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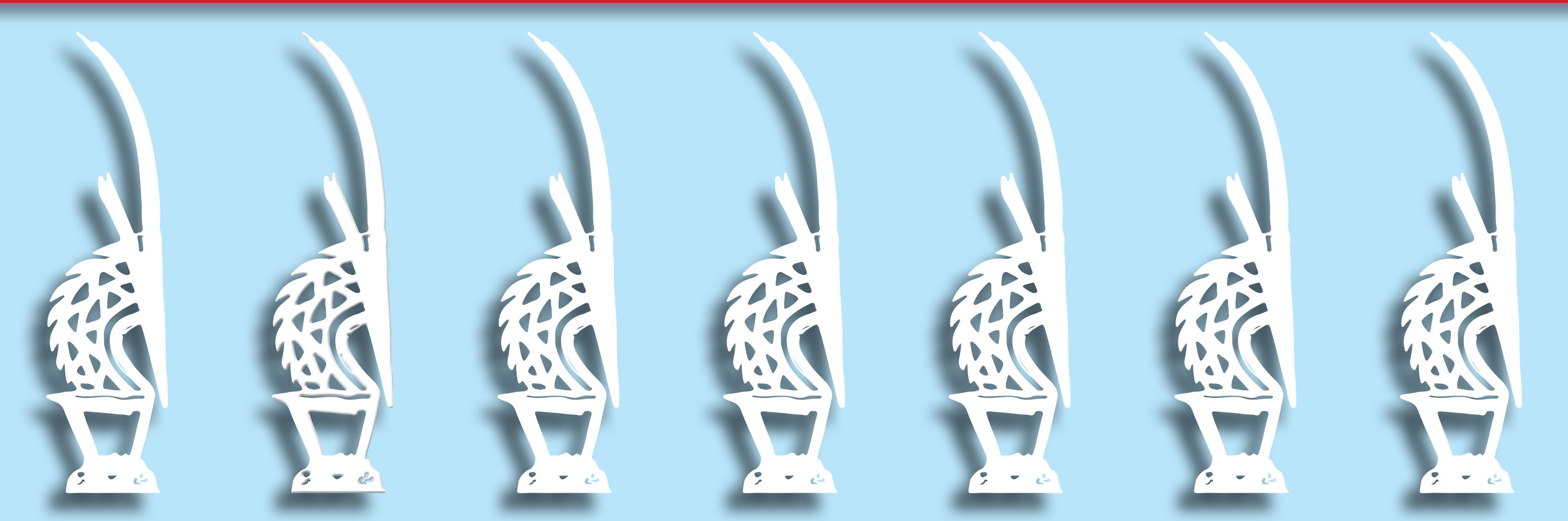
Further Analysis of the Mali Demographic and Health Surveys 2006-2018



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Rukundo K. Benedict[1]
Benjamin K. Mayala[1]
Jean de Dieu Bizimana[2]
Ibrahima Cisse[3]
Idrissa Diabaté[4]
Kissia Sidibe[4]

ICF
Rockville, Maryland, USA

April 2020

[1] The DHS Program, ICF
[2] The DHS Program, Vysnova
[3] Direction Générale de la Santé – Département de la Nutrition
[4] Institut National de la Statistique (INSTAT)

Corresponding authors: Rukundo K. Benedict and Benjamin K. Mayala, The DHS Program, ICF, 530 Gaither Road, Suite 500, Rockville, MD 20850, USA; phone: 301-572-0537; email: Rukundo.benedict@icf.com

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ABSTRACT

Background: Strengthening Mali's multisectoral nutrition policies is key to achieving the Sustainable Development Goals for child malnutrition by 2030. Although the decline in stunting and wasting prevalence over the last decade is promising, we need to understand the reasons for the decline in order to create future policies and programmes. The aim of this study was to examine factors associated with stunting and wasting in Mali in 2006 and 2018 by using geospatial modelling techniques.

Methods: We used Demographic and Health Survey data from 2006 and 2018, and converted key child, maternal, and household variables into geospatial covariates. These variables, together with selected environmental and demographic geospatial covariates, were used in a Bayesian geospatial model to provide estimates for stunting and wasting at the subnational level for 2006 and 2018, respectively. We computed the difference in malnutrition estimates between 2006 and 2018 and then determined the covariates associated with stunting and wasting.

Results: The cercles-level maps show how stunting and wasting estimates varied across Mali and how the estimates changed between the two survey years. Results from the stunting models in 2006 and 2018 showed that children's minimum dietary diversity, mother's education, and mother's body mass index were the leading factors associated with stunting. Children's minimum dietary diversity and aridity were associated with wasting in both years.

Conclusions: With a Bayesian geospatial modelling approach, this study generated subnational estimates of stunting and wasting in Mali, and identified key factors associated with undernutrition. This approach allows the Government of Mali to target programmatic efforts at lower administrative levels and to focus resources on complementary feeding, women's nutrition, and environmental factors related to child undernutrition.

Key words: Mali, stunting, wasting, geospatial modelling

ACRONYMS AND ABBREVIATIONS

ADMIN 2	second subnational administrative level
ANC	antenatal care
BCG	bacille Calmette-Guérin vaccine
BMI	body mass index
CCOSAD	Communal Orientation, Coordination and Monitoring Development Actions
CLOCSAD	Local Orientation, Coordination and Monitoring of Development Actions Committees
CNN	National Nutrition Council
CREDD	Economic Recovery and Sustainable Development Framework
CROCSAD	Regional Orientation, Coordination and Monitoring of Development Actions Committees
CTIN	Intersectoral Technical Committee for Nutrition
DHS	Demographic and Health Survey
DPT	diphtheria, pertussis, and tetanus vaccine
EVI	enhanced vegetation index
GoM	Government of Mali
INLA	integrated nested Laplace approximation
LASSO	least absolute shrinkage and selection operator
LST	land surface temperature
MAE	mean absolute error
MDD	Minimum Diet Diversity
ME	mean error
MFF	Minimum Meal Frequency
PAMN	Multisectoral Nutrition Action Plan
PolNSAN	National Policy for Food and Nutrition Security
RMSE	root mean squared error
SDG	Sustainable Development Goal
SPDE	stochastic partial differential equations
SUN	Scaling Up Nutrition
UNICEF	United Nations Children's Fund
WHO	World Health Organization

1 INTRODUCTION

Optimal nutrition is critical to the health, economic, and social development of nations. Globally, undernutrition in children under age 5 contributes to almost half of all child deaths through a series of interconnected pathways that involve the food and healthcare environment, care practices, infection, and poor nutrient intake (Black et al. 2013; United Nations Children's Fund 2015). Progress on addressing undernutrition has been slow, with over 140 million children stunted and over 45 million children wasted (Development Initiatives 2018; UNICEF/WHO/World Bank Group 2020). Although countries have implemented strategies that address stunting and wasting, evidence suggests that many countries may not be doing enough to meet the global nutrition targets of reducing the number of stunted children by 40% and wasting to less than 5% (Development Initiatives 2018; WHO 2014b; WHO/UNICEF/WFP 2014).

The Government of Mali (GoM) has made under age 5 undernutrition a clear priority. During the last decade, the country experienced an 11% decline in stunting prevalence and a 6% decline in wasting prevalence at the national level (INSTAT, CPS/SS-DS-PF, and ICF 2019). This decline is also found at the regional level, although there is variation in the extent of the decrease across regions (INSTAT, CPS/SS-DS-PF, and ICF 2019).

Mali joined the Scaling Up Nutrition (SUN) movement in 2011 to address malnutrition through coordinated multisectoral responses (Scaling Up Nutrition 2020). In 2013, the country adopted its 10-year National Nutrition Policy that emphasises the importance of the multisectoral nature of nutrition and includes technical and financial partners, civil society, and the private sector (Gouvernement du Mali 2013). To support the implementation of the nutrition policy, the 2014-2018 Multisectoral Nutrition Action Plan was developed to ensure access to adequate food and the population's well-being, and to guarantee sustainable national development (Gouvernement du Mali 2014). The plan also includes several World Health Assembly targets for improving maternal, infant, and young child nutrition (WHO 2014a).

Despite the government's commitment to improving malnutrition, the country may not be able to meet the Sustainable Development Goal (SDG) targets for stunting and wasting among children under age 5 (Osgood-Zimmerman et al. 2018). There is a paucity of literature on the predictors of stunting and wasting in Mali that may be hampering efforts to further improve undernutrition. One 2018 study by Sobgui et al. examined child, household, and community-level variables associated with wasting and stunting. The authors identified several predictors of wasting and stunting such as household diet diversity, livestock ownership, child's age, child's sex, and diarrhoea (Sobgui et al. 2018). However, since the study only focused on rural areas in the Sikasso and Mopti regions, the findings are not generalizable to the entire country (Sobgui et al. 2018).

To support efficient programme implementation, both national and disaggregated data are needed for Mali to continue to combat undernutrition in children. Although national level data are useful for policymakers (Li et al. 2019), analyses at this level do not provide comprehensive estimates at the lower administrative levels where health programmes are designed and implemented. Through the use of geospatial modelling techniques that leverage existing global positioning system coordinates in Demographic and Health Survey (DHS) survey clusters and relationships with geospatial covariates, high resolution maps can be developed that provide estimates of indicators at the lower levels (Gething and Burgert-Brucker 2017; Utazi et al. 2018).

Geospatial modelling techniques can be used to examine changes in health and demographic indicators over time (Cooper et al. 2019; Kinyoki et al. 2020; Osgood-Zimmerman et al. 2018). Much of this research has focused on very large geographical areas, although the techniques can also be applied to individual countries. The purpose of this study is to use geospatial modelling techniques to estimate the prevalence of stunting and wasting at the national and sub-national administrative levels in Mali at two different time points and to compute the change in these estimates over time. The study also aims to explore the child, maternal, household, and environmental factors that are associated with the undernutrition indicators between 2006 and 2018.

1.1 Programmatic Context

The GoM has made concerted efforts over the last decade to end malnutrition and has developed multisector nutrition policies and programmes that ensure coherent, coordinated actions at all levels. Beginning in 2010 with the National Nutrition Forum, the GoM committed to and joined the SUN movement in 2011 and subsequently developed the 10-year National Nutrition Policy in 2013. The success of the National Nutrition Policy has relied on strong, effective, multisectoral coordination at all levels, from the central level to the community level.

At the national level, the GoM introduced the National Nutrition Council (CNN), which includes all ministries involved in nutrition at the highest level, the Food Security Commission, and local authorities, as well as representatives of civil society and the private sector. The CNN's role is to ensure that nutrition is considered in all national strategies, to approve the intersectoral strategic plan for nutrition, and to advocate for nutrition. The GoM also introduced the Intersectoral Technical Committee for Nutrition (CTIN), which is responsible for coordinating multisector plans and implementing, monitoring and evaluating the 2014-2018 Multisectoral Nutrition Action Plan (PAMN). Both the CNN and CTIN are chaired by the Ministry of Health and their work is conducted through the National Coordination Unit.

At the decentralised level, the activities of CNN and CTIN are implemented through existing structures. These include the Regional Orientation, Coordination and Monitoring of Development Actions Committees (CROCSAD); Local Orientation, Coordination and Monitoring of Development Actions Committees (CLOCSAD); and the Communal Orientation, Coordination and Monitoring Development Actions (CCOCSAD). Together, these institutions work to ensure implementation of the National Nutrition Policy throughout the country.

In alignment with the GoM's focus on a multisectoral approach to nutrition, Mali has adopted several other policies and strategies and has implemented nutrition programmes and projects in recent years. One example is the 2017 National Policy for Food and Nutrition Security (PolNSAN). The PolNSAN aligns with Mali's economic and social development priorities, as defined by the Economic Recovery and Sustainable Development Framework (CREDD). The main objective is to improve coordination of sectoral policies, strengthen governance in the areas of food security and nutrition, and promote regional and subregional integration processes (Gouvernement du Mali 2017). Another example is the National Strategy for Feeding Infants and Young Children that aims to improve, through optimal nutrition, the nutritional status, growth, development and health of infants and young children, and is aligned with health sector programming (Gouvernement of Mali 2014).

2 DATA AND METHODS

2.1 Variables included in the Spatial Models

2.1.1 DHS covariates constructed for this analysis

The DHS indicators included in spatial models were taken from the Mali 2006 and 2018 DHS surveys. Selection of the indicators was based on the known associations of these indicators to stunting and wasting, based on the UNICEF conceptual framework for undernutrition and related literature (Frongillo, de Onis, and Hanson 1997; United Nations Children's Fund 2015). We obtained 404 and 345 point clusters with the coordinates of their geographical locations for the 2006 and 2018 surveys, respectively. For this analysis, the DHS covariates were estimated by using the same modelling approach described in **Section 2.2.3**. **Table 1** describes the 17 DHS indicators included in the model, grouped into child, maternal, household, and environmental levels. **Table 1** also describes the coding of the geospatial covariates in the model.

Table 1 Definition of DHS indicators in the study

DHS indicator	Definition	Geospatial DHS indicator coding[a]
Child-level factors		
Anaemia	Children age 6-59 months with any anaemia (haemoglobin < 11g/dL)	Yes/No
Current breastfeeding	Children age 0-23 months who were breastfed the day before the survey	Yes/No
Diarrhoea in the past 2 weeks	Children under age 5 with diarrhoea at any time in the 2 weeks before the survey	Yes/No
Minimum Diet Diversity (MDD)[b]	Children age 6-23 months who consumed foods belonging to at least 5 food groups out of the 8 groups the day before the survey	Yes/No
Minimum Meal Frequency (MMF)[b]	Children age 6-23 months who ate solid, semi-solid, or soft foods (including milk foods for non-breastfed children) the previous day the minimum number of times or more often	Yes/No
Vaccination coverage	Children age 12-23 months who received all age appropriate vaccinations (diphtheria-tetanus-pertussis (DPT) 1-3, measles 1, polio 1-3, BCG)	Yes/No
Vitamin A supplementation	Children age 6-59 months who received vitamin A supplements	Yes/No
Maternal-level factors		
Antenatal care (ANC) attendance	Women age 15-49 who had a live birth in the 5 years before the survey and who had 4+ ANC visits	Yes/No
Education	Women age 15-49 by highest level of education completed	No education/ Any education
Employment status	Women age 15-49 by employment status	Not employed/ Employed
Parity	Number of children born to women age 15-49. (Population mean of 4 children was used as cut-off for coding.)	1-3 children/ 4+ children
Short stature	Women age 15-19 with a height-for-age z-score less than -2SD and women age 20-49 with height <145cm	Yes/No
Overweight/obese body mass index (BMI)	Women age 15-19 with a BMI-for-age z-score greater than +1SD and women age 20-49 with a BMI ≥25.0kg/m2	Yes/No
Underweight BMI	Women age 15-19 with a BMI-for-age z-score less than -2SD and women age 20-49 with a BMI <18.5kg/m2	Yes/No
Household-level factors		
Improved water source	De jure households whose main source of drinking water is an improved water source (tap water, standpipes, pump wells, boreholes, dug wells, protected sources, rainwater, water delivered by a tank truck or by cart with a small tank, and bottled or sachet water)	Yes/No
Open defecation/no toilet facility	Households with no toilet facility or that use a bush/field	Yes/No
Wealth index	Household wealth index is based on household size, water source, type of toilet, primary cooking methods, materials used for housing construction, and ownership of assets	Lower (quintiles 1-2)/ Higher (quintiles 3-5)

[a] The DHS variables are transformed into binary interpolated geospatial variables before being entered into the models.
[b] Indicators for MMF and MDD in 2006 and 2018 are not fully comparable because the food lists included in surveys prior to the 2008 WHO Infant and Young Child Feeding guidelines were different.

2.1.2 Pre-existing geospatial covariates

In addition to the DHS covariates, we assembled geospatial covariates data layers, which were obtained from publicly available remote sensing sources. The geospatial covariates were selected for their potential to predict the stunting and wasting outcomes and because they have previously been shown to correlate with the development of indicators in different settings (Alegana et al. 2015; Gething et al. 2015; Osgood-Zimmerman et al. 2018). **Table 2** describes the geospatial covariates.

Table 2 Definition of geospatial variables in the study

Indicator	Definition	Spatial Resolution
Aridity Index	The ratio of annual precipitation to annual potential evapotranspiration	10x10 km
Elevation	Global elevation above earth's sea level	1x1 km
Enhanced Vegetation Index (EVI)	The average vegetation index value	5x5 km
Daytime Land Surface Temperature (LST)	The average annual land surface temperature during the day	5x5 km
Under 5 population count	Annual population census estimates for males and females in 5-year age groups	1x1 km

The geospatial covariate data layers used in this analysis were acquired from a myriad of data sources, and have different spatial references, projections, extents, and dimensions. We used the 'raster' and 'shapefiles' packages in the R software (R Core Team 2019) to (1) re-project to the same coordinate reference system (the standard-based World Geodetic System 1984), (2) crop and mask to an extent that encompassed the boundaries of the study area, and (3) resample with bilinear interpolation to the same spatial resolution used in the modelling.

2.2 Geostatistical Model

2.2.1 Overview of the modelling approach

Figure 1 provides a conceptual overview of the geospatial modelling framework used for modelling DHS indicators and the underlying covariates, and for producing the subnational level estimates. The approach involved the following steps:

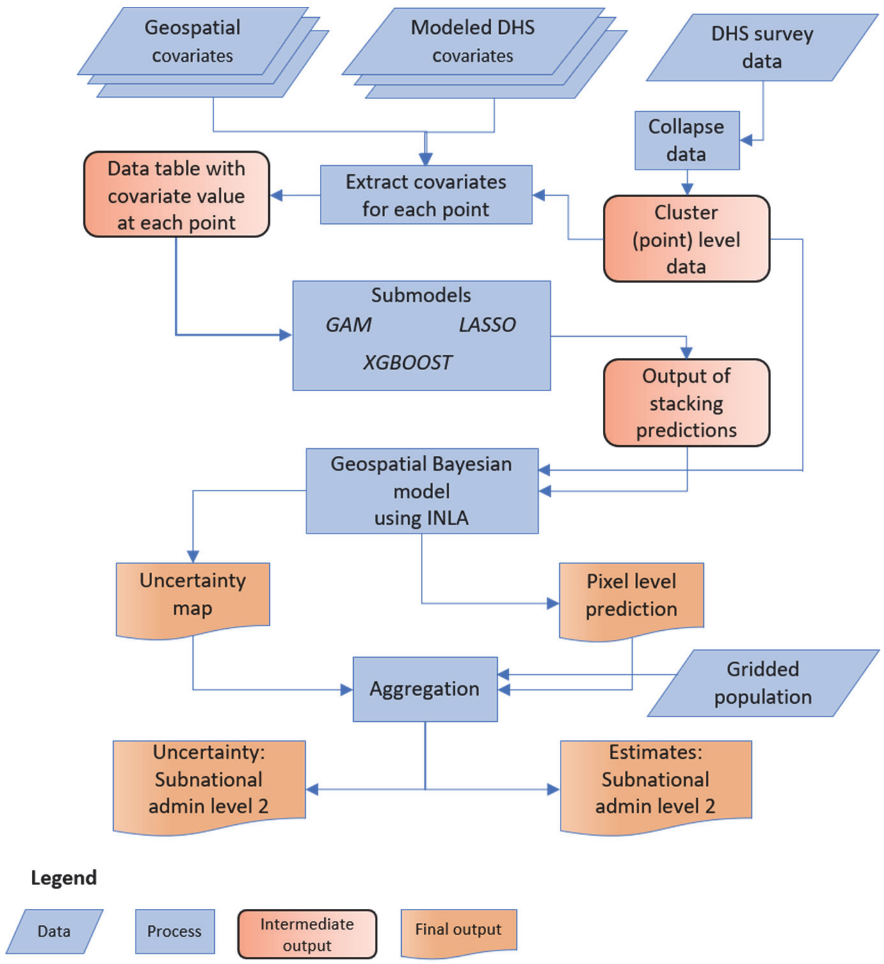
Step 1 We summarised the individual-level DHS survey data to the finest spatial resolution (latitude and longitude) that represented the location of the survey cluster.

Step 2 The covariates and the cluster (point) level data were imported into the R environment for statistical computing. We then applied the 'raster' package to extract the corresponding covariate pixel values at each survey cluster point.

Step 3 The point level data (from Step 2) and their associated covariates were used in the stacked generalisation ensemble model (described in **Section 2.2.2**). The prediction surfaces generated from the stacked ensemble models were then used as covariates to calibrate the final geospatial Bayesian model. The outputs of the final model are pixel-level mean estimates with associated uncertainty at the 5 x 5 km resolution.

Step 4 We aggregated the prediction output from the final model (Step 3) to the second subnational administrative level (ADMIN 2) level.

Figure 1 Geospatial modelling flowchart*



*Modified from Mayala et al. 2019.

2.2.2 Covariate modelling using stacked generalisation

In many applications, the generic geospatial modelling is sufficient to produce a highly predictive model. However, when modelling outcomes in which the underlying process is linked to the covariates and demographic parameters through complex non-linearities and interactions, a simple linear mean of the form βX can be insufficient. We therefore use a framework formed from a body of theory known as "stacked generalisation" to pre-process the covariates through a set of highly predictive machine learning methods (Breiman 1996; Wolpert 1992). Stacked generalisation is a general ensemble modelling approach that combines multiple model algorithmic methods to produce a meta-model that has equal or better predictive performance relative to a single modelling approach.

We employed this approach to capture the potential complex interactions and non-linear effects among the geospatial covariates. The approach has been shown to improve the predictive accuracy of the geostatistical models, as compared to prediction with any single method (Bhatt et al. 2017). Numerous recent studies have implemented the stacking approach to derive continuous estimated surfaces of indicators of interest from DHS household surveys. These include mapping of HIV prevalence (Dwyer-Lindgren et al. 2019), vaccine coverage (Mayala et al. 2019; Mosser et al. 2019), exclusive breastfeeding (Bhattacharjee et al. 2019), child growth failure (Osgood-Zimmerman et al. 2018), education attainment (Graetz et al. 2018), and childhood diarrhoeal diseases (Reiner et al. 2018).

Our choice of algorithmic methods included (1) GAM: generalised additive model (Wood 2017), (2) LASSO: least absolute shrinkage and selection operator regression (Zou and Hastie 2005) and (3) XGBOOST: gradient boosting (Friedman 2001). We fitted the three algorithmic methods (submodels) to each set of the selected DHS indicator survey data by using the geospatial covariates (described in **Table 2**) as exploratory predictors. The submodels were implemented in R statistical for the computing environment by using packages 'caret', 'mgcv', 'xgboost', and 'glmnet' (R Core Team 2019).

To make better predictions and avoid overfitting, each submodel was fit by using five-fold cross–validation, which generated the out-of-sample predictions that were included as exploratory geospatial covariates when fitting the geostatistical model. In addition, each submodel was fit with a full dataset, which produced the in-sample predictions that were then used as covariates when generating predictions from the full geospatial Bayesian model. A logit transformation of the predictions placed the out-of-sample and in-sample predictions on the same scale as the linear predictor in the geostatistical model. This process has been described in detail by Bhatt et al. (2017) and Dwyer-Lindgren et al. (2019).

2.2.3 Model specification and development

As described in the previous section, the stacked generalisation ensemble modelling approach allows for non-linear relationships and interactions between the geospatial covariates to better predict the DHS indicators. Since the approach does not explicitly account for spatial patterns in the data, we used the Bayesian geostatistical modelling framework in our analysis to account for the spatial dependence.

For each indicator of interest, we modelled Y_i, the number of 'positive' individuals among those sampled at cluster location $s_i, i = 1, \dots n$, using a binomial spatial regression with a logit link function (Banerjee, Carlin, and Gelfand 2014; Diggle and Giorgi 2019). If $N_i$is the total number of individuals sampled at cluster s_i, the model can be written as:

$$Y_i \sim Binomial(N_i, p_i)$$

$$logit(p_i) = \beta_0 + \beta X_i + \omega_i + \varepsilon_i$$

$$\omega_i \sim GP(0, \Sigma)$$

Where:

- β_0 denotes the intercept,
- p_i is the probability, representing the underlying prevalence at cluster s_i,

- $X_i = (X_{i1,}X_{i2},\ldots X_{im})$ is the vector of logit-transformed covariates for location s_i obtained from the submodels (*GAM, LASSO, and XGBOOST*), generated from the stacked generalisation modelling (as described in **Section 2.2.2**),

- $\beta = (\beta_1, \beta_2, \ldots \beta_m)$ vector of regression coefficients on the submodels represent their respective predictive weighting and are constrained to the sum of one (Bhatt et al. 2017),

- ω_i is a correlated spatial error term, accounting for spatial autocorrelation between data points, and

- $\varepsilon_i \sim \mathrm{N}(0, \sigma_{nug}^2)$ is an independent error term known as the nugget effect.

The spatial error term ω_i is modelled as Gaussian process with a zero-mean and spatially structured covariance matrix Σ.

The spatial covariance Σ was modelled using a stationary and isotropic Matérn function (Banerjee, Carlin, and Gelfand 2014), given by:

$$\Sigma(s_i, s_j) = \frac{\sigma^2}{\Gamma(\lambda)2^{\lambda-1}}\left(\kappa d(s_i, s_j)^{\lambda} K_\lambda\left(\kappa d(s_i, s_j)\right)\right)$$

Where $d(s_i, s_j)$ is the distance between the two locations and $\sigma^2$is the spatial process variance. The term K_λ denotes the modified Bessel function of second kind and order λ, which measures the degree of smoothness. Conversely, κ is a scaling parameter related to the range r, which is the distance at which the spatial correlation becomes almost null (smaller than 10%), and the definition for the range is given in equation below. See example by Lindgren (2011) for a detailed description.

$$r = \frac{\sqrt{8\lambda}}{\kappa}$$

The Bayesian geostatistical model analysis was implemented through a stochastic partial differential equations (SPDE) approach in the recently developed integrated nested Laplace approximation (INLA) algorithm as applied in the R-INLA package (Rue, Martino, and Chopin 2009). This algorithm provides an effective estimation and spatial prediction strategy for spatial data by specifying a spatial data process, as well as a spatial covariance function depending on the locations and time points at which infection and covariate data are collected (Rue, Martino, and Chopin 2009). The INLA approach offers the advantage of accurate and fast results as compared to the Markov Chain Monte Carlo algorithms, which have problems of convergence and dense covariate matrices that increase the computational time. Thus, for large datasets, spatial and spatiotemporal estimation could require several days of computing time (Blangiardo and Cameletti 2015; Cameletti et al. 2012; Rue, Martino, and Chopin 2009).

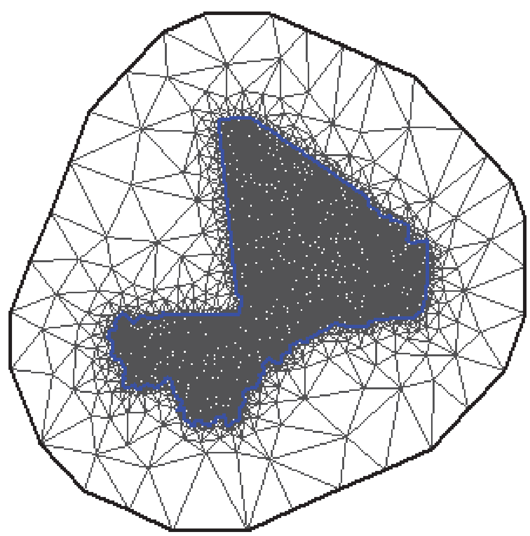
The SPDE allow us to define a grid on spatial data by creating a constrained refined Delaunay triangulation (usually called mesh) over the study region. The mesh needs to cover the region of study and an outer extension to avoid boundary effects, which would increase the variance near the boundary. To fit a mode with this approach, observations are treated as initial vertices for the triangulation. Further vertices are then added or removed to satisfy triangulation quality constraints defined by three parameters: (1) mesh offset,

(2) maximum edge, and (3) cutoff (Blangiardo and Cameletti 2015; Cameletti et al. 2012; Rue, Martino, and Chopin 2009).

We specified a cutoff value to avoid building too many small triangles around the clustered data locations. An offset value defined how far the mesh should be extended in the inner part (within areas where predictions are required) and the outer part (outside the area where predictions are required). The maximum edge value specified the maximum allowed edge length of the triangle in the inner domain and the outer extension. The inner maximum edge value was small enough to allow the triangulation to support functions with small enough features, and typically smaller, than the spatial correlation range of the model (Lindgren, Rue, and Lindström 2011). **Figure 2** provides an example of the finite mesh used for modelling.

As opposed to the regular grid, this approach is more dense in regions where there are more observations and consequently generates more information. Another advantage is that this approach saves computing time because prediction locations are typically much lower in number than those in a regular grid.

Figure 2 INLA mesh triangulation for Mali



Note: The larger triangles show the buffer region surrounding the modelling region (maximum triangle edge length of 5.0 degrees), while the finer inner mesh overlays the modelling region (maximum triangle edge length of 0.1 degrees). The simplified polygon used to define the modelling county boundary is shown in blue.

2.2.4 Pixel-level model estimates

The prediction surfaces generated from the submodels (described in **Section 2.2.2**) were used as input covariates in the geostatistical models implemented in INLA. The final estimates (and uncertainty) for each indicator were generated by taking $k = 1, \ldots 1000$ samples from the posterior predictive distribution. Pixel level estimates that covered the modelling country were produced at a high spatial resolution of 5 x 5 km.

2.2.5 Model estimates at administrative level 2

In addition to the 5 x 5 km pixel level estimates, we overlaid the prediction prevalence surfaces (from **Section 2.2.4**) with the relevant population layer (children under age 5, women age 15 to 49, and total population) for each indicator we modelled. We then constructed estimates of each indicator at the ADMIN 2, or cercles level, by calculating population-weighted averages of prevalence for all grid cells within a given administrative boundary. The procedure was performed for each of the 1,000 posterior predictive samples with final point estimates derived from the mean of these draws and uncertainty intervals from the 2.5 and 97.5 percentiles.

2.2.6 Model validation

For each of the indicator model outputs, we implemented a validation procedure and calculated a set of performance statistics. This involved using a cross-validation with a five-fold hold-out procedure and a comparison of the predicted values at the locations of the hold-out data with their observed values. This procedure was repeated five times without replacement so that every data point was omitted one time across the five validation runs. Standard validation statistics were then computed as measures of the predictive accuracy of the modelled estimates. This included mean absolute error (MAE), mean error (ME) or bias; root - mean - squared - error (RMSE, which summarises the total variance); and 95% coverage of our predictive intervals aggregated to the spatial holdout level. Each predictive metric was calculated by first simulating predictive draws by using a binomial distribution. The predictive metric of interest was then calculated as a sample-size-weighted mean over the ADMIN 2 levels (Mayala et al. 2019; Mosser et al. 2019).

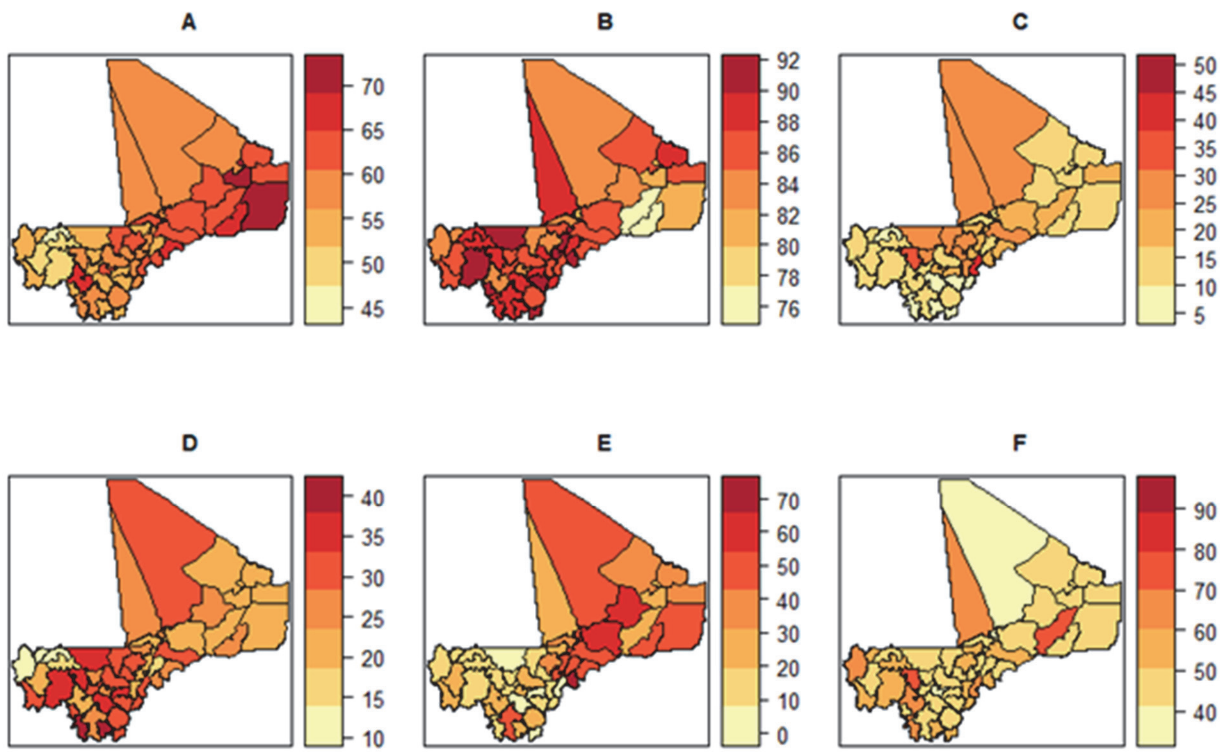
3 RESULTS

3.1 Model Estimates for Select Covariates

The geospatial modelling approach described in **Chapter 2** was used to produce covariate estimates for the cercles. The covariate models were built with data from the 2006 and 2018 Mali DHS. Estimates for selected determinants of childhood stunting and wasting from the 2018 DHS are shown in **Figures 3A** to **3F**. A complete presentation of 5 x 5 km pixel-level estimates for all covariates in 2018 is found in **Appendix Figure 1**.

Figures 3A-F show the variation in estimates by cercles. More than 60% of children are anaemic in the East, South-East and Central regions of Mali (**Figure 3A**). **Figure 3B** shows that breastfeeding is a common practice in all cercles, with more than seven in ten children younger than 24 months breastfed the day before the survey. Among complementary feeding practices, the models show that less than 25% of children met the MDD requirements in most cercles (**Figure 3C**), but slightly more children (30% and higher) met the MMF requirements in many cercles, especially in the West (**Figure 3D**). **Figure 3E** shows that cercles in the East and North of Mali have more than 40% of households that do not have access to toilet facilities and practice open defection. The Northern and Eastern cercles are also associated with low level of access to an improved source of water (**Figure 3F**).

Figure 3 Cercles level estimates of select covariates



Note: (A) Anaemia, (B) Current breastfeeding, (C) Minimum Diet Diversity, (D) Minimum Meal Frequency, (E) Open defecation/No toilet, (F) Improved water source

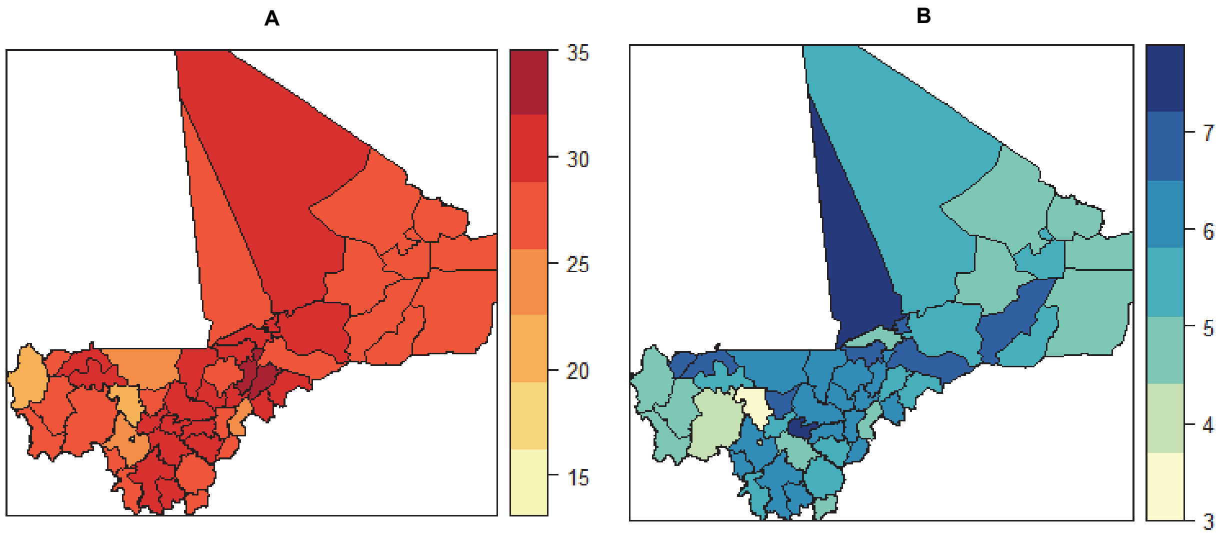
3.2 Cercles-level Estimates of Stunting and Wasting among Children

3.2.1 Prevalence of stunting and wasting in 2018

Figure 4A displays cercle-level stunting estimates in 2018. **Figure 4B** highlights the width of 95% credible intervals for the estimates in each cercle. The prevalence of stunting is the lowest in Bamako (14 %) and ranges from 21% in Kolokani cercle (Koulikolo Region) to 34% in Mopti cercle (Mopti Region). For almost a quarter of the cercles, the prevalence of stunting is 30% or higher. With only a few exceptions, **Figure 4A** highlights that the high burden of stunting is concentrated in cercles located in Central and South-central Mali.

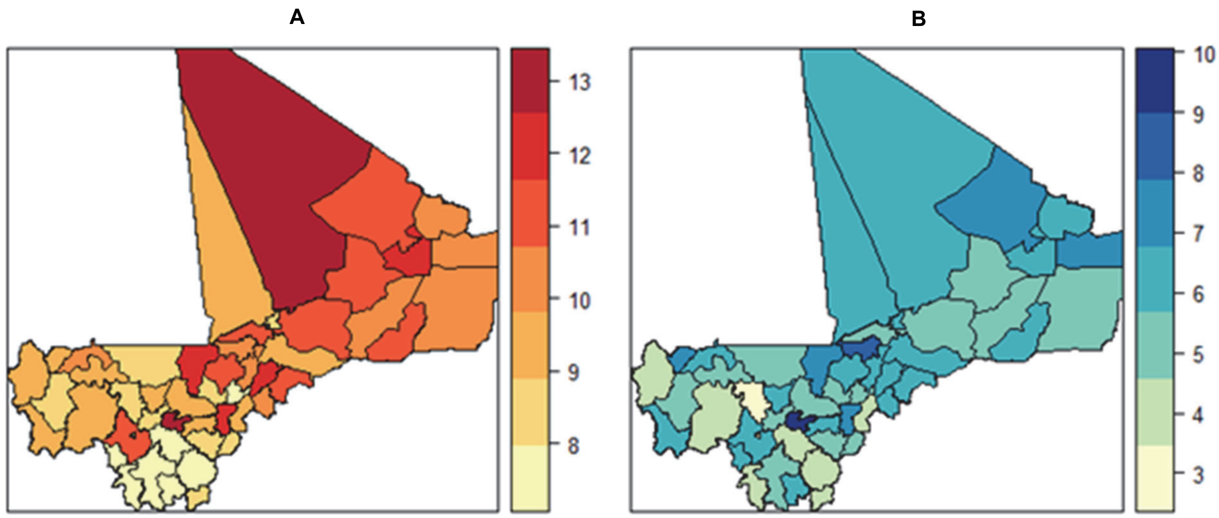
Values used to generate the figures are presented in **Appendix Table 1**.

Figure 4 Prevalence of stunting (A) and the width of 95% credible interval (B) at the cercles level, 2018



Estimates for wasting in 2018 with their 95% width credible interval are displayed in **Figure 5A** and **Figure 5B**. The prevalence of wasting varies from 7% in Dioïla cercles (Koulikoro Region) to 13% Barouéli (Segou Region) and Tombouctou (Tombouctou Region) cercles. Three in ten cercles have an estimated prevalence of wasting that is higher than 10%. **Figure 5A** shows that wasting tends to be higher in Central and Northern Mali.

Figure 5 Prevalence of wasting (A) and the width of 95% credible interval (B) at the cercles level, 2018



3.2.2 Prevalence of stunting and wasting in 2006

Figures 6A and **7A** display cercles-level stunting and wasting estimates in 2006 with their respective 95% credible intervals (**Figures 6B** and **7B**). Similar to 2018, the prevalence of stunting in 2006 was lowest in Bamako (21%) and ranged from 31% in Kolokani cercles (Koulikoro Region) to 49% in Koutiala cercles (Sikasso Region). The prevalence of wasting was lowest (12%) in Ségou (Ségou Region) and Diré (Tombouctou Region) cercles and highest (23%) in Barouéli cercles (Ségou Region)

Values used to generate the figures are presented in **Appendix Table 2**.

Figure 6 Prevalence of stunting (A) and the width of 95% credible interval (B) at the cercles level, 2006

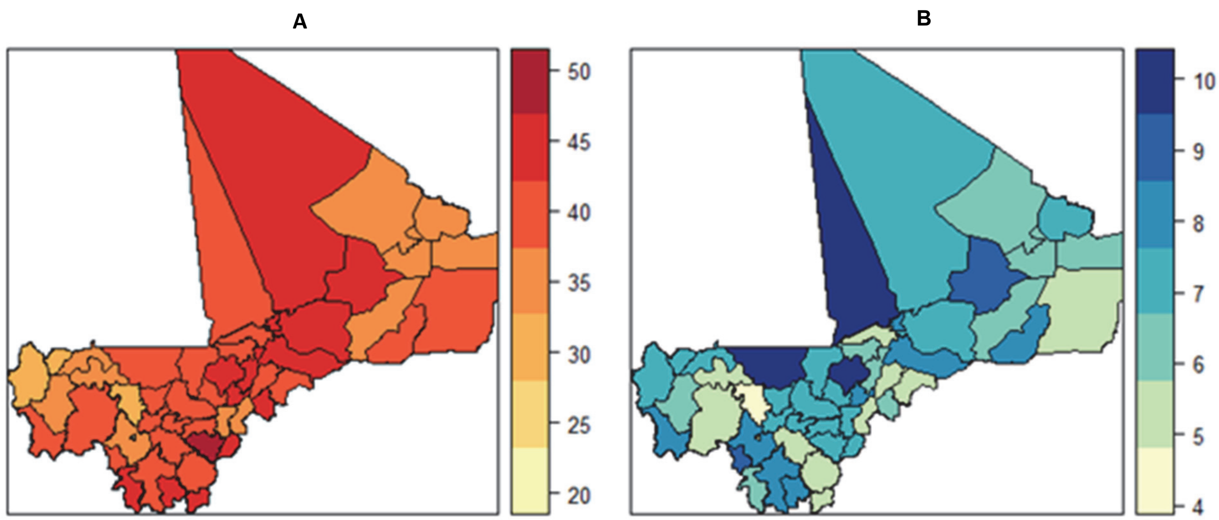
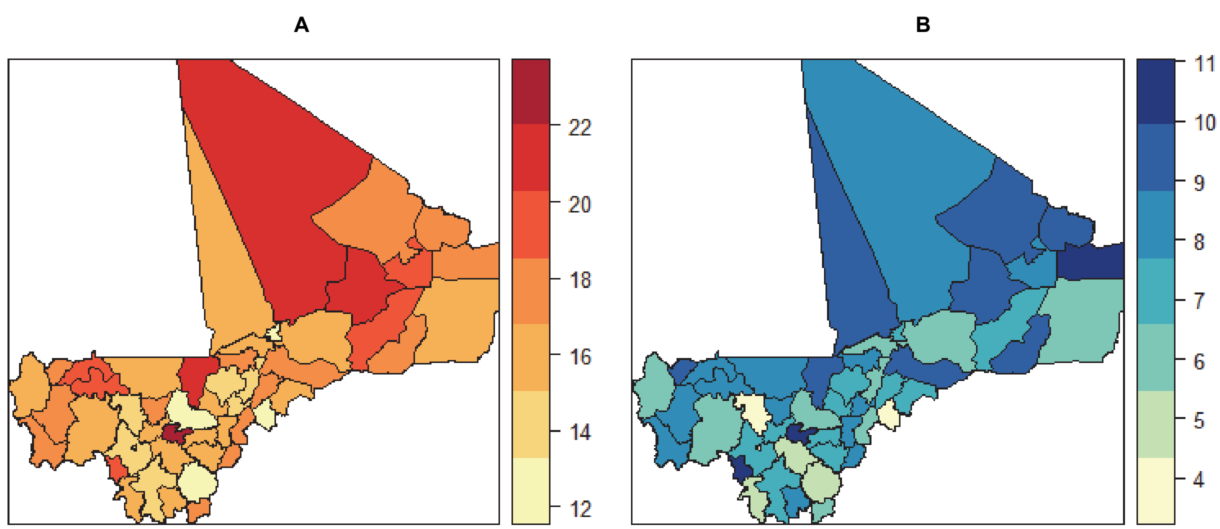


Figure 7 Prevalence of wasting (A) and the width of 95% credible interval (B) at the cercles level, 2006



3.3 Change in Prevalence of Stunting and Wasting between 2006 and2018

Figures 8 and **9** show the change in prevalence for stunting and wasting, respectively, between 2006 and 2018. The results show an overall decrease in both stunting and wasting for the 49 cercles in Mali. The decrease in stunting prevalence ranged from 6% in the Bamako cercles to 18% in the Koutiala cercles. The most notable changes in stunting by cercles were in the northern, and southern parts of the country (mostly in Sikasso and Koulikoro regions) and in the cercles of Bourem (Gao Region), Tenenkou and Douentza (Mopti Region) (**Figure 8**).

Decrease in wasting prevalence ranged from 3% in Bankass cercles to 11% in the Kangaba cercles (**Figure 9**). The most notable changes in wasting prevalence by cercles were in the southern and eastern parts of the country and in the cercles of Diema (Kayes Region), Bourem, Gao (Gao Region), and Baroueli (Segou Region).

Figure 8 Cercles-level percent change in stunting prevalence between 2006 and 2018

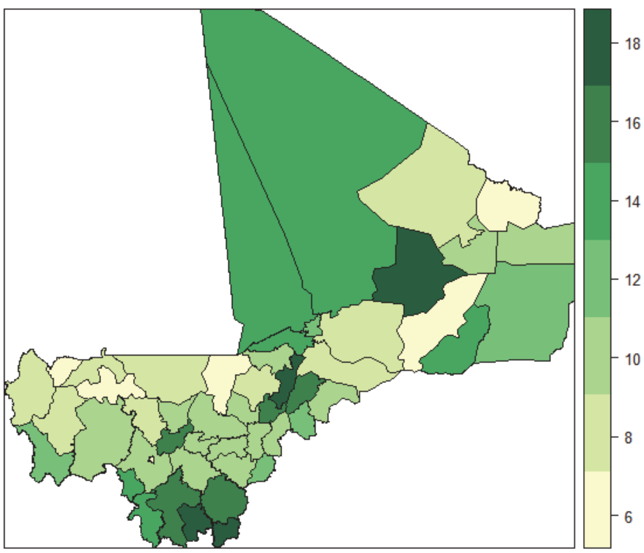
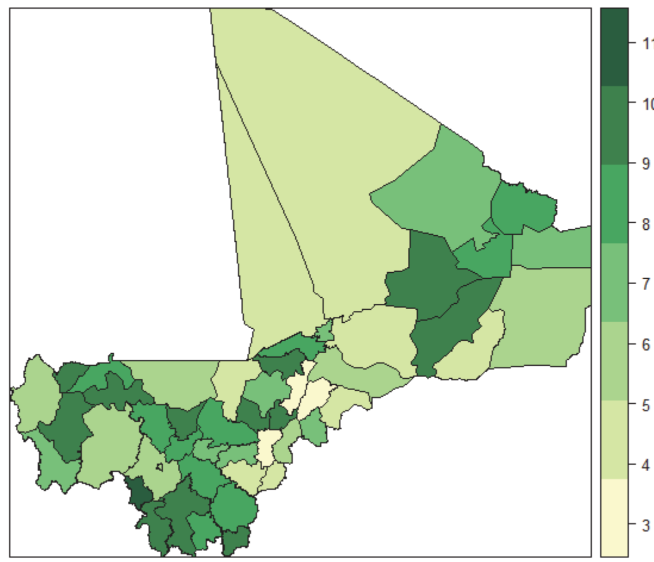


Figure 9 Cercles-level percent change in wasting prevalence between 2006 and 2018



3.3.1 Relative importance of determinants of stunting and wasting

We calculated the relative importance of each covariate using the beta coefficients for each submodel in the final Bayesian geostatistical model as weights. **Figures 10A** and **10B** show that three covariates (i) MDD, (ii) the mother's education, and (iii) the mother's overweight and obesity were ranked as the top three factors that contributed to the stunting models. Other important factors in 2018 included ANC, current breastfeeding, elevation, under age 5 population, and daytime LST, which were all above 5%. In 2006, the factors that contributed more than 5% were different and included under age 5 population, ANC, wealth, improved water source, and parity.

Figure 10 Percentage contribution of covariates to the stunting models in (A) 2006 and (B) 2018

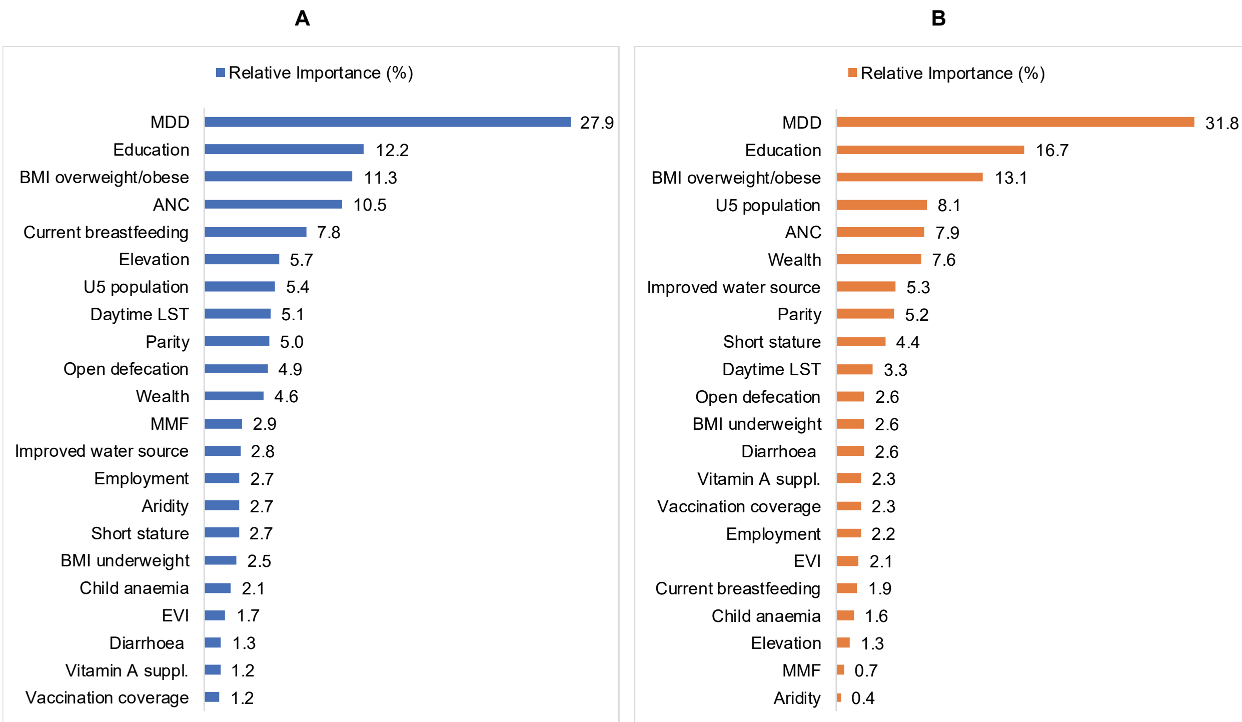
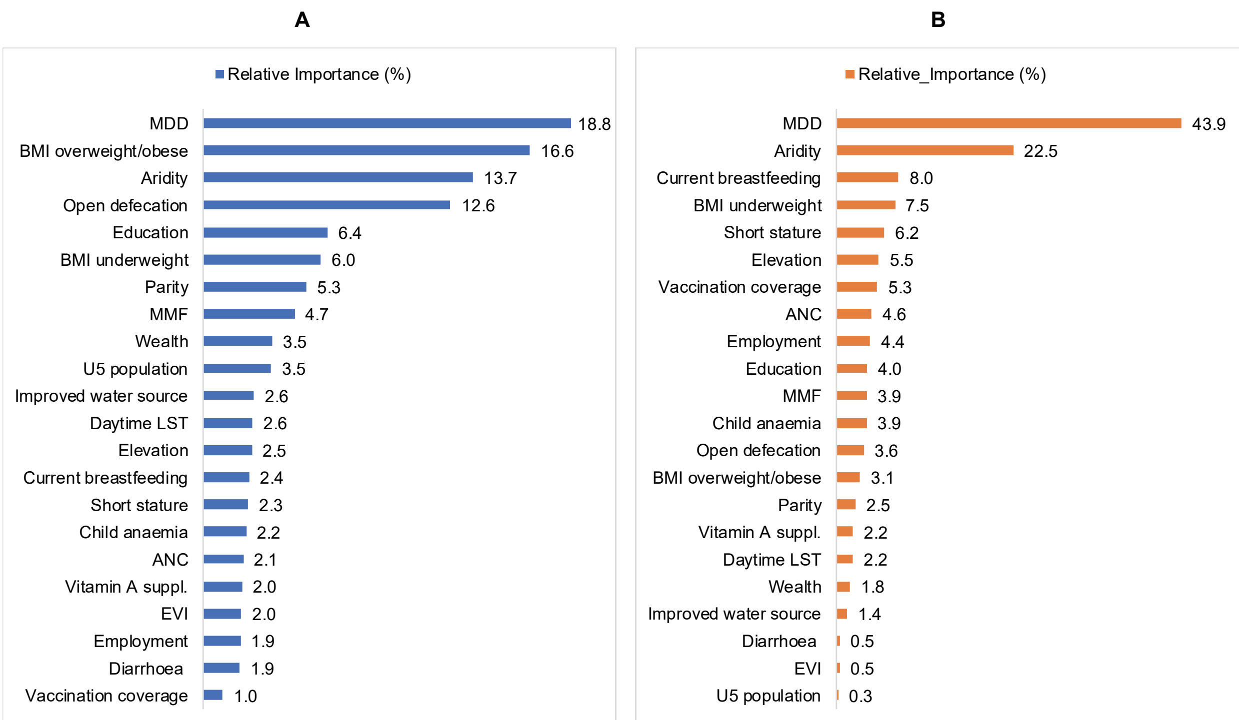


Figure 11A and **11B** depicts the relative covariate importance for wasting. The results indicate that MDD was the covariate that contributed most to the models in 2006 and 2018. Aridity was ranked third in 2006, but second in 2018. For most of the other covariates, their relative importance changed from 2006 to 2018. Other important factors that contributed more than 5% to the models in 2018 were mother's BMI, open defecation, education, and parity. For 2006, the important factors included current breastfeeding, mother's underweight and short stature, elevation, and vaccination coverage.

Figure 11 Percentage contribution of covariates to the wasting models in (A) 2006 and (B) 2018



4 DISCUSSION

The declines in stunting and wasting prevalence over the last decade are evidence of Mali's continued commitment to addressing child undernutrition. However, our study shows that stunting remains high in the Central and South-central areas of the country, while wasting is high in the Central and Northern areas, with much variation across cercles. Among the top factors that contributed to the stunting and wasting in 2018 were children's MDD, mother's education, mother's overweight and obesity, and aridity. These results suggest that improvements in women's and children's diets, social factors, and action on climate change to address the food environment could further reduce both stunting and wasting prevalence in the country.

Our analysis on stunting revealed that the same three factors were the top factors associated with stunting in both 2006 and 2018. This suggests that optimal child feeding, women's education, and women's malnutrition have been and are the key underlying drivers of childhood stunting in Mali. Stunting can result from inadequate feeding practices and recurrent or chronic diseases, as described in UNICEF's conceptual framework of child undernutrition (United Nations Children's Fund 2015). Children's MDD reflects overall diet quality and studies have linked improved diet diversity with lower stunting (Arimond and Ruel 2004; Ruel and Menon 2002). This result was also found study in Mali (Sobgui et al. 2018) that linked low household diet diversity with increased with stunting, (Low education among women in Mali may also contribute to poor stunting through pathways that involve child feeding and other care and health seeking practices (Akombi et al. 2017; Issaka et al. 2015; Pongou, Ezzati, and Salomon 2006). An important factor that emerged in this analysis was women's nutrition and the double burden of malnutrition in households. The rising prevalence of maternal overweight and obesity in Mali is cause for concern and underscores the importance of dual actions that address both stunting in children and overweight and obesity in women (Bosu 2015; WHO 2017).

Interestingly, in 2018, two environmental factors, daytime LST and elevation, were associated with stunting and contributed over 5% to the model. Among the few studies that have examined the role of temperature on undernutrition, one study from India reported a positive association between high average temperatures above 40C in districts and stunting (Bharti, Dhillon, and Narzary 2019). The authors found that for every 1C increase in annual temperature, stunting increased by 0.1% (Bharti, Dhillon, and Narzary 2019). Conversely, another study of multiple countries in sub-Saharan Africa reported that in regions with average temperatures over 35C, children had a lower odds of stunting, but higher odds of wasting and of being both stunted and wasted compared to countries with average temperatures below 30C (Tusting et al. 2020). The role of elevation is less clear, but may be linked to temperature or other environmental conditions. In the literature, the common pathways for the impact of environmental factors on stunting include crop production, food insecurity, infection, and physiological adaption (Bharti, Dhillon, and Narzary 2019; Cooper et al. 2019; Lloyd, Kovats, and Chalabi 2011; Tusting et al. 2020). Given the growing focus on the effects of climate change on health, more studies are needed to understand the relationships and pathways between environmental factors and undernutrition.

The two leading factors associated with wasting were the same in the 2006 and 2018 Mali DHS. This suggested that children's diet and the environment are key to addressing wasting in Mali. Wasting is susceptible to seasonality and may result from inadequate food intake or recent illness (United Nations Children's Fund 2015). Although some studies have reported no association between dietary diversity and wasting (Frempong and Annim 2017; Jones et al. 2014; Pare et al. 2019), many of these studies have not accounted for the underlying environmental factors as we did in this study. High temperatures are linked to aridity (Quan et al. 2013) and with increasing variation in the frequency and length of dry spells in Mali, agricultural production patterns will be disrupted, which may lead to increased food insecurity and lower quality diets (Kinyoki et al. 2016; Osgood-Zimmerman et al. 2018). Reducing the agriculture sectors' vulnerability to the effects of climate change will not only improve food availability, but may also help to address wasting in Mali.

Women's undernutrition and breastfeeding were also important factors associated with wasting in 2018. Breastfeeding protects infants from infection and promotes health growth and development (Victora et al. 2016). Although optimal breastfeeding practices in Mali have consistently improved, fewer than 50% of infants are exclusively breastfed (INSTAT, CPS/SS-DS-PF, and ICF 2019). Further improvements in breastfeeding practices would help to address wasting by protecting infants from infection. Mother's short stature and low BMI reflect the long term and more recent poor nutritional status of the mother. Studies from Guatemala and elsewhere have shown than being a thin mother is associated with a greater risk of wasting and stunting (Akombi et al. 2017; Martorell and Young 2012). Targeting interventions that can improve nutrition for mothers, pregnant women, and women of reproductive age may help reduce the generational effects of poor nutrition and decrease the prevalence of wasting in those most vulnerable.

Our analysis approach has several strengths. The models used several DHS and geospatial covariates known to be associated with the outcomes and which contributed to the high validity of our models (**Appendix Table 3**). We were able to produce stunting and wasting estimates for the 49 cercles of Mali and illustrate the spatial variation of undernutrition in Mali that has not previously been examined. Our estimates align with those from a previous study that assessed stunting and wasting prevalence in rural areas of 5 cercles in the Sikasso and Mopti regions (Sobgui et al. 2018). Our findings also provide insights into the factors associated with stunting and wasting that can help policy makers address undernutrition and advance Mali's progress on meeting the SDGs. It will be important for Mali to examine the factors that have and have not changed in their relative importance between the years, in order to help the government focus its efforts on addressing stunting and wasting.

Although we have estimated the prevalence for each indicator at the cercles level, our study has some key limitations. Computational limitations meant that we could not quantify uncertainty in the covariates and submodel estimates. This may have introduced additional uncertainty into our final stunting and wasting estimates, although based on our validation results, we suspect the effect to be minimal. Nevertheless, more research is needed to develop methods that are capable of propagating uncertainty in both the covariates and submodel estimates (Dwyer-Lindgren et al. 2019; Wakefield et al. 2019). Although our study used geospatial modelling methods to create the cercles-level estimates, the results are cross-sectional and may be affected by confounding factors not included in our models. However, given the expanse of literature on the drivers of undernutrition, our findings align with the broader consensus on the contribution of these factors to stunting and wasting. Further work to strengthen this analysis could include regressions that also control for the temporal changes. The choice of covariates used in the analysis was determined by the availability of high-resolution spatial data for Mali. For example, exclusive breastfeeding among children under age 6 months is an important factor in undernutrition. However, this covariate could not be used for the present study because it was not available for this population at the time we conducted the analysis.

5 CONCLUSION

This is one of the few studies that used the Bayesian geospatial modelling approach to model stunting and wasting prevalence by using both geospatial covariates and DHS underlying risk factors. We generated maps that show areas at high risk and estimated the change in these indicators and factors associated with stunting and wasting between 2006 and 2018 in Mali. The generated estimates of stunting and wasting prevalence and the identified factors (children's diet diversity, mother's education and nutrition, and environmental conditions) provide essential information that can help inform the allocation of resources and programme implementation in areas that need more attention in Mali. Interventions and programmes that can be implemented and directed at much smaller spatial scales by using model-based estimates such as the one described in our analysis could enable better programmatic decisions.

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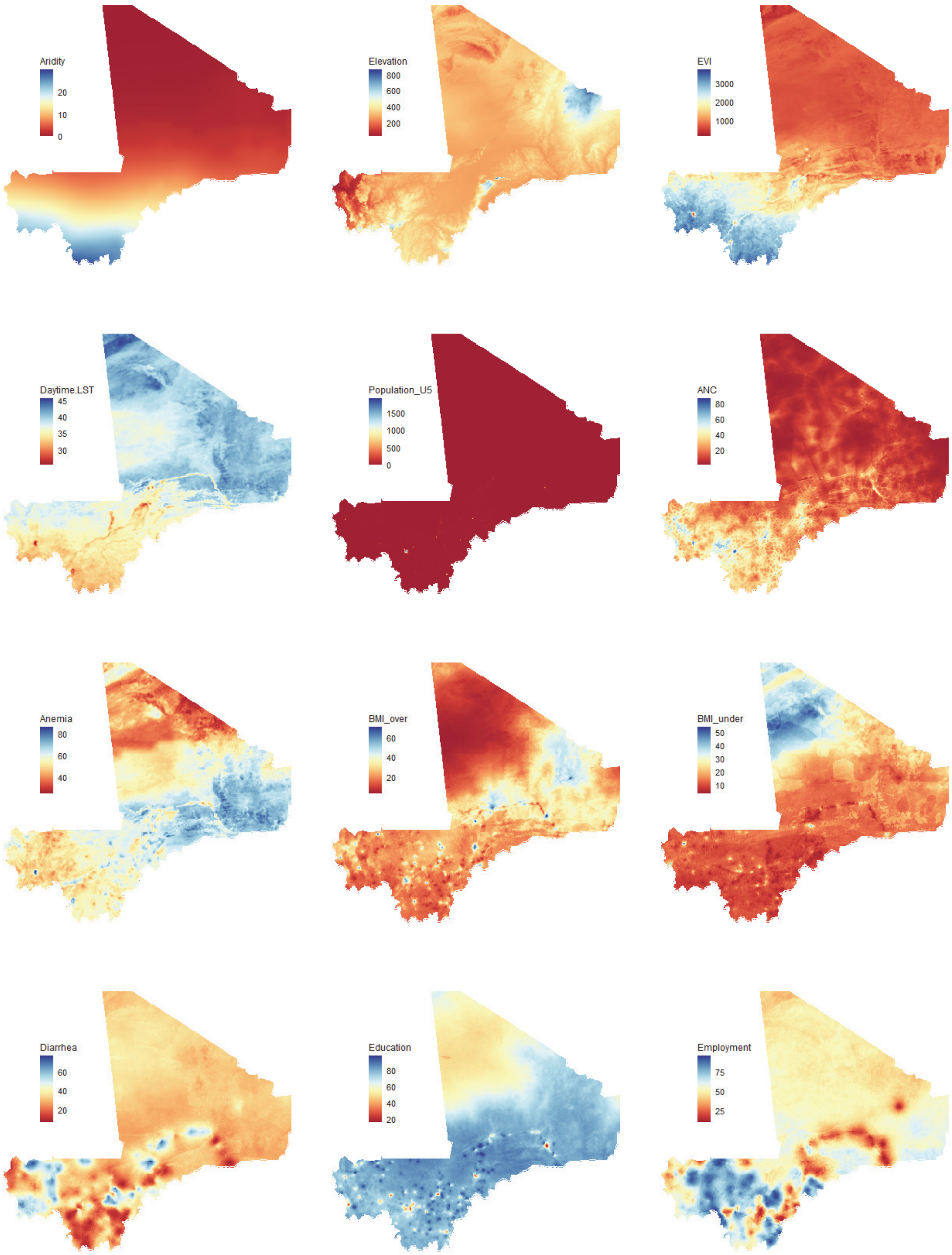
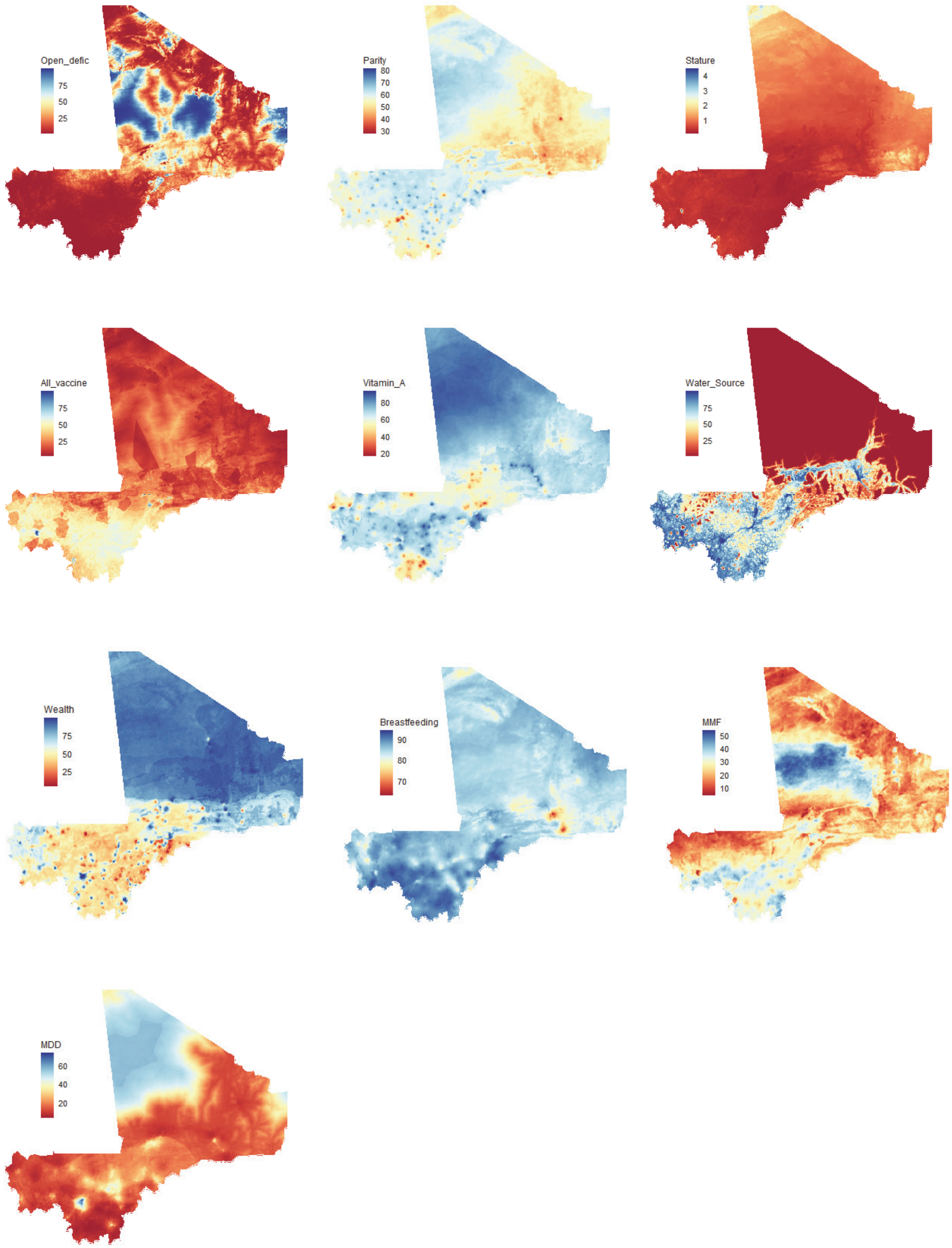
APPENDIX

Appendix Figure 1 DHS covariates maps at the pixel level

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Stature
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Vitamin_A
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Water_Source
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Wealth
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Breastfeeding
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MMF
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Appendix Table 1 Prevalence of stunting, 95% confidence intervals, and change in stunting prevalence by cercles

		Stunting						
		2006			2018			
Region	Cercles	Prevalence	Upper	Lower	Prevalence	Upper	Lower	Change in prevalence
Bamako	Bamako	20.5	23.0	18.0	14.4	16.5	12.6	6.1
Gao	Ansongo	41.7	45.7	37.7	28.6	31.4	26.0	13.1
Gao	Bourem	46.1	50.5	41.8	28.3	30.8	25.9	17.8
Gao	Gao	32.9	36.3	29.9	25.9	29.5	22.8	7.0
Gao	Menaka	38.1	40.5	35.7	26.3	28.8	23.8	11.7
Kayes	Bafoulabe	37.3	40.4	34.0	28.3	30.5	26.0	9.0
Kayes	Diema	37.1	40.1	34.4	30.3	33.3	27.5	6.9
Kayes	Kayes	31.4	34.9	27.9	22.1	24.8	19.9	9.3
Kayes	Kenieba	39.8	43.8	36.0	27.7	30.3	25.2	12.1
Kayes	Kita	37.7	40.3	35.1	27.5	29.7	25.3	10.2
Kayes	Nioro	36.6	40.5	33.1	29.1	32.5	26.0	7.5
Kayes	Yelimane	31.9	35.7	28.2	26.3	29.8	23.3	5.6
Kidal	Abeibara	33.5	37.5	29.9	26.0	28.4	23.4	7.5
Kidal	Kidal	35.4	38.8	32.4	25.7	28.7	22.9	9.7
Kidal	Tessalit	34.5	37.7	31.2	26.1	28.5	23.6	8.4
Kidal	Tin-Essako	36.4	39.6	33.4	26.5	29.0	24.1	10.0
Koulikoro	Banamba	38.7	42.6	35.2	28.0	31.5	24.9	10.7
Koulikoro	Dioila	41.1	43.8	38.4	30.5	32.8	28.2	10.6
Koulikoro	Kangaba	40.7	45.1	36.4	26.3	29.5	23.2	14.5
Koulikoro	Kolokani	31.1	33.3	29.1	20.5	22.3	19.0	10.5
Koulikoro	Koulikoro	37.6	41.0	34.2	28.8	31.7	26.1	8.8
Koulikoro	Nara	40.0	45.3	35.4	25.1	28.3	22.2	14.9
Koulikoro	Kati	36.8	41.1	33.0	23.7	26.9	20.8	13.2
Mopti	Bandiagara	40.1	42.6	37.6	32.5	35.4	29.9	7.6
Mopti	Bankass	46.0	48.9	42.8	29.6	32.7	26.6	16.4
Mopti	Djenne	43.5	47.5	39.2	31.7	35.0	28.5	11.8
Mopti	Douentza	44.1	48.1	40.1	28.5	32.0	25.2	15.6
Mopti	Koro	40.3	43.1	37.6	31.7	34.6	28.8	8.6
Mopti	Mopti	44.2	47.3	41.3	33.7	36.7	30.8	10.5
Mopti	Tenenkou	44.9	50.1	40.3	27.1	30.2	23.9	17.8
Mopti	Youwarou	39.5	42.8	36.3	30.8	34.0	27.5	8.6
Segou	Baroueli	41.2	44.9	37.5	31.7	35.3	28.1	9.5
Segou	Bla	39.4	43.2	35.8	28.9	32.1	25.9	10.5
Segou	Macina	39.3	43.2	35.7	29.5	32.5	26.5	9.8
Segou	Niono	39.1	42.9	35.5	29.3	32.4	26.2	9.7
Segou	San	34.3	37.8	30.7	26.9	30.1	23.9	7.4
Segou	Segou	39.7	43.1	36.3	29.0	32.3	26.1	10.7
Segou	Tominian	36.5	39.2	33.6	25.5	28.1	23.3	11.0
Sikasso	Bougouni	41.1	45.0	37.3	30.7	34.1	27.8	10.4
Sikasso	Kadiolo	43.4	46.4	40.7	28.6	30.8	26.3	14.8
Sikasso	Kolondieba	46.1	50.4	42.0	29.1	32.4	26.0	17.1
Sikasso	Koutiala	49.5	52.9	45.8	31.4	34.2	28.5	18.1
Sikasso	Sikasso	38.5	41.4	35.7	28.5	31.5	25.8	10.0
Sikasso	Yanfolila	44.1	47.5	41.3	28.2	30.9	25.6	16.0
Sikasso	Yorosso	42.3	45.6	38.9	28.7	31.7	25.9	13.6
Tombouctou	Dire	43.5	47.8	39.4	31.7	35.5	28.3	11.8
Tombouctou	Goundam	39.1	44.3	34.2	27.0	30.9	23.3	12.2
Tombouctou	Gourma-Rharous	43.2	46.7	39.9	29.7	32.4	27.1	13.5
Tombouctou	Niafunke	39.5	42.2	37.0	30.4	32.9	28.2	9.1
Tombouctou	Tombouctou	44.8	48.2	41.3	30.3	33.2	27.6	14.5

Appendix Table 2 Prevalence of wasting, 95% confidence intervals, and change in wasting prevalence by cercles

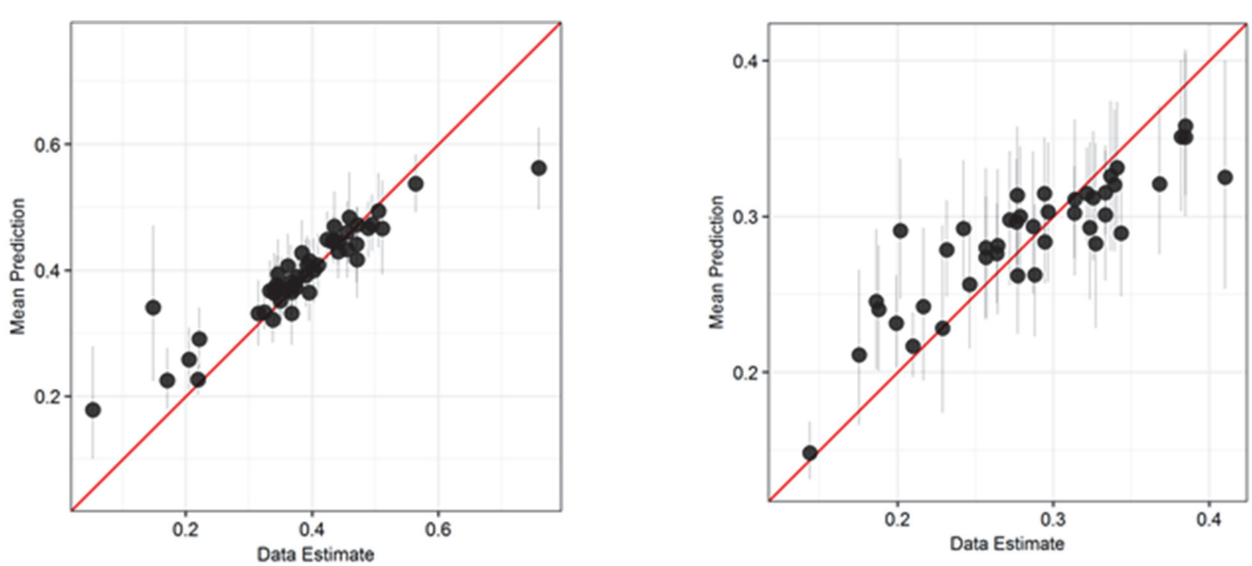
		Wasting						
		2006			2018			Change in prevalence
Region	Cercles	Prevalence	Upper	Lower	Prevalence	Upper	Lower	
Bamako	Bamako	14.3	16.5	12.4	8.2	9.9	6.8	6.0
Gao	Ansongo	16.8	22.1	12.5	11.3	14.5	8.6	5.5
Gao	Bourem	20.3	25.1	16.0	11.0	13.8	8.5	9.3
Gao	Gao	18.8	22.5	15.5	9.9	12.7	7.5	8.9
Gao	Menaka	16.3	19.6	13.5	10.1	12.9	7.7	6.2
Kayes	Bafoulabe	17.7	21.9	14.0	8.7	11.3	6.5	8.9
Kayes	Diema	19.6	23.8	16.1	9.2	11.9	7.0	10.5
Kayes	Kayes	15.1	18.5	12.1	8.9	11.3	6.8	6.2
Kayes	Kenieba	17.1	21.5	13.1	9.7	13.1	7.2	7.3
Kayes	Kita	15.2	18.2	12.1	8.9	11.2	7.0	6.3
Kayes	Nioro	18.9	23.5	15.2	10.6	14.2	7.8	8.3
Kayes	Yelimane	18.2	23.5	13.9	9.7	13.5	6.6	8.5
Kidal	Abeibara	17.9	23.0	13.6	10.2	13.8	7.3	7.7
Kidal	Kidal	20.2	24.9	16.3	12.1	15.8	9.1	8.1
Kidal	Tessalit	17.4	22.7	13.1	10.7	14.7	7.6	6.7
Kidal	Tin-Essako	17.3	23.0	12.4	10.0	14.0	6.9	7.4
Koulikoro	Banamba	18.3	22.6	14.5	9.6	13.1	6.6	8.7
Koulikoro	Dioila	15.2	18.0	12.6	7.4	9.6	5.6	7.8
Koulikoro	Kangaba	18.6	24.0	14.1	7.7	11.1	5.4	10.9
Koulikoro	Kolokani	14.6	16.5	12.8	8.5	10.1	7.2	6.1
Koulikoro	Koulikoro	16.3	20.3	13.0	8.0	10.8	5.7	8.3
Koulikoro	Nara	16.3	21.0	12.8	8.7	11.8	6.4	7.5
Koulikoro	Kati	14.9	18.5	11.9	11.4	14.8	8.6	3.6
Mopti	Bandiagara	17.8	21.5	14.6	11.9	15.2	9.0	6.0
Mopti	Bankass	12.7	14.9	10.6	10.1	13.5	7.7	2.6
Mopti	Djenne	14.9	19.3	10.9	7.6	10.1	5.4	7.4
Mopti	Douentza	17.9	23.2	13.7	9.0	12.6	6.2	8.9
Mopti	Koro	16.6	20.3	13.5	10.9	14.3	8.2	5.7
Mopti	Mopti	14.7	17.9	11.9	10.4	13.4	7.6	4.2
Mopti	Tenenkou	14.2	18.1	10.9	11.3	14.7	8.4	3.0
Mopti	Youwarou	17.8	22.2	13.7	10.6	15.1	6.8	7.2
Segou	Baroueli	23.0	28.3	18.0	12.9	18.5	8.9	10.1
Segou	Bla	15.9	19.7	12.6	9.0	12.1	6.4	7.0
Segou	Macina	15.8	19.8	12.3	8.6	11.6	6.3	7.3
Segou	Niono	20.6	25.5	16.3	11.8	16.2	8.4	8.9
Segou	San	16.6	21.3	12.7	11.7	15.5	8.6	4.9
Segou	Segou	12.3	15.6	9.6	9.2	12.2	6.7	3.1
Segou	Tominian	17.9	21.2	14.9	9.6	12.0	7.6	8.3
Sikasso	Bougouni	13.4	17.2	10.0	7.9	10.7	5.6	5.5
Sikasso	Kadiolo	17.3	20.5	14.4	8.1	10.2	6.2	9.2
Sikasso	Kolondieba	16.2	20.8	12.5	7.7	11.1	5.3	8.5
Sikasso	Koutiala	15.9	19.7	12.8	8.4	11.4	5.9	7.6
Sikasso	Sikasso	12.8	15.3	10.7	7.7	10.1	5.8	5.2
Sikasso	Yanfolila	15.6	18.4	13.2	7.8	9.7	6.1	7.8
Sikasso	Yorosso	18.3	22.6	14.7	8.4	11.1	6.0	9.9
Tombouctou	Dire	12.3	16.3	9.4	8.2	11.3	5.6	4.1
Tombouctou	Goundam	16.4	21.6	11.8	9.4	13.0	6.5	7.0
Tombouctou	Gourma-Rharous	16.1	19.7	13.2	11.3	14.2	8.8	4.8
Tombouctou	Niafunke	16.1	19.4	13.2	11.5	14.3	8.8	4.6
Tombouctou	Tombouctou	20.9	25.2	17.2	13.1	16.1	10.4	7.9

Appendix Table 3 **Prediction metrics for each indicator aggregated at cercles-level**

Indicator	Year	Mean error	Mean absolute error	Variance	95% Data coverage	Correlation
Stunting	2006	-0.0066	0.0187	0.0299	0.9897	0.9512
	2018	-0.0035	0.0202	0.0264	0.9874	0.9305
Wasting	2006	-0.0012	0.0114	0.0178	0.9975	0.9256
	2018	-0.0009	0.0098	0.0139	0.9956	0.9528

Appendix Figure 2 **Comparison of stunting predictions for (A) 2006 and (B) 2018, aggregated at cercles-level with 95% uncertainty intervals, plotted against data observations from the same area aggregated to the cercles-level**

A B



Appendix Figure 3 **Comparison of wasting predictions for (A) 2006 and (B) 2018, aggregated at cercles-level with 95% uncertainty intervals, plotted against data observations from the same area aggregated to the cercles-level**

A B