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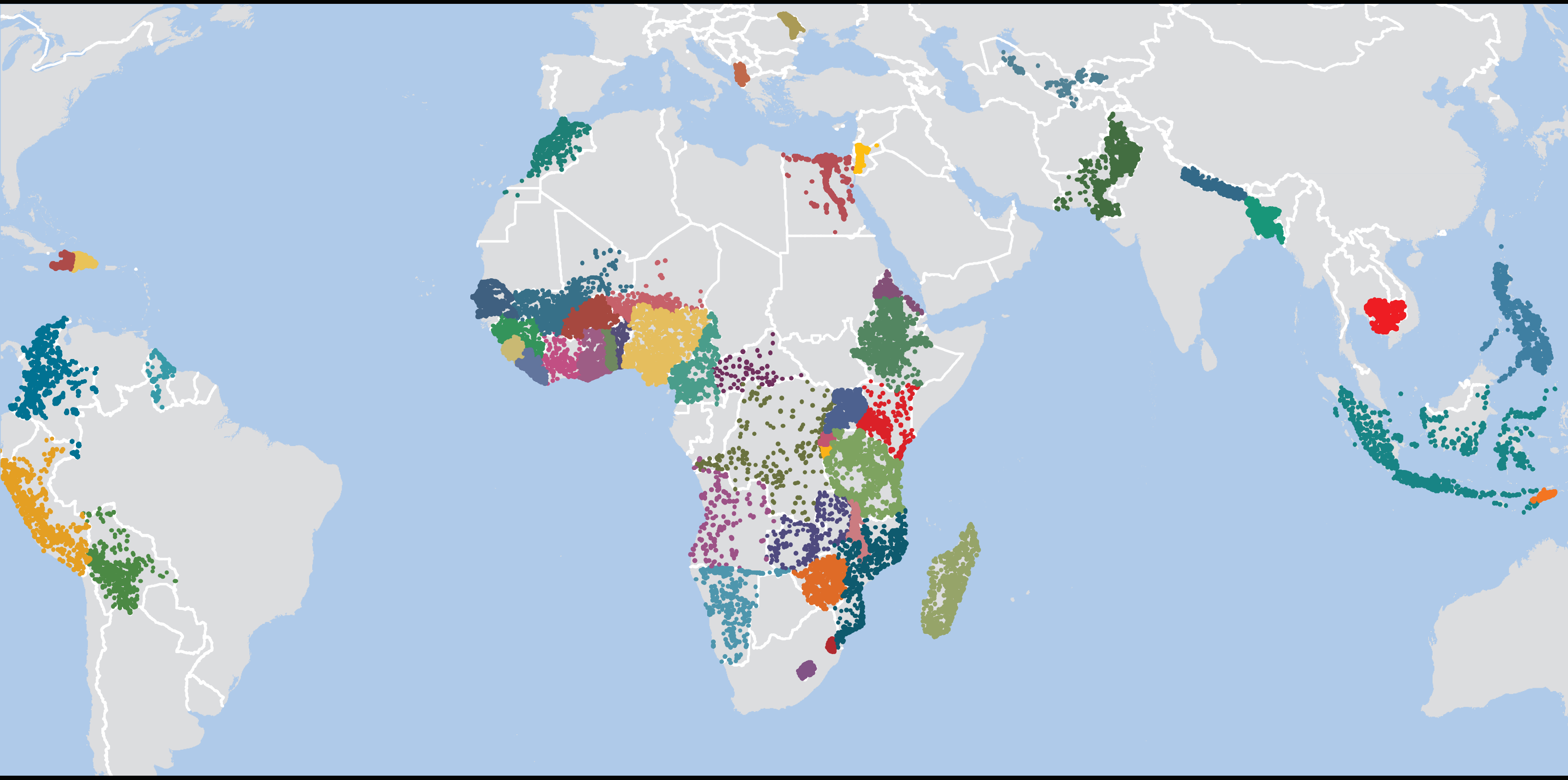
GUIDANCE FOR USE OF THE DHS PROGRAM MODELED MAP SURFACES

DHS SPATIAL ANALYSIS REPORTS 14



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Guidance for Use of The DHS Program Modeled Map Surfaces

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Abbreviations

ANC	Antenatal Care
API	Application Program Interface
DHS	Demographic and Health Surveys
EA	Enumeration Area
GPS	Global Positioning System
km	Kilometer
ITN	Insecticide-Treated Net
MAE	Model Absolute Errors
MBG	Model-Based Geostatistics
MSE	Mean Square Error
PR2	Predictive R-squared
PSU	Primary Sampling Unit
SAR 9	DHS Spatial Analysis Reports 9 “Spatial Interpolation with Demographic and Health Survey Data: Key Considerations,” which describes the key considerations for creation of interpolation surfaces using DHS data (Burgert 2014)
SAR 11	DHS Spatial Analysis Reports 11 “Creating Spatial Interpolation Surfaces with DHS Data,” which describes the pilot study conducted to determine the appropriateness of using MBG methods for interpolating DHS data (Gething et al. 2015)
SDG	Sustainable Development Goal

Glossary

DHS GPS Geo-masking (displacement): Urban clusters are displaced at a distance up to 2 kilometers (km). Rural clusters are displaced at a distance up to 5 km, with a further randomly selected 1% of the rural clusters displaced at up to 10 km. Details on the DHS geo-referenced data displacement process and the spatial variability of the resulting data are found in Burgert et al. 2013.

Interpolation: Method for creating new data values within the range of known data points.

Model-Based Geostatistics (MBG): A class of spatial statistical models for interpolating geo-located point data. The MBG models are generalized linear mixed models, which extend the flexibility of conventional generalized linear regression models (which enable various non-Gaussian data types such as count or proportion data to be fitted, via a link function, in Gaussian space) by using a multivariate normal distribution to represent spatial or spatiotemporal variation.

Modeled surfaces: Specific output from the MBG methods used to create spatial interpolated maps with DHS data.

Spatial interpolation (spatial interpolated maps): For this document, spatial interpolation refers to the general technique or concept of interpolation, but does not refer to the specific method we are using, that of Model-Based Geostatistics (MGB).

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 to meet the increasing interest in a spatial perspective on demographic and health data. The principal objectives of all 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 the DHS Spatial Analysis Reports 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

Improved understanding of geographic variation and inequity in health status, wealth, and access to resources within countries is central to meeting sustainable development goals. The Demographic and Health Survey (DHS) Program's modeled surface contributes to the greater need of the development community for small area estimations of health and demographics. The DHS Program is making publicly available a standard set of spatially modeled surfaces for each population-based survey with a select list of indicators relevant for health, demographic, and development decision-making. The modeled surfaces are created with geo-coded cluster information for current and future population-based DHS surveys and a selection of earlier surveys. The maps are publicly available for download on The DHS Program Spatial Data Repository (http://spatialdata.dhsprogram.com/). This guidance document will provide users with a deeper understanding of The DHS Program modeled surfaces and their potential use in decision-making. The DHS Program has adopted the Model-Based Geostatistics (MBG) approach to creating the modeled surfaces. This is a method for creating statistically rigorous interpolated surfaces that generate new data values for unsampled areas from sampled data points. Such an expansive number of modeled surfaces for a diverse group of health and demographic indicators has never been offered in the past and, as such, the potential uses are still nascent. Many users will find new, innovative ways to use the modeled surfaces that are not discussed or fully analyzed in this document.

Executive Summary

Improved understanding of geographic variation and inequity in health status, wealth, and access to resources within countries is central to meeting sustainable development goals. The Demographic and Health Survey (DHS) Program's modeled surface contributes to the greater need of the development community for small area estimations of health and demographics. The DHS Program is making publicly available a standard set of spatially modeled surfaces for each population-based survey with a select list of indicators relevant for health, demographic, and development decision-making. The modeled surfaces are created with geo-coded cluster information for current and future population-based DHS surveys and a selection of surveys from earlier years. The maps are publicly available for download on The DHS Program Spatial Data Repository (http://spatialdata.dhsprogram.com/).

This guidance document will provide users with a deeper understanding of The DHS Program modeled surfaces and their potential use in decision-making. This document is not a comprehensive review of the modeling process, which is discussed in other literature, and does not provide a complete list of the potential uses of modeled surfaces. The document was written for geospatial specialists and non-geospatial data specialists. Geospatial specialists will find key information on the creation of the modeled surfaces, the limitations of the modeled surfaces, and how to operationalize the modeled surfaces for use in various geospatial analyses. For the non-geospatial specialists, there is basic information about the modeled surfaces and their use in their data analysis activities.

The approach adopted by The DHS Program is Model-Based Geostatistics (MBG), a method for creating statistically rigorous interpolated surfaces that generate new data values for unsampled areas from sampled data points. This activity builds on several years of work by The DHS Program to identify the opportunities and limitations in creating interpolated surfaces with DHS data and a pilot activity that used MBG to create modeled surfaces for three countries and four indicators. The modeled surfaces are produced with publicly available geo-referenced data from both The DHS Program and other relevant spatial data sources such as environmental rasters. This will facilitate replication and comparability across countries, which will promote informed policy and program decision-making. The output of the model is a 5 × 5 km pixel resolution modeled surface. In addition, there are corresponding map surfaces that estimate the uncertainty or potential error associated with the modeled surfaces.

Understanding the limitations and assumptions of the modeling surfaces is essential for their proper use and interpretation. There are several limitations related to urban areas, temporality, and locational bias. In addition, there are considerable differences in the validity of modeling surfaces across different countries and among indicators within a country. This can be due to sampled location distribution, indicator cluster level case count, and the extent to which the covariates are drivers of the process being measured within that country. Finally, the modeling process did not specifically adjust the model to recreate the DHS regions or national level estimates present in the survey's final report.

The DHS Program modeled surfaces can be used to monitor and evaluate situations and programs, and can contribute to informed decision-making about future policies and programs. Included in this document is a discussion of possible approaches to operationalizing the modeled surfaces such as aggregation, burden estimate, and linkage with other data. Many users will find new, innovative ways to use the modeled surfaces that are not discussed or fully developed in this document. Such an expansive number of modeled surfaces for a diverse group of health and demographic indicators has never been offered in the past and, as such, the potential uses are still nascent. The DHS Program looks forward to learning how others use the modeled surfaces in the coming years.

Spatially modeled surfaces created by The DHS Program can help meet the needs of national and international communities for estimates that are more granular and spatially detailed than those currently provided by The DHS Program and most other sources of national level data. These types of maps, whether at 5 × 5 km grid scale or subsequently aggregated to appropriate sub-national decision-making units, can provide information needed for measuring geographic variation in health, demographic, and development indicators. The DHS Program's spatially modeled surfaces offer additional information that will help decision-makers better understand the geographic disaggregation of key demographic and health indicators in the coming years. There is enormous potential for new, innovative uses of the modeled surfaces. It is only in a large community of users who share their experiences that this potential will be fully realized.

Introduction to This Guidance Document

Since September 2016, The Demographic and Health Survey (DHS) Program has begun providing a standard set of indicator packages for spatially modeled surfaces to accompany current and future population-based DHS surveys with geo-coded cluster information, and a selection of surveys from earlier years. The maps are publicly available for download on The DHS Program Spatial Data Repository (http://spatialdata.dhsprogram.com). The maps are produced with a combination of publicly available DHS data and global external datasets, which are used in modeling as covariates, and use standard methods to promote comparability across countries and to facilitate policy and program decision- making. Although the creation of these surfaces is not new, their incorporation as part of a more formal decision-making processes is not yet mainstream. Little or no guidance is available for secondary users of the modeled surfaces to understand the opportunities and limitations in their use, despite increased demand for modeled map surfaces. Many groups have created surfaces for various purposes, although the operational use of these surfaces has yet to be thoroughly explored or widely used. The lack of published usage guidance and non-technical documentation stands in contrast to the growing demand for such material and the increased number of available surfaces across the fields of health and demographics.

This guidance document will provide users with a deeper understanding of The DHS Program modeled surfaces and the potential use of these surfaces for decision-making. This document is not a comprehensive review of the modeling process, which is addressed in other literature (Gething et al. 2015), and does not provide a complete list of potential uses of the modeled surfaces. Since such an expansive number of modeled surfaces on a diverse group of health and demographic indicators has never been provided, the potential uses of such surfaces are nascent. Many users will find new and innovative ways to use the modeled surfaces that are not discussed or explored in depth within this document. The DHS Program looks forward to learning how users use the modeled surfaces in the coming years.

Intended audience of guidance document

The document is intended for geospatial specialists and non-geospatial data specialists.

- Geospatial specialists will find key information on the creation of the modeled surfaces, the limitations that exist in the modeled surface, and the approaches through which the modeled surfaces can be operationalized for use in various geospatial analyses.
- Non-geospatial specialists will find basic information on the modeled surfaces and how they can utilize these surfaces in data analysis activities.

The document allows users to select sections that are relevant or most interesting to them while not reading the entire document. Some users may find parts of the guidance document quite technical, especially Section 3, which is not essential reading for all audiences. However, it is important for all users to understand the limitations and assumptions, discussed in Section 4, which will enable them to use the modeled surfaces appropriately.

Document structure

The document includes five main sections, each of which answers an overarching question:

1. Why is The DHS Program creating modeled surfaces?
2. What modeled surfaces is The DHS Program creating?
3. How are The DHS Program modeled surfaces created?
4. What are the limitations and assumptions of the modeled surfaces?
5. How can The DHS Program modeled surfaces be used?

Each section begins with a summary of the concepts discussed in the section, as well as “Key Questions.” These questions highlight the important issues in each section with short answers that are addressed in greater depth in the subsequent section.

What is The DHS Program?

The Demographic and Health Surveys (DHS) Program has long been a leader in collecting and providing cluster-randomized survey data on core development indicators (http://dhsprogram.com/). In addition to the standard open-source data files in which household and individual survey results can be tabulated by first-order sub-national regions (province or state level) and urban/rural strata, most surveys now provide geo-coded data for individual survey clusters (enumeration areas (EAs)). Global Positioning System (GPS) coordinates for DHS household survey clusters provide local scale information that can be linked with survey outputs for quantifying demographic and health status heterogeneities and inequities.

1 Why is The DHS Program Creating Modeled Surfaces?

Summary

The Demographic and Health Survey (DHS) Program's modeled surfaces contribute to the larger need of the development community for small area estimations of health and demographics. Improved understanding of geographic variation and inequity in health status, wealth, and access to resources within countries is central to meeting sustainable development goals (SDGs). The DHS Program has adopted the Model-Based Geostatistics (MBG) approach to creating modeled surfaces. The MBG approach is a method for creating statistically rigorous interpolated surfaces that creates new data values for unsampled areas from sampled data points. This current activity builds upon several years of work by The DHS Program that focused on identifying the opportunities and limitations in creating interpolated surfaces with DHS data and conducting a pilot activity that used MBG for creating modeled surfaces for three countries and four indicators.

Key Questions

What is interpolation?
Interpolation is a statistical approach in which predicted values are made for unsampled locations based on a weighted combination of nearby data points. See Section 1.2

Would these surfaces replace a large survey?
No, these modeled surfaces use The DHS Program survey data. Without that survey data, there would be no data available for creating the maps. See Section 1.3

Can these surface methods allow for smaller survey sample sizes?
These approaches may allow for smaller sample sizes in some countries, since large samples are not required for estimating the results at the administrative level. However, the precision of the estimates with smaller sample sizes yields more imprecise surfaces. The decision to utilize smaller sample sizes also depends on country needs and budget constraints. See Section 1.3

Can you give information for places that are insecure and where we cannot go for a survey?
Yes, these techniques allow for estimates in places not surveyed. These areas would not be modeled with as much certainty as other areas that were sampled. However, depending on their size and the type of insecurity present, these areas may have different, unique health and demographic outcomes that are not necessarily present in the areas that were surveyed. See Section 1.3

Why has this not been done by The DHS Program before?
The modeling techniques used for these surfaces and applied to health and demographic indicators are relatively new and until recently, have been developed by academic groups as proof of concepts rather than for policy and decision-making. In addition, these modeling techniques rely on external spatial covariates that have become more common and publicly available in recent years. The techniques have also been streamlined to require less computational power as greater computational power has become more available. See Section 1.4

1.1 Context

Improved understanding of geographic variation and inequity in health status, wealth, and access to resources within countries is increasingly recognized as central to meeting the SDGs. Development and health indicators assessed at national levels can often conceal important inequities in smaller administrative/geographic areas, often with the rural poor the least well represented. As international funding for health and development comes under pressure, the ability to target limited resources to underserved groups becomes more crucial. At the same time, gaps exist in progress toward achieving targets for key global health indicators. Monitoring demographic, access, and health status inequalities for targeting interventions and measuring progress towards health and development goals such as the SDGs require a reliable, detailed, and disaggregated evidence base. In addition, as national governments decentralize and policy decisions are made at the local level within small administrative areas, there is a growing need to utilize existing data to accurately target, monitor, and evaluate the impact of programs in smaller geographic areas. Three approaches currently allow for population-based survey indicator estimates for small geographic units.

1. Scaling-up the nationally representative survey data collection process by increasing the sample size, survey costs, and survey time needed to create a representative sample at the desired administrative level.
2. Use of data from routine health information systems from health facilities or communities.
3. Small area estimation including spatially interpolated maps that use modeling and statistical techniques to predict values for small geographic units.

The first approach is often not feasible in an increasingly resource-constrained environment. The quality of the data in the second option is not always reliable. The data are not easily accessible, and are not usually nationally representative. It is the third approach with spatial interpolation that has attracted increased interest in recent years.

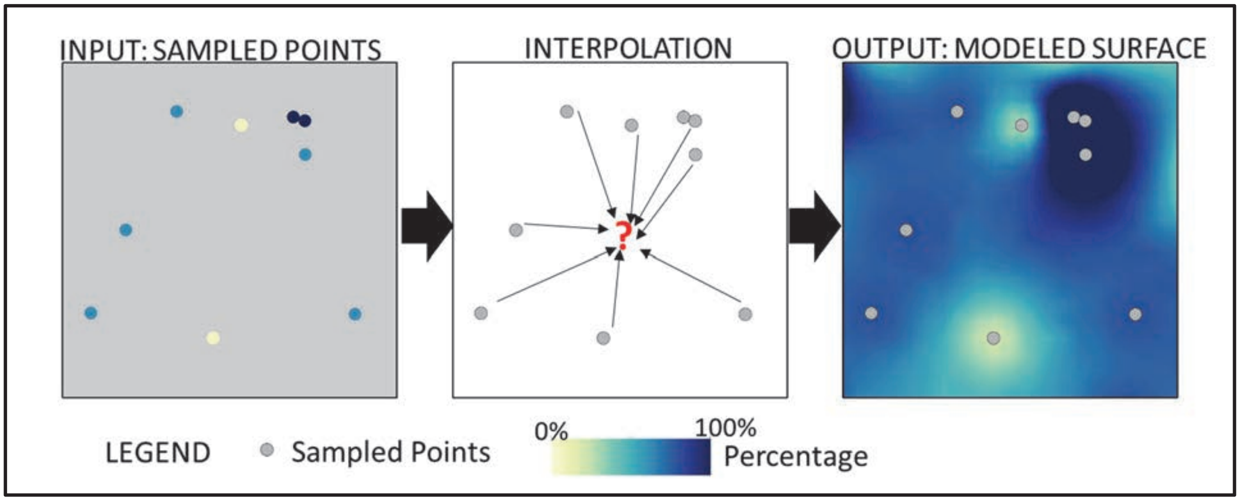
1.2 Basics of spatial interpolation

The term *geostatistics* refers to a collection of statistical tools that aid in the understanding and modeling of spatial variability. The principal motivation is predicting unsampled values dispersed in space (interpolation) (Figure 1). The most widely used tool, Kriging, is an interpolation approach in which predicted values are made for unsampled locations based on a weighted combination of nearby data points. Unlike more simple interpolation algorithms, Kriging provides optimum accuracy of predicted values by identifying the most suitable weights for each data point. This is achieved by characterizing the degree of correlation between points across space with a variogram function.

Bayesian inference is a method of statistical inference based on Bayes' theorem. This allows the combination of any prior knowledge with new information. Bayesian inference is widely used as a flexible, theoretically rigorous approach to fitting statistical models that are based on sampled datasets.

Bayesian geostatistics refers to the implementation of geostatistical models with Bayesian methods of inference. Uncertainty in the data from sampling variation and in the fitted model parameters (such as the shape of the variogram or autocorrelation function, and relationships with covariates) is inferred and propagated, so that it can be measured in the output predictions. In practical terms, this provides a convenient way of propagating uncertainty through all stages of the model fit, and representing this uncertainty in mapped outputs as a posterior distribution for each predicted pixel value.

Figure 1. Interpolation process



1.3 Spatial interpolation and household surveys

Spatial interpolation techniques for estimating values at small geographic units do not replace the need for nationally representative household surveys. The key input into the spatial interpolation modeling process is the indicator value for each geo-referenced DHS location. These techniques may allow for smaller sample sizes in some countries, since large samples are not required for estimating the results at small geographic units. However, estimates with smaller sample sizes yield more imprecise map surfaces. Ultimately, the sample size is dependent on factors that include the types of indicators being measured (rare events such as mortality require a larger sample size), the level of representativeness in the sample (national versus a sub-national area), other survey requirements needs, and budget constraints.

Spatial interpolation techniques do allow for estimating indicator values in locations that were not surveyed in general and in areas excluded from a survey due to insecurity. However, large areas that were not sampled would not be modeled with as much certainty as other areas that were sampled. In addition, depending on their size and the type of insecurity present, these areas may have different, unique health and demographic outcomes that are not necessarily present in the surveyed areas.

1.4 Previous relevant work by The DHS Program

1.4.1 DHS Spatial Analysis Report 9

The DHS Program convened a meeting of key stakeholders in June 2013 to discuss the use of geographic data from DHS population-based surveys for spatial interpolation. This meeting took place within the following context:

- Advances in technology that included faster computing power, more accessible GPS data, and less expensive hardware.
- Desire of decision-makers to use data at small administrative units and other relevant geographic areas (livelihood zones).
- Increased use and adoption of DHS data in spatial modeling techniques generally and more specifically, in interpolation techniques.

Participants also discussed the particularities of the DHS household survey geo-referenced data, which could limit some applications. The DHS Spatial Analysis Report 9 (SAR 9) (Burgert 2014) summarizes key discussions and recommendations from that meeting that also included indicator selection, methods, and limitations.

1.4.2 DHS Spatial Analysis Report 11

After meeting in June 2013, The DHS Program began exploring the potential use of Bayesian MBG for the production of interpolated modeled surfaces from the DHS population-based survey GPS-located cluster data. As a proof of concept, the MBG methods were tested on four indicators in three DHS country surveys: Ghana DHS 2008, Tanzania DHS 2010, and Uganda DHS 2011. The four indicators included prevalence of HIV testing in women (during the last 12 months), prevalence of stunting and anemia in children, and household access to improved sanitation. The DHS Spatial Analysis Report 11 (SAR 11) (Gething et al. 2015) summarizes the detailed results of this proof of concept activity, and includes the assessment of method validity, covariates, and uncertainty. In general, with the exception of the HIV testing indicator, the models performed reasonably well for all indicators with small bias values and average errors less than 20 percentage points and closer to 10 percentage points in most cases (Figure 2). Low mean square error (MSE) values indicate that the model fit with minimal overall bias. Not surprisingly, the geographic variations in a variable such as access to HIV testing, which has principally non-biophysical drivers, were less receptive to capture by the suite of principally environmental covariates, with generally lower predictive R-squared (PR2) values. Despite this, overall absolute errors (MAE) were relatively low.

In addition, the report explores the impact of DHS GPS located cluster geo-masking on the production of interpolated surfaces. The 5 × 5 km pixel resolution was chosen to reduce the impact of the geo-masking of DHS survey GPS located clusters on the final model surface and to match the resolution of the covariate inputs of the model. Finally, the report investigated the potential for novel methodologies and covariates to address the challenge of mapping within urban areas. The full model output from the proof of concept activity included 12 modeled surfaces with 5 × 5 km pixel squares on the predicted mapped surface and uncertainty map surface.

Figure 2. Summary of validation statistics for pilot activity

2 What Modeled Surfaces is The DHS Program Creating?

Summary

The DHS Program is making publicly available a standard set of spatially modeled surfaces for each population-based survey for a select list of indicators (Table 1). Each modeled surface will be produced with standardized geostatistical modeling methods (a type of spatial interpolation) and a standardized set of covariates across countries (Table 2). The modeled surfaces are produced with publicly available geo-referenced data from both The DHS Program and other relevant spatial data sources (environmental rasters) (Table 2). This will facilitate replication and comparability across countries, which in turn will promote informed policy and program decision-making. There will also be corresponding map surfaces with estimates of the uncertainty or potential error associated with the modeled surfaces. The maps are publicly available for download on The DHS Program Spatial Data Repository at http://spatialdata.dhsprogram.com/.

Key Questions

Why are you not using the detailed census data from my country as a model input?
The DHS Program chose to use a standardized approach that would be applicable across different countries and over time. This means that globally available covariate datasets are being used instead of country specific data such as census data or other country health data. Country datasets are not always publically available and using standardized global datasets is easier when producing a large number of datasets over time. See Section 2.1

Can you do this for my specific topic?
Theoretically, the modeling approach can be applied to a broad range of topics, although there are limitations for certain types of indicators that may not be modeled as well with these techniques. These limitations are summarized in this section and explained more completely in SAR 9 (Burgert 2014). See Section 2.1.1

Why is only one survey sample used instead of all surveys conducted in a country?
Incorporating surveys from multiple time points requires the use of spatiotemporal interpolation that is considerably more complex and often requires temporally varying covariates that are not always available. In addition, the availability of multiple surveys varies between countries and their incorporation would have led to less standardization between countries. For simplicity and consistency, only one survey per year was modeled. See Section 2.1.2

Do covariates have the same timeframe as the survey?
The covariates have various timeframes although they are generally close in time to the survey date. Table 2 summarizes the details of the covariates used in the modeling. See Section 2.1.3

Are map datasets publicly available? Where can I download them?
Yes, the modeled surfaces are publicly available for download from The DHS Program Spatial Data Repository at http://spatialdata.dhsprogram.com/. See Section 2.2

2.1 Standardized modeled surfaces

There is an important distinction between creating the "best possible maps" for a specific country and "standardized maps" for the whole world or a set of countries. Construction of the best possible map for a given country might entail the use of numerous country-specific covariate datasets (such as national census data) as well as bespoke mapping resolution and methodologies. While they might potentially optimize map accuracy, these country-specific components would inevitably prevent direct comparison between maps from other countries with different components. Only those covariates available as global products were included in the models to ensure a standardized approach across all countries. Further, The DHS Program uses publicly available geo-referenced data both from the DHS (GPS locations) and from external covariate sources so that the surfaces can be reproducible. In practice, this meant that the covariates (Table 2) were derived primarily from satellite remote sensing, although such data have been widely used and shown to perform as useful predictors of a wide range of social, economic, and health indicators.

2.1.1 Selection of indicators for standard map set

All indicators that can be derived from a DHS dataset may not be appropriate for use in a modeled surface creation process. The DHS Spatial Analysis Report 9 (SAR 9) (Burgert 2014) summarizes the following indicator characteristics for selecting indicators that are suitable for any type of the spatial interpolation technique:

- Indicator measures well in DHS surveys and is a robust measurement that is not subject to significant recall error.
- Indicator does not measure a rare event such as neonatal mortality. This is important because the first step in the model surface process requires calculation of the indicator at the cluster level. A relatively rare event may have many locations with zero data. Although zero or generally small numerator/denominator values at locations are accepted in the model, too many instances of zero in a dataset will lead to surfaces with considerable uncertainty that limits the surface's use.
- Indicator is spatially heterogeneous and varies across geographical space.
- Indicator has a specific reference period—not an indefinite reference period or reference period that is spatially linked to the outcome (ever tested for HIV versus fever in the past two weeks).
- Indicator is not temporally or micro-seasonally restricted and, therefore, is not likely to change substantially over the course of data collection, which can last many months. For example, school attendance and the use of mosquito nets were excluded due to temporality concerns. This means that locations may be surveyed in the same physical area at different points in time. In addition, across an entire country, different seasonal determinates may complicate the understanding of certain temporally related indicators. For example, campaign-based activities such as vaccinations or bednet distribution may also occur at different times in different places.
- Indicator relates to the current location of the respondent, and not maternal mortality by the sisterhood method that relies on interviewing respondents about the survival of all their adult sisters.

With these criteria as a guide, an initial set of 15 indicators was selected to create spatial map surfaces using DHS data for public release in September 2016. These indicators are summarized in Table 1. The standard indicator definition was used for each indicator with national estimates compared against The DHS API (http://api.dhsprogram.com/) values before modeling began. Additional details on the individual indicators and how they are collected are available on The DHS Program website (http://dhsprogram.com/). These indicators were relevant to the larger development community including the SDGs and other programmatic priorities, and important for balancing household and individual (women, men, and children) indicators. This list may change over time, with indicators added or deleted as their relevance to the larger development community are assessed, and their overall utility in potential decision-making is further understood. Not all indicators are available for each survey, either because the appropriate data are not available (not all countries conduct the men's survey) or the indicator is collected in a non-standard manner in the country such as 3-year versus 5-year estimates.

Table 1. Summary of indicators included in September 2016 data release

Indicator	Definition
Population living in households using an improved water source	Percentage of the de jure population living in households whose main source of drinking water is an improved source
Population living in households using no toilet facility (practicing open defecation)	Percentage of the de jure population living in households whose main type of toilet facility is no facility (open defecation)
Persons with access to an ITN	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
Married women currently using any modern method of contraception	Percentage of currently married or in union women currently using any modern method of contraception
Demand for family planning satisfied by modern methods	Percentage of demand for family planning satisfied by modern methods is calculated as the number of currently married women using modern methods of family planning divided by the number of currently married women with demand for family planning (either with unmet need or currently using any family planning)
Unmet need for family planning	Percentage of currently married or in union women with an unmet need for family planning
Women 15-49 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)
Antenatal visits for pregnancy: 4+ visits	Percentage of women who had a live birth in the five years preceding the survey who had 4+ antenatal care visits
Place of delivery: Health facility	Percentage of live births in the five years preceding the survey delivered at a health facility
Women who are literate	Percentage of women age 15-49 who are literate
DPT3 vaccination received	Percentage of children 12-23 months who had received a third dose of DPT
Measles vaccination received	Percentage of children 12-23 months who had received Measles vaccination
Children stunted	Percentage of children under age five years stunted (below -2 SD of height-for-age according to the WHO standard)
Men who are literate	Percentage of men age 15-49 who are literate
Tobacco use among men	Percentage of men age 15-49 who use tobacco

2.1.2 DHS data considerations

In most DHS household surveys, the sampling clusters are the primary sampling unit (PSU), which includes preexisting geographic areas known as census enumeration areas (EAs). The boundaries of the EAs are defined by the country's census bureau, as are the urban and rural status of each cluster. An EA can be a city block or apartment building in urban areas, while in rural areas an EA is typically a village or group of villages. The population and size of sampled clusters vary between and within countries. Typically, clusters contain 100-300 households, of which 20-30 households are randomly selected for survey participation. The estimated center of each cluster is recorded as a latitude/longitude coordinate, which is obtained from a GPS receiver or derived from public online maps or gazetteers. The actual physical size or boundaries of the survey cluster are publically available, although in recent years it has become more common for countries to have census EA boundary files that are used to calculate the center of the EA.

To ensure confidentiality, the geo-coded cluster locations are geo-masked (displaced) prior to dataset release (Burgert et al. 2013). Urban clusters are displaced to a distance up to two km. Rural clusters are displaced up to a distance up to five km, with a further randomly selected 1% of the rural clusters displaced at a distance up to ten km. The modeled surface creation process uses the geo-masked datasets that are made publicly available by The DHS Program.

The modeling approach used a single survey as the DHS input. It is possible to create spatiotemporal models that use multiple survey inputs to create a single surface. This approach can increase the model's predictive power but requires a number of other considerations such as the time of surveys and timing of covariates. For the purposes of the DHS standard spatially modeled surfaces, a single survey year approach simplified the model processing and interpretation.

2.1.3 Geospatial covariate considerations

An important aspect of geostatistical modeling is the exploitation of geospatial covariates that are relevant or related to the indicator of interest, can partially explain variation in that indicator, and allow for more accurate predictions across the map. As discussed above, global covariate datasets were used instead of country-specific data, since this ensures standardization across countries. A suite of geospatial covariates was chosen from existing libraries that have previously demonstrated broad utility in geospatial mapping (Gething et al. 2015; Weiss et al. 2014). The geospatial data sources described in Table 2 were obtained in a variety of spatial resolutions and geographic extents. (Details on the covariates are available on each dataset's website provided in the table.) In addition, the land-sea templates differed slightly between products, so that the precise definition of coastlines and the inclusion or exclusion of small islands and peninsulas was not consistent. These factors precluded the direct use of these data in a single spatial model. To overcome these incompatibilities and to generate a fully standardized suite of input grids on an identically defined geographic template, a processing chain was developed with the following stages:

1. Each input data source was re-projected, where necessary, by using a standardized equirectangular Plate Carrée projection under the World Geodetic System 1984 coordinate system.

2. Input grids that were defined at differing spatial resolutions were re-sampled to 5 × 5 km.

3. Grids were either extended or clipped to match a standardized country extent.

4. A bespoke algorithm was developed that compared each rectified and re-sampled grid to a "master" land-sea template for each country. This used a simple interpolation and/or clipping procedure to align new grids to this master template, which ensured that all coastlines were perfectly consistent on a pixel-by-pixel basis.

The geospatial covariates can be static (one point in time), multi-temporal (multiple spatial layers representing several consistently spaced points in time), or synoptic (over a long time period and summarized to show a long-term average or other general trends). The time period (date) that the covariates represent vary and do not necessarily match the exact time period of the DHS survey being modeled. Possible limitations of the covariates within the model are discussed further in Section 4.1.2.

Table 2. Summary of covariates used in modeling for September 2016 data release

Short name	Description	Original Data Source	Temporal	Date
Access	Travel time to cities with > 50k via all transport methods	http://forobs.jrc.ec.europa.eu	Static	2000
Aridity	Mean annual aridity	http://csi.cgiar.org/Aridity/	Synoptic	1950−2000
NTL	VIIRS nighttime lights−2012	http://ngdc.noaa.gov/eog/	Static	2012
Elevation	SRTM Near−global digital elevation models (DEMs)	http://webmap.ornl.gov/	Static	2000
EVI	Enhanced vegetation index	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
GPW	GPW population density	http://sedac.ciesin.columbia.edu/	Static	2010
LST.day	Land surface temperature in the daytime	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
LST.delta	Land surface temperature daily fluctuation range	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
LST.night	Land surface temperature in the nighttime	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
PET	Mean annual potential evapotranspiration	http://csi.cgiar.org/Aridity/	Synoptic	1950−2000
PRECIP	Average monthly rainfall	http://www.worldclim.org/	Synoptic	1950−2000
TCB	Tasseled−cap brightness	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
TCW	Tasseled−cap wetness	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014

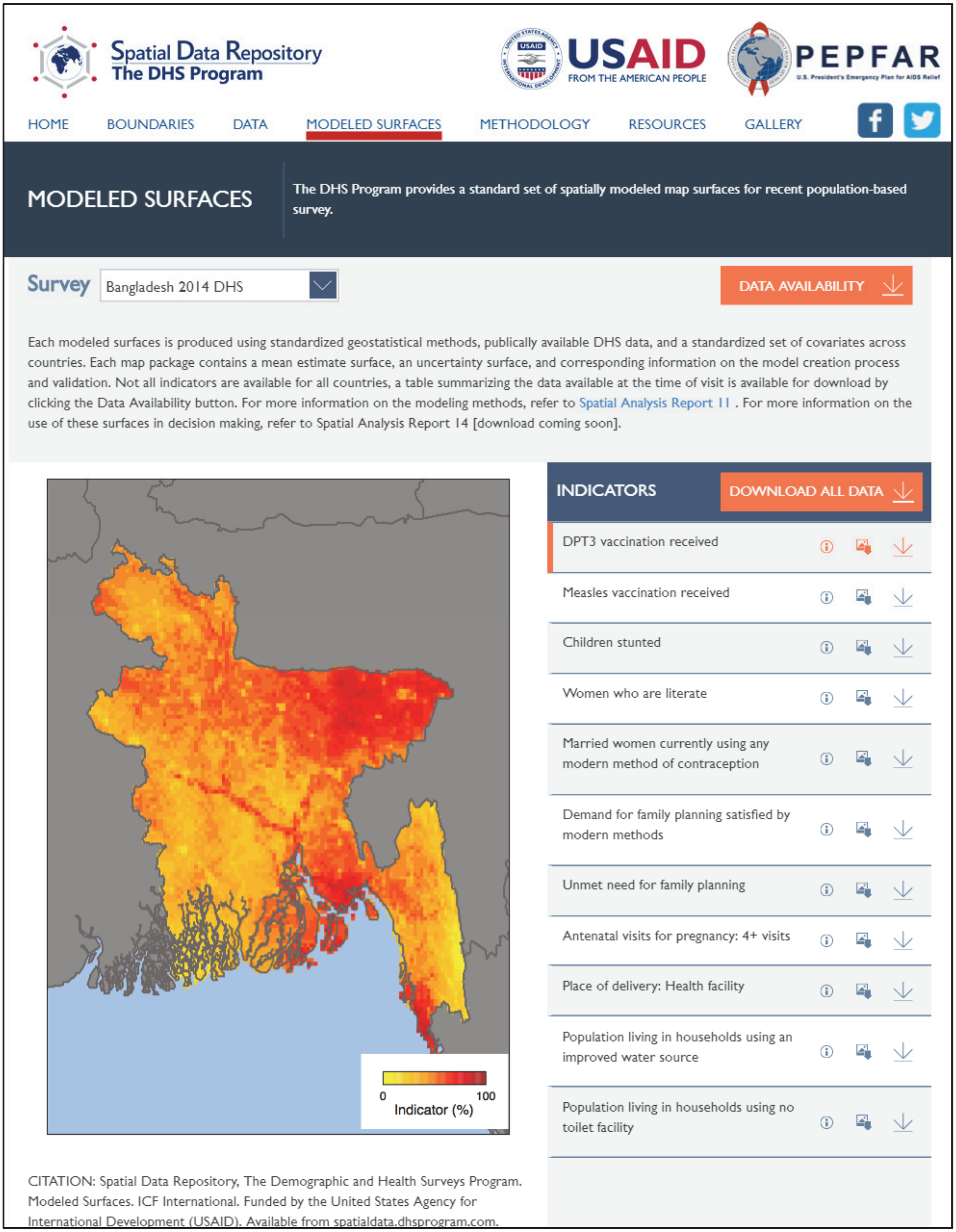
2.2 Availability of modeled surfaces

The modeled surfaces are publicly available for download on The DHS Program Spatial Data Repository (http://spatialdata.dhsprogram.com/). Figure 3 shows the website. A table summarizing the data available at the time of visit is available for download from the site; this indicates the country survey year available and the indicators are available for each.

The download package is a ZIPPED folder that contains 5 components:

- Point estimate modeled surface at 5 × 5 km resolution (GeoTIFF format)
- Uncertainty estimate modeled surface at 5 × 5 km resolution (GeoTIFF format)
- Image of mean estimate modeled surface (PNG format)
- Image of uncertainty estimate modeled surface (PNG format)
- Indicator specific document on modeling procedures (PDF format)

Figure 3. Screenshot of modeled surface download website



2.2.1 Model surfaces dataset and associated files naming conventions

The modeled surface package naming conventions follow a standard derived from The DHS Program API (application program interface). The API provides standard names for country surveys and indicators, and allows users to find corresponding information about the country survey and associated information on the specific indicator. Each dataset has a standard naming convention that identifies the country, survey year, indicator, type of data, and version number. The fields are described below.

- Field 1: SurveyID (From DHS API, see http://api.dhsprogram.com/rest/dhs/surveys?f=html)
- Field 2: SDRID (Short form of Indicator Id from DHS API, see http://api.dhsprogram.com/rest/dhs/indicators?returnFields=IndicatorId,SDRID,Label,Definition&f=html)
- Field 3: MS (modeled surfaces)
- Field 4: TYPE (either MEAN for point estimate or CI for uncertainty estimate)
- Field 5: v# (Dataset version number should be "v01" in most cases unless a dataset was reissued)

These fields are combined for each component of the data packages. These are described in Table 3 with an example for the Ghana 2008 DHS survey and the children under age 5 stunted indicator.

Table 3. Modeled surface naming conventions

	Generic	Example
Folder name	SurveyID _SDRID_MS_v#	GH2008DHS_CNNUTSCHA2_MS_v01
Datasets	SurveyID _SDRID_MS_TYPE_v#	GH2008DHS_CNNUTSCHA2_MS_MEAN_v01 GH2008DHS_CNNUTSCHA2_MS_CI_v01
Image files	SurveyID _SDRID_MS_TYPE_v#	GH2008DHS_CNNUTSCHA2_MS_MEAN_v01 GH2008DHS_CNNUTSCHA2_MS_CI_v01
Documentation	SurveyID _SDRID_MS_v#	GH2008DHS_CNNUTSCHA2_MS_v01

2.2.2 Attribution

The DHS modeled surface datasets are publically available, free of charge. You must give appropriate credit when using the DHS modeled surface datasets. Data users should cite the Spatial Data Repository as the source of all derived analyses, reports, publications, presentations, and other products. To use the recommended citation, simply replace the accessed date with the actual date of download.

For a single modeled surface dataset:

> *Spatial Data Repository, The Demographic and Health Surveys Program. Modeled Surfaces. SurveyID_SDR-API_ID_MS_v#. ICF. Funded by the United States Agency for International Development (USAID). Available from spatialdata.dhsprogram.com. [Accessed DAY MONTH YEAR]*

For multiple modeled surface datasets:

> *Spatial Data Repository, The Demographic and Health Surveys Program. Modeled Surfaces. ICF. Funded by the United States Agency for International Development (USAID). Available from spatialdata.dhsprogram.com. [Accessed DAY MONTH YEAR]*

3 How are The DHS Program Modeled Surfaces Created?

Summary

This section describes the preparation of point geo-referenced survey cluster data on each selected DHS indicator, the assembly and exploration of a suite of gridded geospatial covariate layers, and the use of these inputs in a series of bespoke Bayesian model-based geostatistical (MBG) models to generate final modeled surfaces for each indicator. The output of the model is a 5 × 5 km pixel resolution modeled surface. A more in-depth description of the modeling process can be found in SAR 11 (Gething et al. 2015).

Key Questions

Can I replicate these modeled surfaces myself?

All the details of the model inputs (covariates) and general model structure are shared in this and other accompanying documents. In theory, with the right skills, you can create your own modeled surfaces; however, your surfaces may look different from The DHS Program surfaces because certain modeling decisions take place in the model cycle that may change the final outcome. See Section 3.1

Which covariates form each map?

All covariates are used as input for every map. However, a fitting procedure is used that automatically weighs the influence of each covariate according to how much useful information it contains on the indicator of interest. The associated documentation for each surface describes the relative contribution of each covariate in the final fitted model (expressed as a percentage). See Section 3.1.3

Why do areas have different levels of error?

Error in this context refers to the ability of the model to predict the correct value of an indicator in a particular place. This depends on multiple factors such as the number of cluster locations in the survey, the density of survey clusters around a prediction location, the number of case count respondents within each cluster, the strength of correlations between covariates and the indicator, and the inherent degree of spatial variation displayed by the indicator. The overall predictive ability of the model is summarized in the mean absolute error validation statistic. See Section 3.3

Can the mean estimate value and uncertainty maps be displayed simultaneously?

Yes, there are several different ways to display the data simultaneously. See Section 3.3

3.1 Explanation of modeled surface creation process

Figure 4 illustrates the DHS modeled surface creation process from the model inputs to the model outputs. The process is further described for each numbered step in the figure in the subsequent sections.

The details of the approach are explained in the Spatial Analysis Report 11 (Gething et al. 2015). A Bayesian model−based geostatistical (MBG) approach (Diggle and Ribeiro 2007; Diggle, Tawn, and Moyeed 1998) was used to generate the modeled surfaces. Building on techniques originally conceived for detailed mapping of malaria prevalence (Gething et al. 2011; Hay et al. 2009), MBG models represent the observed variation in cluster-level survey data using four components.

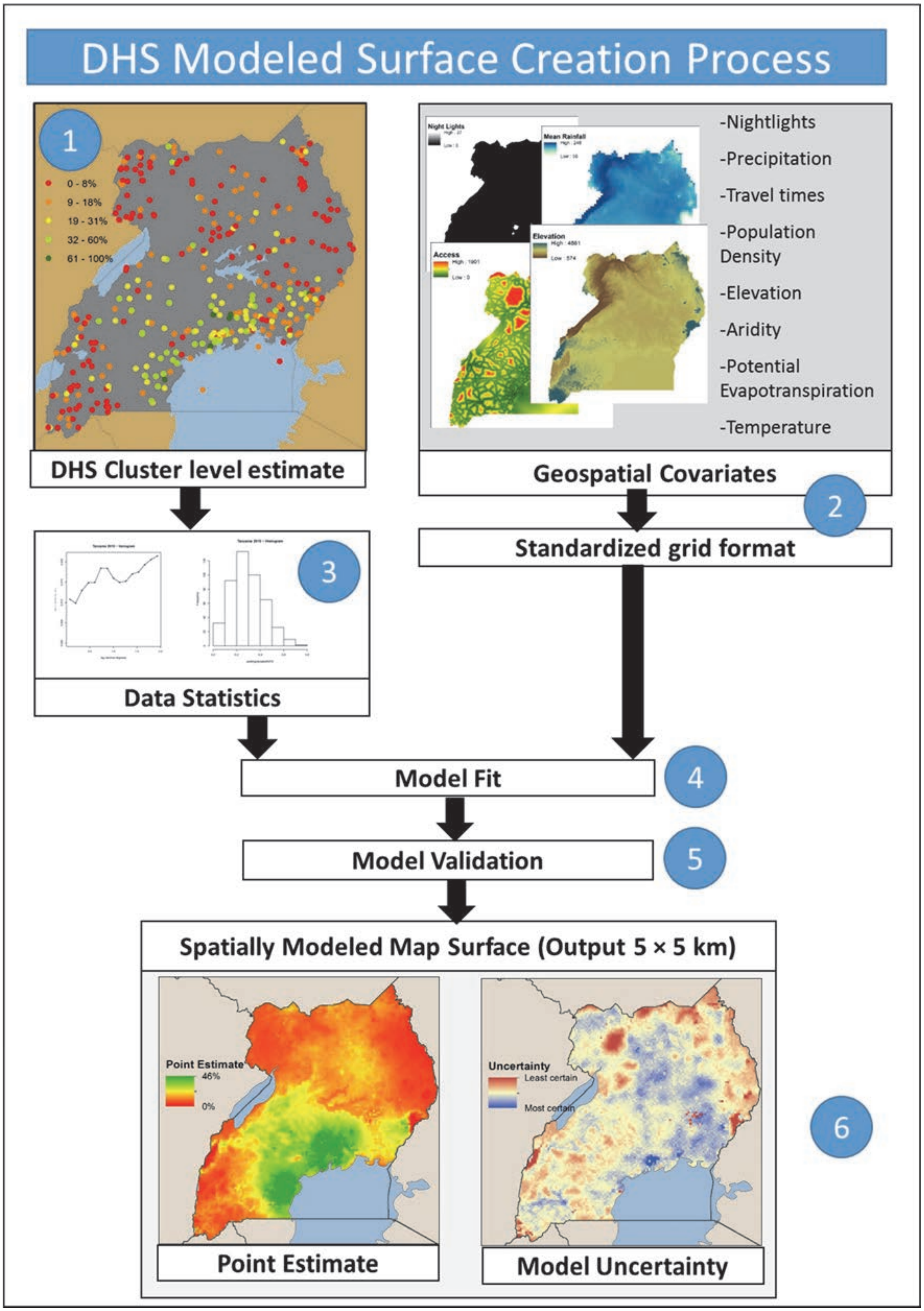
- Sampling error, which can often be large given the small sample sizes in individual clusters, is represented with a standard sampling model; this is usually the binomial when the indicator in question is a proportion.
- Some non-sampling variation can be explained using fixed effects, whereby a multivariate regression relationship is defined by linking the indicator variable with a suite of geospatial covariates.
- Additional non-sampling errors not explained by the fixed effects are usually spatially auto-correlated, and are represented by using a random effects component. A spatial multivariate normal distribution known as a Gaussian Process is employed and parameterized by a spatial covariance function.
- Any remaining variation not captured by these components is represented with a simple Gaussian noise term equivalent to that employed in a standard non-spatial linear model.

3.1.1 Model inputs (Steps 1 & 2)

Two types of data are used into the modeled surface process (Step 1 and 2 in Figure 4).

1. DHS cluster level observations: The cluster level numerator and denominator for the indicator are created with the publicly available DHS data (individual and household recode files). This information is then linked to the cluster level GPS location data.
2. Geospatial covariates: A range of covariate grids is included as possible explanatory covariates. An important aspect of geostatistical modeling is the exploitation of geospatial covariates that are correlated with the outcome of interest, can partially explain variation in that response, and allow for more accurate predictions across the map. As described above, a suite of covariates was chosen from existing libraries at the University of Oxford, based on factors that have previously been shown to correlate with demographic and health indicators in different settings. The covariates are standardized to a 5 × 5 km raster grid within a uniform coastline.

Figure 4. Schematic diagram summarizing the DHS modeled surface creation process

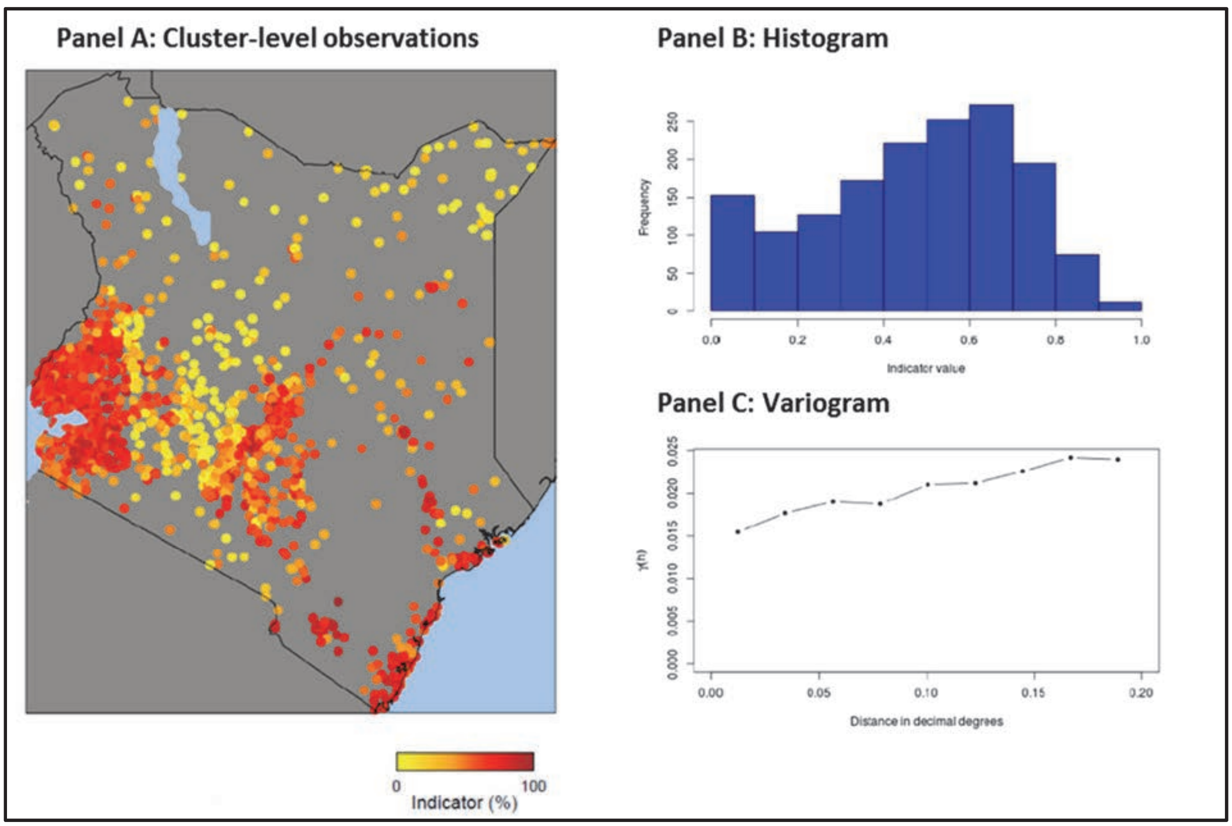


3.1.2 Data statistics (Step 3)

Three basic analyses explored the characteristics of the raw data (Step 3 in Figure 4).

- **Cluster-level observations**: A map showing the location and observed values of the indicator for each geo-located DHS survey cluster, wherein each cluster is represented by a dot (Figure 5, Panel A).
- **Histogram**: A simple empirical histogram to assess statistical distribution which is useful in interpreting the indicator and resulting maps (Figure 5, Panel B). Histograms with values across a large number of indicator values will result in a map with a spectrum of values while maps with the majority of values grouped together will produce a map with a more uniform look.
- **Variogram**: The spatial autocorrelation structure present across clusters is assessed via an empirical variogram (Figure 5, Panel C). A variogram plots semi-variance (the average dissimilarity in the indicator values between two cluster points) against spatial lag (the geographical distance separating two points). Where data are spatially structured, a characteristic variogram form will show steadily increasing semi-variance with increasing lag. Conversely, data with no spatial structure leads to a flat variogram. Variables with greater spatial autocorrelation tend to be more amenable to spatial interpolation and more reliable maps.

Figure 5. Example of data statistics



3.1.3 Model fit (Step 4)

After considering the preliminary data statistics, the next step in the modeling process is parameterizing the model to determine the set of model parameter values that lead to the best possible fit with the data (Step 4 in Figure 4). The MBG models have three categories of parameters, which involve determining the characteristics of the Gaussian process (random effects), the nature and magnitude of the contribution of each covariate (fixed effects), and the uncorrelated residual error (the non-spatial component). The spatial Gaussian process is governed by a spatial covariance function (the Matern function was used for flexibility) which is parameterized by a scale parameter (which determines the spatial distance over which points are autocorrelated) and a variance parameter (which determines the magnitude of that autocorrelation) (see Table 4, model parameters).The fixed effects have a more complex parameter structure that allows for non-linear relationships between the covariates and the response variable as well as interactions between them. A "regularization" approach allows the full suite of covariates to be used in the model without the risk of over-fitting. All covariates remain in the model although their relative contributions to the final predictions can be large or almost zero in order to maximize predictive performance. These contributions are described as a percent covariate contribution (see Table 4, covariate contributions). This approach differs slightly from the approach described in SAR 11 in which there was an initial covariate selection process with only the selected covariates included in the final model. The new approach provides consistently higher performance and has the additional advantage of reducing the subjective input of an analyst in refining the selection of covariates. The uncorrelated residual error is parameterized by a single variance parameter (see Table 4, model parameters). All parameters are jointly estimated in a single fitting exercise using Bayesian inference with vague priors.

Table 4. Example of model parameters, covariate contributions, and validation statistics

Model parameters	
Covariance function	Matern
Spatial scale of correlation (km)	70.9
Variance of spatially structured component	0.5
Variance of non-spatial component	0.58
Covariate contributions	
Mean annual aridity	12%
VIIRS nighttime lights−2012	8%
Enhanced vegetation index	4%
SRTM near−global digital elevation models (DEMs)	14%
GPW population density	4%
Land surface temperature in the daytime	18%
Land surface temperature daily fluctuation range	4%
Land surface temperature in the nighttime	6%
Mean annual potential evapotranspiration	6%
Tasseled−cap brightness	6%
Tasseled−cap wetness	9%
Travel time to cities with > 50k via all transport methods	6%
Average monthly rainfall	6%
Validation statistics	
Correlation	88%
Mean absolute error	9%
Mean square error	1%

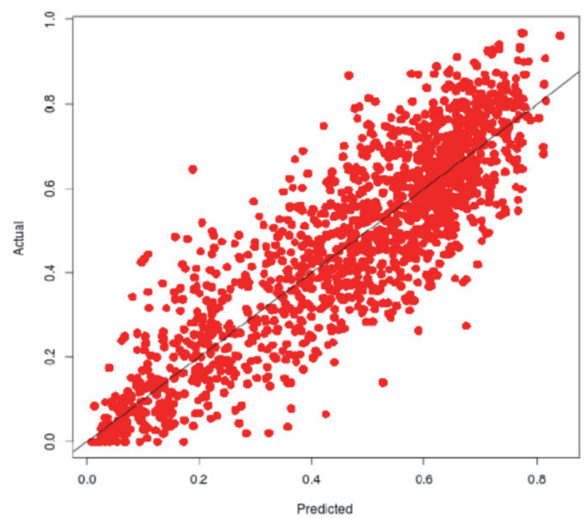
3.1.4 Model validation (Step 5)

Model validation and the corresponding statistics are an important measure of the predictive performance of the geostatistical model (Step 5 in Figure 4). Performance is assessed by out-of-sample validation that includes a four-fold, hold-out procedure in which 25% of the data points were randomly withdrawn from the dataset. The model is then run in full with the remaining 75% of data, and the predicted values at the locations of the hold-out data compared to their observed values. This process is repeated four times without replacement so that every data point is held out one time throughout the four validation runs. Standard validation statistics are then computed as measures of model precision:

- Degree of linear association between the observed and predicted values (correlation, COR).
- Mean absolute error (MAE) that quantifies model precision, which is the average magnitude of difference between observed and predicted values. This is computed in the same units as the variable being predicted; for example, if the indicator is a rate expressed on a scale from 0-100%, the MAE will also be a value between 0-100%.
- Mean square error (MSE) that indicates the model's accuracy, and encapsulates bias and error with values close to zero an indication that the model is more accurate and close to one less accurate.

Examples of these statistics are shown in Table 4 (validation statistics). Figure 6 below shows a scatterplot with the distribution of actual (observed) versus predicted points from the model.

Figure 6. Example of validation scatterplot

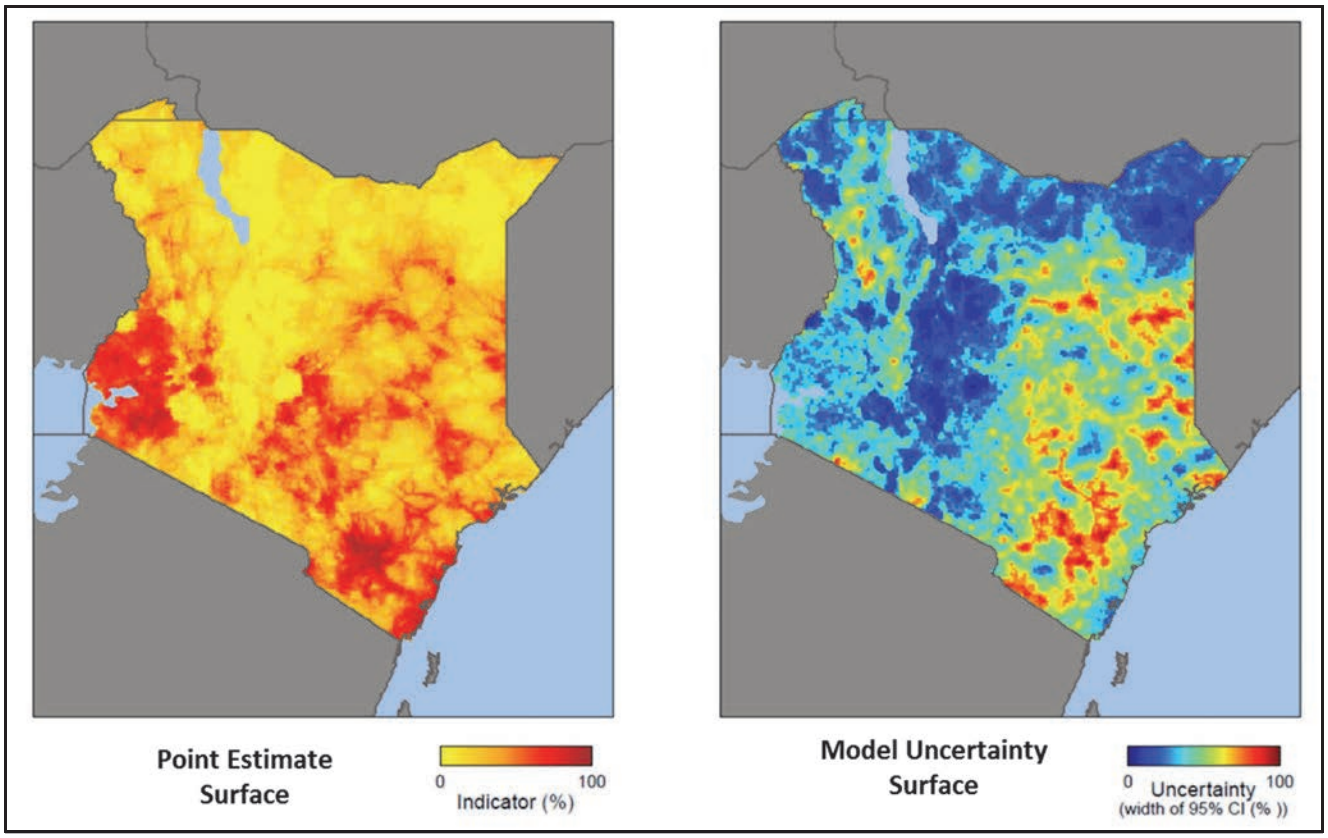


3.1.5 Model outputs (Step 6)

In the download package, the model has two map surface outputs with 5 × 5 km pixel resolution (Step 6 in Figure 4): the point estimate surface and the model uncertainty surface. The MBG models generate estimates of the variable of interest at each location on a gridded surface. For each of those pixels, the full model output is a posterior distribution for the predicted indicator that represents a complete model of the uncertainty around the estimated value. These can be summarized with a point estimate (such as the posterior mean) to generate a mapped surface. Additional summary statistics from each posterior distribution can then be mapped to illustrate the degree of uncertainty associated with each predicted value.

- **Point Estimate Surface:** The map plots the modeled point estimate value for each 5x5 km pixel based on geo-located, cluster-level data from the survey. This value effectively represents the expected value of the indicator within that 5 × 5 km region. Since the indicators being modeled are rates (prevalence or proportion variables), all rates lie on a scale between 0 and 1 (or 0% and 100%) (Figure 7, left).
- **Model Uncertainty Surface:** An accompanying uncertainty map summarizes the level of certainty associated with the values shown in the point estimate map by displaying the full width of the 95% credible interval (also called confidence interval or CI) for each pixel value (Figure 7, right). In a situation with complete uncertainty about a pixel's value, the 95% CI would span the entire range and the true value could lie anywhere between zero and one. Conversely, when a variable is predicted with very high certainty, the width of the 95% CI might be very narrow. In other words, there is a 95% probability that the true value lies within a narrow range of possible values; this indicates that the prediction has low uncertainty.

Figure 7. Example of point estimate surface and model uncertainty surface



3.2 Example of modeled surface documentation

The following pages describe an example of the modeled surface documentation included in each zip file that can be downloaded from The DHS Program Spatial Data Repository website. Each indicator country survey has its own document with the figures and information relevant for that modeled surface. The main text, which is standard across all documents, helps users understand the information in the figures.

USAID
FROM THE AMERICAN PEOPLE

Spatial Data Repository
The DHS Program

Persons with access to an ITN
Kenya 2014 Demographic and Health Survey

The DHS Program

The Demographic and Health Survey (DHS) Program has been a leader in collecting and providing cluster-randomized survey data on core development indicators since 1984. DHS surveys are configured to provide indicator estimates at the national and in more recent surveys first level administrative level. In more recent years, the availability of the Global Positioning System (GPS) coordinates for DHS household survey clusters provides highly local scale information that can be linked with survey outputs for quantifying demographic and health status heterogeneities and inequities. In 2016, The DHS Program started publically providing a standard set of spatially modeled map surfaces. The surfaces use publicly available spatial covariate data, are standardized across countries, and are comparable in order to facilitate policy and program decision-making at levels below the current survey representative sub-national areas. The DHS Program is funded by the U.S. Agency for International Development (USAID) (http://dhsprogram.com/).

Indicator definition: Persons with access to an ITN

Full definition: 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
Numerator: De facto household population who could sleep under an ITN if each ITN in the household were used by up to two people
Denominator: De facto household population
API ID: ML_ITNA_P_ACC

Geospatial modelling

A Bayesian model-based geostatistical (MBG) approach (Diggle and Ribeiro 2007; Diggle, Tawn, and Moyeed 1998) was used to generate the interpolated surfaces shown below. Building on techniques originally conceived for detailed mapping of malaria prevalence (Hay et al., 2009, Gething et al 2011), MBG models represent the observed variation in cluster-level survey data using four components. (i) Sampling error, which can often be large given the small sample sizes in individual clusters, is represented using a standard sampling model, usually the binomial. (ii) Some non-sampling variation can often be explained using fixed effects, whereby a multivariate regression relationship is defined linking the indicator variable with a suite of geospatial covariates. (iii) Additional non-sampling errors not explained by the fixed effects are usually spatially autocorrelated, and this is represented using a random effects component. A spatial multi-variate normal distribution known as a Gaussian Process is employed, parameterized by a spatial covariance function. (iv). Finally, any remaining variation not captured by these components is represented using a simple Gaussian noise term equivalent to that employed in a standard non-spatial linear model. This approach is explained in full in the DHS Spatial Analysis Reports No. 11 (Gething et al, 2015).

Maps

MBG models generate estimates of the variable of interest at each location on a gridded surface. The maps below were defined on a grid where each individual pixel measures approximately 5x5 km. The full model output is, for each of those pixel, a posterior distribution for the predicted indicator, representing a complete model of the uncertainty around the estimated value. These can be summarized using a point estimate (such as the posterior mean) to generate a mapped surface (as shown in Figure 1). Additional summary statistics from each posterior distribution can also be mapped to illustrate the degree of uncertainty associated with each predicted value. Figure 2 shows one such metric of uncertainty – the width of the 95% credible intervals, with large values representing areas of the highest uncertainty, and vice versa.

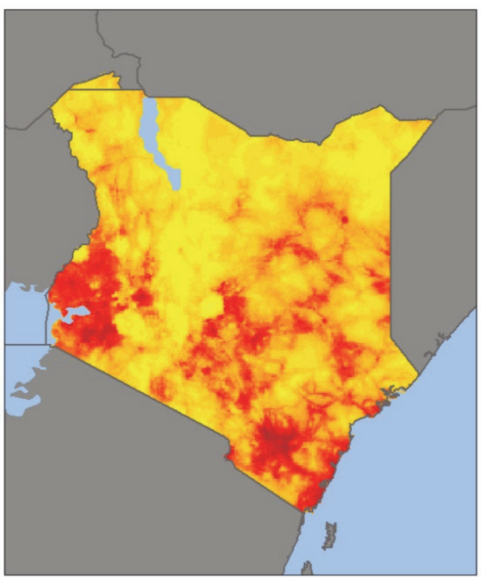


Figure 1. Interpolated surface for the indicator. The map plots the point estimate for each 5x5 km pixel based on geo-located cluster-level data from the survey.

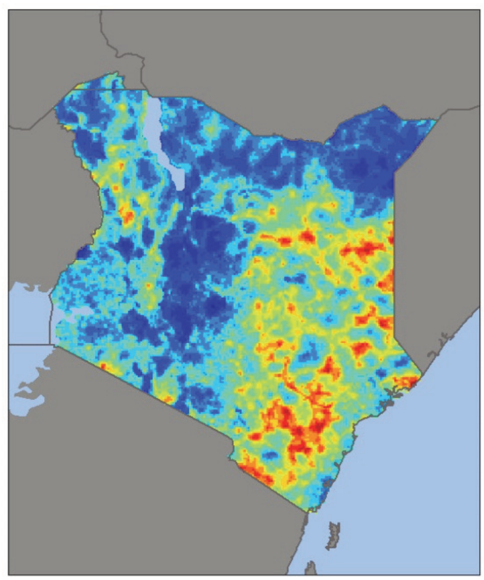


Figure 2. Uncertainty surface for the indicator. The map plots the uncertainty for each pixel, measured using the width of the 95% credible intervals.

This document can be cited as follows: Spatial Data Repository, The Demographic and Health Surveys Program. Modeled Surfaces. KE2014DHS_MLITNAPACC_MS_v01 ICF International. Funded by the United States Agency for International Development (USAID). Available from spatialdata.dhsprogram.com. [Accessed DAY MONTH YEAR]

Persons with access to an ITN
Kenya 2014 Demographic and Health Survey

Data statistics

Figure 3 shows the location and observed values of the indicator for each geo−located DHS survey cluster. Two basic exploratory analyses were undertaken to explore the characteristics of these raw data. First, a simple empirical histogram were generated to assess statistical distribution which can be useful in interpreting the indicator and resulting maps. This is shown in Figure 4 (top). Second, the spatial autocorrelation structure present in the indicator values across clusters was assessed via an empirical variogram (Figure 4 (bottom)). A variogram plots semivariance (the average dissimilarity in the indicator values between two cluster points) against spatial lag (the geographical distance separating two points). Where data are spatially structured, a characteristic variogram form is for semivariance to steadily increase with increasing lag. Conversely, data with no spatial structure lead to a flat variogram. Variables with greater spatial autocorrelation tend to be more amenable to spatial interpolation and more reliable maps.

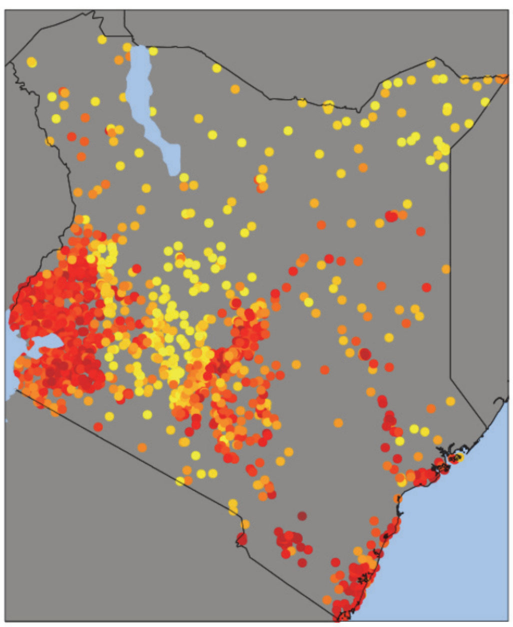


Figure 3. Cluster−level observations of the indicator. These geo−located data formed the basis for the modeled interplated surface.

0 100
Indicator (%)

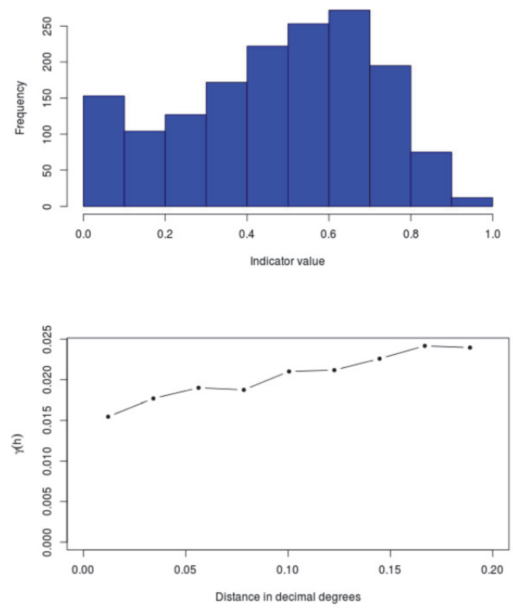


Figure 4. Histogram (top) and variogram (bottom) of the cluster−level indicator data from the survey.

Geospatial covariates

An important aspect of geostatistical modeling is the exploitation of geospatial covariates that are correlated with the indicator of interest, and thus partially explain variation in that indicator, allowing more accurate predictions across the map. A suite of geospatial covariates were chosen from existing libraries that have previously demonstrated broad utility in geospatial mapping (Weiss et al 2014, Gething et al, 2015) − listed in full in Table 1. A 'regularization' approach was used which allows a large suite of covariates to be used in the model witout risking over−fitting: all covariates remain in the model but their relative contributions to the final predictions can be large or almost zero in order to maximize predictive performance. Table 2 describes the relative contributions of each covariate to the predictions presented here.

Short name	Description	Original Data Source	Temporal	Date
Access	Travel time to cities with > 50k via all transport methods	http://forobs.jrc.ec.europa.eu	Static	2000
Aridity	Mean annual aridity	http://csi.cgiar.org/Aridity/	Synoptic	1950−2000
NTL	VIIRS Nighttime Lights−2012	http://ngdc.noaa.gov/eog/	Static	2012
Elevation	SRTM Near−global Digital Elevation Models (DEMs)	http://webmap.ornl.gov/	Static	2000
EVI	Enhanced vegetation index	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
GPW	GPW population density	http://sedac.ciesin.columbia.edu/	Static	2010
LST.day	Land surface temperature in the daytime	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
LST.delta	Land surface temperaturedaily fluctuation range	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
LST.night	Land surface temperature in the nighttime	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
PET	Mean annual Potential Evapotranspiration	http://csi.cgiar.org/Aridity/	Synoptic	1950−2000
PRECIP	Average monthly rainfall	http://www.worldclim.org/	Synoptic	1950−2000
TCB	Tasseled−cap brightness	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014
TCW	Tasseled−cap wetness	http://modis.gsfc.nasa.gov/	Multitemporal	2001−2014

Table 1. Further details of geospatial covariates included in the model

This document can be cited as follows: Spatial Data Repository, The Demographic and Health Surveys Program. Modeled Surfaces. KE2014DHS_MLITNAPACC_MS_v01
ICF International. Funded by the United States Agency for International Development (USAID). Available from spatialdata.dhsprogram.com. [Accessed DAY MONTH YEAR]

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Spatial Data Repository
The DHS Program

Persons with access to an ITN
Kenya 2014 Demographic and Health Survey

Model fit and validation

The predictive performance of the geostatistical model was assessed via out-of-sample validation. This consisted of a four-fold hold-out procedure whereby 25% of the data points were randomly withdrawn from the dataset, the model run in full using the remaining 75% of data, and the predicted values at the locations of the hold-out data compared to their observed values. This was repeated four times without replacement such that every data point was held out once across the four validation runs. Standard validation statistics were computed as measures of model precision (mean absolute error, MAE), bias (mean square error, MSE), and the degree of linear association between observed and predicted values (correlation, COR). The MAE quantifies model precision, while the MSE indicates how biased the model is, with values close to zero providing an indication that the model is unbiased. These statistics are listed in Table 2, and a scatterplot showing the distribution of observed versus predicted points in Figure 5.

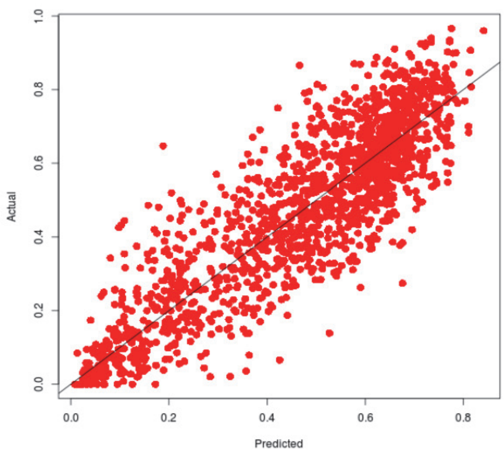

Figure 5. Validation scatterplot. For each point in the out-of-sample validation exercise, the observed value is plotted against the predicted value, with the 1:1 line shown for reference.

Model parameters	
Covariance function	Matern
Spatial scale of correlation (Km)	70.9
Variance of spatially structured component	0.5
Variance of non-spatial component	0.58
Covariate contributions	
Mean annual aridity	12%
VIIRS Nighttime Lights-2012	8%
Enhanced vegetation index	4%
SRTM Near-global Digital Elevation Models (DEMs)	14%
GPW population density	4%
Land surface temperature in the daytime	18%
Land surface temperature daily fluctuation range	4%
Land surface temperature in the nighttime	6%
Mean annual Potential Evapotranspiration	6%
Tasseled-cap brightness	6%
Tasseled-cap wetness	9%
Travel time to cities with > 50k via all transport methods	6%
Average monthly rainfall	6%
Validation statistics	
Correlation	88%
Mean absolute error	9%
Mean square error	1%

Table 2. Model fit and validation statistics. Detailed are the relative contributions of ech covariate to the final model fit, and the results of the validation exercise.

Model surface uncertainty and interpretation

The ability of the MGB process to accurately predict any given indicator is dependent on several factors. First, each indicator will have different inherent properties such as the overall amount of variation across the country, the extent to which this is spatially autocorrelated (with more autocorrelation meaning a more organized geographic pattern that is easier to predict), and the statistical distribution of values (with bi-modal, heavily skewed, or other unusual distributions often being more difficult to predict accurately). Second, the extent to which the environmental covariates are correlated with the indicator will influence predictive accuracy, with higher correlations allowing greater accuracy. Third, the density of cluster points and the sample size (e.g. number of respondents) at each cluster will have an important effect, with denser surveys and larger sample sizes yielding greater accuracy. Given these factors, it is expected that some indicators will be predicted with greater accuracy in some countries than in others. An important element of the model surface outputs is therefore the uncertainty estimates. Uncertainty takes into account the error in the mean estimate and is estimated for each grid square (pixel level). The uncertainty surface helps users understand the robustness of an estimate at any given area on the map. This uncertainty of the modeled surface is shown in Figure 2 with each grid square (pixel) value representing the width of the 95% credible interval (CI) of the mean estimate value for that pixel. It is possible to have very low confidence width values while it is also possible to have values that are equivalent to a 95% CI of 0%-100%.

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ICF International. Funded by the United States Agency for International Development (USAID). Available from spatialdata.dhsprogram.com. [Accessed DAY MONTH YEAR]

3.3 Model surface uncertainty and interpretation

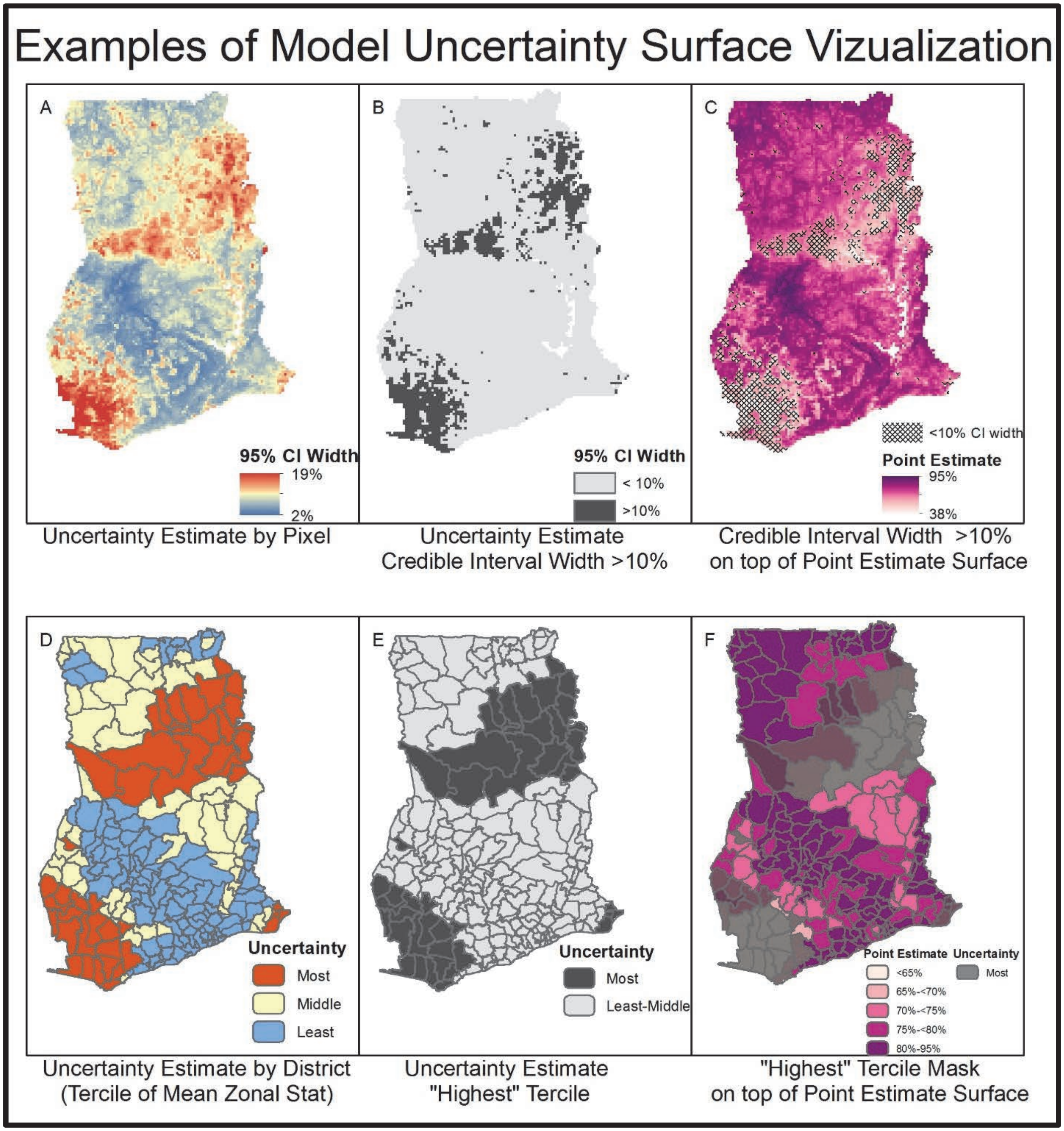
An important element of the model surface output is the uncertainty estimates. The prediction uncertainty maps provide an indication of the likely precision of the mean estimate for each grid square (pixel level). The uncertainty surface helps users understand the robustness of an estimate at any given location on the map. Uncertainty can vary across a modeled surface for several reasons such as the sparseness of DHS point location data, rareness of the indicator being estimated, and the extent to which the model explains the variance. More uncertainty in a location indicates that the model poorly estimates the indicator value in that location, while less uncertainty indicates that the model is better able to estimate the indicator value in that location. This uncertainty of the modeled surface is provided as a standard output in the form of a raster surface with each grid square (pixel) value representing the width of the 95% CI of the point estimate indicator value for that pixel. It is possible to have very low confidence width values and values that are equivalent to a 95% CI of 0% to 100%. These uncertainty surfaces are separate from the validation statistics, which provide a summary of the overall model performance rather than the precision at different locations. Although the relationship between them is complex, generally a model with good validation statistics (high correlation, low MAE and MSE) would also have lower levels of uncertainty on a pixel-by-pixel basis, and *vice-versa*.

When using the modeled surfaces for decision-making, it is important to consider the uncertainty of the estimate. The interpretation of the uncertainty values for a modeled surface is not obvious, and is often ignored by users. However, it is an important element of the model and is worth consideration by users, who can gain a general sense of the model's uncertainty and the difference in uncertainty in specific areas. Individual users must decide on an acceptable level of uncertainty depending on the given context or indicator, and the amount of uncertainty that they are willing to accept.

Figure 8 illustrates several ways that the uncertainty surface can be transformed to be more useful in the decision-making process. Displaying the uncertainty surface as a continuous value with a divergent color scheme (Figure 8 Panel A) allows users to identify areas with more or less certainty. Another approach requires the user to select a credible interval threshold with the amount of error they are willing to accept such as 10%. The map can then display those areas that meet the threshold and those that do not. It is also possible to super-impose those areas that do not meet the threshold onto the mean estimate map either as a mask or hatching (Figure 8 Panel B and C).

Unlike the point estimate interpolated surface, it is not appropriate to aggregate (average) the uncertainty surface to larger geographic polygons (areas) by a simple averaging method and then using these results directly as an estimate of the 95% CI of the aggregated mean estimate value for the same area. Since the uncertainty is evaluated at the pixel level (the certainty of the mean estimate at that pixel only), it cannot be averaged over a larger area because the level of error is not independent across pixels. There may be some ways to account for this problem of joint probabilities that occur in the aggregation of the uncertainty surface, but it would be necessary to know the exact purpose and level of aggregation needed for the indicator (Gething, Patil, and Hay 2010). This is appropriate when making a single specific map for analytical purposes, although the purpose and level of aggregation will vary for every user of The DHS Program modeled surfaces. It may be appropriate to aggregate the uncertainty surface to larger geographic areas if the relative uncertainty is being evaluated versus the absolute width of the 95% CI. Averaging the 95% CI for a given area and then comparing it to other areas can provide a sense if one area is likely to have more or less uncertainty when compared to other areas. Operationalizing this might involve calculating the average width of the 95% CI values for the geographic areas of interest (by averaging the pixel values within the geographic unit), creating terciles of the values, and then displaying them as high, medium, and low relative uncertainty without any actual values (Figure 8 Panel D, E, and F).

Figure 8. Examples of model uncertainty surface visualization



4 What are the Limitations and Assumptions of the Modeling Surfaces?

Summary

Understanding the limitations and assumptions of the modeling surfaces is essential for their proper use and appropriate interpretation. There are several model limitations related to urban areas, temporality, and locational bias. In addition, there can be considerable differences in modeling surface validity across different countries and among indicators within a country. This may be due to sampled location distribution, indicator cluster level case count, and the extent to which the covariates are drivers of the process being measured within that country. Finally, the modeling process did not specifically adjust the model to recreate the DHS Regions or national level estimates present in the survey final report.

Key Questions

Are some geographic areas modeled better or worse than others?
The pilot modeling activity (SAR 11) indicated that urban areas were not as well modeled as other areas of a country. This is due in part to the large heterogeneity in urban areas that may not be captured by the covariate library as well as the impact of the 0-2 km geo-masking (displacement) of the urban geo-coded cluster location. See Section 4.2

Why do areas have different levels of error across indicators and countries?
Error in this context refers to the ability of the model to predict the correct value of an indicator in a particular place. This depends on multiple factors such as the density of survey clusters around a prediction location, the sample size (number of case count respondents) within each cluster, data points available and location in the survey (more data points provide better predictions), the strength of correlations between covariates and indicators, the indicator and covariate association, and the inherent degree of spatial variation displayed by the indicator. The overall predictive ability of the model is summarized in the mean absolute error validation statistic. See Section 4.2

Are maps comparable across different countries?
Yes, the maps are comparable between different countries but limitations remain as described in earlier sections; these include the varying amount of error in the map and the predictive ability of the model. See Section 4.2

Can I recreate the DHS final report national or sub-national estimates from the modeled surface map?
The modeling process did not specifically adjust the model to recreate the DHS regions or national level estimates present in the survey final report. In many cases, the modeled surface aggregated values will be within the 95% CI of the DHS final report estimates. See Section 4.3

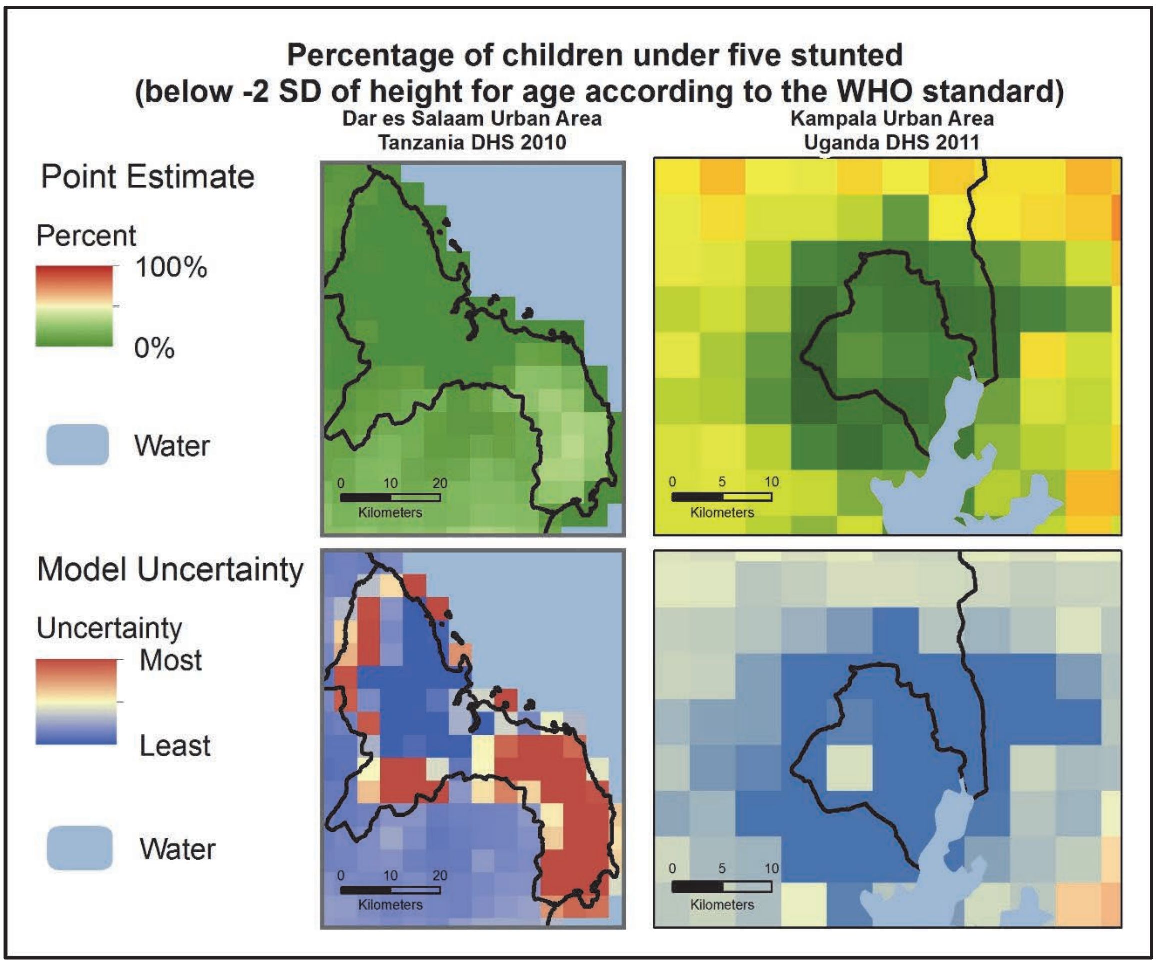
4.1 Model limitations

There are several assumptions and limitations that must be considered when using and interpreting the spatial modeled surfaces. These relate to urban areas, temporality, and locational bias.

4.1.1 Urban areas

A key limitation of the modeling approach is urban area mapping. In all national-level spatially modeled surfaces created in the pilot and described in SAR 11, urban areas were predicted with relatively uniform values (Figure 9). This is due in part to the size of the final pixel resolution and the availability of urban specific covariates, which may differ from those in rural areas. In reality, large urban areas typically exhibit substantial heterogeneities in health and development indicators that occur at shorter scales than the 5 km pixel diameter. This is an important issue since close to 50% of residents in the majority of countries that were mapped reside in urban areas and the population in urban areas is growing. The SAR 11 report explored some possible approaches to mitigating these factors including using higher resolution covariates in urban areas (Gething et al. 2015). Specific conclusions related to urban areas should be considered carefully and with an understanding that the predicted 5 × 5 km value of urban pixels represents a mean that cannot show the considerable within-pixel variability.

Figure 9. Example of urban area point estimates surface and model uncertainty surface



4.1.2 Temporality

There are several temporal or seasonal limitations and assumptions that apply when considering a modeled surface. These limitations are similar to the temporal issues that exist in selecting an indicator described in Section 2.1.1. Issues include the survey timing, length of the fieldwork, and covariate timing. These are particularly relevant for temporally bounded indicators or those related to the time when the survey was conducted such as the rainy season or school year.

A recent review of 18 recent DHS surveys indicates that fieldwork typically lasts between 2 to 9 months, with an average of 5 months. The dates of survey fieldwork are available on the DHS website (http://dhsprogram.com/). The length of fieldwork varies between countries, and this variation can have an impact on specific indicators within a country. For example, if a particular indicator has a seasonal association with the survey date in any particular cluster, the location will not be the same as other parts of the country and nearby locations may not be surveyed at the same time.

The timing of the raster covariate datasets is an additional limitation on the model map surfaces. Although some geospatial covariates may not vary greatly within a given year or over many years, some may vary considerably. Table 2 summarizes the temporal nature of each raster and their date(s) of collection. The use of the standard covariates instead of the best covariates for any given country means that the timing of any given covariate may not align exactly with the survey dates. This could reduce the predictive ability of the model.

4.1.3 Locational bias

There are two potential sources of locational bias in the modeled surface. The first relates to the error associated with the measurement of the centroid of the cluster point location; the other is the assumption that the event measured by a specific indicator occurred at a given cluster point location.

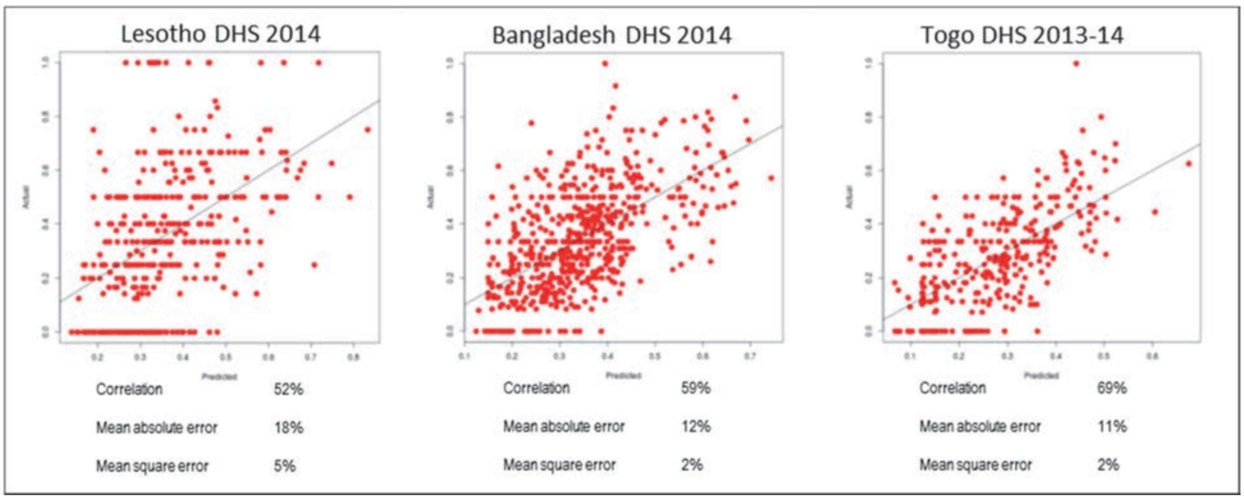
As mentioned previously, the DHS cluster location data used in the spatial modeling process are an estimated center of the survey cluster, a point location that actually represents an area of unknown size with fairly large variability across a country, especially between urban and rural locations. In addition, these point locations are geo-masked from 0-2 km in urban locations and 0-5 km in rural locations, with 1% of rural locations up to 10 km (Burgert et al. 2013). These two issues add spatial error to the model although previous work discussed in SAR 11 has shown that the impact of displacement on modeling error is small (Gething et al. 2015).

The methods used to produce the modeled surfaces assume that an event measured by an indicator occurred in the place the survey took place. However, the event could have occurred in a different place. This type of bias occurs when an event takes place in a different location from that of the respondent being interviewed. The bias can be minimized if the reference period is given proper consideration. For example, shorter reference periods such as one year versus a lifetime are likely to reduce locational bias. The intended purpose of the modeled surface may also be relevant when considering locational bias. For example, if an interpolated surface of women age 15-49 who were tested for HIV in the past 12 months was created, the surface may or may not accurately measure the impact of an HIV testing campaign in a specific area. Some respondents may have been tested for HIV in a different location from the one where they were interviewed. However, if the surface was to be used to target future campaigns in areas with low levels of HIV testing, it might be a good targeting tool. In contrast, some indicators do not have locational bias because the indicator is only reflective of the place where the survey took place. Examples include household assets, access to water, and sanitation practices.

4.2 Difference in modeling across indicators and countries

The ability of the MGB process to accurately predict any given indicator depends on several factors. First, each indicator has different inherent properties such as the overall amount of variation across the country, the extent to which this is spatially autocorrelated (with more autocorrelation reflecting a more organized geographic pattern that is easier to predict), and the statistical distribution of values (with bi-modal, heavily skewed, or other unusual distributions more difficult to predict accurately). Second, the extent to which the environmental covariates are correlated with the indicator will influence the predictive accuracy, with higher correlations allowing for greater accuracy. Third, the density of cluster points and the sample size (number of respondents) at each cluster will have an important effect, with denser surveys and larger sample sizes yielding greater accuracy. Given these factors, some indicators will be predicted with greater accuracy in some countries than in others. Figure 10 show validation scatter plots and validation statistics for stunting in children in three countries.

Figure 10. Validation scatter plots and validation statistics for stunting in children



4.3 Aggregation of point estimate interpolated surface to DHS national level or sub-national areas

The modeled surfaces can aggregate up from the 5 × 5 km pixel resolution to different administrative levels or other geographic areas. However, the modeling process did not specifically adjust the model to recreate the DHS regions or national level estimates in the survey final report. In many cases, the aggregated data should be within the 95% CI of the estimate generated directly from the primary DHS survey data files. Table 5 shows a summary of data created in the SAR 11 pilot study for the child stunting indicator in Tanzania. The datasets estimate and upper/lower bound of the 95% CI represent the estimate value and 95% CI obtained when the indicator is calculated directly from the DHS recode dataset. The point estimate averaged value column is the aggregated estimate from the map surface. This is the average pixel value for that region. With child stunting in Tanzania, there are 26 regions, of which 12 map surface estimates are within the 95% CI credible of the dataset estimate (shown in green). Six regions are less than two percentage points of the 95% CI (yellow), while all other estimates were between two percentage points to ten percentage points above the dataset estimate. Examination of the other indicators in Tanzania, Ghana, and

Uganda created in SAR11 showed similar mixed results with no obvious pattern, although specific regions and some indicators were generally better estimates than others.

Table 5. Data versus model surface estimate for child stunting in Tanzania by DHS region

Region	Dataset Estimate	Dataset Upper bound	Dataset Lower bound	Point Estimate Averaged Value
Dodoma	59.0	51.7	65.9	54.5
Arusha	41.5	35.9	47.2	52.8
Kilimanjaro	28.9	20.3	39.3	41.8
Tanga	48.8	39.7	58.0	47.4
Morogoro	40.9	33.7	48.5	51.5
Pwani	29.3	23.0	36.5	42.9
Dar es Salaam	15.7	9.3	25.2	28.3
Lindi	50.0	41.2	58.9	56.7
Mtwara	41.2	35.1	47.5	48.3
Ruvuma	46.1	40.5	51.7	51.8
Iringa	50.8	42.1	59.4	58.3
Mbeya	41.4	29.2	54.6	55.7
Singida	38.5	32.0	45.4	46.9
Tabora	30.9	27.3	34.7	44.0
Rukwa	49.7	39.1	60.2	51.1
Kigoma	47.9	42.1	53.8	51.8
Shinyanga	42.5	36.9	48.3	48.9
Kagera	43.1	36.9	49.6	49.2
Mwanza	40.1	34.5	45.9	41.4
Mara	30.2	25.3	35.7	39.7
Manyara	46.5	40.7	52.3	50.2
Unguja North	38.8	32.2	45.8	36.3
Unguja South	25.6	19.7	32.4	33.3
Town West	19.4	14.0	26.3	20.5
Pemba North	37.3	29.3	46.0	38.3
Pemba South	29.0	23.5	35.2	38.0

5 How can The DHS Program Modeled Surfaces be Used?

Summary

The following section provides an overview of the use of interpolated surfaces to monitor and evaluate situations and programs, and to contribute to informed decision-making about future policies and programs. Included in this section is a discussion of possible approaches for operationalizing the modeled surfaces and the limitations to these approaches.

Key Questions
Can I use these maps to advocate for program support? Yes, these modeled surfaces can evaluate areas where programs were active in the past or identify areas of need for future programs. See Section 5.1 ***Can I compare my program intervention areas to other areas of the country?*** Yes, the modeled surface can be summarized to represent administrative or other geographic zones, and then compared to non-intervention areas. See Section 5.1. ***How can I make this useable for my level of decision making, the 5 × 5 km pixel do not correspond to areas useful for program decision-making?*** The data can be aggregated to any number of higher-level administrative units, programmatic activity areas, or operational areas such as health facility catchments or livelihood zones. See Section 5.2 ***Can the modeled surfaces be used with other data such as health facility or population density to make program decisions?*** Yes, many geographic data sources can be overlaid in a single map to augment understanding of the map context. In addition, the data can be linked specifically to intervention points or areas. See Section 5.2.3

5.1 Decision-making with modeled surfaces

Spatially modeled surfaces can help in several ways to improve decision-making for many development sectors that include health, population, nutrition, and water and sanitation programs on multiple levels.

1. Monitoring and evaluation: analysis and evaluation of past initiatives (applied use) or understanding existing situations.
2. Program planning: future planning of appropriate programs and policies. There are some approaches that apply to both approaches such as having contextual information for improved map understanding.

Monitoring and evaluation specialists can use the data in the modeled surfaces to evaluate past programs or to better understand existing situations. Such evaluations can help to understand deviations from the norm, attribute cause, or to conduct impact evaluations, which analyze what would have happened to the population of an area if a program had not implemented. Transforming model map surface to useful products (operationalization)

The modeled surfaces can be used for many different decision-making purposes as described in the previous section. However, the surfaces usually need to be transformed or operationalized by the data user. This operationalization can be done in many ways, three of which are discussed in this section: aggregation, burden estimate, and linkage to other data.

Table 6 summarizes the possible approaches for both monitoring and evaluation, and program planning. These include understanding deviation from the norm, comparing intervention areas to non-intervention areas, estimation of burden, and linking with other data for contextual understanding. Program managers can also use modeled surfaces to plan, target, and develop interventions and programs that aim to improve situations in targeted geographic areas. Interventions can be targeted more precisely, which saves money, time, and human resources in the search for the most effective outcomes.

5.2 Transforming model map surface to useful products (operationalization)

The modeled surfaces can be used for many different decision-making purposes as described in the previous section. However, the surfaces usually need to be transformed or operationalized by the data user. This operationalization can be done in many ways, three of which are discussed in this section: aggregation, burden estimate, and linkage to other data.

Table 6. Approaches for monitoring and evaluating past programs with modeled surfaces

Goal	Summary	Monitoring & Evaluation	Program Planning
Understanding deviations from the norm	With widespread health and social problems, it can be difficult to determine which areas are better off than others. In addition, it can be difficult to discern whether new observations at a location are anomalous or within expected bounds. The uncertainty measures provided in the predictive surfaces provide a means by which one can evaluate whether observed differences between locations are meaningful in the context of the broader scale.	✓	
Comparing intervention areas to non-intervention areas (demonstrating success of program/securing advocates)	Impact evaluations compare the outcomes of a program against a counterfactual to show how an area would have developed (or stagnated) without the program; this validates the value of the program, which can help with finding advocates for future interventions.	✓	
Overlay data for better contextual placement	Prevalence surfaces in combination with high-resolution population estimates make it possible to estimate the total numbers of individuals within certain categories. These predictions could then be used with other GIS measures and survey data, such as the placement of roads or staffing levels at facilities, to determine optimal positioning for new schools or the optimal resources needed in a new health facility.	✓	✓
Improved program targeting and planning	Program managers will be able to answer questions such as: Where do I need to put effort to obtain the most effective outcomes? Where is the greatest need for a certain intervention? Where are certain factors present to implement specific actions?		✓
Improving burden estimates	Currently, national level or coarse administrative unit level mapping masks heterogeneities and misses possible hotspots and inequalities. There is potential for the modeled surfaces to better identify these and to work with population maps to more accurately quantify and map burdens of disease and other health related issues.		✓

5.2.1 Aggregation

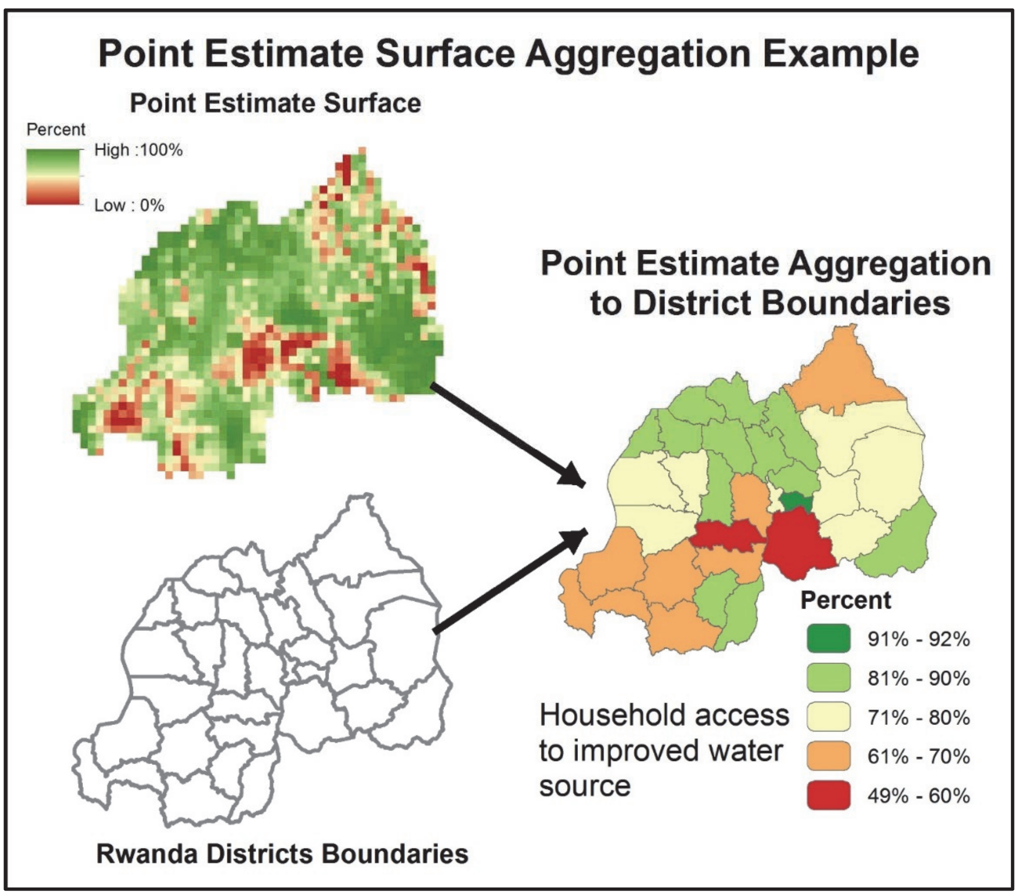
Aggregation from the point estimate model surface pixels to administrative areas, such as provinces, districts, or other relevant policy areas such as livelihood zones, is one of the main ways that modeled surfaces can be operationalized for use in decision-making. The aggregation, also called averaging or zonal statistics, can be completed in two ways:

1. Simple mean zonal statistics: values for the polygon are calculated by using the average value of all the grid squares (or portions of grid squares) within the area.
2. Population weighted mean zonal statistics: use similar methods but take into account the likely population in each grid square and the contribution of each grid square to the estimate for the whole area.

Figure 11 illustrates the aggregation process inputs, the point estimate surface, and administrative units (in this case, districts in Rwanda). The point estimates are aggregated by simple averaging to the administrative units to produce a new map that illustrates the mean estimate value for each unit.

The weighted population approach is likely to provide a more directly appropriate result when decisions are focused on optimizing impact across populations. However, this approach also requires additional data and computational steps. It is important to remember that input data used for the population weighting may need to be standardized to the grid squares locations and pixel size/resolution used in the DHS modeled surfaces. Further considerations of the population data are discussed in the "Burden Estimate" section.

Figure 11. Example of modeled surface aggregation to administrative units

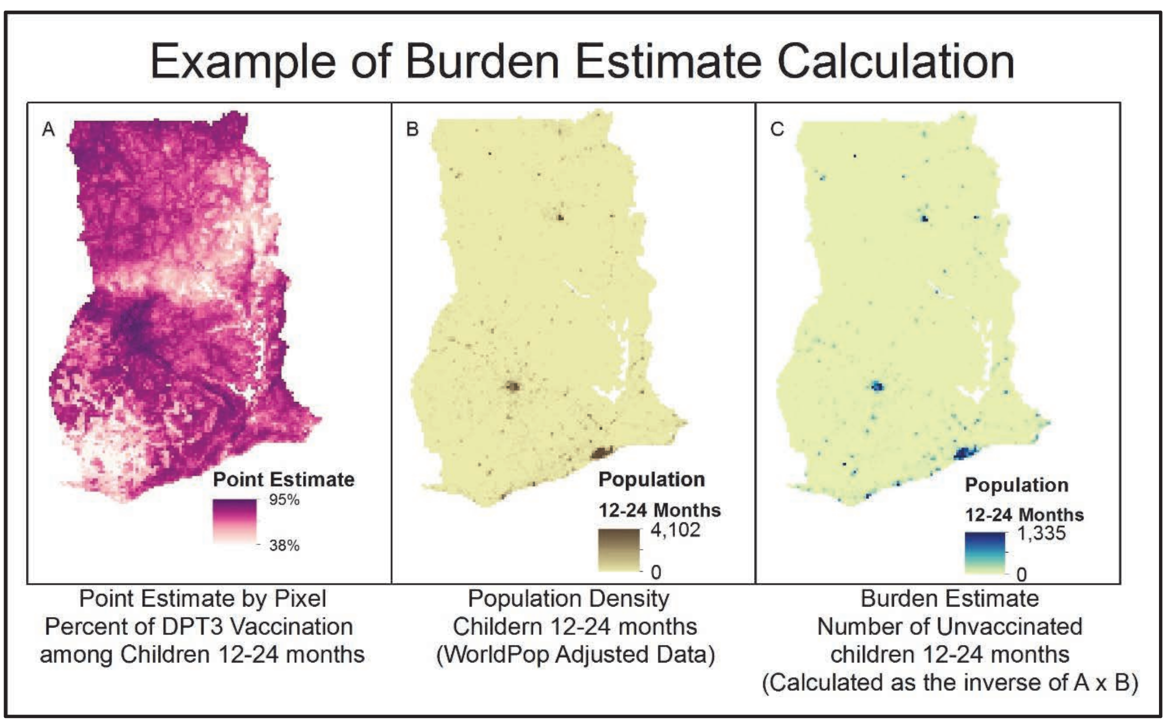


5.2.2 Burden estimates

Burden estimates begin with the prevalence estimate from the modeled surface and convert it into population count (numbers of individuals) affected. The choice of population data can influence the results. Several different groups have worked on producing modeled surfaces of population density. It is essential that the correct reference population layer be used for the denominator estimation that includes country, age-range, and gender. The limits also include the denominator population from which the indicator is being estimated. For vaccination, the denominator would be children age 12-23 months, and for delivery in a health facility, pregnant women. Figure 12 illustrates the burden estimate process for DPT3 vaccination in Ghana starting from the two inputs (1) point estimate surface (Panel A) and (2) population density surface (from WorldPop) (Panel B), and the final output of number of children unvaccinated (Panel C). The number of children vaccinated is calculated by taking the inverse of the multiplying the percent of vaccinated by the number of children.

Publicly available population datasets with some options for accounting for population distribution and gender include: WorldPop (http://www.worldpop.org.uk/) and Gridded Population of the World (GPW) (http://sedac.ciesin.columbia.edu/data/collection/gpw-v4). The WorldPop are population raster surfaces that are re-sampled and estimated using some methods similar to those being used in the DHS modeled surfaces that include the use of spatial covariates. The GPW uses a real weighting to distribute the population across space with only census data and no additional covariates. Estimating the portion of the population at risk can be done by using census data (where available) and DHS or other household surveys that include detailed population structure data. Those data can be applied to the population raster to estimate the number of individuals at risk (such as number of children under age 5 within the population). This can cause issues of collinearity (two inputs to the same model being highly correlated) in the burden estimates, although this is minimal given the overall modeling process used for both the population surfaces and The DHS Program modeled surfaces.

Figure 12. Illustration of burden estimate calculation process



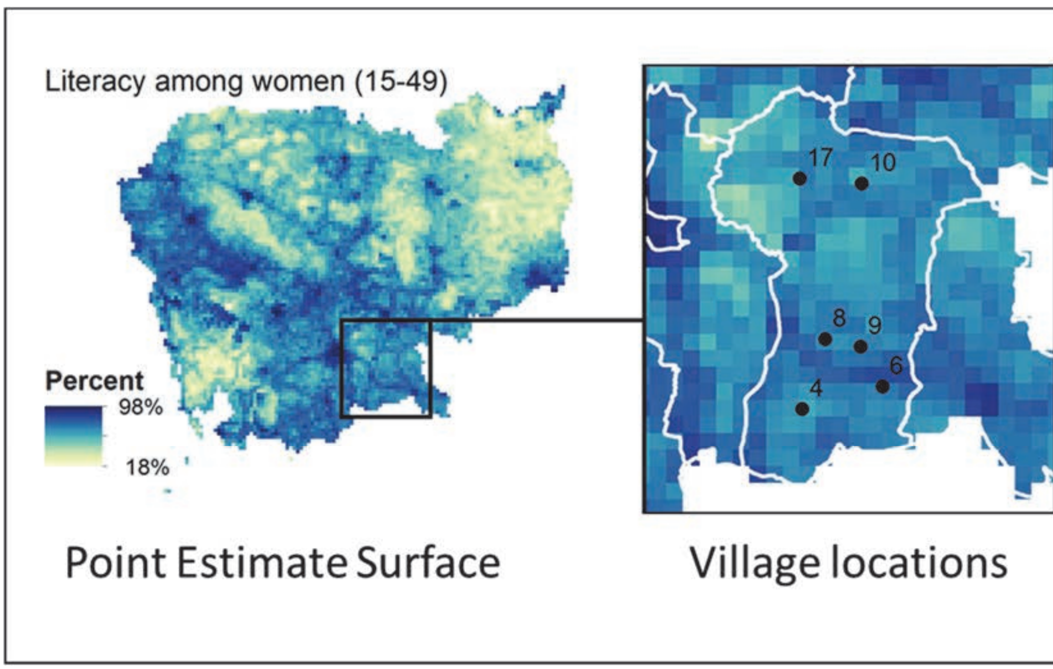
5.2.3 Linkage with other data

The modeled surfaces can be linked with other geospatial data to enhance understanding of context and needs. The two most common approaches are point data extraction and inclusion of the modeled surface point estimate values to create an analytically relevant modeled surface that combines several DHS modeled surfaces or other program-relevant surfaces.

Point extraction is most useful when the data available for linkage are point data (point locations with known latitude and longitude) and when the data are not from a program area polygon where the aggregation techniques might be applied. For example, a program worked in certain areas of a district, and the GPS location of the villages where the program was implemented are available. In this case, a buffer extraction may allow for understanding the value of one or many indicators around a given location. It is important to note that a point extraction of values can be somewhat misleading, and that an area around the point would provide a better sense of the context. This extracted buffer value can then be included as an input to a more standard analysis.

Combining several DHS modeled surfaces or combining DHS modeled surfaces with other relevant modeled surfaces has analytical potential, although careful considerations must be made for collinearity of the data inputs. The DHS modeled surfaces are created with a suite of covariates (see Table 2 for summary of possible covariates in the model, and refer to the indicator documentations for the specific covariates included in that surface for that specific indicator). Including any of those covariates with the DHS modeled surfaces to create another combined surface could lead to collinearity in the dataset. Use of the covariate table within the documentation will provide some guidance about the collinearity that may be likely with the correlation between the surface and a similar covariate included in the model.

Figure 13. Illustration of value extraction from modeled surface to village locations



Village ID	Modeled Surface Value
4	63%
6	74%
8	70%
9	73%
10	68%
17	74%

5.3 Use considerations and limitations

There are a few key considerations that may limit the use of the modeled surfaces in certain areas or for certain decisions. The previous section outlined some of the limitations of the modeled surfaces related to size of the urban areas, temporality, locational bias, and differences in indicator modeling and model uncertainty.

Comparisons or decisions about large urban areas where the model has considerable homogeneity do not allow for smaller scale understanding of the differences that may exist within these areas. Thus, fine-scale planning or decisions based on using the modeled surfaces within these areas would be potentially erroneous. However, decision-making focused on the relative need of some areas as compared to other areas of a country than urban areas could be analyzed as a large combined unit.

The timing of the survey and the relationship to the other data in use, such as program intervention activities, needs to be carefully considered, along with the reference period of the indicator. For example, if an antenatal care (ANC) activity began in a certain area of Ghana in early 2013 and the program manager would like to compare the results from that area with other areas using the 2014 DHS modeled surface for ANC 4+ visits, the results would be a somewhat misleading outcome. The ANC 4+ indicator captures data on births that occurred in the last 5 years, which in this case would be 1-2 years of the program and 3 or more years when the program was not active.

When evaluating the impact of a program, it is important to know what other programs may have been active in the same areas or in the control areas in order to have a complete understanding of the program at the time of the survey.

Final Thoughts

Spatially modeled surfaces based on the MBG approach can help meet the needs of national and international communities for more granular, spatially detailed estimates than those currently provided by The DHS Program and most other national level data sources. These types of maps, whether at 5 × 5 km grid scale or subsequently aggregated to appropriate sub-national decision-making units, can provide information that is needed for measuring geographic variation in health indicators. The DHS Program's spatially modeled surfaces will be one source of additional information that will help decision-makers better understand the geographic disaggregation of key demographic and health indicators in the coming years. There is enormous potential for new, innovative uses of the modeled surfaces, but it is only in a large community of users who are sharing their experiences that this potential will be fully realized. Users are encouraged to submit their cases and other feedback to The DHS Program.

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