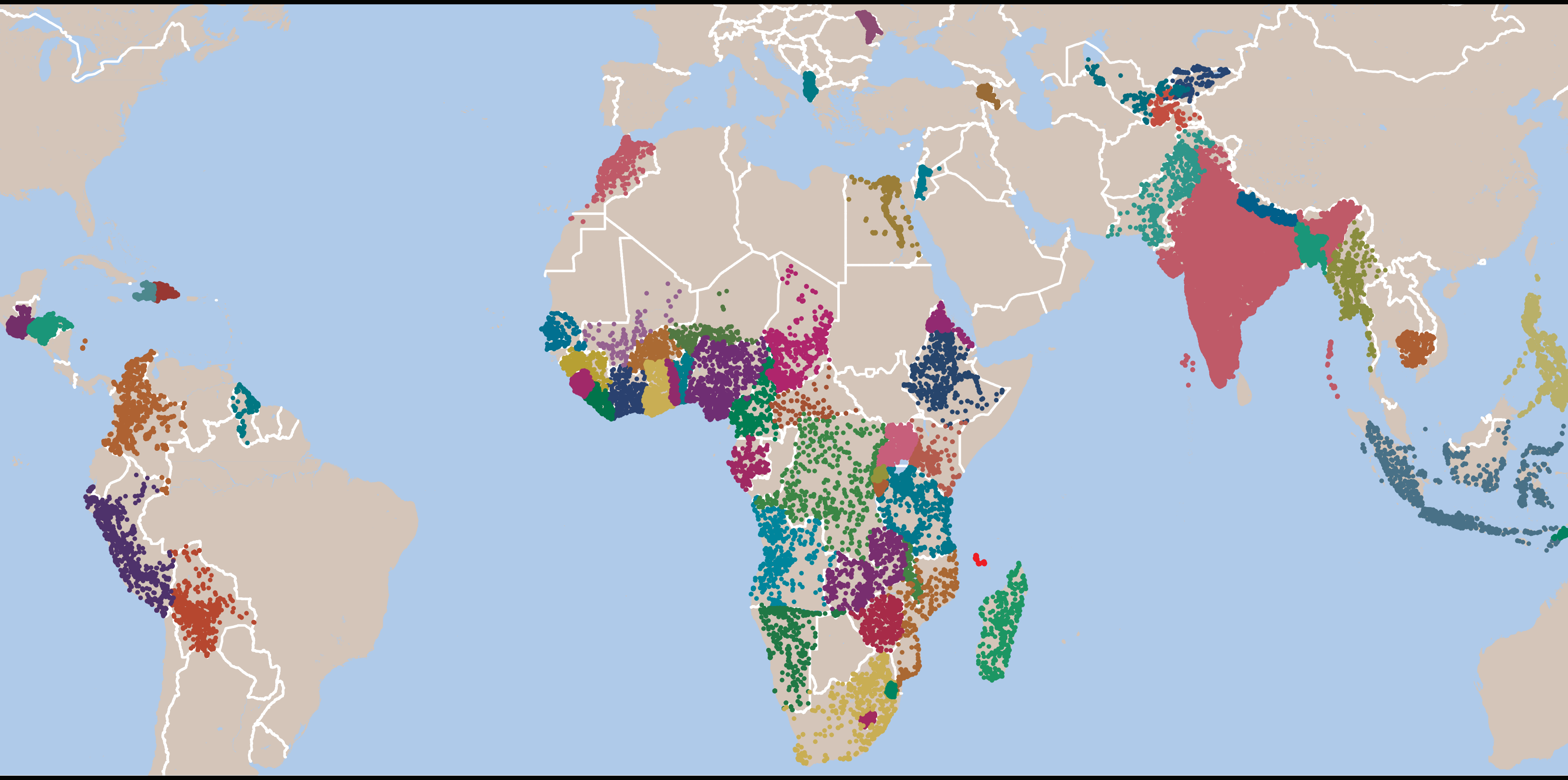
GUIDANCE AND RECOMMENDATIONS FOR THE USE OF INDICATOR ESTIMATES AT SUBNATIONAL ADMINISTRATIVE LEVEL 2

DHS SPATIAL ANALYSIS REPORTS 20



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Guidance and Recommendations for the Use of Indicator Estimates at Subnational Administrative Level 2

Bradley Janocha
Rose E. Donohue
Thomas D. Fish
Benjamin K. Mayala
Trevor N. Croft

The DHS Program
ICF
Rockville, Maryland, USA

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Corresponding author: Bradley Janocha, The DHS Program, ICF, 530 Gaither Road, Suite 500, Rockville, MD 20850, USA; phone: 301-407-6500; fax: 301-407-6501; email: bradley.janocha@icf.com

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The DHS Program assists countries worldwide in the collection and use of data to monitor and evaluate population, health, and nutrition programs. Additional information about The DHS Program can be obtained from ICF, 530 Gaither Road, Suite 500, Rockville, MD 20850 USA; telephone: +1 301-407-6500, fax: +1 301-407-6501, email: info@DHSprogram.com, internet: www.DHSprogram.com.

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PREFACE

The Demographic and Health Surveys (DHS) Program is one of the principal sources of international data on fertility, family planning, maternal and child health, nutrition, mortality, environmental health, HIV/AIDS, malaria, and provision of health services.

The DHS Spatial Analysis Reports supplement the other series of DHS reports that respond to the increasing interest in a spatial perspective on demographic and health data. The principal objectives of all the DHS report series are to provide information for policy formulation at the international level and to examine individual country results in an international context.

The topics in this series are selected by The DHS Program in consultation with the U.S. Agency for International Development. A range of methodologies are used, including geostatistical and multivariate statistical techniques.

It is hoped that the DHS Spatial Analysis Reports series will be useful to researchers, policymakers, and survey specialists, particularly those engaged in work in low- and middle-income countries, and will be used to enhance the quality and analysis of survey data.

Sunita Kishor
Director, The DHS Program

ABSTRACT

The Demographic Health Surveys (DHS) are designed to provide reliable estimates of survey indicators primarily at the national level, as well as the first subnational administrative level. During the last several years and within the framework of the Sustainable Development Goals, there has been an expressed need to improve the measurement and understanding of local geographic patterns in support of more decentralized decision-making and more efficient program implementation. To better address the need for fine spatial and lower level (district) estimates, geospatial modeling techniques that can leverage existing survey data, spatial relationships between survey clusters, and relationships with geospatial covariates have become increasingly popular for mapping key development indicators at high spatial resolutions. The DHS Program has produced modeled surfaces for indicators in 50 standard surveys. Each pixel of a modeled surface represents a 5 x 5 km space on Earth and contains a predicted value for the modeled indicator. Modeled surfaces help to meet the demand for fine-scale demographic and health data, but they can be difficult to interpret for data users focused on administrative areas. Instead, 5 x 5 km surfaces can be aggregated to a country's second administrative level (Admin 2). In this report, we explain how Admin 2 estimates can be used by policymakers and program managers in DHS Program partner countries, especially by those working at a country's first administrative level. We advocate for the routine production and subnational dissemination of Admin 2 estimates, so that these estimates can become part of decision-making. We also provide a list of 18 standard DHS indicators to model. By routinely modeling this selected set of indicators, the value of the estimates will increase as the Admin 2 data are modeled and compared over time.

KEY DEFINITIONS

Admin 1	First subnational administrative level (states or provinces)
Admin 2	Second subnational administrative level (districts)
Cluster	Groups of households used as enumeration areas for Demographic and Health Surveys
Covariates	Variables that may help predict an outcome but are not of interest to a study; for example, a study interested in predicting anemia in children at unsampled locations may use household-level anemia data as well as the covariates, population distribution, and elevation
Decentralization	Shift of power and resources from one source (national capital and figurehead) to multiple smaller sources (regional capitals and technocrats)
Geographic information systems	Software that compiles geospatial data for analysis and use
Geospatial	Something related to a specific location on Earth
Geostatistics	Statistical methods built to analyze geospatial data and to predict human and environmental geographic phenomena
Interpolation	Statistical method used to predict values at unsampled locations
Modeled surfaces	Digital maps whose pixels correspond to square geographic locations on Earth; the pixels also include values that correspond to a measurement (elevation) or a prediction (population estimate)
Scale	Level at which a phenomenon is measured or observed; a small-scale map displays a smaller level of detail for a larger part of the world (a map of southern Africa), while a large-scale map displays a higher level of detail for a smaller part of the world (a map of Lusaka)
Uncertainty intervals	Range of values that describes the uncertainty surrounding an indicator estimate; for example, a data user can be highly confident that the true value falls between an estimate's lower and upper uncertainty interval limits
Under-5 mortality rate	Probability of a child dying before their fifth birthday (in the 5 years preceding data collection) per 1,000 live births

ACRONYMS AND ABBREVIATIONS

ACT	artemisinin-based combination therapy
ANC	antenatal care
COVID-19	coronavirus disease 2019
DHS	Demographic and Health Survey
DPT	diphtheria-pertussis-tetanus
EVI	enhanced vegetation index
GIS	geographic information system
HMIS	health management information system
IFA	iron and folic acid
ITN	insecticide-treated net
LST	land surface temperature
MBG	model-based geostatistics
NMCP	National Malaria Control Program
PET	potential evapotranspiration
PLWHA	people living with HIV/AIDS
SDG	Sustainable Development Goal
SDR	Spatial Data Repository
STI	sexually transmitted infection
SUMMER	Spatio-Temporal Under-Five Mortality Methods for Estimation in R
U5M	under-5 mortality rate
WASH	water, sanitation, and hygiene

1 INTRODUCTION

Demographic and Health Survey (DHS) indicators are estimated at the national, urban/rural, and first subnational administrative levels. The background characteristics of the respondents and their households in the surveys can reveal inequitable health outcomes based on age, marital status, wealth, education, and geographic location. The geographic locations used as background characteristics are often the country's largest administrative divisions, which are typically called states, provinces, or regions. While useful in understanding the distributions of health and demographic phenomenon, this first administrative level (Admin 1) may obscure inequalities in health outcomes that can only be seen at a finer scale (Li et al. 2019).

Key Questions Box 1
What is the Admin 2 level?
Admin 2 level is the second administrative level in a country. Admin 2 names differ from country to country, but, in many cases, are called 'districts.' See Appendix Table A.1 for a list of administrative names by DHS partner country. Admin 2 levels contain fewer people and take up a smaller geographic area than primary administrative levels, or Admin 1s.
Why should indicators be estimated at the Admin 2 level?
Indicators estimated at a fine scale may reveal inequalities that are concealed at a larger scale. For example, there may be geographical disparities between populations ***within*** an administrative unit, in addition to geographic disparities ***between*** the administrative units. See Section 2 for details.
Can all DHS indicators be estimated at the Admin 2 level?
We currently have tested the modeling approach for over 60 indicators. While some indicators are better suited for estimation with this approach than others, we will continue testing additional indicators. The DHS Program will not be creating Admin 2 estimates for every indicator. Instead, estimates will be produced for priority indicators selected by DHS Program survey stakeholders. A list of 18 standard Admin 2 indicator estimates is included in Section 4.
Who can create Admin 2 indicator estimates?
All indicators are modeled using the GPS data available on The DHS Program website along with the publicly available covariate datasets. Anyone interested in modeling DHS indicator data can follow the methodology described in Mayala et al. (2019). A brief overview of this methodology is described in Section 2.3.

In an effort to reveal inequalities at a finer scale, The DHS Program routinely produces modeled 5 x 5 km estimates for selected indicators. These estimates are produced using a Bayesian model-based geostatistical (MBG) approach. Although 5 x 5 km estimates are useful to visualize differences in indicators at a fine scale, their use in programmatic decision-making is limited because programmatic decisions are not made for individual 5 x 5 km areas, and decision-making often happens for administrative areas, such as the district, province, or state. The DHS Program provides indicator estimates at the national and Admin 1 levels in addition to the modeled 5 x 5 km estimates, but no standard estimates exist at a scale between the

5 x 5 km modeled surface maps and the Admin 1 level estimates. Robust subnational estimates are needed by local officials to allow for data-driven policymaking because health decision-making and program implementation are decentralized and often occur at the second subnational administrative level (Admin 2). In addition, ambitious international development goals require a better understanding of local geographic patterns in order to identify priority populations that may be overlooked (United Nations General Assembly 2021).

Given the limitations of 5 x 5 km estimates in programmatic decision-making, and the expressed need for estimates at a lower level than Admin 1, The DHS Program has developed a methodology to predict survey indicators and produce estimates at the Admin 2 level. Decision-makers at the district, provincial, or state level can use the Admin 2 estimates to assess demographic and health outcomes at a finer scale and develop interventions accordingly. As with all data produced by The DHS Program, the host country owns the Admin 2 estimates and can use them to evaluate programs, plan interventions, and develop policies.

Although Admin 2 estimate maps have the potential to be an incredibly useful tool for policymakers, these maps have not been routinely incorporated into formal decision-making (Howes et al. 2019; Kim et al. 2016). Potential reasons include a lack of awareness of map availability and a lack of understanding of appropriate map interpretation. As The DHS Program produces these Admin 2 estimates, there is a need to increase awareness of their availability and to clearly communicate how policymakers can use Admin 2 estimate maps so that these tools can be formally adopted into routine decision-making. In this report, we seek to promote the use of Admin 2 estimates by providing guidance for program managers and policymakers.

1.1 Intended Audience

This guidance document is not a comprehensive review of the modeling process, which is addressed in other literature (Gething et al. 2015; Mayala et al. 2019), and does not provide a complete list of potential uses of the Admin 2 estimates. Instead, the guidance is intended for non-geospatial specialists, and more specifically, program managers and policymakers who work in DHS Program partner countries. As explained further in Section 2, fine-scale estimates of demographic and health indicators can lead to targeted interventions and more equitable delivery of services. The goal here is to provide a resource that outlines potential uses for Admin 2 estimates for public health professionals who work at both the first and second administrative levels. The user stories presented in Section 3 address this audience.

A secondary audience for this document includes professionals at national and international institutions that monitor public health programs. Demographers and epidemiologists who work in national statistical offices or ministries of health will find Admin 2 estimates to be valuable in their work. Staff at funding organizations, such as the United States Agency for International Development (USAID) and UNICEF, can also use these estimates in their monitoring and evaluation projects and programs. For both groups, this document will be an essential resource.

This report is intended primarily for an audience with limited technical knowledge on geospatial topics, although geospatial professionals may also find this to be a useful guide. The high-level discussion of the utility and creation of Admin 2 estimates may help geospatial professionals communicate the importance of small area estimation in the context of global health programs.

1.2 Document Structure

In Section 2, we summarize the demand for Admin 2 estimates, review the reasons The DHS Program is poised to meet that demand, and briefly review the process for modeling DHS indicators at the Admin 2 level. Section 3 discusses data use. We provide the context in which Admin 2 estimates may be used and provide specific examples. The section focuses on three indicators from the 2018 Zambia DHS and provides user stories that exemplify the utility of Admin 2 estimates. We compare the interpretation of Admin 2 estimates at the national level and the first administrative level. We discuss the indicators that The DHS Program will routinely produce in Section 4. Section 5 summarizes the discussion and conclusion. The appendix includes three tables that complement the tables and figures in the body of this report.

2 WHY AND HOW IS THE DHS PROGRAM PRODUCING ADMIN 2 ESTIMATES?

2.1 Demand for Admin 2 Estimates

The benefits of using Admin 2 estimates may appear obvious to some readers, but it is important to place these estimates in the current context of global health equity. At the time of this report's publication, the international community continues addressing the COVID-19 pandemic. Among the remaining challenges are the inequitable distribution of vaccines, the exacerbation of pre-pandemic health disparities, and a decrease in access to maternal, neonatal, and child health services (Abrams and Szefler 2020; Ashish et al. 2020; Townsend et al. 2021; Wanyana et al. 2021; WHO 2020). During this pandemic and after it subsides, there will continue to be a need for fine-scale health and demographic data. Understanding the distribution of health outcomes at the Admin 2 level is essential for evaluating disparities and measuring progress towards equitable health delivery (Li et al. 2020; Mayala, Bhatt, and Gething 2020).

Key Questions Box 2
What is the purpose of Admin 2 estimates?
When estimating an indicator at a country's second administrative level, The DHS Program is hoping to answer two questions. First, how does the indicator of interest vary geographically in a country? Also, how confident can we be in the estimated variation of that indicator?
Who will use Admin 2 indicator estimates?
While The DHS Program hopes to increase the availability of Admin 2 indicator estimates for program managers and policymakers in DHS Program partner countries, these estimates also can address the needs of a wide variety of public health professionals and researchers. These include those working in clinical, logistic, research, and governance settings. Ultimately, anyone interested in the variation of an indicator at a country's second administrative level should have access to this data. Section 3 provides an in-depth exploration of the uses of Admin 2 estimates.
How often will The DHS Program create Admin 2 estimates?
The DHS Program aims to integrate geospatial modeling into the standard DHS process. The DHS Program partner countries interested in Admin 2 estimates can request their creation during survey design.

Local officials and in-country partners have long expressed a desire for more localized DHS estimates. Prior to this new modeling approach, however, obtaining reliable Admin 2 estimates for DHS indicators required an expensive and cost-prohibitive increase in survey sample size. Countries now have an even greater demand for this data as health program planning and implementation are increasingly decentralized to subnational levels, including the Admin 1 and Admin 2 levels. Decision-makers at these levels are often constrained by a lack of routinely available local data for key indicators that would allow for data-driven policymaking (Wickremasinghe et al. 2016). A need exists for local data that is routinely produced, encompasses a variety of demographic and health subject areas, and is easily accessible and interpretable. As local needs demand, this data can be used for priority setting at the Admin 1 and Admin 2 levels, identification of poorly performing localities, and equitable resource allocation.

In addition to local needs, international development goals also help to drive the demand for Admin 2 estimates (Utazi et al. 2021). During the last several years and within the framework of the Sustainable Development Goals (SDGs), there has been an expressed need to improve the measurement and understanding of local geographic patterns to support more decentralized decision-making and more efficient program implementation (United Nations General Assembly 2015). In an effort to improve health outcomes for all, the SDGs prioritize reducing within-country inequalities because within-country heterogeneity was often overlooked when progress was monitored with national averages (Hosseinpoor, Bergen, and Magar, 2015).

As countries improve health outcomes, more ambitious goals are being set. For example, the Global Nutrition Targets include reducing and maintaining the rate of childhood wasting to < 5% and achieving a 40% reduction in stunting among children under age 5 by 2025 (WHO 2014). Inequalities in geographic locations are explicitly cited as needing to be monitored and addressed (WHO 2018). Yet, a survey of global nutrition stakeholders found that 82% of respondents cited lack of data availability at the desired geographic level as a challenge (Buckland et al. 2020). The authors concluded that high-quality and actionable nutrition data were needed to make progress towards the global targets. Ultimately, achieving ambitious global goals will require the identification and targeting of persistent areas of high need. To do this, fine-scale data, such as Admin 2 estimates, will become increasingly important.

2.2 Rationale for Creating Admin 2 Estimates

Although The DHS Program has selected a spatial modeling approach to estimate Admin 2 indicators, other options have also been explored. A report by Burgert-Brucker and others (2016) reviewed the three possible approaches The DHS Program could take to address the need for fine spatial and lower-level estimates:

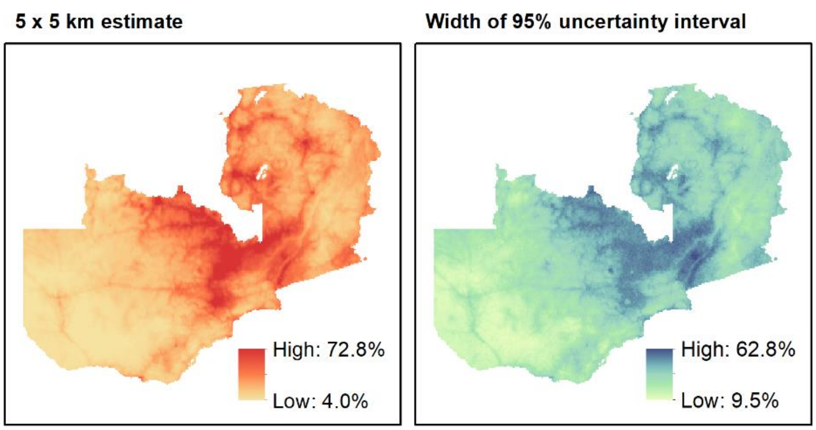
1. Scaling up the nationally representative survey data collection process by increasing the sample size needed to create a representative sample at the desired administrative level.
2. Using data from routine health management information systems (HMIS) from health facilities or communities.
3. Creating and aggregating spatially interpolated maps that use modeling techniques to predict values at non-surveyed locations.

The third approach, which leverages existing survey data, spatial relationships between survey clusters, and relationships with geospatial covariates to create Admin 2 estimates, has been adopted by The DHS Program and has proven to be a viable option. This approach is more affordable than a scaled-up survey and, at the same time, allows for error estimation not often included in an HMIS.

A key component in producing Admin 2 estimates are the 5 x 5 km modeled surfaces used to create them. As mentioned in Section 1, The DHS Program has created 5 x 5 km modeled surfaces for DHS indicators over the past 7 years. We have produced and published between 15 and 20 modeled surfaces for 50 different surveys.[1] These 5 x 5 km modeled surfaces provide detailed insights into how indicators vary at a small geographic scale, and are an important tool for microtargeting and understanding the influence of environmental heterogeneity.

While these 5 x 5 km modeled surfaces provide detailed fine-scale data, policymakers and program managers generally make decisions based on the administrative boundaries of their jurisdiction. The high-resolution details of these interpolated maps, as shown in Figure 2.1, make them inherently difficult to interpret for audiences focused on administrative areas. Therefore, policymakers seeking to monitor progress and conduct subnational planning would be better served by modeled estimates that directly represent the relevant administrative boundaries.

Figure 2.1 Population living in households using an appropriate water treatment method estimated at the 5 x 5 km resolution and level of uncertainty, Zambia 2018 DHS



2.3 Methods

The DHS Program currently uses two modeling approaches to estimate Admin 2 indicators. The standard method used for most indicators is a Bayesian model-based geostatistical (MBG) approach. This MBG approach involves creating the 5 x 5 km modeled surfaces discussed above and then aggregating to the Admin 2 level. The 5 x 5 km modeled surfaces currently available on the Spatial Data Repository (SDR) are all created with the MBG approach. The second approach is used for complex indicators, such as mortality and fertility rates. For under-5 mortality (U5M), The DHS Program has begun using the Spatio-Temporal Under-5 Mortality Methods for Estimation (SUMMER) package in R (Li et al. 2020; Wu et al. 2021). While this report does not provide technical details of either method, this section provides a high-level description of both the MBG approach and SUMMER package.

The standard MBG approach used by The DHS Program has been refined since its initial introduction to the Program in 2014 (Gething et al. 2014). The current process is described in the report by Mayala and others (2019). There are five key steps in producing Admin 2 estimates:

1. Summarize DHS indicator data at the household to cluster level,
2. Combine DHS indicator data and geospatial covariates to obtain covariate values at each cluster,

[1] These modeled surfaces can be accessed via The DHS Program's Spatial Data Repository: https://spatialdata.dhsprogram.com/modeled-surfaces/.

3. Use several submodels to generate prediction surfaces,
4. Use prediction surfaces from submodels as covariates in the MBG approach to produce pixel-level estimates with associated uncertainty at a 5 x 5 km resolution, and
5. Aggregate prediction output to the Admin 2 level using gridded population data.

While we could create bespoke modeling approaches for each indicator, using a standard approach and set of covariates improves the reproducibility of this work. The standard covariates included in our MBG approach are displayed in Table 2.1 below. As with the software used to produce these estimates (the R programming language and various open-source packages), the covariates are all publicly available.

Table 2.1 Covariates used in DHS indicator modeling

Geospatial covariate	Resolution	Source
Travel time to nearest settlement >50,000 inhabitants	5x5 km	Malaria Atlas Project
Aridity	10x10 km	Climatic Research Unit gridded Time Series
Diurnal temperature range	10x10 km	Climatic Research Unit gridded Time Series
Precipitation	10x10 km	Climatic Research Unit gridded Time Series
Potential evapotranspiration (PET)	10x10 km	Climatic Research Unit gridded Time Series
Daily maximum temperature	10x10 km	Climatic Research Unit gridded Time Series
Elevation	1x1 km	National Oceanic and Atmospheric Administration
Nightlights	1x1 km	National Oceanic and Atmospheric Administration
Enhanced vegetation index (EVI)	5x5 km	National Aeronautics and Space Administration
Daytime land surface temperature (LST)	5x5 km	National Aeronautics and Space Administration
Diurnal difference in LST	5x5 km	National Aeronautics and Space Administration
Nighttime LST	5x5 km	National Aeronautics and Space Administration
Population distribution	1x1 km	WorldPop

A second modeling approach is used for complex indicators, such as the U5M rate, which differ from the many other indicators modeled by The DHS Program. While most DHS indicators are simple proportions or ratios, complex indicators such as mortality and fertility rates require more complex combinations of elements to be calculated. Similarly, these complex indicators also require different models. In this report, The DHS Program, in collaboration with the University of Washington (Department of Biostatistics), estimated the U5M rates presented in Section 3 by using a small-area estimation spatial model implemented with the SUMMER package. For more details about this approach, please refer to the paper by Li et al. (2020) or the package's page on the Comprehensive R Archive Network.[2]

2.4 Who Will Be Producing these Admin 2 Estimates?

The DHS Program is in an ideal position to address the demand for Admin 2 estimates. The Program has the capacity and expertise to produce Admin 2 estimates routinely along with the release of DHS final reports and datasets. With this report's publication, the Program has created Admin 2 estimates for over 60

[2] The SUMMER package's Comprehensive R Archive Network page can be found at the following URL: https://cran.r-project.org/web/packages/SUMMER/index.html.

different DHS indicators (see Appendix Table A.3). Currently, this collaborative process involves professionals at ICF, the University of Washington, Imperial College London, and the Malaria Atlas Project.

The DHS Program places country ownership at the center of its mission. The DHS Program partner countries are the first and foremost owners of the surveys and data. This ownership extends to the data produced through geospatial modeling. Partner country ownership is not only essential for data use, but it is also core to the values of USAID and The DHS Program. With this principal in mind, the DHS Program staff have begun the ongoing process of collecting end-user input on the modeling of DHS indicators. When the routine production of Admin 2 estimates begins, the DHS Program and the implementing agency staff will determine indicators collaboratively. Ultimately, The DHS Program hopes to involve implementing agencies in the entire geospatial modeling process. This will require capacity-strengthening activities that complement the geospatial technical assistance we provide.

3 HOW ARE ADMIN 2 ESTIMATES USED?

3.1 Contextualizing Admin 2 Estimates

Until now, Admin 2 estimates of DHS indicators have been calculated at the specific request of various stakeholders. However, as mentioned in Section 2, there is growing demand for a process to routinely produce Admin 2 estimates for DHS Program surveys. When this is achieved, the estimates will be disseminated along with a series of other data products. To understand how Admin 2 estimates should be used, it is important to first place them in the context of The DHS Program's other data products. These estimates are not meant to replace the nationally and regionally representative data, nor are they meant to replace further analysis of the cluster, household, and population datasets. Instead, these Admin 2 estimates add value to DHS Program surveys and may uncover hidden health inequalities when looking at the Admin 1 level. The estimates will also prompt inquiries about the survey results that can be further explored through the analysis of downloaded DHS datasets.

Key Questions Box 3
Can Admin 2 estimates be used to plan public health programs?
Yes, Admin 2 estimates can be helpful in planning public health programs. These fine-scale estimates add value to the other data released by The DHS Program. While Admin 2 indicators will be available for entire countries, they may be particularly useful for program managers and policymakers working at a country's first administrative level or below. Examples are provided in Section 3.2.
What are uncertainty intervals?
Admin 2 indicator estimates will be disseminated with their associated 95% uncertainty intervals. Uncertainty intervals represent the range of values within which the true value is likely to lie. Each interval has a lower and upper limit, and the width of the interval represents the difference between these limits.
How should the uncertainty be interpreted?
The uncertainty intervals released with Admin 2 estimates are synonymous with those released for statistics in a standard DHS and should be interpreted as uncertainty intervals are in Appendix B of DHS Final Reports. The data user can be highly confident that the true value of an indicator will fall within the lower and upper uncertainty limits. Wider uncertainty intervals indicate greater uncertainty about the estimate. See Section 3.3 for an example and a deeper explanation.

Standard DHS results are disseminated at the global, national, and subnational levels. We anticipate Admin 2 estimates produced for a survey will be included in both national and subnational dissemination. Program managers and policymakers at the national and Admin 1 levels can use Admin 2 indicator estimates for program planning. The user stories in this report focus on the use of Admin 2 estimates by professionals at the Admin 1 level in order to simplify the static maps by focusing on a small number of districts. However, we expect the Admin 2 estimates will also be useful for national-level planning and the prioritization of high-need districts.

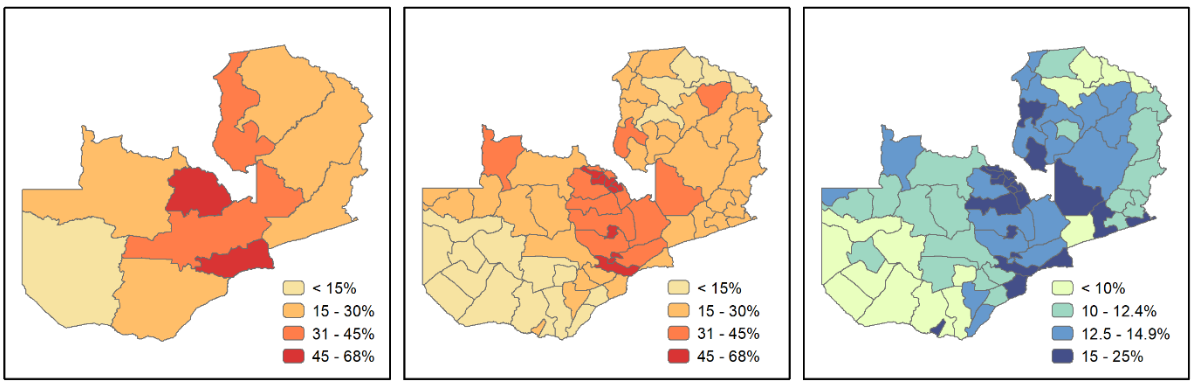
3.2 Interpreting Admin 2 Estimates

We will begin our exploration of Admin 2 estimates at the national level. Figure 3.1 shows maps of three indicators estimated at the provincial (Admin 1) and district (Admin 2) levels for the Zambia 2018 DHS, as well as the uncertainty map for the Admin 2 estimates. The three indicators included in this report are (1) percentage of the population living in households using an appropriate water treatment method; (2) percentage of children stunted; and (3) under-5 mortality rate. The uncertainty maps represent the full width of the 95% uncertainty interval, which is the difference between the upper uncertainty limit and the lower uncertainty limit. Therefore, the margin of error above and below each estimate is half of the uncertainty interval's full width.

Figure 3.1 Three indicators from the Zambia 2018 DHS modeled at the Admin 2 level

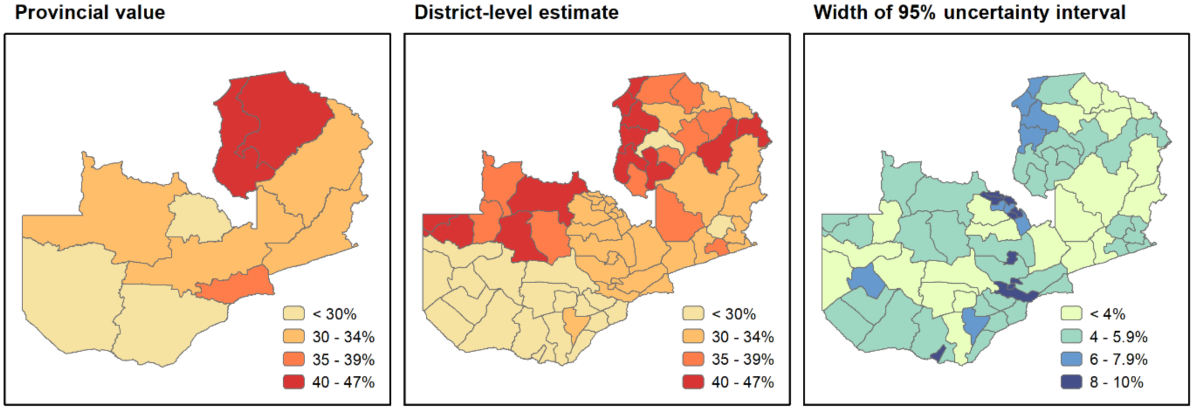
Population living in households using an appropriate water treatment method

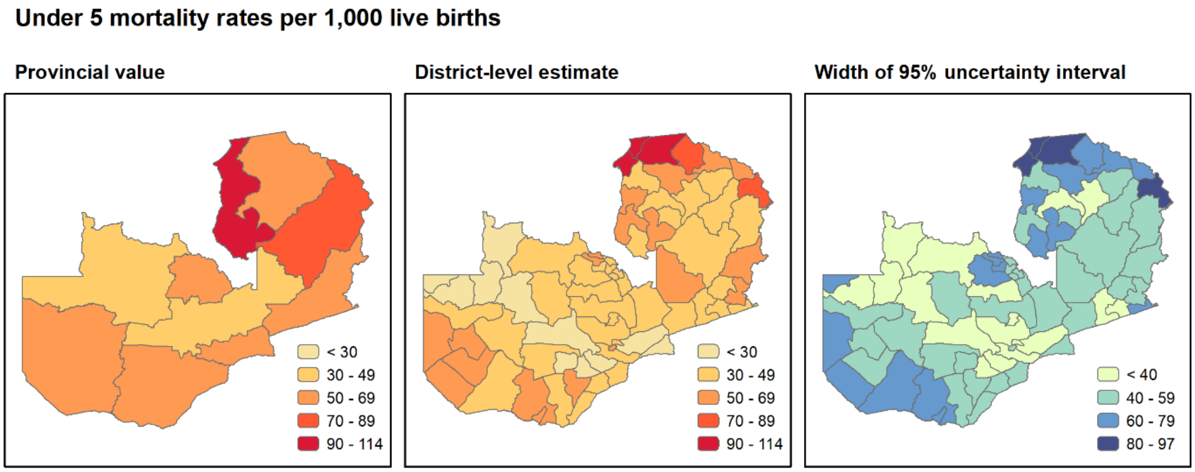
Provincial value | **District-level estimate** | **Width of 95% uncertainty interval**



Percentage of children stunted

Provincial value | **District-level estimate** | **Width of 95% uncertainty interval**



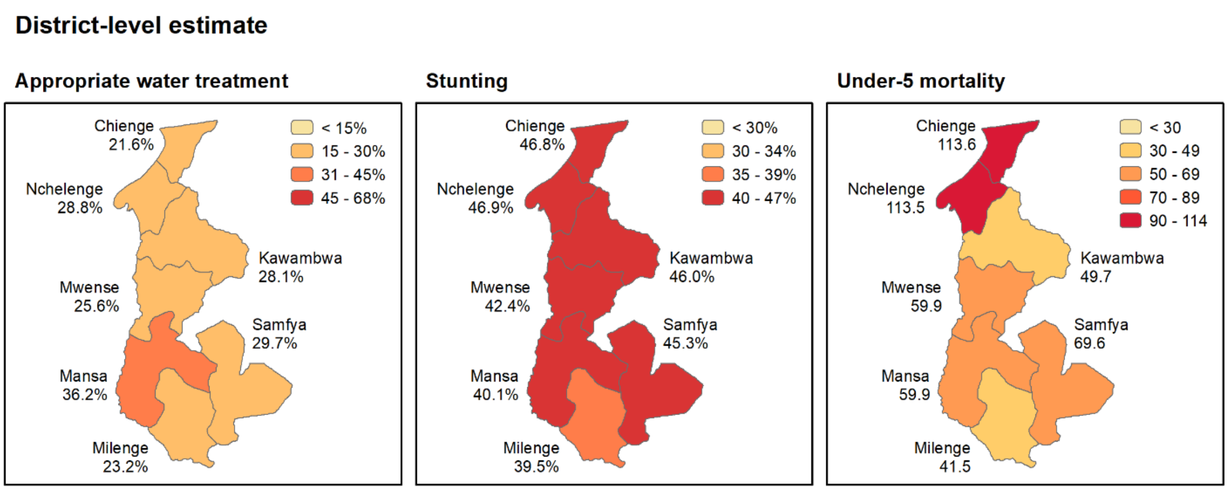


By including both the Admin 1 and Admin 2 estimates, users can visually assess the distribution of health and demographic phenomena. Static maps that include high numbers of features, such as districts in Zambia shown in Figure 3.1, can be difficult to read. In such cases, users should refer to the tabular output of estimates. A full table of Admin 2 estimates for the indicators depicted below is found in Appendix Table A.2.

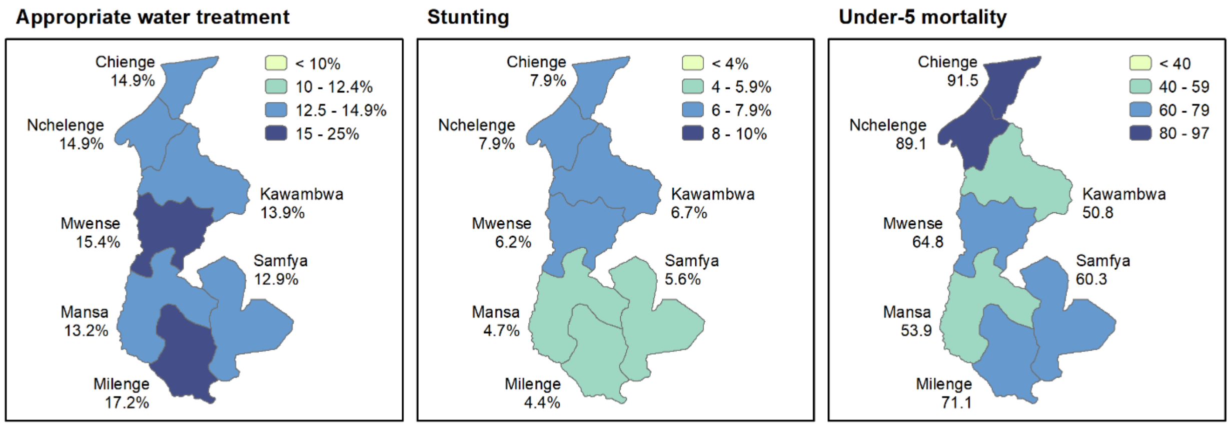
National-level maps and tables will be made available for indicators modeled at the second administrative level. However, program managers and policymakers at the provincial level may also find maps isolated to their province to be helpful. The maps in Figure 3.2 show the same Admin 2 estimates displayed in Figure 3.1, but these maps focus on one Admin 1, Luapula Province.

Rather than reviewing all of Zambia's districts, program managers and policymakers working in Luapula Province can use maps and tables isolated to their districts. The maps shown in Figure 3.2 and their corresponding table below, Table 3.1, reveal disparities in health outcomes among the districts in Luapula.

Figure 3.2 Maps for the three indicators in Zambia's Luapula Province



Width of 95% uncertainty interval



Although the province-level indicators in the DHS results can be helpful to these professionals, knowing the distribution of health and demographic phenomena at the district level adds value to the Admin 1 estimates. The Admin 2 estimates allow for a comparison of indicators between districts and a comparison of indicators at the district-level over time. Specifically, the analyst can assess which districts have a higher prevalence of childhood stunting, higher rates of U5M, and lower percentages of households that use appropriate water treatment methods. Further, incorporating Admin 2 estimates provides a baseline estimate for comparison with future DHS surveys to evaluate how indicators in the districts of Luapula Province change over time.

Table 3.1 Three indicators for districts in Zambia's Luapula Province

Location[3]	Mean Water Treatment	Lower	Upper	Mean Stunting	Lower	Upper	Mean U5M	Lower	Upper
Chienge	21.6%	15.0%	29.8%	46.8%	42.8%	50.6%	114	73	164
Kawambwa	28.1%	21.6%	35.5%	45.9%	42.4%	49.1%	50	29	80
Mansa	36.2%	30.0%	43.2%	40.1%	37.8%	42.5%	60	37	90
Milenge	23.2%	15.5%	32.6%	39.5%	37.4%	41.8%	42	16	87
Mwense	25.6%	18.6%	34.0%	42.4%	39.4%	45.5%	60	33	98
Nchelenge	28.8%	21.8%	36.7%	46.9%	43.0%	51.0%	114	72	162
Samfya	29.7%	23.4%	36.3%	45.3%	42.5%	48.1%	70	44	105
Province	**32.1%**	**25.2%**	**39.8%**	**44.9%**	**40.2%**	**49.5%**	**99**	**79**	**119**
National	**34.5%**	**28.9%**	**40.6%**	**34.6%**	**33.3%**	**35.8%**	**60**	**53**	**67**

When interpreting DHS data, it is important to consider the uncertainty of the indicator estimates. The Admin 2 estimates are released with the widths of their 95% uncertainty interval.[4] The data user can be highly confident that the true value of that indicator falls between the lower and upper values. Wider

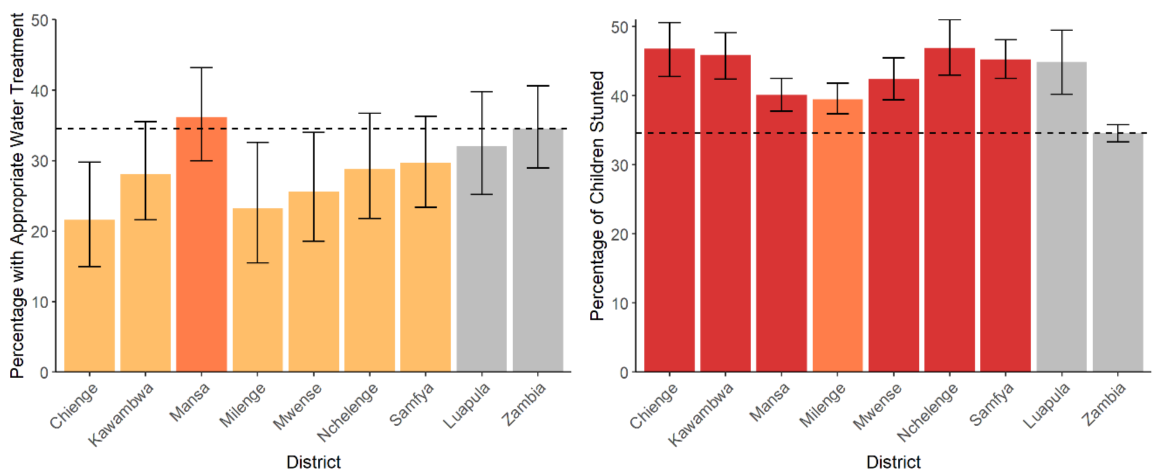
[3] The district-level estimates in this table were estimates via models, while the provincial and national estimates come directly from the 2018 Zambia DHS.
[4] It is worth noting that the choice of a 95% uncertainty interval is subjective. We could choose an interval of 90%, for example, which would result in a smaller interval and indicate that we are 90% confident that the true estimate lies within the presented interval.

uncertainty intervals indicate that we are less certain of the estimate, while more narrow uncertainty intervals indicate that we are more certain of the estimate. As we further refine the models and decrease the uncertainty, which results in more narrow uncertainty intervals, we anticipate providing decision-makers with even more precise indicator estimates.

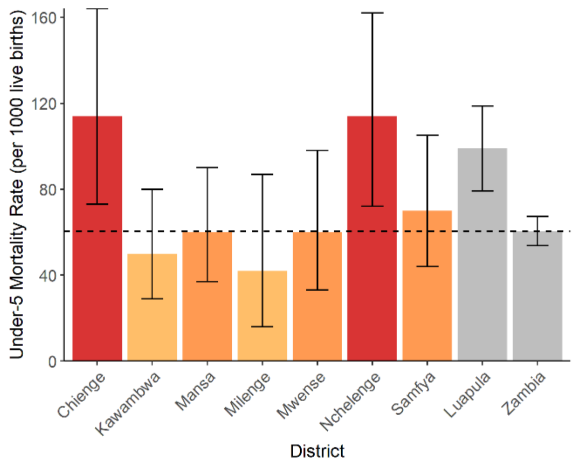
The uncertainty intervals can be used by nontechnical users to help interpret differences between indicator estimates. Data users can compare whether the uncertainty intervals overlap to estimate how certain we are that a true difference exists between districts. Although comparing overlapping uncertainty intervals is not strictly correct, this simplified approach is easier for nontechnical users to understand and increases the likelihood that users will consider uncertainty when comparing estimates. In cases where the uncertainty intervals of districts do not overlap, we are highly confident that there is a true difference between the districts. In cases where the uncertainty intervals do overlap, there is not strong enough evidence to conclude that the districts are different.

The uncertainty intervals are difficult to compare in the table above. Bar charts can also be used to visually compare the estimates' uncertainty. The bar charts in Figure 3.3 depict the model-derived indicator estimates and 95% uncertainty intervals for appropriate water treatment, stunting, and U5M in the districts of Luapula Province, Zambia. The bar charts also include the mean indicator estimate for Luapula Province as a whole and for Zambia, which are taken directly from the survey data. The 95% uncertainty intervals for these estimates, found in Appendix B of the 2018 Zambia DHS final report,[5] were added to the charts. A reference line extends from the national indicator estimate to improve the charts' readability.

Figure 3.3 Uncertainty intervals for districts in Zambia's Luapula Province



[5] The uncertainty intervals for the water treatment indicator are not included in Appendix B of the final report. These were calculated with the 2018 Zambia DHS household member recode (PR) file.



3.3 User Stories

To provide a deeper understanding of how Admin 2 estimates can be interpreted, we include three user stories, one for each indicator.

3.3.1 Stunting

Nutritionists working in Luapula Province may begin their analysis by looking at the estimates alone. The 2018 Zambia DHS revealed that 34.6% of children were stunted in the country. Alarmingly, this is within the World Health Organization's 'very high' prevalence threshold for stunting (Onis et al. 2019). In Luapula Province, the situation was worse: 44.9% of children were stunted. While the Admin 2 estimates show that all districts exceeded the national stunting prevalence, stunting was higher than the provincial estimate in four districts. Chienge, Kawambwa, Nchelenge, and Samfya districts had means for stunting of 46.8%, 45.9%, 46.9%, and 45.3%, respectively. While stunting is high across the province, Chienge and Nchelenge have the highest stunting estimates.

When examining the uncertainty intervals, the nutritionists will see that the lowest stunting estimates, Mansa and Milenge, do not overlap with those of the highest stunting estimates, Chienge and Nchelenge. This allows them to conclude with a high degree of certainty that Chienge and Nchelenge districts have higher proportions of children stunted than the districts of Mansa and Milenge. They can also confidently say that Luapula Province and all its districts are above the national stunting average.

With this information, the nutritionists can examine the underlying causes of stunting and evaluate why every district in Luapula has a higher estimated proportion of children stunted than the national estimate. Furthermore, nutritionists may consider focusing on the districts with the highest proportion of children stunted, Chienge and Nchelenge, and consider taking steps to understand the reasons for this variation. Nutritionists can also investigate and evaluate previous nutrition-related interventions in these districts. While we don't convert the stunting prevalence into the absolute number of children stunted in this report, a nutritionist can also consider this data point. A district with the highest stunting prevalence might not be the district where the highest number of stunted children reside.

3.3.2 Appropriate water treatment methods

A policymaker concerned with water, sanitation, and hygiene (WASH) in Luapula Province can use the Admin 2 estimates to assess the status of appropriate water treatment. Looking at the district-level indicator estimates alone, six of the seven districts fall below both the provincial estimate of 32.1% and the national estimate of 34.5%. In one district, Mansa, more than 3 in 10 residents (36.2%) live in households with treated water.

When comparing the uncertainty of these estimates across districts, the interpretation is less straightforward for the WASH policymaker. The 95% uncertainty intervals for these estimates almost all overlap, with the exception of Mansa and Chienge. While the policymaker can say with confidence that there is a difference in the average use of appropriate water treatment between these two districts, there is not strong enough evidence to confirm that a difference exists between the remaining districts. The district-level estimates are still valuable to the policymaker, however. In cases where districts have similar estimates, the policymaker might consider a more equal allocation of resources across these districts. Furthermore, the estimates in each district can be compared over time to evaluate how the use of appropriate water treatment changed between DHS surveys. In addition, the policymaker may further investigate the causes behind the difference between outcomes in Mansa and Chienge before planning any new WASH programs.

As with the stunting estimates, an important step in this analysis will be the conversion of prevalence into absolute numbers. The policymaker can use information on the population and number of households within each district to determine how many people use appropriate water treatment methods.

3.3.3 Under-5 mortality

In the 5 years before the 2018 Zambia DHS, 61 children died before their fifth birthday per 1,000 live births in the country. Luapula Province had an even higher U5M rate of 99 per 1,000 live births. An epidemiologist working at Mansa General Hospital in the capital of Luapula Province can use this information to justify an investigation into the leading causes of death for children under 5 in the province. Looking at the Admin 2 estimates alone, U5M varies across Luapula Province, with U5M estimates ranging from 42 in Milenge to 114 in the northernmost districts of Chienge and Nchelenge.

Looking again at the 95% uncertainty intervals, the widths of the uncertainty intervals for the two highest U5M rates, 114 in both Chienge and Nchelenge, overlap with those of the other districts. There is not strong enough evidence for the epidemiologist to state that the U5M rate is higher in Chienge and Nchelenge than in the other districts. However, in the absence of any other district-level estimates, this information is still valuable as it helps us gain a preliminary insight into inequalities within the province. Furthermore, while there may not be enough evidence based on the visual comparison of the uncertainty intervals to determine that Chienge and Nchelenge have higher U5M rates than the other districts in Luapula Province, Figure 3.3 clearly illustrates that the Chienge and Nchelenge have rates significantly above the national estimate. This information is useful to the epidemiologist at Mansa General who can lead an investigation into why these districts have an U5M that exceeds the national average and, in turn, advocate for policies or programs that may help reduce U5M in the future. In cases where districts have similar estimates, the policymaker might consider a more equal allocation of resources across these districts.

4 WHICH INDICATORS ARE BEING MODELED?

4.1 Indicators Already Modeled at the Admin 2 Level

The DHS Program has produced and tested Admin 2 estimates for over 60 different indicators (see Appendix Table A.3) and plans to continue testing the modeling approach for additional indicators to expand the options available for countries. Geostatistical modeling is an affordable solution for obtaining finer-scale indicator estimates, although there is a cost to producing these models.

The DHS Program has selected a list of 18 indicators to model routinely (Table 4.1). By focusing on these indicators, The DHS Program can streamline the cost of production, while producing a set of indicators that can be compared between countries and over time. These 18 indicators were selected because they represent the range of topics covered by The DHS Program such as maternal, newborn, and child health; nutrition; family planning and reproductive health; women's empowerment; water, sanitation, and hygiene; malaria; and HIV/AIDS.

Table 4.1 The 18 DHS indicators to be routinely modeled at Admin 2

DHS Program indicators	
1. Under-5 mortality rate	10. Children with all basic vaccinations
2. Stunting	11. 4+ antenatal care (ANC) visits
3. Modern contraceptive prevalence rate	12. Children with any anemia
4. Unmet need for family planning	13. Diarrhea treatment
5. Basic access to drinking water	14. Insecticide-treated net (ITN) availability
6. Improved toilet facility	15. Artemisinin-based combination therapy (ACT) use
7. Open defecation	16. Facility delivery
8. Women's education	17. Intimate partner violence
9. Children with 3 doses of diphtheria-pertussis-tetanus (DPT3) vaccine	18. Discriminatory attitudes towards people living with HIV/AIDS (PLWHA)

As discussed in Section 2.3, complex indicators, specifically U5M rates, require a different modeling process than the standard MBG approach. With these indicators, The DHS Program and its partners use a different approach (Li et al. 2020; Wu et al. 2021).

4.2 Choosing Indicators to Model for DHS Program Surveys

The goal of these estimates is to empower decision-makers who work at various levels in DHS Program partner countries. With this aim in mind, The DHS Program and its partners will prioritize modeling the indicators that are most important to the survey stakeholders. To accomplish this, the decision about which indicators to model will be made in collaboration with implementing agencies and national funders during the design of Demographic and Health Surveys.

5 FINAL THOUGHTS

There has been an increasing demand by countries for fine-scale health and demographic indicator estimates in recent years. Decentralization of authority from the national to sub-national and local governments has led to greater management of resources and programs at these more local levels. In response, policymakers and program managers at subnational levels desire high-quality data at a finer scale to inform priority setting and resource allocation within their jurisdictions (Wickremasinghe et al. 2016). While The DHS Program produces subnational indicator estimates at the Admin 1 level, producing reliable Admin 2 estimates would require a cost-prohibitive increase in survey sample size. In an effort to produce reliable and affordable Admin 2 estimates, The DHS Program has developed a geospatial modeling approach to routinely produce modeled Admin 2 estimates. These estimates can reveal localized progress or lack thereof to help program managers and policymakers identify possible routes towards eliminating diseases and achieving universal service provision.

During the past 37 years, The DHS Program has built a strong reputation for collecting and disseminating accurate, nationally representative data on health and demographics. The Program has built the capacity and expertise to produce Admin 2 estimates and has relationships with public health institutions working around the world. By producing and disseminating these estimates, The DHS Program will fulfill unmet data needs. Public health professionals working at a country's national and provincial (Admin 1) levels will now have DHS indicators for the districts (Admin 2) within their jurisdiction. It is the hope of The DHS Program that this new data product, Admin 2 estimates of DHS indicators, will provide further insights into the health and demographics of populations, so that care and services can be more equitably delivered.

Ultimately, DHS partner countries are the owners of DHS Program data. As The DHS Program provides this new line of technical assistance, the Admin 2 estimates will become increasingly tailored to meeting the needs and interests of the data owners. In addition, The DHS Program aims to increase the involvement of DHS implementing agency staff in the modeling process by pairing our technical assistance with capacity-strengthening efforts.

REFERENCES

Abimbola, S., L. Baatiema, and M. Bigdeli. 2019. "The Impacts of Decentralization on Health System Equity, Efficiency and Resilience: A Realist Synthesis of The Evidence." *Health Policy and Planning* 34 (8): 605-617. https://doi.org/10.1093/heapol/czz055.

Abrams, E. M. and S. J. Szefler. 2020. "COVID-19 and the Impact of Social Determinants of Health." *Lancet Respiratory Medicine* 8 (7): 659-661. https://dx.doi.org/10.1016%2FS2213-2600(20)30234-4.

Ashish, K. C., R. Gurung, M. V. Kinney, A. K. Sunny, M. Moinuddin, O. Basnet, et al. 2020. "Effect of the COVID-19 Pandemic Response on Intrapartum Care, Stillbirth, and Neonatal Mortality Outcomes in Nepal: A Prospective Observational Study." *Lancet Global Health* 8 (10): e1273-e1281. https://doi.org/10.1016/S2214-109X(20)30345-4.

Buckland, A. J., A. L. Thorne-Lyman, T. Aung, S. E. King, R. Manorat, L. Becker, E. Piwoz, R. Rawat, and R. Heidkamp, R., 2020. "Nutrition Data Use and Needs: Findings from an Online Survey of Global Nutrition Stakeholders." *Journal of Global Health* 10 (2). https://dx.doi.org/10.7189%2Fjogh.10.020403.

Burgert-Brucker, C. R., T. Dontamsetti, A. Marshall, and P. Gething. 2016. "Guidance for Use of the DHS Program Modeled Map Surfaces." *DHS Spatial Analysis Reports No. 14*. Rockville, Maryland, USA: ICF International. http://dhsprogram.com/pubs/pdf/SAR14/SAR14.pdf.

Cressie, N. and C. K. Wikle. 2011. *Statistics for Spatio-Temporal Data*. Indianapolis, Indiana, USA: John Wiley & Son, Inc. https://www.wiley.com/en-us/Statistics+for+Spatio+Temporal+Data-p-9780471692744.

Gething, P., A. Tatem, T. Bird, and C. R. Burgert-Brucker. 2015. "Creating Spatial Interpolation Surfaces with DHS Data." *DHS Spatial Analysis Reports No. 11*. Rockville, Maryland, USA: ICF International. http://dhsprogram.com/pubs/pdf/SAR11/SAR11.pdf.

Gething, P. W., A. P. Patil, D. L. Smith, C. A. Guerra, I. R. F. Elyazar, G. L. Johnston, A. J. Tatem, and S. Hay. 2011. "A New World Malaria Map: Plasmodium Falciparum Endemicity in 2010." *Malaria Journal* 10 (378). https://doi.org/10.1186/1475-2875-10-378.

Ghilardi et al. 2020. "How Useful are Malaria Risk Maps at the Country Level? Perceptions of Decision-Makers in Kenya, Malawi and The Democratic Republic of Congo." *Malaria Journal* 19 (353). https://doi.org/10.1186/s12936-020-03425-z.

Gosoniu, L., A. M. Veta, and P. Vounatsou, 2011. "Bayesian Geostatistical Modeling of Malaria Indicator Survey Data in Angola." *PLoS One* 5 (3): e9322. https://doi.org/10.1371/journal.pone.0009322.

Gosoniu, L., P. Vounatsou, N. Sogoba, and T. Smith. 2006. "Bayesian Modelling of Geostatistical Malaria Risk Data." *Geospatial Health* 1 (1): 127-139. https://doi.org/10.4081/gh.2006.287.

Hay, S. I., C. A. Guerra, P. W. Gething, A. P. Patil, A. J. Tatem, A. M. Noor, C. W. Kabaria, et al. "A World Malaria Map: Plasmodium Falciparum Endemicity in 2007." *PLoS Medicine* 6 (10): e1000048. https://doi.org/10.1371/journal.pmed.1000048.

Hosseinpoor, A. R., N. Bergen, A. Schlotheuber, and J. Grove. 2018. "Measuring Health Inequalities in the Context of Sustainable Development Goals." *Bulletin of the World Health Organization* 96 (9): 654–659. https://doi.org/10.2471/BLT.18.210401.

Howes, R. E., K. Hawa, V. F. Andriamamonjy, T. Franchard, R. Miarimbola, et al. 2019. "A Stakeholder Workshop about Modelled Maps of Key Malaria Indicator Survey Indicators in Madagascar." *Malaria Journal* 18 (90). https://doi.org/10.1186/s12936-019-2729-7.

Kazembe, L., I. Kleinschmidt, T. Holtz, and B. Sharp. 2006. "Spatial Analysis and Mapping of Malaria Risk in Malawi Using Point-referenced Prevalence of Infection Data." *International Journal of Health Geographics* 5 (1): 41. https://doi.org/10.1186/1476-072X-5-41.

Khan, M. S., S. Rego, J. B. Rajal, V. Bond, R. K. Fatima, A. K. Isani, J. Sutherland, and K. Kranzer. 2021. "Mitigating the Impact of COVID-19 on Tuberculosis and HIV Services: A Cross-Sectional Survey of 669 Health Professionals in 64 Low and Middle-Income Countries." *PLoS ONE* 16 (2): e0244936. https://doi.org/10.1371/journal.pone.0244936H

Kim, D., M. Sarker, and P. Vyas. 2016. "Role of Spatial Tools in Public Health Policymaking of Bangladesh: Opportunities and Challenges." *Journal of Health, Population and Nutrition* 35 (1). https://doi.org/10.1186/s41043-016-0045-1.

Li, Z. R., B. D. Martin, T. Qi Dong, G-A. Fuglstad, J. Godwin, J. Paige, A. Riebler, S. Clark, and J. Wakefield. 2020. "Space-Time Smoothing of Demographic and Health Indicators using the R Package SUMMER." *stat.AP*. https://arxiv.org/pdf/2007.05117.pdf.

Li, Z., Y. Hsiao, J. Godwin, B. D. Martin, J. Wakefield, S. J. Clark, et al. 2019. "Changes in the Spatial Distribution of the Under-Five Mortality Rate: Small-Area Analysis of 122 DHS Surveys in 262 Subregions of 35 Countries in Africa." *PLoS ONE* 14 (1): e0210645. https://doi.org/10.1371/journal.pone.0210645.

Mayala, B. K., S. Bhatt, and P. Gething. 2020. "Predicting HIV/AIDS at Subnational Levels using DHS Covariates Related to HIV." *DHS Spatial Analysis Reports No. 18*. Rockville, Maryland, USA: ICF. https://www.dhsprogram.com/pubs/pdf/SAR18/SAR18.pdf.

Mayala, B. K., T. Dontamsetti, T. D. Fish, and T. N. Croft. 2019. "Interpolation of DHS Survey Data at Subnational Administrative Level 2." *DHS Spatial Analysis Reports No. 17*. Rockville, Maryland, USA: ICF. http://dhsprogram.com/pubs/pdf/SAR17/SAR17.pdf.

Noor, A. M., P. W. Gething, V. A. Alegana, A. P. Patil, S. I. Hay, E. Muchiri, E. Juma, and R. W. Snow. 2009. "The Risks of Malaria Infection in Kenya in 2009." *BMC Infectious Diseases* 9 (180). https://doi.org/10.1186/1471-2334-9-180.

Onis, M. E., E. Borghi, M. Arimond, P. Webb, T. Croft, K. Saha, L. M. De-Regil, F. Thuita, et al. 2019. "Prevalence Thresholds for Wasting, Overweight and Stunting in Children under 5 Years." *Public Health Nutrition* 22 (1). https://doi.org/10.1017/S1368980018002434.

Raso, G., N. Schur, J. Utzinger, B. Koudou, E. Tchicaya, F. Rohner, and E. N'Goran. 2012. "Mapping Malaria Risk among Children in Cote d'Ivoire using Bayesian Geo-statistical Models." *Malaria Journal* 11 (1): 160. https://doi.org/10.1186/1475-2875-11-160.

Riedel, N., P. Vounatsou, J. M. Miller, L. Gosoniu, E. Chizema-Kawesha, V. Mukonka, and R. W. Steketee. 2011. "Geographical Patterns and Predictors of Malaria Risk in Zambia: Bayesian Geostatistical Modelling of the 2006 Zambia National Malaria Indicator Survey (ZMIS)." *Malaria Journal* 9: 37. https://doi.org/10.1186/1475-2875-9-37.

Soko, R. N., R. M. Burke, H. R. A. Feasey, W. Sibande, M. Nliwasa, M. Y. R. Henrion, M. Khundi, et al. 2021. "Effects of Coronavirus Disease Pandemic on Tuberculosis Notifications, Malawi." *Emerging Infectious Diseases* 27 (7): 1831-1839. https://doi.org/10.3201/eid2707.210557.

Steele, J. E., P. R Sundsøy, P. Carla, V. A. Alegana, T. J. Bird, B. Joshua, B. Johannes, et al. 2017. "Mapping Poverty using Mobile Phone and Satellite Data." *Journal of the Royal Society, Interface* 14 (127): 20160690. https://doi.org/10.1098/rsif.2016.0690.

Townsend, R., B. Chmielewska, I. Barratt, E. Kalafat, J. van der Meulen, I. Gurol-Urganci, P. O'Brien, E. Morris, T. Draycott, S. Thangaratinam, and K. Le Doare, 2021. "Global Changes in Maternity Care Provision during the COVID-19 Pandemic: A Systematic Review and Meta-analysis." *EClinicalMedicine* 37:100947. https://doi.org/10.1016/j.eclinm.2021.100947.

Utazi, C. E., K. Nilsen, O. Pannell, W. Dotse-Gborgbortsi, and A. J. Tatem. 2020. "District-Level Estimation of Vaccination Coverage: Discrete vs Continuous Spatial Models." *Statistics in Medicine* 40 (9): 2197-2211. https://doi.org/10.1002/sim.8897.

Utazi, C. E., J. Thorley, V. A. Alegana, J. M. Ferrari, S. Takahashi, C. J. E. Metcalf, J. Lessler, and A. Tatem. 2018. "High Resolution Age-structured Mapping of Childhood Vaccination Coverage in Low and Middle Income Countries." *Vaccine* 36 (2018): 1583-1591. https://doi.org/10.1016/j.vaccine.2018.02.020.

World Health Organization (WHO). 2020. "COVAX: The Vaccines Pillar of the Access to COVID-19 Tools (ACT) Accelerator, Structure and Principles." Geneva, Switzerland: WHO Publications. https://www.who.int/publications/m/item/covax-the-vaccines-pillar-of-the-access-to-covid-19-tools-(act)-accelerator.

World Health Organization (WHO). 2018. "Reducing Stunting in Children: Equity Considerations for Achieving the Global Nutrition Targets 2025." Geneva, Switzerland: WHO Publications. https://www.who.int/publications/i/item/9789241513647.

World Health Organization (WHO). 2014. WHA Global Nutrition Targets 2025: Wasting Policy Brief." Geneva, Switzerland: WHO Working Papers. http://www.who.int/nutrition/topics/globaltargets_wasting_policybrief.pdf.

Wanyana, D., R. Wong, and D. Hakizimana. 2021. “Rapid Assessment on the Utilization of Maternal and Child Health Services during COVID-19 in Rwanda. *Public Health Action* 11 (1):12-21. https://doi.org/10.5588/pha.20.0057.

Wickremasinghe, D., I. E. Hashmi, J. Schellenberg, and B. I. Avan. 2016. “District Decision-making for Health in Low-income Settings: A Systematic Literature Review.” *Health Policy and Planning* 31(suppl_2): ii12-ii24. https://doi.org/10.1093/heapol/czv124.

Wu, Y., Z. R. Li, B. K. Mayala, G. A. Fuglstad, P. Gao, H. Wang, J. Godwin, C. Moe, J. Paige, R. E. Donohue, T. Okonek, T. N. Croft and J. Wakefield. 2021 (under review). *Spatial Modeling for Subnational Administrative Level 2 Small-Area Estimation*. DHS Spatial Analysis Reports No. 21. Rockville, Maryland, USA: ICF.

Zambia Statistics Agency, Ministry of Health Zambia, and ICF. 2019. *Zambia Demographic and Health Survey 2018*. Lusaka, Zambia, and Rockville, Maryland, USA. https://www.dhsprogram.com/pubs/pdf/FR361/FR361.pdf.

Zon, H., M. Pavlova, and W. Groot. 2020. “Regional Health Disparities in Burkina Faso during the Period of Health Care Decentralization. Results of a Macro-Level Analysis.” *International Journal of Health Planning and Management* 35 (4): 939-959. https://doi.org/10.1002/hpm.2979.

APPENDIX

Appendix Table A.1 Administrative-level names for DHS Program countries

Country	Admin 1 Name	Admin 2 Name
Afghanistan	provinces	districts
Albania	counties	municipalities
Angola	provinces	municipalities
Armenia	provinces	municipalities
Azerbaijan	districts	raions
Bangladesh	divisions	districts
Benin	departments	communes
Bolivia	departments	provinces
Botswana	districts	sub-districts
Brazil	states	municipalities
Burkina Faso	regions	provinces
Burundi	provinces	communes
Cambodia	provinces	districts
Cameroon	provinces	departments
Cape Verde	municipalities	parishes
Central African Republic	prefectures	sub-prefectures
Chad	regions	departments
Colombia	departments	municipalities
Comoros	autonomous islands	prefectures
Congo (Brazzaville)	departments	districts
Congo (Kinshasa)	provinces	territories
Cote d’Ivoire	regions	provinces
Dominican Republic	provinces	municipalities
Ecuador	provinces	cantons
Egypt	governorates	aqsam
El Salvador	departments	municipalities
Equatorial Guinea	provinces	districts
Eritrea	regions	districts
Eswatani	regions	tikhundla
Ethiopia	regions	zones
Gabon	provinces	departments
Gambia	regions	districts
Ghana	regions	districts
Liberia	counties	districts
Madagascar	faritra	districts
Malawi	regions	districts
Maldives	atolls and cities	islands
Mali	regions	cercles
Mauritania	regions	departments
Mexico	states	municipalities
Moldova	villages, sectors, and cities	districts and municipalities
Morocco	regions	provinces
Mozambique	provinces	districts
Myanmar	states	districts
Namibia	regions	constituencies
Nepal	provinces	districts
Nicaragua	departments	municipalities
Niger	regions	departments
Nigeria	states	local government areas
Pakistan	provinces	divisions
Papua New Guinea	provinces	districts
Paraguay	departments	districts
Peru	regions	provinces
Philippines	regions	provinces
Rwanda	intara	uturere
Samoa	itumalo	faipule districts
Sao Tome and Principe	districts	settlements
Senegal	regions	departments
Sierra Leone	provinces	districts
South Africa	provinces	municipalities
Sri Lanka	provinces	districts
Sudan	wilaya’at	districts
Tajikistan	viloyatho	nohiya
Tanzania	mkoa	wilaya
Thailand	changwat	amphoe
Timor-Leste	municipalities	administrative posts

Continued...

Appendix Table A.1—*Continued*

Country	Admin 1 Name	Admin 2 Name	Country	Admin 1 Name	Admin 2 Name
Guatemala	departments	municipalities	Togo	regions	prefectures
Guinea	regions	prefectures	Trinidad and Tobago	regions and municipalities	electoral districts
Guyana	regions	neighborhood councils	Tunisia	wilaya'at	mutamadiyat
Haiti	departments	arrondissements	Turkey	provinces	districts
Honduras	departments	municipalities	Turkmenistan	regions	districts
India	states and union territories	districts	Uganda	districts	counties
Indonesia	provinces	regencies	Ukraine	regions	districts
Jordan	governorates	districts	Uzbekistan	regions	districts
Kazakhstan	regions	raions	Vietnam	provinces	districts
Kenya	counties	sub-counties	Yemen	muhafazat	districts
Kyrgyz Republic	provinces	raions	Zambia	provinces	districts
Laos	provinces	districts	Zimbabwe	provinces	districts
Lesotho	districts	constituencies			

Appendix Table A.2 Admin 2 estimates and 95% uncertainty width, Zambia 2018 DHS

Admin 1	Admin 2	Mean Water Treatment	Lower	Upper	Mean Stunting	Lower	Upper	Mean U5M	Lower	Upper
Central	Chibombo	40%	34%	47%	33%	30%	35%	34	20	52
Central	Kabwe	61%	53%	70%	33%	29%	37%	30	16	55
Central	Kapiri-Mposhi	42%	35%	49%	33%	30%	35%	43	25	69
Central	Mkushi	42%	35%	50%	35%	33%	36%	41	23	66
Central	Mumbwa	22%	16%	28%	30%	28%	32%	28	15	46
Central	Serenje	35%	27%	44%	37%	35%	38%	58	33	93
Copperbelt	Chililabombwe	45%	33%	58%	33%	29%	38%	53	25	101
Copperbelt	Chingola	53%	41%	63%	32%	27%	37%	58	29	99
Copperbelt	Kalulushi	47%	38%	55%	32%	29%	36%	47	22	87
Copperbelt	Kitwe	54%	45%	62%	32%	28%	36%	40	23	63
Copperbelt	Luanshya	50%	41%	59%	33%	29%	37%	36	18	68
Copperbelt	Lufwanyama	36%	29%	44%	34%	32%	36%	49	25	86
Copperbelt	Masaiti	46%	38%	54%	34%	31%	38%	40	22	68
Copperbelt	Mpongwe	39%	31%	48%	32%	31%	34%	31	15	54
Copperbelt	Mufulira	38%	29%	50%	33%	29%	37%	47	24	83
Copperbelt	Ndola	51%	42%	61%	33%	29%	37%	40	21	69
Eastern	Chadiza	26%	18%	33%	35%	33%	37%	46	20	89
Eastern	Chama	18%	12%	23%	33%	31%	34%	48	27	77
Eastern	Chipata	26%	21%	32%	34%	32%	36%	60	40	89
Eastern	Katete	20%	14%	26%	36%	33%	38%	38	22	59
Eastern	Lundazi	20%	14%	25%	33%	32%	35%	69	43	101
Eastern	Mambwe	15%	10%	21%	29%	26%	31%	46	24	83
Eastern	Nyimba	31%	22%	40%	33%	31%	34%	34	19	55
Eastern	Petauke	18%	13%	23%	34%	33%	36%	34	17	60
Luapula	Chienge	22%	15%	30%	47%	43%	51%	114	73	164
Luapula	Kawambwa	28%	22%	36%	46%	42%	49%	50	29	80
Luapula	Mansa	36%	30%	43%	40%	38%	43%	60	37	90
Luapula	Milenge	23%	16%	33%	40%	37%	42%	42	16	87
Luapula	Mwense	26%	19%	34%	42%	39%	46%	60	33	98
Luapula	Nchelenge	29%	22%	37%	47%	43%	51%	114	72	162
Luapula	Samfya	30%	23%	36%	45%	43%	48%	70	44	105
Lusaka	Chongwe	37%	31%	43%	34%	32%	36%	29	15	48
Lusaka	Kafue	52%	43%	59%	32%	28%	37%	40	23	61
Lusaka	Luangwa	22%	14%	32%	30%	28%	33%	29	11	61
Lusaka	Lusaka	68%	61%	74%	34%	29%	38%	62	42	92
North-Western	Chavuma	22%	15%	29%	45%	42%	47%	21	4	64
North-Western	Kabompo	20%	15%	26%	38%	36%	40%	26	12	47
North-Western	Kasempa	20%	15%	26%	38%	36%	40%	34	17	61
North-Western	Mufumbwe	20%	14%	26%	44%	41%	46%	28	13	51
North-Western	Mwinilunga	33%	27%	40%	38%	36%	41%	20	9	39
North-Western	Solwezi	18%	13%	24%	43%	41%	46%	34	21	56
North-Western	Zambezi	17%	12%	22%	41%	39%	44%	22	9	43

Continued...

Appendix Table A.2—*Continued*

Admin 1	Admin 2	Mean Water Treatment	Lower	Upper	Mean Stunting	Lower	Upper	Mean U5M	Lower	Upper
Northern	Chilubi	22%	17%	29%	38%	36%	40%	39	20	68
Northern	Chinsali	22%	16%	29%	43%	41%	45%	49	30	76
Northern	Isoka	16%	11%	23%	42%	40%	44%	89	56	136
Northern	Kaputa	23%	17%	29%	38%	36%	40%	105	63	161
Northern	Kasama	23%	16%	30%	37%	34%	39%	41	24	63
Northern	Luwingu	13%	7%	22%	30%	27%	32%	33	17	56
Northern	Mbala	11%	7%	16%	34%	33%	36%	59	34	95
Northern	Mpika	18%	12%	25%	34%	32%	35%	46	28	70
Northern	Mporokoso	12%	8%	18%	32%	31%	34%	59	32	97
Northern	Mpulungu	13%	9%	19%	39%	37%	40%	82	48	126
Northern	Mungwi	37%	31%	44%	36%	34%	38%	36	19	61
Northern	Nakonde	11%	7%	15%	30%	29%	32%	66	37	100
Southern	Choma	19%	13%	26%	31%	28%	34%	59	35	89
Southern	Gwembe	12%	8%	18%	29%	26%	31%	37	16	74
Southern	Itezhi-tezhi	10%	6%	16%	28%	26%	29%	26	11	51
Southern	Kalomo	13%	9%	17%	29%	28%	31%	47	26	74
Southern	Kazungula	11%	8%	15%	26%	24%	28%	53	28	94
Southern	Livingstone	26%	17%	37%	23%	19%	29%	57	28	103
Southern	Mazabuka	21%	16%	28%	30%	28%	32%	26	13	46
Southern	Monze	15%	10%	22%	29%	27%	33%	23	12	40
Southern	Namwala	11%	7%	17%	28%	26%	30%	39	17	75
Southern	Siavonga	20%	12%	29%	30%	27%	33%	40	20	73
Southern	Sinazongwe	14%	9%	22%	30%	27%	32%	44	21	79
Western	Kalabo	7%	4%	10%	29%	28%	31%	59	34	96
Western	Kaoma	12%	8%	16%	30%	28%	31%	43	26	69
Western	Lukulu	8%	5%	11%	30%	28%	31%	34	17	60
Western	Mongu	13%	9%	19%	28%	25%	31%	57	33	91
Western	Senanga	9%	6%	13%	26%	24%	28%	55	31	88
Western	Sesheke	8%	5%	13%	25%	23%	27%	46	23	84
Western	Shangombo	8%	5%	13%	26%	24%	28%	61	29	105

Appendix Table A.3 Indicators modeled by The DHS Program

Indicator	Definition
1. Children with any anemia	Percentage of children under age 5 classified as having any anemia
2. Women with any anemia	Percentage of women classified as having any anemia (<12.0 g/dl for non-pregnant women and <11.0 g/dl for pregnant women)
3. Children stunted	Percentage of children stunted (below -2 SD of height for age according to the WHO standard)
4. Children wasted	Percentage of children wasted (below -2 SD of weight for height according to the WHO standard)
5. Children underweight	Percentage of children underweight (below -2 SD of weight for age according to the WHO standard)
6. Short stature	Women age 15-19 with a height-for-age z-score less than -2SD and women age 20-49 with height <145cm
7. Overweight/obese body mass index (BMI)	Women age 15-19 with a BMI-for-age z-score greater than +1SD and women age 20-49 with a BMI ≥25.0kg/m2
8. Children consuming vitamin A supplements	Percentage of children age 6-59 months who received vitamin A supplements
9. Parity	Number of children born to women age 15-49. (Population mean of 4 children was used as cut-off for coding.)
10. Current breastfeeding	Percentage of youngest children under age 2 living with the mother who are currently breastfeeding
11. Minimum dietary diversity	Percentage of children age 6–23 months who consumed foods and beverages from at least five out of eight defined food groups during the previous day
12. Minimum meal frequency	Percentage of children age 6–23 months who consumed solid, semi-solid or soft foods (but also including milk feeds for non-breastfed children) the minimum number of times or more during the previous day
13. Diarrhea in the past 2 weeks	Children under age 5 with diarrhea at any time in the 2 weeks before the survey
14. Antenatal care (ANC) attendance	Percentage of women age 15-49 who had a live birth in the 5 years before the survey and who had 4+ ANC visits
15. All basic vaccines	Percentage of children age 12-23 months who had received all 8 basic vaccinations
16. Diphtheria-pertussis-tetanus (DPT1) vaccination received	Percentage of children age 12-23 months who had received DPT 1 vaccination
17. Diphtheria -pertussis-tetanus (DPT3) vaccination received	Percentage of children age 12-23 months who had received DPT 3 vaccination
18. Measles vaccination received	Percentage of children age 12-23 months who had received Measles vaccination
19. Women who are literate	Percentage of men who are literate
20. Women who are literate	Percentage of women who are literate
21. Employment (occupation)	Percentage of women employed in the 12 months before the survey: Total
22. Women in agricultural occupation	Percentage of women employed in the 12 months before the survey whose occupation is in agriculture
23. Women in non-agricultural occupation	Percentage of men employed in the 12 months before the survey whose occupation is other
24. Basic water	Percentage of the de jure population living in households with basic water service, defined as an improved water source with either water on the premises or round-trip collection time of 30 minutes or less.

Continued...

Appendix Table A.3—*Continued*

25. Improved water source	Percentage of the de jure population living in households whose main source of drinking water is an improved source
26. Water treatment	Percentage of the de jure population living in households using an appropriate treatment method, including boiling, bleaching, filtering, or solar disinfecting.
27. Travel time to water	Percentage of the de jure population living in households with water 30 minutes away or less round trip
28. Water source on premises	Percentage of the de jure population living in households with an improved water source on the premises
29. Place for washing hands	Percentage of households where a place for washing hands was observed
30. Soap and water for washing	Percentage of households where a place for washing hands was observed with soap available, including soap or detergent in bar, liquid, powder, or paste form
31. Open defecation	Percentage of the de jure population living in households whose main type of toilet facility is no facility (open defecation)
32. Improved toilet	Percentage of the de jure population living in households with an improved sanitation facility
33. Improved toilet facility – shared	Percentage of the de jure population living in households with improved sanitation facilities that are shared by two or more households
34. Improved toilet facility – non-shared	Percentage of the de jure population living in households with improved sanitation facilities that are not shared with other households
35. Unmet need for family planning	Percentage of currently married or in union women with an unmet need for family planning
36. Modern method of contraception	Percentage of currently married women or in union currently using any modern method of contraception
37. Traditional method of contraception	Percentage of currently married women or in union currently using any tradition method of contraception
38. Modern method of contraception (all women)	Percentage of women currently using any modern method of contraception
39. Married women	Percentage of currently married or in union women
40. Modern method of contraception (unmarried women)	Percentage of unmarried women currently using any modern method of contraception
41. Traditional method of contraception (unmarried women)	Percentage of unmarried women currently using any tradition method of contraception
42. Unmet need (unmarried women)	Percentage of unmarried women with an unmet need for family planning
43. Condom use (for family planning)	Percentage of women currently using condom for family planning
44. Oral contraceptive (pills)	Percentage of women currently using an oral contraceptive (pills)
45. Other modern method of contraception	Percent of women using other modern methods of contraception
46. Intrauterine contraceptive device (IUD)	Percentage of women currently using IUD method of contraception
47. Contraceptive injection	Percentage of women currently using injection method of contraception
48. Contraceptive implants	Percentage of women currently using implants
49. Female sterilization	Percentage of women with female sterilization
50. Wealth Index (upper & lower)	Household wealth index is based on household size, water source, type of toilet, primary cooking methods, materials used for housing construction, and ownership of assets

Continued...

Appendix Table A.3—*Continued*

51. Solid fuel (indoor air pollution)	Percentage of households using solid fuel for cooking, including coal/lignite, charcoal, wood, straw/shrubs/grass, agricultural crops, and animal dung
52. Iron and Folic Acid (IFA)	Percentage of women with a birth in the 5 years preceding the survey who took iron tablets
53. Under-5 mortality (U5M) rate	Probability of dying before the fifth birthday (in the 5 years preceding the survey) per 1,000 live births
54. Condom use (high-risk sex)	Percentage of condom use at last high-risk sex with a non-cohabiting, non-marital partner
55. Current marital status	Percentage currently married or living in union
56. Ever had sexual intercourse (age 15-24)	Percentage of those who ever had sexual intercourse between age 15-24
57. Number of sex partners	Number of sex partners in lifetime, calculated by grouping number of sexual partners in lifetime into (5)
58. Partners live elsewhere	Percentage of women (men) whose partners live elsewhere
59. Reporting a sexually transmitted infection (STI)	Percentage reporting an STI
60. Reporting STI symptoms	Percentage reporting an STI and symptoms
61. HIV positivity	Percentage of who tested HIV positive
62. Access to an insecticide-treated mosquito net	Percentage of the de facto household population who could sleep under an ITN if each ITN in the household were used by up to two people