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ACRONYMS AND ABBREVIATIONS

BFDHS	Burkina Faso Demographic and Health Survey
CEDA	Center for Environmental Data Analysis
DHS	Demographic and Health Surveys
EVI	enhanced vegetation index
GPS	global positioning system
INLA	integrated nested Laplace approximation
SE	standard error
SMART	standardized monitoring and assessment of relief and transitions
SPDE	stochastic partial differential equation
UNICEF	United Nations Children's Fund
WHO	World Health Organization
WPS	Web Processing Service

ABSTRACT

Undernutrition and child food poverty constitute a critical public health problem, particularly in the context of climate change. However, evidence on the links between climate and nutrition outcomes is not sufficiently available. The objectives of this study were to (1) examine the impacts of climate change on undernutrition and child food poverty and (2) apply geostatistical models to produce maps of undernutrition and child food poverty prevalences in Burkina Faso to identify hotspots more accurately.

The study utilized geostatistical modeling through data from the 2021 Burkina Faso Demographic and Health Survey, supplemented by remote-sensed information (covariates), to improve estimates of stunting, wasting, and child food poverty prevalences. Geostatistical models were developed at the cluster level considering all spatial and nonspatial covariates. Additionally, two models were developed for each individual covariate—one model assuming and the other not assuming the spatial locations of the clusters.

Results showed that the enhanced vegetation index (EVI), which takes several climate variables into account, was very strongly associated with wasting and stunting but was not associated with child food poverty. Positive associations were found between stunting prevalence and both low maternal education and open defecation. Wasting prevalence was associated with open defecation, and child food poverty was associated with maternal education and richer wealth quintiles. The maps showed that certain locations in Sahel, Centre Nord, and Est regions were at greater risk of stunting and wasting than other locations, as the maps made it possible to visualize intercluster disparities. We also validated the model, showing correlations between observed and predicted prevalences.

Through this study, we demonstrated the relationship between climate and undernutrition. This calls for the integration of climate considerations into nutrition commitments. We also demonstrated the value of applying geostatistical analyses to identify pockets of concentrated undernutrition and child food poverty to better guide intervention strategies. These methodologies present an opportunity for predicting the prevalences of stunting, wasting, and child food poverty in areas where access to traditional nutrition surveys is problematic.

Key words: Burkina Faso, child food poverty, climate, geostatistical models, undernutrition

1 BACKGROUND

Undernutrition and food insecurity constitute a serious public health problem. The Sustainable Development Goals and many national nutrition policies aim to reduce all forms of malnutrition, including the ambitious World Health Organization (WHO) target of a 40% reduction in stunting by 2025.[1] However, major challenges remain in reaching this target, particularly in sub-Saharan African countries such as Burkina Faso, where limited resources are affected by security issues and the deleterious effects of climate change.

According to the 2020 National Nutrition Survey, referred to as the standardized monitoring and assessment of relief and transitions (SMART) survey, 25% of children under 5 in Burkina Faso are stunted. This is considered high according to the 2017 WHO and United Nations Children's Fund (UNICEF) public health prevalence thresholds, but is lower than the average for the Africa region (30.7%).[2] The stunting prevalence has improved in Burkina Faso since 2003, when the prevalence nationwide was 43%.[3] Wasting affects 9% of children under 5 in Burkina Faso, which is considered a "medium" prevalence according to the WHO/UNICEF thresholds and is higher than the average for the Africa region (6.0%).[1,4] Poor infant and young child feeding practices are pervasive in Burkina Faso and are likely drivers of stunting and wasting in the country. Inadequate complementary feeding is also highly prevalent in Burkina Faso, as only 29% of children age 6–23 months receive a minimally acceptable diet.[2]

The 2020 UNICEF Conceptual Framework on Maternal and Child Nutrition acknowledges the increasing triple burden of malnutrition—undernutrition, micronutrient deficiencies, and overweight status—and highlights the role of diets and care as immediate determinants of maternal and child nutrition.[1] The underlying determinants are the food, practices, and services available to children and women in their households, communities, and environments that enable good nutrition.[1]

Studies have confirmed that mother's education, mother's work status, poor maternal nutrition, area of residence, wealth index, and lack of water and sanitation are associated with malnutrition in some parts of sub-Saharan Africa.[5] Undernutrition and child food poverty remain a critical public health problem, particularly in the context of climate change. However, evidence on the links between climate and nutrition outcomes is not sufficiently available.[6]

Spatial maps are important for evidence-based planning and decision-making, as they help identify populations in need of targeted interventions and can be used to monitor progress toward achieving Sustainable Development Goal targets. Additionally, in many countries, standard nutrition surveys, such as those using SMART or similar methodologies, are often hindered by limited access to certain localities. In such cases, geospatial models offer a valuable solution for overcoming these challenges.

This study aimed to (1) investigate the impacts of climate change on undernutrition and child food poverty, and (2) apply geostatistical models to data from the most recent Burkina Faso Demographic and Health Survey to generate prevalence maps of undernutrition and child food poverty, enabling precise identification of hotspots. This research introduces a novel geostatistical approach for assessing the spatial heterogeneity of key nutritional outcomes, specifically stunting, wasting, and child food poverty. The resulting prevalence maps reveal significant spatial disparities in these outcomes across Burkina Faso, providing actionable insights to support evidence-based planning and targeted interventions.

2 METHODS

2.1 Survey Population and Design

This study utilized data from the 2021 Burkina Faso Demographic and Health Survey (BFDHS) and accompanying geospatial data. In this BFDHS, a two-stage stratified cluster sampling design was implemented. In the first stage, clusters—defined as primary sampling units in the survey and enumeration areas in the population census—were selected with probability proportional to cluster size (number of households) within each of the stratum. In the second stage, households were systematically sampled within each cluster. Stratification was based on Burkina Faso's administrative regions at the time of the survey and their urban-rural classification. Further details on the survey design are available in the 2021 BFDHS final report.[2]

2.2 Data Sources

The Demographic and Health Surveys (DHS) Program collects child anthropometric data, including age, sex, length/height, and weight, as well as other child nutrition and geospatial variables. Children born in the 5 years preceding a survey are eligible for collection of length/height and weight data. Since 2000, geographical coordinates of the sampled clusters have been collected through the global positioning system (GPS). However, the geographical coordinates are displaced by up to 5 km in rural settings and up to 2 km in urban settings to protect the identity of the participants in the DHS surveys.

In this study, anthropometric information from the 2021 BFDHS was used to calculate child height-for-age, weight-for-age, and weight-for-height *z* scores using World Health Organization (WHO) child growth standards[7] for Burkina Faso. Children were considered stunted if their height-for-age *z* scores were more than two standard deviations below the median of the relevant WHO reference population.[8] In a similar way, children were considered wasted if their weight-for-height *z* scores were more than two standard deviations below the median of the WHO reference population.

2.3 Outcomes Variables

Analyses were carried out for three nutrition outcome variables:

- **Stunting:** We determined the proportion of children under 5 who were stunted at the time of the survey. All children for whom valid height-for-age *z* scores were available constituted the total sample of children for this analysis.

- **Wasting:** We determined the proportion of children aged 6–59 months who were wasted at the time of the survey. All children for whom valid weight-for-height *z* scores were available constituted the total sample of children.

- **Child food poverty:** We determined the proportion of children age 6–23 months who had consumed foods and beverages from four or fewer of eight defined food groups during the previous day, based on the United Nations Children's Fund (UNICEF) definition of food poverty for children under 5.[9] Severe child food poverty referred to the percentage of children who had consumed foods and beverages from zero, one, or two of the eight defined food groups, and moderate child food poverty referred to the percentage who had consumed foods and beverages from three or four of the eight groups.

The BFDHS included 6,344 children from 600 sampled clusters. The locations of the sampled clusters were mapped to assess the spatial dispersion of the clusters (homogeneity or heterogeneity). To take the design of the survey into account while developing our geostatistical models, we used weighted numbers of stunted children and children observed in the survey, specific to each cluster, as was done previously by Chandra and colleagues.[10]

We considered geographical coordinate displacement in extracting remote-sensed information (covariates) for the sampled clusters by using buffers to ensure that the correct cluster centroids were captured in model predictions. To achieve this, we created a 2-km buffer for urban clusters and a 5-km buffer for rural clusters following recommended approaches.[11]

2.4 Covariates

Both geospatial and non-geospatial covariates were examined (Table 1).[2,5,13,14,] The geospatial covariates included aridity, enhanced vegetation index (EVI), insecticide-treated net (ITN) coverage, mean annual precipitation, mean annual temperature, and mean travel time to the nearest health center. These variables served as environmental, climatic, and socioeconomic factors that may influence stunting prevalence.[11,15] During extraction of these covariates, displacement of the GPS coordinates for the sampled clusters was considered using the recommended 5-km buffer for rural settings and 2-km buffer for urban settings.[16] The files of geospatial maps of these covariates for Burkina Faso were used.

Aridity was calculated as the ratio of the mean monthly precipitation (mm) to the average monthly potential evapotranspiration (mm). Monthly gridded precipitation and potential evapotranspiration data were extracted at 0.5-degree resolution from the Center for Environmental Data Analysis (CEDA) Web Processing Service (WPS) (https://cedawps-ui.ceda.ac.uk/processes) by selecting the time period and spatial area of interest. The aridity index data was generated in R50.

The EVI data were derived from the EVI band of the MOD13A1 image collection in Google Earth Engine. Images were masked for cloud and cloud shadow and subsetted to Burkina Faso. The EVI bands were exported as image files with 5-km resolution. ITN coverage data were downloaded from the Malaria Atlas Project (https://malariaatlas.org/data-directory/). ITNs help prevent malaria, which can cause fever that contributes to wasting.

Annual precipitation (mm) was derived from monthly precipitation, downloaded from the CEDA WPS as described for aridity. Annual precipitation was calculated as the sum of the monthly precipitation rasters in R. Annual mean temperature (Celsius) was derived from monthly near-surface temperature data in the CEDA WPS, calculated as the mean of all monthly near-surface temperature values for the DHS year.

Data on travel time were downloaded from the Malaria Atlas Project and cropped to Burkina Faso. The average time (minutes) required to reach a high-density urban center was calculated from the area within the 2-km (urban) or 10-km (rural) buffer surrounding the DHS survey cluster.[17]

The non-geospatial covariates of mother's education, mother's work status, access to improved water, open defecation, and wealth index were used in alignment with the 2020 UNICEF Conceptual Framework.[15,18,19]

Table 1 Geospatial and non-geospatial covariates examined in this study

Covariate	Description	Source of derived dataset
GEOSPATIAL		
Population under 5	The WorldPop average number of people under 5 within the 2-km (urban) or 10-km (rural) buffer surrounding the DHS survey cluster location.	WorldPop https://www.worldpop.org/
EVI	Index derived from the EVI band of the MOD13A1 image collection in Google Earth Engine. Images were masked for cloud and cloud shadow and subsetted to Burkina Faso. The EVI bands were exported as image files with 5-km resolution. EVI was a value between 0 (least vegetation) to 10,000 (most vegetation).	Vegetation Index and Phenology (VIP) Phenology EVI-2 Yearly Global 0.05Deg CMG V004 https://lpdaac.usgs.gov/dataset_discovery/measures/measures_products_table/vipphen_evi2_v004/
ITN coverage	Proportion of the population protected by ITNs based on the average number of people within the 2-km (urban) or 10-km (rural) buffer surrounding the DHS survey cluster location who slept under an ITN the night before the survey. ITN coverage data for Burkina Faso was downloaded from the Malaria Atlas Project.	Malaria Atlas Project ITN Coverage in Africa 2000–2015 https://malariaatlas.org/ data-directory/
Mean annual precipitation	Annual precipitation (mm) derived from monthly precipitation, downloaded from CEDA WPS. Precipitation was measured within the 2-km (urban) or 10-km (rural) buffer surrounding the DHS survey cluster in a given year.	CRU TS v. 4.01 https://crudata.uea.ac.uk/cru/data/hrg/
Mean annual temperature	Calculated as the mean of all monthly near-surface temperature values for the DHS year.	CRU TS v. 4.01 https://crudata.uea.ac.uk/cru/data/hrg/
Mean travel time	Travel time data downloaded from the Malaria Atlas Project and cropped to Burkina Faso. The average time (minutes) required to reach a high-density urban center was calculated, from the area within the 2-km (urban) or 10-km (rural) buffer surrounding the DHS survey cluster location, based on infrastructure data from 2015.	Malaria Atlas Project Accessibility to Cities https://malariaatlas.org/ data-directory/
NON-GEOSPATIAL		
Unmet need for family planning	Percentage of currently married or in-union women with an unmet need for family planning. Studies have shown a link with undernutrition, due to early cessation of breastfeeding.	
Measles vaccination received	Percentage of children age 12–23 months who had received both doses of the measles vaccination. Measles outbreaks can contribute to undernutrition.	
Four or more ANC visits during pregnancy	Percentage of women who had a live birth in the 5 years preceding the survey who attended at least four ANC visits. ANC helps prevent low weight at birth.	
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 was no facility (open defecation).	

Continued…

Table 1—*Continued*

Covariate	Description	Source of derived dataset
Mother's education	Whether mother was educated • Uneducated • Educated	https://www.dhsprogram.com/data/available-datasets.cfm
Access to improved water source	Access to improved water • No • Yes	https://www.dhsprogram.com/data/available-datasets.cfm
Wealth index	Wealth index • Poorer wealth quintiles • Richer wealth quintiles	https://www.dhsprogram.com/data/available-datasets.cfm

ANC = antenatal care; CEDA = Center for Environmental Data Analysis; DHS = Demographic and Health Surveys; EVI = enhanced vegetation index; ITN = insecticide-treated net; WPS = Web Processing Service

2.5 Geostatistical Analysis

We employed geostatistical modeling to investigate spatial risk factors for stunting, wasting, and child food poverty. In the model, yd represents the number of children stunted out of the total number of children (nd) sampled per geographical cluster. Conditional on the true prevalence P(xd) at location xd, the number of stunted children out of the total number of children sampled follows a binomial distribution:

$$yd|P(xd) \sim \text{Binomial}(nd, P(xd)) \text{ and } \text{logit}(P(xd)) = \alpha + d(xd)T\_ + S(xd) \quad (1)$$

where α is the intercept parameter assigned a Gaussian prior with mean and precision of zero, d(.) is a vector of observed spatial covariates at location xd associated with the outcome value yd, and _ is a vector of spatial regression coefficients for the covariates assigned a Gaussian prior with mean zero and precision 0.001. The spatially structured random effect, S(.), follows a zero-mean Gaussian process with variance σ2 and a given correlation function:

$$\rho(u) = \text{correlation}(S(xd), s(xd')) \quad (2)$$

where u is the Euclidean distance between locations xd and xd′. We set the priors for our precision parameters of the scaled models as Gamma (1, 0 ·00005). In deciding on our priors, we followed the noninformative approach due to lack of reliable existing information about our model parameters—an approach also used in the R-INLA package.[21]

Noninformative priors do not unnecessarily influence the model parameters and are more objective because they allow the data to have a greater influence on the posterior distribution. There are various parametric families for ρ(u), as previously outlined.[22] In the current analysis, we used the Matérn class of covariance function:[12]

$$\text{cov}(S(xd), s(xd')) = (3)\sigma 22\upsilon - 1\hat{W}(\upsilon)\ (k\|xd - xd'\|)\upsilon K\upsilon\ (k\|xd - xd'|)$$

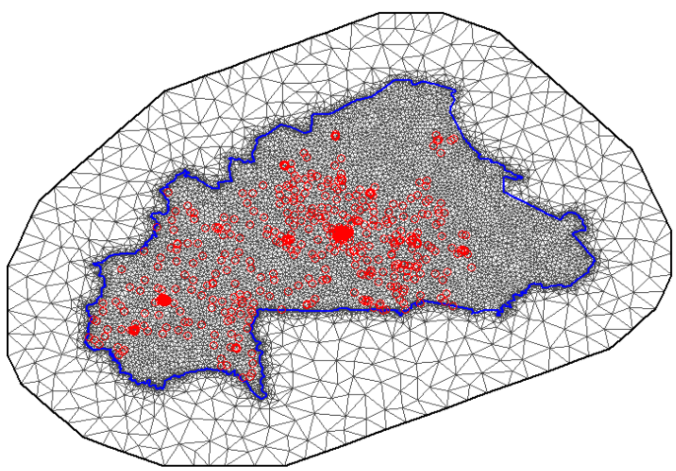
where σ2 represents the variance and Kυ (.) is the modified Bessel function of the second kind and order υ > 0. The shape parameter υ determines the smoothness of $S(x)$, in the sense that $S(x)$ is (υ − 1)-times mean-square differentiable and k > 0 is related to the practical range ρ = sqrt(8υ k), which is the distance at which the spatial correlation is close to 0.1.

The model was implemented in R under the integrated nested Laplace approximation (INLA) approach[20] with the stochastic partial differential equation (SPDE) strategy.[13] As our data were point data without explicit neighbors, unlike areal data, a mesh for the SPDE strategy was needed. How we created the mesh, SPDE, and projector matrices, as well as the other procedures implemented, have been described in detail previously.[23]

We developed both nonspatial and spatial models for estimating stunting, wasting, and child food poverty prevalences. The nonspatial models were created by ignoring the spatial locations of the clusters, and the spatial models were created by considering them. The performance of the developed models was assessed through the Watanabe-Akaike information criterion,[24,25] which is asymptotically equivalent to leave-one-out cross-validation information criteria.[23]

The 95% confidence intervals of the model-based estimates for stunting, wasting, and child food poverty prevalences were calculated to quantify uncertainties around the estimates. Based on the best geostatistical model, we estimated exceedance probabilities (that is, probabilities that estimated outcome prevalences at given locations exceeded certain thresholds, such as 25%) across each cluster, which helped to identify hotspots that were behind in meeting Sustainable Development Goal 2 for stunting, wasting, and child food poverty. The geostatistical modeling was undertaken in R-INLA.[26,27]

Figure 1 Integrated nested Laplace approximation mesh triangulation



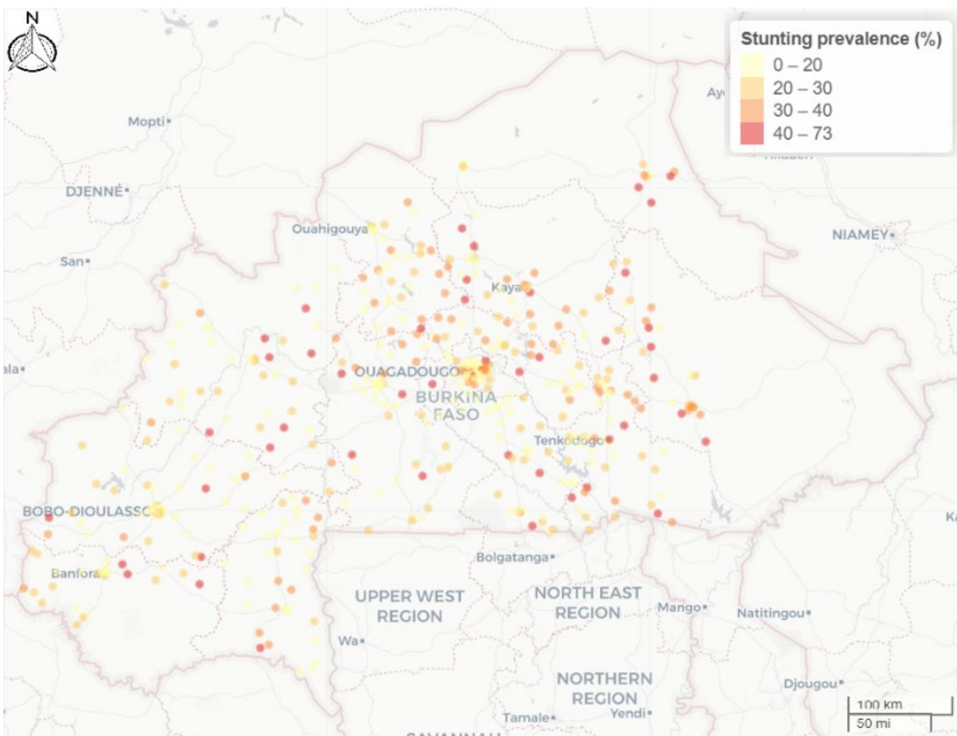
3 RESULTS

3.1 Prevalences of Stunting, Wasting, and Child Food Poverty

According to data from the 2021 Burka Faso Demographic and Health Survey (BFDHS), 22.6% of children under 5 were stunted and 10.6% were wasted at the national level. However, we observed substantial localized geographical variation in both stunting (Figure 2) and wasting (Figure 3), with no data available in some parts of the Sahel and Eastern regions due to insecurity/conflicts.

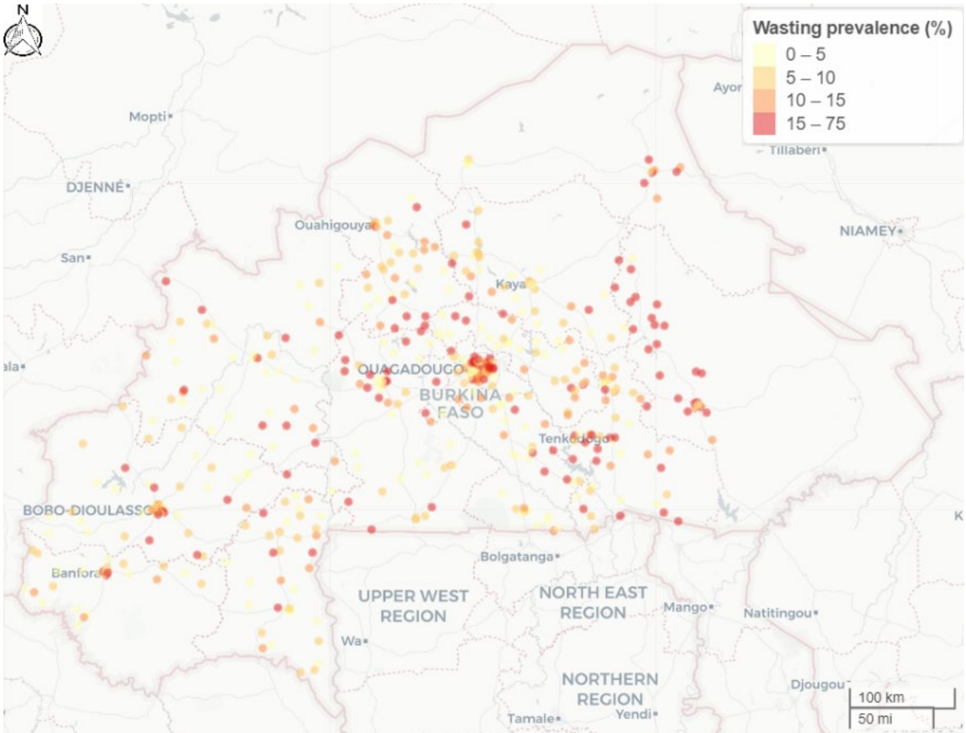
At the national level, among children age 6–23 months, 31.6% of the children had severe child food poverty (consumed fewer than three of the eight food groups) and 80% had child food poverty (severe and/or moderate food poverty). As with stunting and wasting, levels of global food poverty varied subnationally (Figure 4), with some parts of the Sahel and Eastern regions lacking data due to insecurity/conflicts.

Figure 2 Observed stunting prevalences among children under 5 in Burkina Faso, 2021 BFDHS



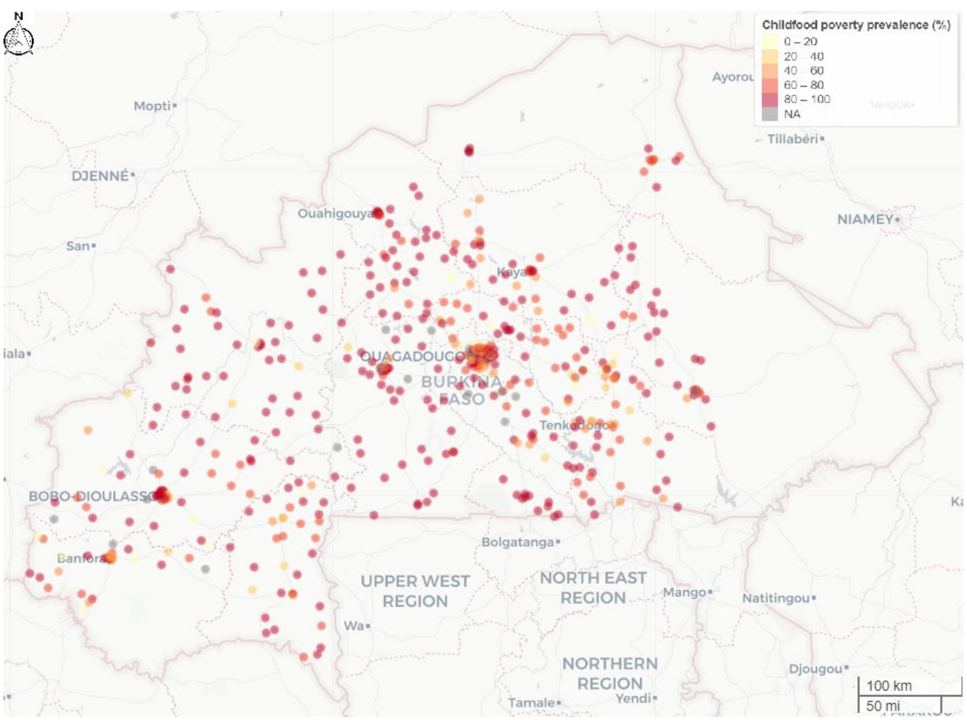
Note: Each circle represents a study location.

Figure 3 **Observed wasting prevalences among children under 5 in Burkina Faso, 2021 BFDHS**



Note: Each circle represents a study location.

Figure 2 **Observed child food poverty prevalences among children age 6–23 months in Burkina Faso, 2021 BFDHS**



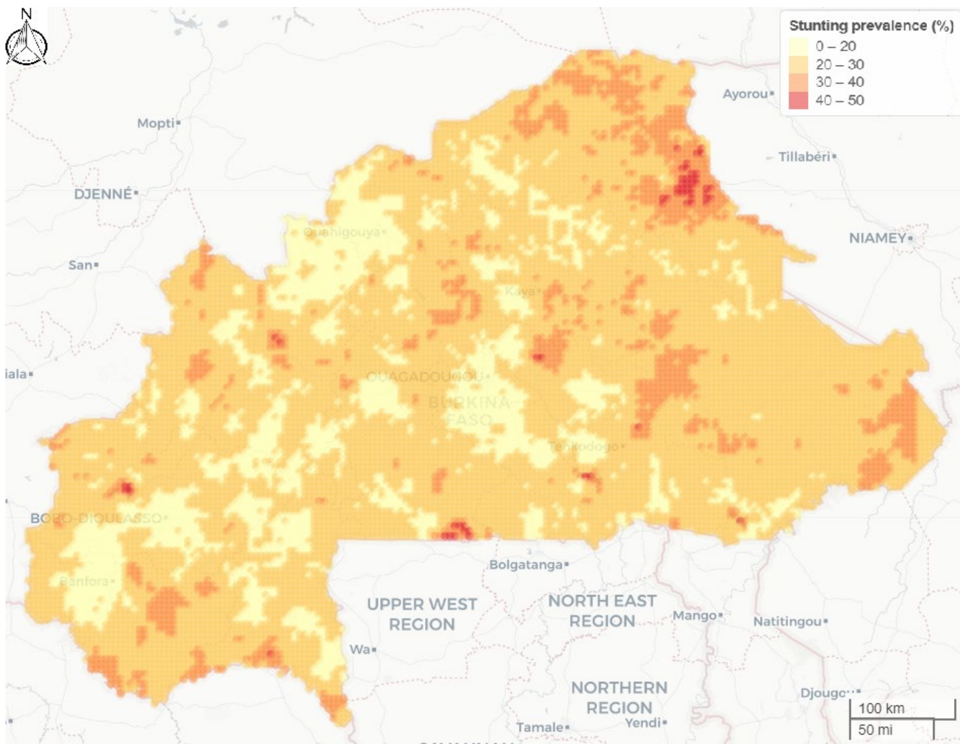
Note: Each circle represents a study location.

3.2 Geostatistical Models

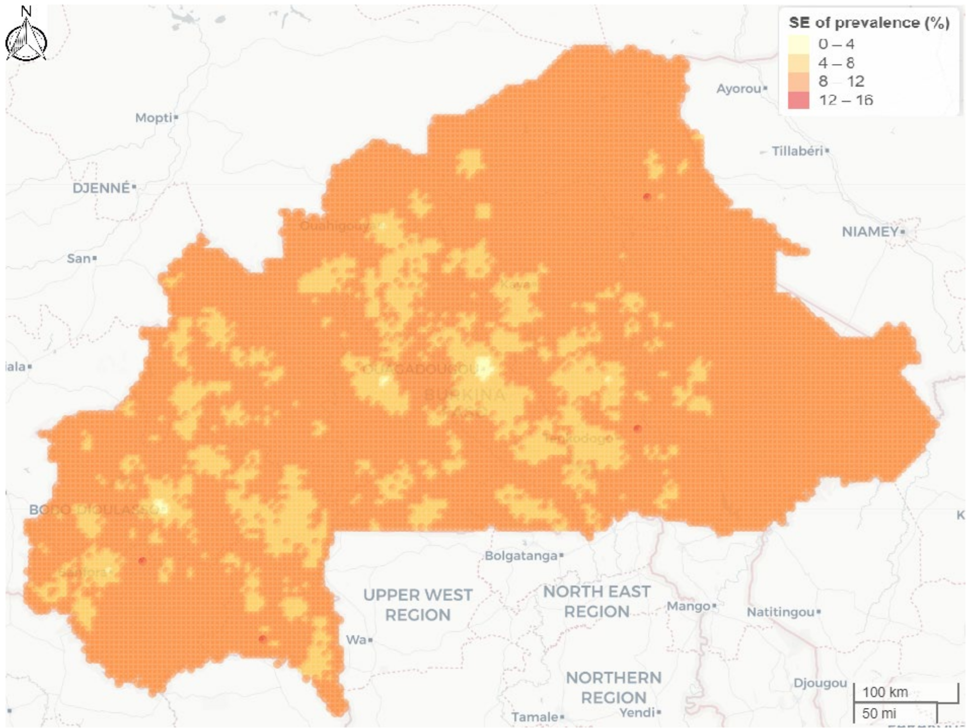
Geostatistical models that considered all covariates were developed at the cluster level. The predicted stunting prevalence at the cluster level ranged from 0–20% to 40–50%. Considerably higher predicted stunting prevalences were observed mainly in certain locations in the Sahel and East regions (Figure 5a). The estimated standard errors (SEs) of the predicted stunting prevalences were small, and regions with very high prevalences had larger SEs (Figure 5b). Figure 5c shows variability in predicted stunting prevalences at the provincial (admin 2) level.

Figure 5 Predicted stunting prevalences (and standard errors) among children under 5 in Burkina Faso

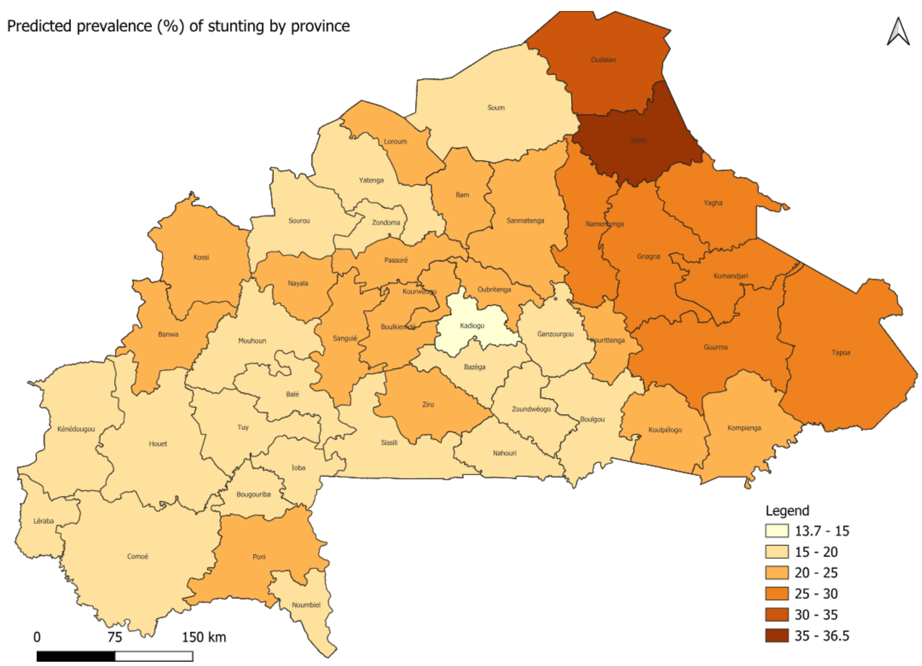
(a) Predicted stunting prevalences



(b) Standard errors of predicted stunting prevalences



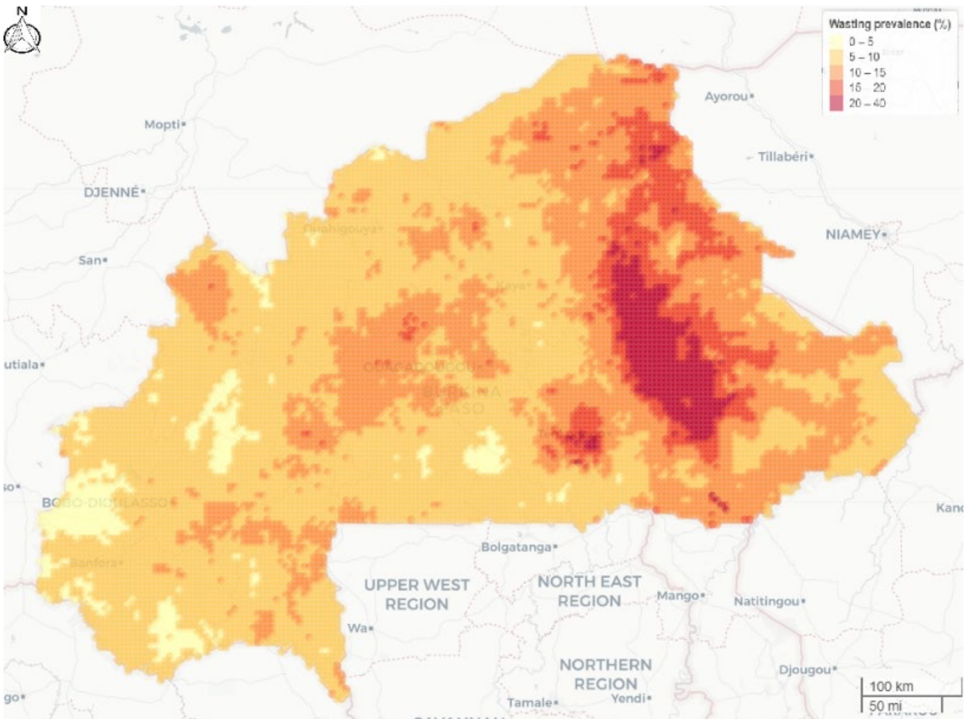
(c) Predicted stunting prevalences among children under 5 at the provincial (admin 2) level in Burkina Faso



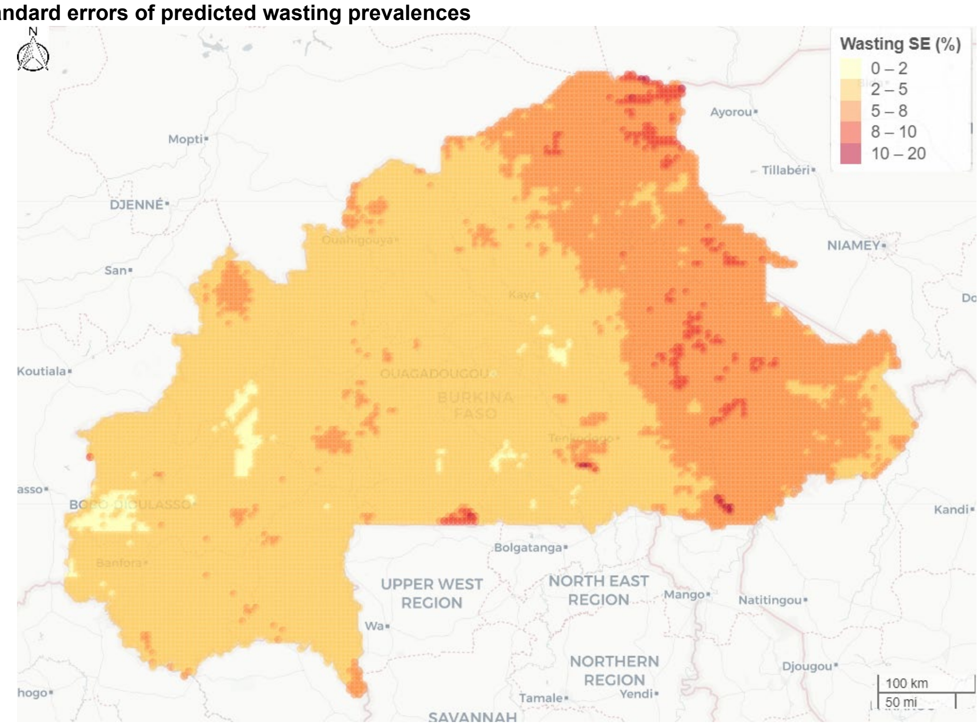
The overall predicted wasting prevalence at the cluster level ranged from 0–5% to 20–40%. Considerably higher predicted wasting prevalences were observed mainly in certain locations in the Sahel, Centre Nord, and Est regions (Figure 6a). The estimated SEs of the predicted wasting prevalences were small, and regions with very high prevalences had larger SEs (Figure 6b). Figure 6c shows variability in predicted wasting prevalences at the provincial (admin 2) level.

Figure 6 Predicted wasting prevalences (and standard errors) among children under 5 in Burkina Faso

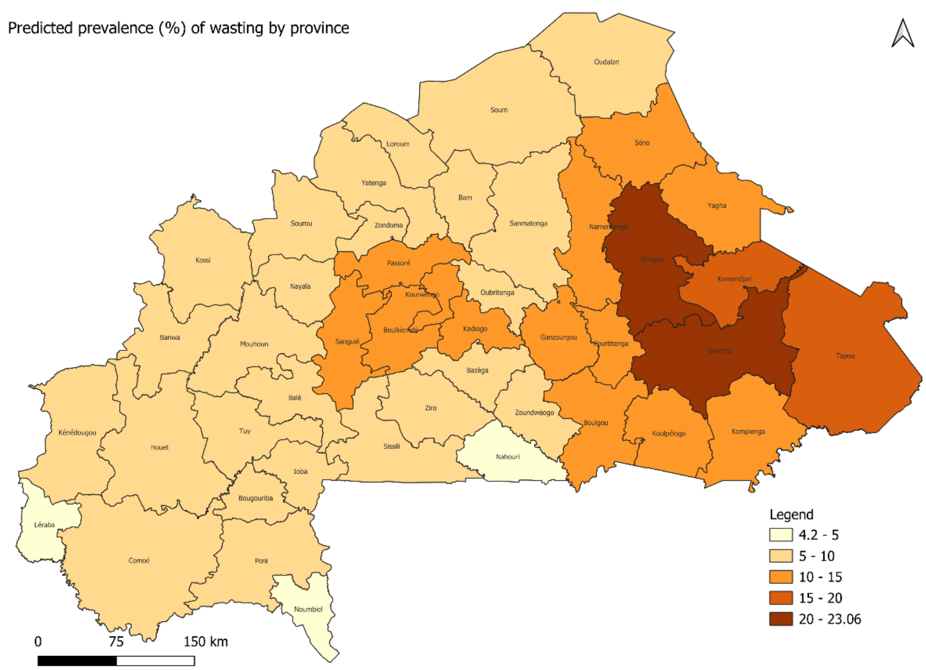
(a) Predicted wasting prevalences



(b) Standard errors of predicted wasting prevalences



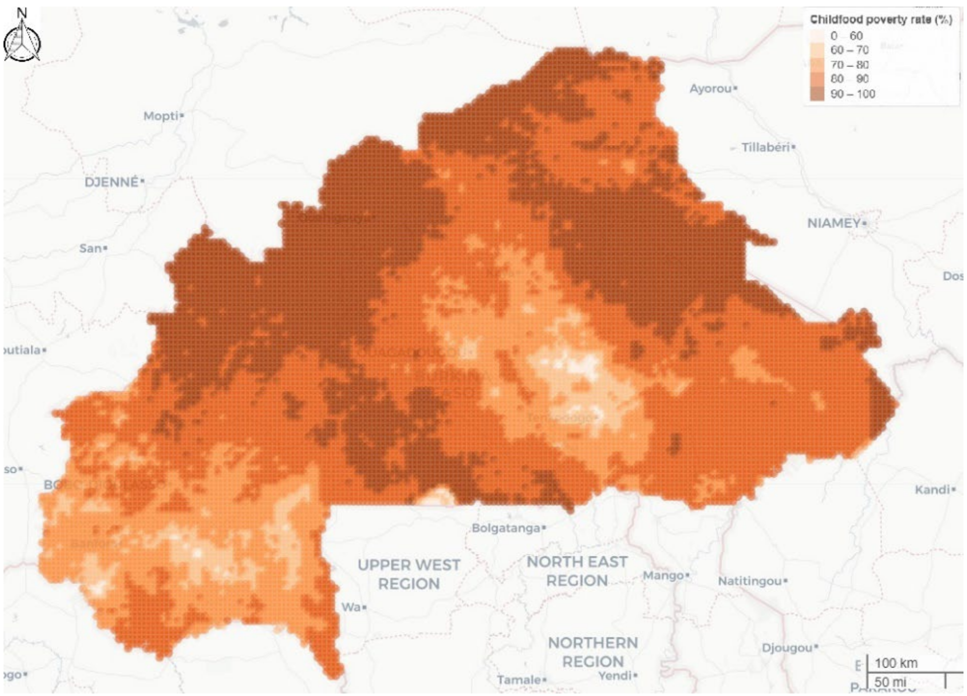
(c) Predicted wasting prevalences among children under 5 at the provincial (admin 2) level in Burkina Faso



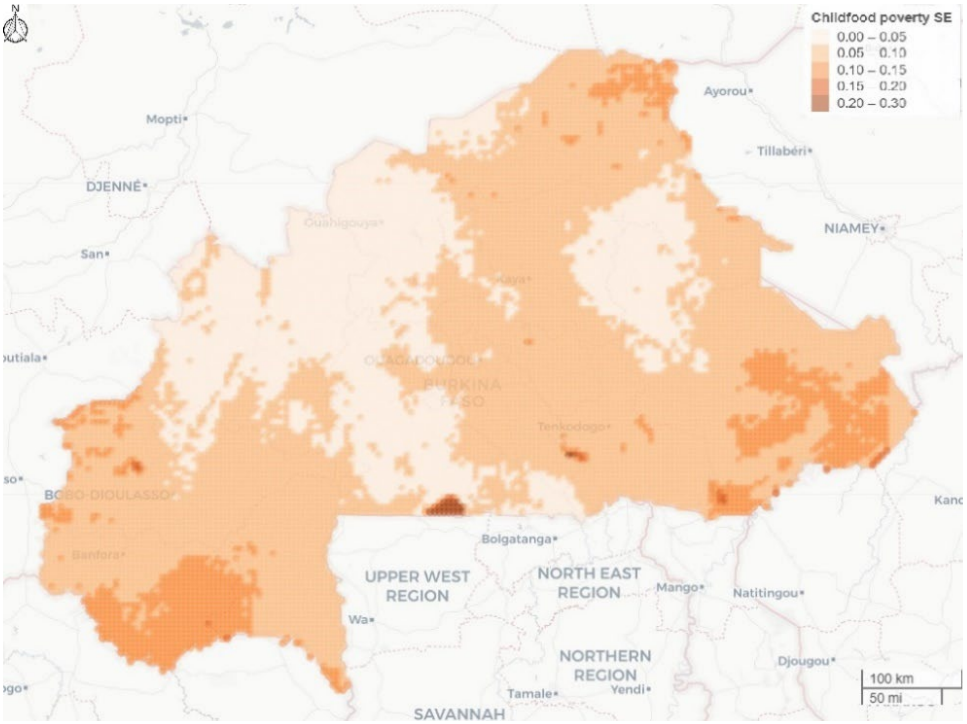
The overall predicted child food poverty prevalence at the cluster level ranged from 0–60% to 90–100%. Considerably higher predicted child food poverty prevalences were observed mainly in certain locations in the Boucle du Mouhoun, Nord, Sahel, Centre Nord, and Est regions (Figure 7a). The estimated SEs of the predicted wasting prevalences were small, and regions with very high child food poverty prevalences had smaller SEs (Figure 7b). Figure 7c shows variability in predicted child food poverty prevalences at the provincial (admin 2) level.

Figure 7 Predicted child food poverty prevalences (and standard errors) among children age 6–23 months in Burkina Faso

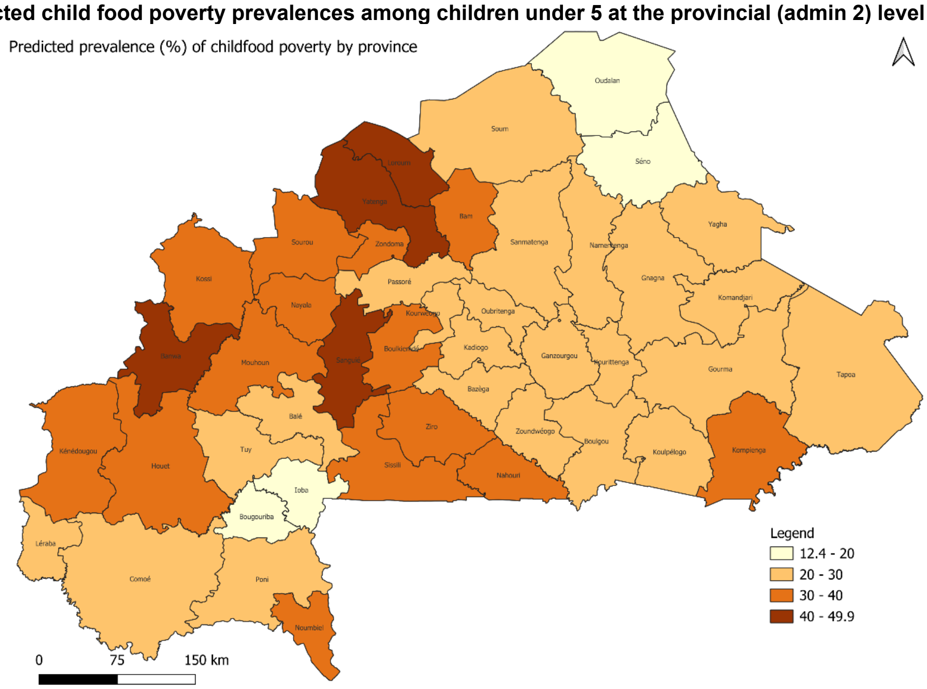
(a) Predicted child food poverty prevalences



(b) Standard errors of predicted child food poverty prevalences



(c) Predicted child food poverty prevalences among children under 5 at the provincial (admin 2) level in Burkina Faso



Two separate models were also developed for each covariate—one model that assumed the spatial location of the clusters and one that did not. Table 2 shows the associations of each covariate with stunting, wasting, and child food poverty in the two models.

The variables significantly associated with stunting were mother's education, the richer wealth quintiles, at least four antenatal care visits, open defecation, and climate variables incorporated into the enhanced vegetation index (EVI). Two of these—open defecation and climate variables incorporated into the EVI—were also significantly associated with wasting. For child food poverty, we found significant associations with mother's education, wealth index, unmet need family planning, and insecticide-treated net coverage.

Table 2 Predictors of stunting, wasting, and child food poverty in non-geospatial and geospatial Bayesian models among children in Burkina Faso

Parameter	Mean log odds [95% confidence interval]			Deviance information criterion		
Country	Stunting	Wasting	Child food poverty	Stunting	Wasting	Child food poverty
Full nonspatial model				1,861	1,475	983.26
Intercept	2.466 [-1.306, 6.238]	-2.959 [-0.832, 2.400]	-4.726 [-12.797, 3.450]			
Population under 5	0.000 [0.000, 0.000]	0.000 [0.000, 0.000]	-0.1365 [-0.275, 0.003]			
Mother's education	0.041 [0.026, 0.057]	-0.013 [-0.036, 0.010]	-0.038 [-0.068, -0.007]			
Richer wealth quintiles	0.003 [0.012, 0.018]	0.026 [0.026, 0.047]	0.058 [0.024, 0.091]			
4+ ANC visits	-1.028 [-1.847, -0.210]	0.159 [-0.970, 1.287]	1.103 [-0.785, 2.991]			
Measle vaccinated	-0.014 [-0.863, 0.835]	-0.839 [-2.037, 0.359]	-1.661 [-3.393, 0.070]			
Access water	-0.011 [0.009, -0.005]	0.002 [-0.021, 0.020]	0.012 [-0.022, 0.046]			
Open defecation	0.617 [0.226, 1.008]	1.038 [0.500, 1.577]	0.026 [-0.814, 0.866]			
Unmet need family planning	1.366 [-0.537, 3.269]	-1.096 [-3.708, 1.516]	-5.219 [-9.208, -1.231]			
ITN	0.494 [0.438, 1.352]	-0.672 [-1.885, 0.541]	3.562 [1.912, 5.213]			
Precipitation	0.007 [-0.001, 0.020]	0.026 [0.007, 0.045]	-0.014 [-0.037 ,0.010]			
EVI	-4.481 [-7.736, -1.225]	-7.695 [-12.248, -3.141]	2.298 [-3.870, 8.467]			
Temperature	-0.100 [-0.190, -0.009]	0.030 [-0.098, 0.158]	0.175 [-0.013, 0.364]			
Travel time	0.000 [-0.002, 0.002]	-0.004 [-0.006, -0.001]	0.003 [-0.001, 0.007]			
Full spatial model				1,790	1,422	957.62
Intercept	3.288 [-1.930, 8.528]	-2.623 [-9.804, 4.499]	-1.692 [-11.692, 8.510]			
Population under 5	0.000 [0.000, 0.000)	-0.047 [-0.178, 0.084]	-0.110 [-0.289, 0.070]			
Mother's education	0.043 [0.023, 0.630]	-0.005 [-0.031, 0.021]	-0.029 [-0.062, 0.004]			
Richer wealth quintiles	0.002 [-0.018, 0.023]	0.022 [-0.005, 0.049]	0.058 [0.021, 0.096]			
4+ ANC visits	-1.158 [-2.321, 0.007]	0.024 [-1.655, 1.678]	1.222 [-1.196, 3.633]			
Measle vaccinated	0.104 [-0.030, 0.009]	-0.775 [-2.397, 0.847]	-1.445 [-3.786, 0.904]			
Access water	-0.011 [-0.026, 0.057]	-0.014 [-0.040, 0.012]	-0.007 [-.0.022, 0.046]			
Open defecation	0.562 [0.049, 1.073]	0.856 [0.162, 1.545]	0.026 [-0.814, 8.666]			
Unmet need family planning	1.729 [-1.001, 4.454]	-1.382 [-5.303, 2.522]	-5.219 [-9.208, -1.231]			
ITN	0.377 [-0.837, 1.590]	-0.504 [-2.488, 1.631]	3.562 [1.912, 5.213]			
Precipitation	0.006 [-0.014, 0.025]	0.012 [-0.016, 0.040]	-0.014 [-0.037, 0.010]			
EVI	-4.686 [-9.103, -0.025]	-4.064 [-10.022, -4.087]	2.298 [-3.870, 8.462]			
Temperature	-0.118 [-0.240, 0.003]	0.036 [-0.130, 0.035]	0.175 [-0.013, 0.364]			
Travel time	0.001 [-0.002, 0.003]	-0.003 [-0.006, 0.000]	0.003 [-0.001, 0.007]			

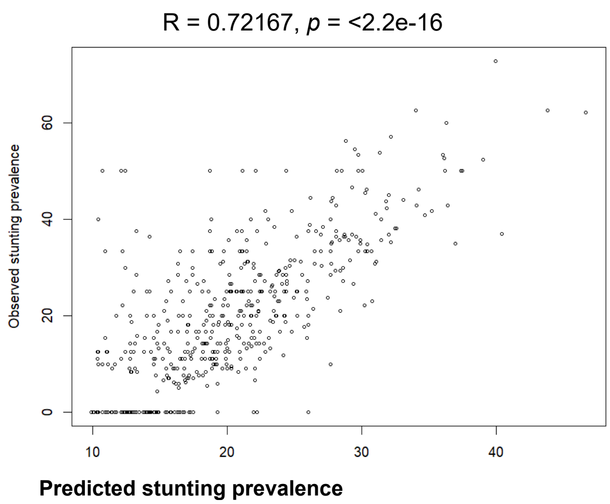
ANC = antenatal care; EVI = enhanced vegetation index; ITN = insecticide-treated net

3.3 Validity of the Geostatistical Models

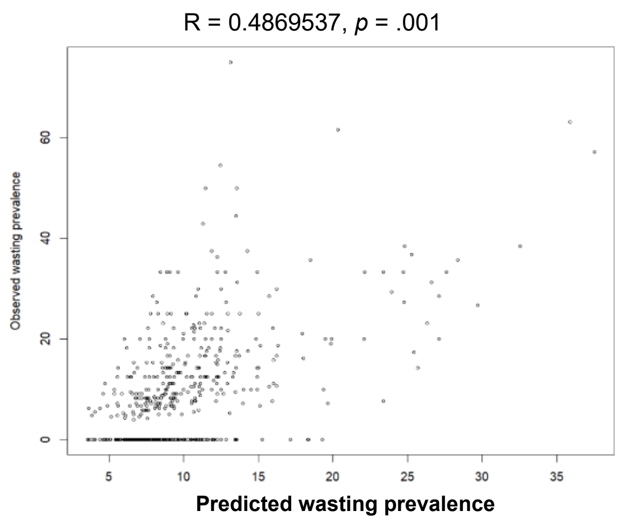
When we compared the predicted prevalences of stunting, wasting, and child food poverty from the geostatistical models with the observed prevalences from the 2021 BDHS, the correlation coefficients were significant for all three outcome variables. However, the correlation between models was much stronger for stunting (R = 0.722, $p < 2.2e^{-16}$) than for either wasting (R = 0.486, *p* = .001) or child food poverty (R = 0.480, *p* =.001) (Figure 8).

Figure 8 Validation plots of observed and predicted stunting, wasting, and child food poverty

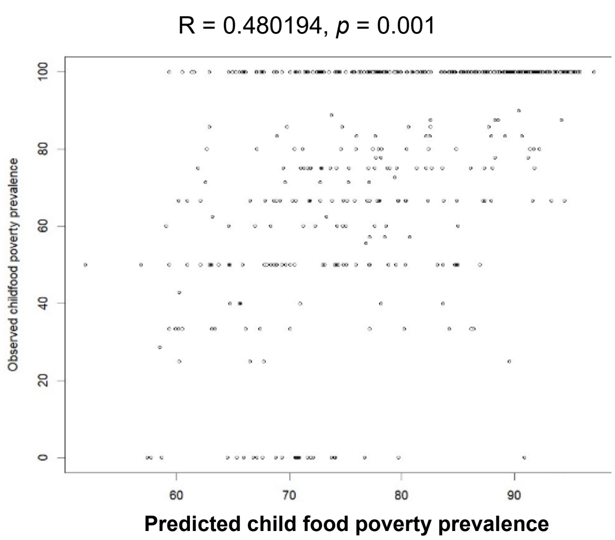
(a) Stunting among children under 5



(b) Wasting among children under 5



(c) Child food poverty among children age 6–23 months



4 DISCUSSION

4.1 Model Validity

The results of this study demonstrate the validity of using geostatistical models to predict the prevalences of stunting, wasting, and child food poverty in Burkina Faso. However, the correlation between the models and data from the 2021 Burkina Faso Demographic and Health Survey was strongest for stunting ($R = 0.72$), indicating the best predictive value from our final models.

A negative association was observed between stunting and the enhanced vegetation index (EVI), suggesting higher stunting prevalence in areas with sparse vegetation. This finding shows the role of climate-related variables in influencing stunting. Positive associations of stunting prevalence with low maternal education and open defecation were also observed. These results are consistent with existing literatures,[8,12,19] suggesting that literate mothers have greater access to sources of information, means of prevention, and services than illiterate mothers. Furthermore, the geostatistical models predicted high stunting prevalences in the Sahel, Eastern, and Cascade regions. These results corroborate the findings observed in the 2021 national standardized monitoring and assessment of relief and transitions (SMART) nutrition survey.[2] However, the results of the present study provide prevalences at smaller cluster levels. They make it possible to visualize intercluster disparities and to understand pockets of undernutrition.[5,13,14,28]

Our study also found that wasting prevalence was positively associated with open defecation and negatively associated with EVI. Although EVI is known to be associated with stunting, it is even more widely associated with wasting.[8] This result suggests a higher prevalence of wasting in areas with less dense vegetation and demonstrates the link between wasting and EVI, which takes several climate variables into account.

For child food poverty, the analysis revealed associations with maternal education, wealth index, unmet need for family planning, and insecticide-treated net (ITN) coverage. Notably, no significant association was found between EVI and child food poverty, suggesting that unlike stunting and wasting, child food poverty is not directly influenced by climate variables in this context.

4.2 Limitations of the Study

Certain determinants of undernutrition, particularly those related to the provision and quality of health and nutrition services, were not included in the 2021 BFDHS dataset, limiting the scope of our analysis. Despite these constraints, this study represents the first geostatistical analysis of undernutrition in Burkina Faso.

4.3 Policy and Program Implications

Geostatistical modeling is a good tool for analyzing links between nutrition outcomes and climate, enabling additions to the existing scientific literature on the relationship between climate change and nutrition. This geostatistical tool can also be used to make predictions in the context of insecurity. It is therefore an alternative for estimating nutritional prevalences in areas with high security challenges where a classic SMART nutrition survey cannot be carried out because of access issues. Our results show that prevalence is high in these hard-to-reach areas, and that preventive and curative measures to combat undernutrition need to be stepped up. Considerations should include disseminating this method at the country level, and possibly using it to analyze additional indicators of malnutrition.

4.4 Conclusion

The results of this study showed the relationship between climate and undernutrition. This calls for the integration of climate considerations into nutrition commitments. The study also demonstrated the value of applying geostatistical analyses to identify pockets of concentrated undernutrition and child food poverty to better guide intervention strategies. These methodologies present an opportunity for predicting the prevalences of stunting, wasting, and child food poverty in areas where access to traditional SMART or other nutrition surveys is problematic.

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