. Fertility is critical to making accurate indirect estimates because it determines the amount of mortality risk (in time) children born to mothers of certain ages are exposed to. This is why the fertility ratios are multiplied by $\frac{CD_i}{CEB_i}$ in the first equation. By using survey-specific fertility ratios, however, the standard indirect method explicitly assumes that this period measure of fertility represents the fertility experience of all maternal cohorts in the data.

In 2010, Rajaratnam and colleagues[6] proposed a suite of new methods for indirect estimation using summary birth histories. A major advancement brought by their approach was to fit empirical models directly from data rather than relying on simulations. The authors used data from 166 DHS surveys, where $5q0$ could be estimated directly from $CBH_i$, and where aggregate measures of $CD_i$ and $CEB_i$ were also available for the same mothers. The new methods could broadly be categorized on the basis of estimation - either by maternal age cohort (MAC) or maternal age period (MAP). Variants based on time since first birth, rather than maternal age, were also tested, as this information is also available in some censuses.

Following the standard indirect method, the MAC method is also based on aggregate SBH information from 5-year age cohorts of women surveyed to localize $5q0$ estimates in time for each age group. Similar to the standard indirect method, the MAC method utilizes two models, one to estimate $q$ and another to estimate reference time. The equations differ from the standard indirect method in a number of key ways: $\frac{CD_i}{CEB_i}$ is logit transformed, $CEB_i$ is also included as a covariate, fertility ratios are included but not interacted with $\frac{CD_i}{CEB_i}$, and country random intercepts are included. Models are fit directly on DHS data using logit(5q0) as the response, thus removing the need to rely on model life
tables. By modeling cohort-specific $5q_0$ directly, the MAC method resolves the young mother bias, but still relies on young mothers for more recent $5q_0$ estimates and does not make use of information about more recent mortality of children from older mothers.

The maternal age period (MAP) method computes period-derived estimates based on frequency distributions from the same DHS database. Empirical distributions describing the proportion of children born as well as the proportion of children died to mothers in each year preceding the survey are tabulated from CBH data. Separate distributions are produced by maternal age and $CEB$ for each of five global regions. These distributions are then applied to each mother on the basis of her region, age, and $CEB$ in order to project back patterns of mortality risk and fertility likelihood, thus assigning each woman-year prior to the survey an expected number of births and deaths. These expected births and deaths are summed across the survey population by year and regressed on logit($5q_0$) for that year. This generally yields coefficients near 1, indicating close agreement between the imputed annual $\frac{CD}{CEB}$ and observed logit($5q_0$). The MAP method may over-generalize trends over time, since they are taken at the regional level. As such, individual and survey-level variation may not be well captured.

They then use loess smoothing to combine MAP, MAC, and their time since first birth variants to produce a combined result. Estimates resulting from this method are used for the Global Burden of Disease Study. We refer to this as the GBD-combined method. Using smoothed direct estimates from their DHS database as validation, they generally find large predictive improvements over the standard indirect approach, which has since been further verified by others.[7]

More recently Golding and Burstein, et al.[8] developed a method to approximate age-specific binomial samples for their mapping of child mortality in Africa. They again used a large training set of data where both CBH and SBH were available. Their method involved fitting two models, one to estimate a child-age and period-specific mortality probability, $q$, and another for the expected number of child months lived in the surveyed population for a specific child-age and period. Time lag and age indicator variables were used and interacted with logit($\frac{CD}{CEB}$) instead of fitting a separate reference time model in order to localize mortality risk in time, and variables for fertility ratios, year, and maternal age compositions were also included, along with country random effects. Reasonable predictive validity was achieved. Again, this method may also over generalize across time and space, since it relies on lag indicators and global coefficients for the other covariates. Furthermore, the model was fit and predicted on aggregate, rather than individual data.

Several other approaches to indirect estimation have also been described. For example, Kenneth Hill and colleagues [9,10] have proposed the cohort change and birth history imputation methods. The cohort change approach looks at change among true maternal cohorts between two surveys in order to estimate the $5q_0$ for the inter-survey period. The birth history imputation approach involves imputing complete birth histories from summary birth histories, by using complete birth histories from a different survey in the same country and matching based on maternal characteristics. The birth history imputation approach has the benefit of producing age-period specific mortality estimates, though in their preliminary investigations, the authors report disappointing validation results.
References


Chapter 3: Geographic accessibility and utilization of facility-based care in Zambia: a geostatistical analysis

Background

Understanding who accesses healthcare, why, and for what type of services is critical for planning health systems, which ultimately ought to be responsive and available to all potential users. Patterns of utilization can be used to identify differences in treatment seeking among key populations or geographic areas. In certain cases, differences in utilization rates can result in diverging health trajectories, thus reinforcing health inequalities. In practice, a better understanding of healthcare utilization can be used to more efficiently target allocation of resources to health facilities, and to improve burden estimation via linked health facility information systems, where for example passive surveillance can miss a large proportion of cases, especially those occurring further away.

Numerous studies have investigated the determinants of utilization. The healthcare utilization model developed by Andersen posited that specific factors ultimately determine utilization; these include “predisposing” factors, or characteristics viewed as less mutable, such as race and age; “enabling” factors, or potential drivers and constraints to utilization, like insurance affiliation and travel time to health facilities; and need for healthcare. Empirical studies often aim to quantify the effects of various utilization determinants using multiple regression. In particular, assessments of geographic accessibility – the physical distance or travel time between a user and health services – have consistently shown a negative relationship between greater distance or travel time and healthcare utilization. In many African countries, this relationship exists to some degree across a variety of healthcare services, including deliveries and antenatal care, preventative services such as vaccinations, HIV services, and treatment for acute illnesses in children. A number of studies have also shown that distance to care is a strongly associated with morbidity and mortality outcomes.

Several studies have attempted to exploit the strong association observed between distance to health services and utilization in order to predict utilization rates across geographic areas. One notable example is a study by Alegana and colleagues, wherein the authors combined household location and healthcare seeking behavior for febrile children from a Namibian Demographic and Health Survey (DHS) with a theoretical surface of travel to health facilities. These data were then used to fit curves representing the decay in utilization over travel time. Using the fitted distance decay function and the theoretical surface of travel times, they predicted out a gridded surface representing the probability of attendance in facilities by febrile children. Similar procedures were recently used to produce gridded surfaces of ANC attendance in the Lake endemic zones of Kenya. Other studies used theoretical surfaces of travel times to describe geographic accessibility to essential surgery and emergency care across sub-Saharan Africa, as well as geographic accessibility to primary care in single countries such as Mozambique and South Sudan.

Efforts to quantify the relationship between distance and utilization and then predict utilization rates onto gridded geospatial surfaces have been subject to considerable data and methodological limitations. For instance, researchers have often resorted to using approximate measures of household and
population locations with respect to health facilities. There are several reasons for this. First, most countries do not have a fully geo-referenced census of health facilities. Second, when georeferenced data are collected, GPS coordinates of households are often ‘jittered’ up to ten kilometers to support confidentiality; this is particularly common for publicly available data sets such as the DHS, which is commonly used in this type of analysis. Despite knowledge of this jittering, extant studies have generally treated scrambled GPS coordinates as if the measurements are true and without introduced error. Furthermore, geographic accessibility, defined as the distance or travel time to healthcare, is sometimes measured using straight-line distance, which is likely an over-simplified model of human mobility as it ignores networked paths and roads and barriers to movement.

Studies that model utilization geographically are often univariate, viewing travel time as the only determinant and not accounting for other potentially important drivers or confounders. Past analyses generally focus on one condition (eg, childhood malaria or suspected malaria), which results in discarding potentially useful data on other conditions. Furthermore, most studies are limited to subnational areas and thus do not map utilization across an entire country. To date, no analyses have utilized a full probabilistic geostatistical model to account for correlated spatial residuals; instead, they have relied exclusively on one or more covariates. Finally, we are not aware of any studies that report uncertainty in their gridded predictions of utilization, making it impossible assess the utility of these predictions.

Since 1990, Zambia has made marked progress in increasing the coverage of many maternal and child health interventions and improving rates of childhood survival. Nonetheless, national levels of under-5 mortality still exceeded 59 per 1,000 livebirths in 2016, wherein malaria and diarrhea accounted for 18% of child deaths and 10% of total national disease burden that year. Health service delivery is largely dominated by the public system: about 90% of patients who seek care do so in government-run facilities. Improving access to primary healthcare is a priority for the Ministry of Health, which as a stated mission “to provide equitable access to cost-effective, quality health services as close to the family as possible.” In 2011, the government abolished user fees for all services in primary healthcare facilities, and patients should expect free curative services for malaria and diarrhea at all levels of care. Despite this, potential barriers to healthcare utilization at facilities remain, including transportation cost and perceived poor quality. Previous studies have found associations between utilization with a number of predisposing, enabling, and need factors, including distance to care, educational attainment, and reported health status.

In this study, we sought to overcome limitations in accessibility and utilization mapping using a triangulation of data sources from Zambia in order to answer three main questions: First, what is the status of geographic accessibility to health facilities in Zambia? Next, how does travel time to nearest health facility affect utilization rates? And finally, can we make a reasonable map of utilization rates using a geostatistical model?

Using a census of health facility locations, we first quantified geographic accessibility as travel time to nearest health facility across Zambia at a resolution of 1 x 1-kilometer (km) pixels. Then, based on household survey data with precise locations, we developed a geostatistical model, leveraging individual and household covariates and a flexible non-linear distance decay function, to simultaneously predict the probability of healthcare utilization for a number of different types of illness episodes for each 1 x 1-
km pixel in Zambia. We compared our mapped predictions to those made using a method from the literature. We used the results from our geostatistical model to better understand individual determinants of healthcare utilization, with a particular focus on the effect of geographic accessibility. Finally, we combined our predicted gridded surfaces with similarly resolved estimates of incident cases of diarrhea to approximate unmet need for corresponding healthcare services at the population level.

Data
Utilization

Utilization data came from the 2014 Zambia Household Health Expenditure and Utilization Survey (ZHHEUS), a nationally-representative two-stage household sample survey conducted by the Zambian Central Statistical Office, with support from the Ministry of Health and the Department of Economics at the University of Zambia. The ZHHEUS included 11,944 households and 59,514 individuals surveyed from January to March 2014. Respondents or their proxies answered a number of demographic, economic, and health questions, including those focused on subjective health status and presence of acute or chronic illnesses. Specifically, respondents were asked whether they were ill within the past four weeks, and if so, what type of illness and symptoms they experienced and whether they sought care from a health provider. For this paper, we focus specifically on reported fever, malaria, and diarrhea, but indicators for 18 illnesses plus a free-response were recorded. Since we focus specifically on treatment in facilities, we coded responses claimed to have sought care at pharmacies, religious healers, herbalists, and from community health workers as not seeking care in a health facility. In total, these responses comprised less than 5% care sought by ill people.

We combine reported malaria and fever into one category for “febrile illness”. Given high endemicity in much of Zambia, we can assume that many of these reported malaria/fever episodes were indeed malaria. Since the survey asked about a combination diseases and symptoms, it is difficult to assess the degree to which respondents could have known if they had truly had malaria. Henceforth, for brevity, we refer to this measure of fever and/or malaria as febrile illness in this manuscript.

To enable geo-positioning of households and utilization in relation to health facilities, we used exact GPS locations as recorded by ZHHEUS interviewers. All households in the data had GPS data.

Health facility locations

We triangulated multiple health facility data sources in an effort to approach data coverage of all health facilities. Our goal was to produce a complete georeferenced listing of health facilities in the country. First, we used the Ministry of Health’s 2012 List of Health Facilities in Zambia as a baseline list \((n = 1,956)\). Since this facility list lacked GPS coordinates, we merged this dataset with facility and GPS information provided by the 2005-2006 Zambia Health Facility Census. We also supplemented these data with an unpublished list of geo-located facilities provided by the Zambian Central Statistical Office; facility coordinates from the 2011-2012 Access, Bottlenecks, Costs, and Equity (ABCE) facility survey; and publically-available location data from www.zaplaces.com and www.facebook.com for any other facilities without GPS information. Last, if ZHHEUS respondents reported visiting facilities that were not
included in the master list, we appended these facilities to the master list and sought to link corresponding GPS information to those facilities.

This effort resulted in a final list of 2,020 facilities, 85% of which (n = 1,726) could be geo-located. Of the facilities missing GPS coordinates, 55% (n = 155) were marked with certainty as urban clinics. Urban areas have a higher density of facilities and so we expect their missingness to have minimal effects of estimates of travel time to nearest health facility.

Surface of theoretical travel times to health facilities

We constructed a 30 arc second (1x1 km at the equator) resolution gridded surface of theoretical travel times to the nearest health facility, wherein each pixel represented the amount of time it would take to travel from it to the nearest health facility. As a basis for a realistic and validated model of mobility, we used the global friction surface developed by Weiss and colleagues. The friction surface generically quantifies the time it takes to travel across a pixel. Data on road networks were merged with geospatial layers representing land cover and elevation and then scaled by estimated travel times across these different surfaces. With the facility locations as inputs, and using an accumulated cost algorithm based on Dijkstra's algorithm, we calculated the travel time from each pixel in the friction surface to its nearest health facility. The result was a gridded surface of theoretical travel times to health facilities. Finally, we extracted the travel time values at each household location using recorded GPS readings from ZZHEUS.

Other geographic layers

We accessed several geographic data layers, representing incidence rates of diarrhea, under-5 and total population counts, and urban extents for each 1x1 km pixel in Zambia.

Gridded layers for incidence of diarrhea in children under-5 have been produced by the Institute for Health Metrics and Evaluation at the 5x5 km resolution. We used candidate maps representing 1000 draws from the posterior predictive distribution in order to propagate uncertainty in estimates of incidence rates. We disaggregated each pixel-draw to match the 1x1 km resolution of this analysis. Incidence rates were used in combination with gridded population data of under-5s to estimate cases per pixel. The WorldPop project provides population count estimates for children under 5.

We also produced a map which classified ‘urban extents’ by matching urban classification in the ZHHEUS data. We extracted data from the Global Human Settlement Layer project and log-transformed total population from WorldPop for each household in the ZHHEUS data and fit a logistic regression on whether the household was considered urban in the sample. The area under the receiver operating characteristic curve was 0.93, indicating a very good fit. A resulting surface representing the probability each pixel is urban was used for prediction from the geostatistical utilization model described in the next section.
Ethical approval

Ethical approval was granted by the University of Washington Human Subjects Division IRB (#51398: “Estimating Spatial Patterns in Health Care Utilization in Zambia”).

Methods

Statistical model

We developed a statistical model representing the probability that an individual, given illness in the past four weeks, would seek care from a health facility. With this model, we had the dual goal of making inference on the effects of certain covariates on treatment seeking, as well using it to ultimately predict a surface representing utilization rates. We first subset the ZHHEUS data to the 13,150 (22% of total) respondents who reported having an illness in the past four weeks. The choice to seek treatment at a health facility was then encoded as a binary choice variable $Y_i$, with 0 representing not seeking care and 1 representing that the respondent did seek care. We then modeled the choice to seek in-facility treatment for individual $i$, living in household $j$, from location $k$ as a Bernoulli random variable with probability $p_{ijk}$, where $p_{ijk}$ represents the individual probability of seeking healthcare. The logit transformation of $p_{ijk}$ was further modelled a linear combination of individual and household level covariates, and structured and unstructured random effects. The model can be written as:

$$Y_{ijk} \sim Bernoulli(p_{ijk})$$
$$\text{logit}(p_{ijk}) = \alpha + f(tt_j) + \text{ill}_F \beta_m + \text{ill}_O \beta_d + X_i \beta_i + X_j \beta_j + U_j + S_k$$
$$U_j \sim \text{Normal}(0, \sigma^2_j)$$
$$S_k \sim \text{GP}(0, K)$$
$$f(tt_j) = \sum_{b=1}^{n} \beta_b X_b$$
$$\beta_b \sim N(\beta_{b-1}, \sigma^2_b)$$

where $f(tt_j)$ is the sum of cubic spline basis functions on travel time to nearest health facility, which comprises the distance decay function. We placed spline knots at 0.02, 0.05, 0.15, 0.31, 0.76 hours, corresponding to the 16.7%, 33.3%, 50%, 66.7% 83.3% quantiles of the data, respectively. We placed additional knots at 1.5 and 2.5 hours in order to increase coverage in more remote locations. A boundary knot, beyond which the function would be forced to be linear, was placed at 4.6 hours, the most remote household observed in the data.

A number of covariates were selected in order to capture the individual and household level predisposing factors, enabling factors, and needs which could lead to treatment seeking. $\text{ill}_F$ and $\text{ill}_O$ are binary indicators for whether the respondent reported a febrile illness nor any illness other than diarrhea or a febrile illness, respectively. Reported diarrhea was used as the reference category. $X_i$ are individual-level covariates including an indicator for whether or not the observation was for a child under the age of five, and an indicator for female sex. ZZHEUS did not ask about illness severity, so instead we used an indicator for whether or not the respondent claimed to have more than one illness in the past four weeks. $X_j$ are household-level covariates. We used the log household expenditure per
capita as an indicator of household wealth. As a sensitivity analysis, we also tried an asset index, and found our results were robust to both specifications, and chose to use expenditure to keep our specification similar to a previous analysis of this dataset. We included an indicator for whether or not the head of the household had ever been to school, and finally an indicator for whether the household was in an urban area.

Our model also included two random effects. \( U_j \) is a random effect for each household, meant to capture variation not explained by the covariates. We attempted to also include a cluster-level random effect, but found model identifiability issues if both a household and cluster level random effect were kept. \( S_k \) is a spatially correlated random effect term, modeled as a Gaussian process with covariance matrix \( K \), which was structured using the Matérn covariance function. Sample weights from the survey were used to weight the contribution of each observation in the log-likelihood.

First order random walk priors were used to penalize spline bases in order to impose smoothness. Imposing this structure on spline smoothness allowed us to use a larger number of bases functions while avoiding overfitting. The standard deviation of the household random effect, \( \sigma^2_j \), had a \text{gamma}(1,1)\ prior. Priors for the hyper-parameters of the Matérn covariance function were \( \log(\tau) \sim \text{Normal}(0,0.9) \) and \( \log(\kappa) \sim \text{Normal}(0,0.9) \). All fixed effects coefficients which were not spline bases had zero mean normal priors with a standard deviation of 10.

The model was fit using Template Model Builder package in R version 3.5.1. Maximum a posteriori inference was implemented using a non-linear optimizer. Within this framework, the spatial effects were fitted using the stochastic partial differential equation (SPDE) approximation on a finite elements mesh, with maximum edge lengths set to 0.05 degrees (see Supplementary Figure 1). Uncertainty in predictions was calculated using 10,000 multivariate normal draws from the fitted joint precision matrix across all model parameters.

We used draws of the fitted model parameters to construct gridded prediction surfaces wherein each pixel represented the individual probability of seeking healthcare for either febrile illness or diarrhea in children. Individual level covariate values which were not used in mapping were integrated out using a Monte Carlo approach by drawing randomly with replacement from their observed joint distributions in the data. Certain covariates were set to specific values for prediction. For example, to predict a map of utilization given childhood diarrhea, we set the under-5 indicators to one, and the febrile illness and other illness indicators to zeros. Furthermore, since we had a map of urbanicity with values for each location, those mapped values were used for prediction.

Model comparison

In order to compare our model with previous methods, we applied the method used by Alegana and colleagues to the ZHHEUS data. In their paper, the authors used a theoretical travel time surface as a univariate predictor of utilization. The distance decay curve was assumed to take the following form:

\[
\text{Prob}(\text{Utilization}) = \frac{C}{1 + e^{\frac{A - \text{travel time}}{B}}}
\]
where $A$, $B$, and $C$ are parameters to be fitted. Using data subsets for children under-5 with either febrile illness or diarrhea, we fitted two curves based on this method by minimizing the sum of squared errors in each sample. We compared predictions against those from our model using receiver operating characteristic (ROC) curves.

**Results**

Table 1 reports basic descriptive statistics for the respondents who reported an illness in past four weeks in the ZZHUES data. Of the 59,514 people surveyed, 13,150 (22%) reported an illness, and are included in Table 1. Of those reporting an illness 7,566 (58%) sought care from a health facility during that time. Of the 2164 children under 5 who were ill in the preceding four weeks, 1387 (64%) had a reported case of fever or malaria and 357 (17%) had a reported case of diarrhea. In total those with febrile illness and diarrhea collectively comprised 75% of all reported childhood illnesses. Of those children with febrile illness 925 (66%) sought care at a facility, while 224 (63%) of those with diarrhea sought care.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Mean</th>
<th>$N$ or (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sought care from health facility</td>
<td>57.5%</td>
<td>7566</td>
</tr>
<tr>
<td>Travel time to nearest health facility</td>
<td>0.4</td>
<td>(0.6)</td>
</tr>
<tr>
<td>Illness: Diarrhea</td>
<td>7.6%</td>
<td>1002</td>
</tr>
<tr>
<td>Illness: Febrile</td>
<td>52.9%</td>
<td>6962</td>
</tr>
<tr>
<td>Ln(HH expenditure per capita)</td>
<td>4.1</td>
<td>(1.6)</td>
</tr>
<tr>
<td>Younger than 5</td>
<td>16.5%</td>
<td>2164</td>
</tr>
<tr>
<td>Urban residence</td>
<td>30.9%</td>
<td>4063</td>
</tr>
<tr>
<td>Female</td>
<td>54.3%</td>
<td>7145</td>
</tr>
<tr>
<td>&gt;1 reported illness</td>
<td>35.4%</td>
<td>4651</td>
</tr>
<tr>
<td>Head of HH any schooling</td>
<td>88.9%</td>
<td>11,695</td>
</tr>
</tbody>
</table>

Table 1: Descriptive table of variables used in the regression model. Data was subset on those who had an illness (13,150). For binary variables, we report the percentage and number reporting. For continuous variables (Ln(Household expenditure per capita) and Travel time to nearest facility), we report the mean and standard deviation in the sample. There were no missing values for any of the variables used.

**Geographic accessibility**

Figure 1A shows the 1 x 1-km gridded surface of travel times to Zambian facilities, overlaid with health facility locations. Travel times in Zambia ranged from 0 minutes (in grid cells with health facilities), up to 13.5 hours. As expected, travel time across Zambia was unevenly distributed; for instance, travel time was lowest along roads, since travel speeds were assumed to be much faster on roads. To better understand how travel times are distributed among the population, we extracted travel times at all ZHHEUS survey locations, giving us estimates of travel time to healthcare from each household in the survey data. We also overlaid the same travel time surface with matching pixel-level estimates of total population from WorldPop. Figure 1B shows the cumulative population distributions across travel time.
as measured by both of these population data sources. We found that 97.7% of the weighted ZHHEUS sample lived within 2 hours of the health facility. This differed significantly from estimates produced using pixel-level population data from WorldPop, wherein 88.7% of the population lived within 2 hours of a facility and 97.7% lived within 4.5 hours from a health facility. Using the WorldPop surface, we calculated the average travel time to the nearest health facility throughout Zambia to be 45 minutes, while using the ZZHEUS sample, the average estimated time was 19 minutes.

![Figure 1. The map in (A) represents the gridded surface of theoretical travel times to the nearest health facilities, with all georeferenced health facilities indicated with white dots. (B) shows the cumulative population by distance to nearest health facility. The black line represents the cumulative weighted population from ZHHEUS, while the green line represents the cumulative weighted population from the WorldPop gridded population dataset.](image)

Determinants of treatment seeking

Table 2 presents results from the geostatistical logistic regression. Results were largely in line to those reported by a previous analysis of this dataset, with one key difference. All else equal, the odds of seeking care for febrile illness was 59% (95% uncertainty interval: 30%-95%) higher than that for diarrhea. The odds of seeking care were much higher for children under-5 (OR = 1.67, 1.48-1.89) relative to anyone older than 5, and for females (OR = 1.10, 1.01-1.21) relative to males. Having a household head with any education was associated with a 42% (22%-64%) higher odds of treatment seeking. Having multiple ailments also significantly increased the odds of seeking care. Furthermore, household expenditure had little measurable effect on treatment seeking (OR=1.01, 0.97-1.04). Interestingly, urban residence was significantly negatively associated with care seeking relative to rural residence (OR = 0.77, 0.63-0.93). In a sensitivity model run without travel time, the effect was positive. This indicates that urban residence could stand as a proxy for geographic accessibility, but that controlling for accessibility reveals a possible structural negative association. Variance inflation factor tests did not indicate that this was a spurious result due to multicollinearity (VIF < 2).
The fitted spatial hyper-parameters guiding the Matérn covariance function of the Gaussian process indicate that, after accounting for these covariates, some local spatial correlation remained; that is, 90% of the residual spatial correlation was diminished within 0.74 (0.50-1.07) decimal degrees. Supplementary figure 4 provides density plots of the priors and posteriors of the model hyper-parameters.

<table>
<thead>
<tr>
<th><strong>Fixed effects</strong></th>
<th><strong>OR</strong></th>
<th><strong>95% UI</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.05</td>
<td>0.72-1.52</td>
</tr>
<tr>
<td>Travel Time</td>
<td></td>
<td>&lt; sum of bases functions &gt;</td>
</tr>
<tr>
<td><strong>Diarrhea</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Febrile Illness</td>
<td>1.59</td>
<td>1.30-1.95</td>
</tr>
<tr>
<td>Other Illness</td>
<td>1.23</td>
<td>1.01-1.51</td>
</tr>
<tr>
<td>ln(HH expenditure/person)</td>
<td>1.01</td>
<td>0.97-1.04</td>
</tr>
<tr>
<td><strong>Older than 5</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 or younger</td>
<td>1.67</td>
<td>1.47-1.89</td>
</tr>
<tr>
<td><strong>Rural residence</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban residence</td>
<td>0.77</td>
<td>0.63-0.93</td>
</tr>
<tr>
<td><strong>Male</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>1.10</td>
<td>1.01-1.21</td>
</tr>
<tr>
<td><strong>Head of HH no schooling</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Head of HH some schooling</td>
<td>1.42</td>
<td>1.22-1.64</td>
</tr>
<tr>
<td><strong>1 reported illness</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;1 reported illness</td>
<td>1.31</td>
<td>1.19-1.44</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Hyper-parameters</strong></th>
<th><strong>median</strong></th>
<th><strong>95% UI</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>SD of P-spline Random Walk</td>
<td>0.20</td>
<td>0.10-0.40</td>
</tr>
<tr>
<td>SD of HH Random Effect</td>
<td>0.45</td>
<td>0.35-0.57</td>
</tr>
<tr>
<td>Matern Range (Degrees)</td>
<td>0.74</td>
<td>0.50-1.07</td>
</tr>
</tbody>
</table>

Table 2. Fitted parameter estimates from the geospatial regression model. Fixed effects coefficients have been transformed into odds ratios. Covariates in italics are reference levels and thus do not have coefficient estimates.

Effect of travel time on utilization

Figure 2 shows the predicted marginal distance decay curves from the fitted smoothing splines representing the effects of travel time on utilization. We held other model covariates at average values such that the decay curves represented the expected response on treatment for the hypothetical average person in our data. We held illness indicators constant such that we could produce marginal smooths for diarrhea and febrile illness independently.
The probability of utilization declined quickly between 0 and 60 minutes from a health facility, and continued to decline less rapidly thereafter. This quick initial decline in utilization goes contrary to distance decay curves published in the literature, which do not typically drop off quickly.\textsuperscript{21,25,35,64} Due to data sparsity of households located farther than 3 hours from a facility, uncertainty increased substantially beyond this threshold, to the extent that distance decay curves for febrile illness and diarrhea largely overlapped after 3 hours’ distance.

The inset plot shows a close of the first five hours from the nearest health facility. Points indicate empirical estimates of utilization from the ZHHEUS data for febrile illness and diarrhea in red and blue, respectively across bins of travel time. This indicates that this quick drop-off is supported by the data. The empirical estimates also indicate that decay functions for the two conditions of interest do indeed appear to be proportional to each other, thus supporting the modelling choice of pooling data across conditions and using intercept shifts, rather than independent smooths, to represent different utilization rates across them.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Marginal smooth curves representing the distance decay curves, or the effect of increasing travel time on probability of seeking care. Separate curves are drawn for diarrhea and febrile illness. Other covariates were set at their means. Shaded areas represent the 95% uncertainty interval. Black spikes across the x-axis represent travel time values of the input data.}
\end{figure}

**Utilization mapping**

Figure 3 shows the predicted utilization surfaces with uncertainty for febrile illness. The values of each grid cell represent the expected probability that a given individual residing within a grid cell will seek care. The map of utilization given diarrhea look very similar to febrile illness, except with lower utilization due to the intercept shift in the model (see Supplementary Figure 2). Higher utilization was generally found in places with lower travel times, as the influence of travel times is evident in this map. Though the uncertainty interval around prediction utilization rate was generally narrower in more populated areas, uncertainty remained fairly high across the country. Higher confidence in predictions in populated areas was due to the combined effects of the increased certainty in the fitted Gaussian process random effects where data were available and because remote and less populated areas
experienced high travel time values which were not available in the ZHHEUS data that the model was fit on. For instance, the average width of predicted grid cell uncertainty intervals across Zambia was 0.49, but this value narrowed to 0.19 when population was taken into account in the averaging.

Figure 3. Maps of median prediction and 95% uncertainty interval for probability of utilization in children with febrile illnesses. For similar maps of diarrhea utilization, see Supplementary Figure 2.

Population metrics

To translate what these utilization measures could mean at the population level, we multiplied the gridded estimates of diarrhea utilization rates with incidence rates and with population counts for children under-5. This calculation produced gridded surfaces of numbers of diarrhea episodes that did not seek healthcare. At the national level, the facility-based utilization rate for diarrhea episodes in children under-5 was 51% (95%UI: 40%-60%). The estimated number of diarrhea cases seen at a health
facility was 4.1 million (3.2 million – 5.1 million), while the number not seen at a health facility was estimated at 3.3 million (2.5 million – 4.2 million). Table 3 shows these numbers aggregated to provincial level. While uncertainty is high, there is some discernable subnational variation in utilization rates. For example, in Northern province, for each diarrhea case seen at a health facility 1.6 [1.5-1.7] do not seek treatment at a facility. While in Eastern province, for each case that does not seek treatment at a health facility, 1.9 (1.8-2.1) do go to a health facility, indicating a three-fold difference in utilization between the two provinces.

<table>
<thead>
<tr>
<th>Province</th>
<th>Cases Utilized</th>
<th>Cases Not Utilized</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
<td>95% UI</td>
</tr>
<tr>
<td>Central</td>
<td>361,958</td>
<td>[264,858 - 474,133]</td>
</tr>
<tr>
<td>Copperbelt</td>
<td>587,154</td>
<td>[443,751 - 763,061]</td>
</tr>
<tr>
<td>Luapula</td>
<td>301,870</td>
<td>[218,785 - 402,398]</td>
</tr>
<tr>
<td>Lusaka</td>
<td>653,520</td>
<td>[490,128 - 855,856]</td>
</tr>
<tr>
<td>Muchinga</td>
<td>238,682</td>
<td>[175,600 - 313,668]</td>
</tr>
<tr>
<td>North-Western</td>
<td>203,877</td>
<td>[145,914 - 268,963]</td>
</tr>
<tr>
<td>Northern</td>
<td>273,801</td>
<td>[194,050 - 367,971]</td>
</tr>
<tr>
<td>Southern</td>
<td>509,452</td>
<td>[384,247 - 651,528]</td>
</tr>
</tbody>
</table>

Table 12: Estimated number of diarrhea cases which did and did not utilize healthcare across the 10 Zambian provinces in 2015.

Comparison with prior method for utilization mapping

In our replication of the method used by Alegana and colleagues, we estimated the parameters of the logistic curve A, B, and C to be 6.9, -1.8, and 0.8 and 5.9, -1.7, and 0.8 for febrile illness and diarrhea, respectively. Similar to the modeled smoothing splines, these curves declined immediately before starting to flatten out (see Supplementary Figure 3). The distance decay curves modelled from ZHHEUS data fundamentally differed from most other published curves, which typically decay slowly at first before dropping off quickly. Figure 4 shows that comparison of ROC curves for febrile illness and diarrhea between our model and the method described in Alegana and colleagues. Area under the curve (AUC) for the median estimate from our model was 0.74 febrile illness and 0.73 for diarrhea, while AUCs using the approach by Alegana and colleagues were 0.57 and 0.60. ROC curves shown in figure 4 from our model were plotted for each draw from the posterior. Despite the uncertainty in our estimates, there were no draws from our model with lower AUCs than those produced using Alegana and colleagues’ approach.
Figure 4. Receiver operating characteristic (ROC) curves for febrile illness and diarrhea. Colored curves are from 10,000 estimated draws from our model. Black curves are produced using the method from Alegana et al.

Discussion

In this analysis, we generated the most comprehensive geo-located dataset of Zambian health facilities, and used these data in combination with geospatially resolved layers of travel time and household information on utilization to generate a maps of healthcare access and utilization patterns in Zambia. Our results provide an update to the last national estimate of geographic accessibility conducted by Moise and colleagues, which was based on a listing of 568 facilities in 2002 and estimated that 62% of the population lived within 15 km of a health facility.

We found that a large proportion of the Zambian population lives relatively close to facility care, but that small differences in travel time within the first hour from a health facility seem to impact utilization rates more than those same differences in distances for households that are further away from health facilities. Both findings go contrary to common perceptions, but have some support from a recent cross-country study by Karra and colleagues. While a non-linear distance decay curve has been modelled in the past, the shape is typically concave – declining slowly at first then more rapidly – rather than the convex shape we observed. One possible explanation for this difference is the random ‘jittering’ of GPS coordinates used in previous studies.

Other factors associated with increased utilization were largely consistent with previous studies in sub-Saharan Africa and included higher education, female sex, younger age. Interestingly though, we found that, when controlling for travel time, urban residence was negatively associated with utilization. This indicates that models that do not control for travel time and see a positive relationship with urban residence could be picking up a proxy effect of urban as representing geographic accessibility. Our
analysis indicated that, holding accessibility constant, there was a systematic tendency for less facility-based care in urban areas. More research is needed to better understand this phenomenon in the Zambian setting.

It is important to emphasize that this study focuses specifically on facility-based healthcare utilization. Our intention was to measure this phenomenon, not to make claims on whether care ought to be sought health facilities in all cases. In certain cases, people may seek effective care outside of health facilities. For example, diarrhea can be treated with for oral rehydration solution stocked at home from previous healthcare visits, interactions with community health workers, and informal shops or privately owned pharmacies.

By combining information on travel times and household survey data, we offer the first-ever application of model-based geostatistics for healthcare utilization mapping. While the present analysis focuses on febrile illness and diarrhea in children as a use case, our method and underlying geostatistical framework could readily accommodate for estimation of utilization for other conditions, pending data collection and availability on a broader set of conditions. Accessibility to health facilities for each household were independently measured using a combination of precise GPS readings and the gridded surface of theoretical travel times, and thus did not rely on self-report. By estimating healthcare utilization in a joint probabilistic model, we could quantify uncertainty in our mapped estimates, an endeavor that has not been reported in previous work. Our study indicates that spatially resolved estimates of utilization were difficult to achieve with any practical degree of certainty, despite showing predictive performance improvements over previous models. These findings emphasize how the complex factors associated with the decision to seek care in a health facility go far beyond geographic accessibility or other geographic factors. As the science of utilization mapping evolves and improves, researchers should provide uncertainty estimates as to more transparently communicate the strength (or lack thereof) of evidence provided by these types of analyses.

This research also uncovered a disagreement between the implied population distribution from the representative sample of ZHHEUS and gridded population data from WorldPop. Depending on source population data, 75% to 92% of the country’s residents live within an hour of a health facility. This is despite the fact that both sources utilize the 2010 census as either a basis for sampling or estimation. It is currently unclear the extent to which this difference is due to an under-sampled (and under-weighted) rural population in ZHHEUS or an over-allocation of rural population in the gridded WorldPop surface. This discord has practical implications for health planners in Zambia who aim to provide ‘services as close to the family as possible,’ whereas based on these two sources, at a national level it is unknown whether 25% or 8% of the population which lives further than an hour from healthcare.

By further combining utilization rate estimates with spatially resolved estimates of disease incidence to estimate cases unseen by healthcare, we provide an important use case of utilization mapping. Results from this geospatial approach could in theory be used to give public health planners a better sense of where these unseen cases are likely to be found. Future research should focus on the application of utilization mapping as a possible approach to adjusting under-reporting of cases in administrative data sources such as DHIS2.

Limitations and future research directions
The results of this study should be interpreted in light of several important limitations.

We needed to make simplifying assumptions due to a number of data limitations. First, our analysis was limited to an analytical resolution of 30 arc-seconds (approximately 1 x 1-km) due to the available resolution of the input friction surface,\(^5\) implying that all travel within a pixel was treated as homogenous. Second, ZHHEUS provided limited data on remote households, and as a result the distance decay functions beyond 2 hours had high uncertainty. While this likely represents a small proportion of the population, it is also a particularly vulnerable one. Third, we assumed that self-reported illness episodes correctly captured illness experiences in the population. This could bias results, if, for example, respondents tended to report they had malaria only if they were diagnosed at a clinic, thus artificially increasing the utilization rates for febrile illness in our analysis. Furthermore, due to a lack of information about episode severity in the ZHHEUS questionnaire, we assumed a homogenous distribution of severity across the population. In an ideal model we would account for known effect modification in the distance decay function due to severity of illness.\(^5\) Finally, utilization patterns were measured as part of a cross-sectional survey during what is usually considered the rainy season in Zambia, potentially affecting physical access due to flooding, and/or incurring atypical utilization rates as related to heightened risk for illnesses like malaria and diarrhea.

We assumed that distance to nearest health facility accurately operationalizes geographic accessibility in all cases. For some people, a nearby health facility may not be effectively accessible to due to poor perceived quality, wait times, or stigma. These are important potential gaps in access to healthcare which should be considered in future utilization mapping work.

Finally, spatial covariates could help improve accuracy and precision of predictions in future utilization, assuming that covariates of interest in fact vary spatially. In this analysis, we had the dual goal of inference and prediction. In lieu of making valid inference on the effect of covariates, it could be possible to produce improved geospatial predictions. For example, a spatial layer on maternal education\(^6\) would likely be highly predictive of utilization, but itself was constructed from a model which relied heavily on travel times as a covariate, thus introducing strong multicollinearity into the model. Furthermore, error-in-covariate models should be considered when dealing with uncertain spatial covariates.

**Conclusion**

While at least three quarters of Zambians live within an hour of a health facility, we found that small differences in travel time to healthcare are independently associated with large declines in utilization rates within the first hour. The decision to seek care at a health facility is a complex process that is not easily reduced to geography. As such, a univariate model based solely on geographic accessibility is not sufficient for accurate prediction of utilization across a gridded surface. Improved prediction using a probabilistic model is possible but uncertainty remains high.
References


47. MOH. The 2012 List of Health Facilities in Zambia. (Zambia Ministry of Health).


Supplementary Information for Chapter 3

Supplementary Figure 26: Finite elements mesh used to make approximate inference on the Gaussian process random effects.
Supplementary Figure 27: Maps of median prediction and 95% uncertainty interval for probability of utilization in children under 5 with diarrhea.
Supplementary Figure 28: Distance decay curves for febrile illness (red) and diarrhea (blue) in children under 5 using the method in Alegana et al.

Supplementary Figure 29: Density functions of priors and posteriors of model hyper-parameters.