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Spatio-temporal variation in childhood growth in Nigeria: a comparison of aggregation and interpolation

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ABSTRACT

The mean height-for-age *Z*-score (HAZ) of children under five is an important indicator of the health status of a population. HAZ values are frequently aggregated and reported at the national level, potentially obscuring important within-country variation. We evaluated aggregation and interpolation methods to provide sub-national estimates over space and time, using survey data from Nigeria in 1990, 2003, 2008, and 2013. We aggregated HAZ values by region and by state, and interpolated the values spatially and spatio-temporally using thin plate splines. The results were evaluated with cross-validation using the root mean squared error (RMSE) as a measure of goodness of fit. Mean HAZ values increased from 1990 to 2013, but values rose more sharply in southern Nigeria than in the North. All methods performed better than assuming a constant national average. The state-level aggregation, and the spatial and spatio-temporal interpolations had similar RMSE values, but the interpolation methods showed more detailed spatial variation. Spatio-temporal interpolation produced good results in all conditions, including in years with sparse sampling and when extrapolating to years for which there were no observations.

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KEYWORDS

Height-for-age; health surveys; DHS; prediction; stunting

1. Introduction

The mean height at a given age, or 'height-for-age', of children under five is commonly used as an indicator of the health status of children in a population (WHO 1995; Pradhan, Sahn, and Younger 2003; Adekanmbi, Kayode, and Uthman 2013). It is a useful measure because low mean height for age is generally caused by an accumulation of dietary deprivation and disease, rather than by incidental or infrequent deprivation. Moreover, height-for age-distributions of healthy children under the age of five are relatively invariant across differences in genetic background (Habicht et al. 1974), making it a suitable measure for comparisons within and between countries (WHO 1995). Height-for-age is usually expressed as a *Z*-score, the number of standard deviations a child's height is away from the mean of a healthy reference population. Children are considered to be 'stunted' if their height is two standard deviations below the mean of the reference population (Z-score < -2).

Height-for-age *Z*-scores (hereafter referred to as 'HAZ') can be obtained with non-invasive surveys and are commonly reported by country or by large sub-national region (Rannan-Eliya et al. 1970; WHO 1995; Spray et al. 2013; Manyanga et al. 2014; Ullah et al. 2014). Such aggregated data can obscure important differences between populations. Data at higher spatial resolutions could be used to design more efficient and effective intervention strategies. Specifically, governments and aid organizations could allocate more resources to the areas with the most severe problems, and

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the search for causes of poor health status could be refined (Williamson 1965; Balk et al. 2005; Margai 2007; Adekanmbi, Uthman, and Mudasiru 2013; Brown et al. 2015).

Health surveys are often far apart in time, if they are repeated at all. This lack of temporal continuity hampers our ability to understand how health indicators, like HAZ, change over time. It also makes it more difficult to evaluate the success or failure of intervention strategies. Increasing the frequency and spatial coverage of health surveys would be helpful, but it may not always be feasible. Therefore, it is useful to examine if we can use existing survey data to obtain estimates of HAZ values at higher spatial and temporal resolution. Here we evaluate the use of aggregation and interpolation techniques to estimate spatio-temporal variability of HAZ in Nigeria over the past 25 years.

We use data from the Demographic and Health Survey (DHS) program in Nigeria (NBSN, FMH, and ICF International 2014). DHS conducts nationally representative household surveys that collect data on a wide range of population, health, and nutrition indicators. Whether aggregation or interpolation methods can be used to meaningfully estimate sub-national variation in HAZ is an empirical question that cannot be answered a priori. It depends on the degree of the variation within and between sites, and on the presence of spatial autocorrelation. Jankowska et al. (2012) and Grace et al. (2012) modeled variation in HAZ in response to environmental variables, but they did not provide sub-national estimates. Margai (2007) interpolated HAZ values for a single survey in Burkina Faso, but the accuracy of the interpolation was not evaluated in this study.

In this paper we assess the quality of sub-national estimates of HAZ obtained by aggregating survey site data to sub-national divisions, and by spatial and spatio-temporal interpolation of survey site data. We also evaluate the ability of all of these methods to predict changes in spatial patterns over time.

2. Methods

The data analyzed in this paper came from the 1990, 2003, 2008, and 2013 DHS program surveys in Nigeria (NBSN, FMH, and ICF International 2014). DHS uses a population weighted national cluster sampling strategy in their surveys. Numerators collected height, weight, and age data for all children under five from each household sampled. Records were taken for 5513 children from 3466 households at 297 sites (‘clusters’) in 1990; 4239 children from 2795 households at 358 sites in 2003; 19,103 children from 12,473 households at 885 sites in 2008; and 24,534 children from 15,611 households at 888 sites in 2013 (Figure 1). The number of children per household ranged from 1 to 9, and the number of households per site was between 1 and 35. The average number of children per site was 21.9 and the number of households per site was 14.1. We computed HAZ for each child using the WHO Child Growth Standards (WHO MGRSG 2006). Individual HAZ values were averaged by household, and household means were then averaged by site. The mean number of sites per state was 8 in 1990 (11 states had less than 5 sites), 8 in 2003 (4 states had less than 5 sites), and 24 in 2008 and 2013 (all states had at least five sites in these two years).

We used the *R* environment for statistical computing (R Core Team 2015) to estimate HAZ at the country, regional, state, and local level. Country-, regional-, and state-level data were computed by aggregation: we averaged the site values in each of Nigeria’s 37 states and 7 large regions as defined by DHS. We aggregated by taking the arithmetic mean of all the data points in a given area and then assigning that value to the area. This is a common low variance method of statistical analysis and for generating choropleth maps. DHS data are sometimes aggregated to a few regions, but not to a much lower level of aggregation, such as the Nigerian states that we explore here.

Thin plate spline (TPS) interpolation of the site data, as implemented by Nychka, Furrer, and Sain (2015) in the *R* package ‘fields’, was used to estimate HAZ for one arc-minute (about 3.4 km^2) grid cells. We refer to estimates for these grid cells as ‘local level’ estimates. There are many interpolation methods available (see Luo, Taylor, and Parker 2008; and Chai et al. 2011, for reviews). We used thin plate splines because it lends itself to interpolating noisy data with high levels of uncertainty. As an ‘inexact interpolator’, thin plate splines will not necessarily return the observed value for a sampled

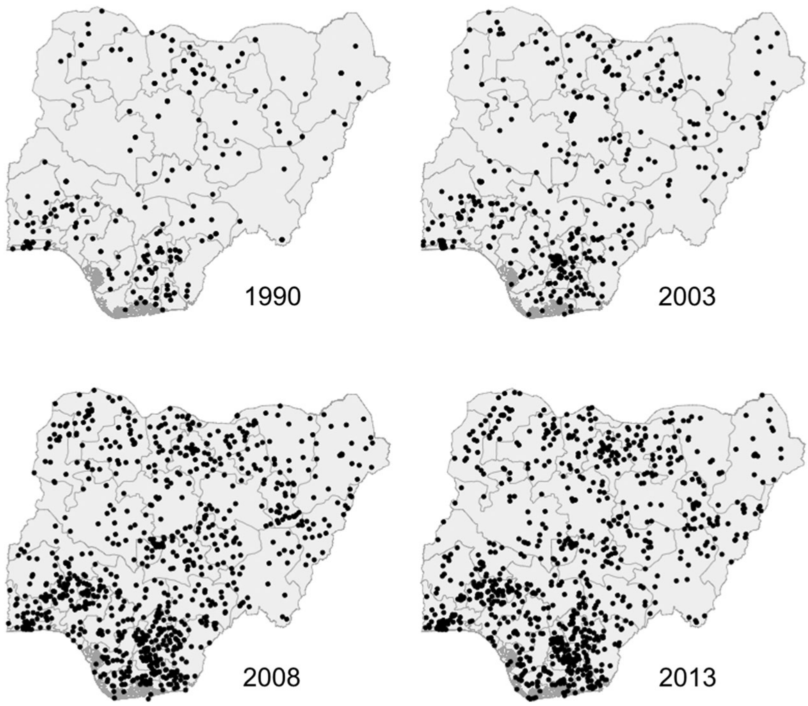

Figure 1. Demographic and Health Survey sites in Nigeria, by year. The number of sites was 297 in 1990, 358 in 2003, 885 in 2008, and 888 in 2013. State boundaries are shown with gray lines.

point. This helps guard against over-fitting (Hutchinson 1995), especially for noisy datasets where the observations themselves are estimates based on small samples. We fit HAZ surfaces using two approaches. In the spatial interpolation approach, we fit a TPS model for each year separately. This led to four separate models. In the second approach, we fit a single space-time model. This model was smooth in space and time with respect to the observations, and hence allowed for non-linear responses to time in a particular location, and for non-linear responses to space at a particular time (see Appendix A.1).

We evaluated the quality of the aggregated and interpolated HAZ estimates with five-fold cross-validation using the root mean square error (RMSE) as the error metric. The national-level mean served as a null-model, under which observed spatial variation is assumed to be random noise.

In addition to spatial prediction, all methods were also evaluated for their ability to predict over time. For the space-time interpolation, we fitted a TPS model with one year left out, and then used the model to make predictions for that year. To make temporal predictions with the aggregated values and the spatial TPS models, we used linear interpolation between the nearest two years, or, if the prediction was for a boundary year, by linear extrapolation of the trend from the nearest two years (see Appendix A.2). We also used these methods to predict the spatial distribution of HAZ for Nigeria in 2018.

The estimated change in HAZ at a particular location may be affected by changes in sampling locations and density. To evaluate whether predicted differences between years were due to changes in sample size and location, we implemented a subsampling procedure. For each of the sites in the smaller survey (year), the nearest three sites in the larger survey (year) were selected. The nearest neighbor values were then averaged using linear inverse distance weighting, and that mean value was assigned to the corresponding location at the smaller survey. Consequently, the subsampled data set had locations from the smaller survey but HAZ values from the larger survey. These values were interpolated and compared with the interpolations obtained with the complete datasets.

3. Results

Mean HAZ for the sampled sites Nigeria increased from −1.72 in 1990 to −1.09 in 2013 (Figure 2). The fraction of stunted children (HAZ < −2) at these sites was 34% in 1990, and decreased to 18% by 2013. The site- and state-level HAZ values had positive spatial autocorrelation for all years ($p < .001$, Table 1), suggesting that HAZ should be amenable to lower level spatial aggregation and interpolation.

All approaches for estimating sub-national HAZ values were superior to using the national-level estimates, with RMSE values that were 7–35% lower than the null model (Table 2). Differences in accuracy between estimation methods were small. Spatial interpolation preformed a little better than using the state or regional averages and spatio-temporal interpolation best predicted HAZ for years with small sample sizes (1990 and 2003). The RMSE was lowest for the 1990 and 2013 data, but the average improvement relative to the national-level null model was much higher in 2013 (Table 2).

The similarity in the cross-validation results between methods is reflected in the similarity between the mapped patterns (Figure 3). A north–south spatial gradient in HAZ in Nigeria is clearly visible in the regional and state-level means as well as in the interpolated values. In addition, while HAZ values have consistently increased in southern Nigeria since 1990, they have stagnated in many parts of northern Nigeria, reinforcing the north–south gradient. In particular, it appears that HAZ has been persistently low in the northwest, though it as has increased in the northeast corner of the country (Figure 3).

The seven regions capture much of the sub-national spatial variation (Figure 3). Nevertheless, state-level data shows substantial variation within regions, and the interpolated values suggest

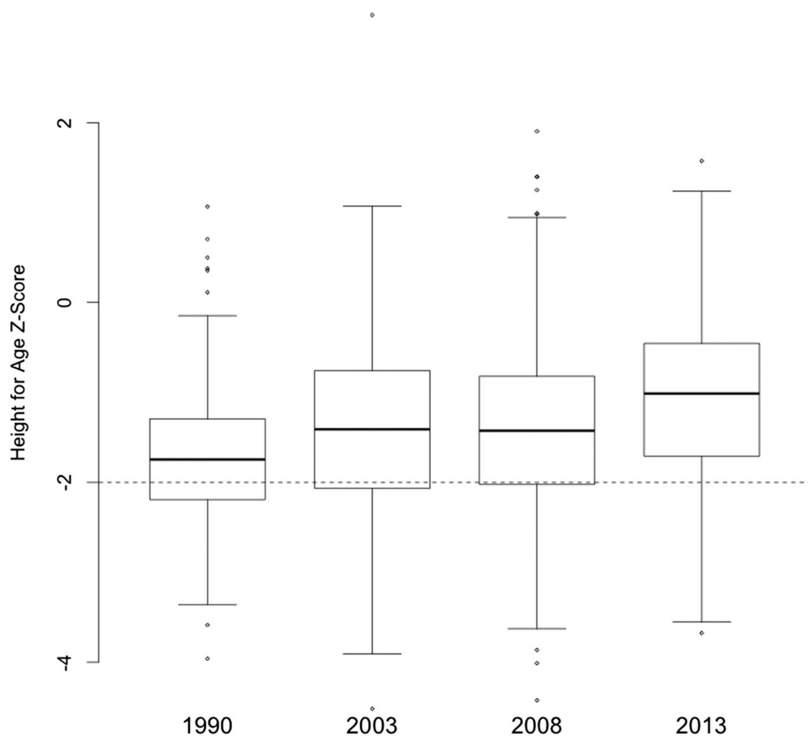

Figure 2. Distribution of mean site Height for Age Z-score for Nigeria by year. The median is denoted by thick horizontal lines, the four quartiles by thin horizontal lines, and outliers by points. The dotted line at $Z = -2$ indicates the level below which a person is considered stunted.

Table 1. Moran's *I* statistic of spatial autocorrelation in children's height for age by year for survey sites and states of Nigeria.

	Sites		States	
Year	*I*	*P*	*I*	*P*
1990	0.196	<.0001	0.343	.00025
2003	0.282	<.0001	0.658	<.0001
2008	0.258	<.0001	0.582	<.0001
2013	0.495	<.0001	0.676	<.0001

Binary distance matrices were used to compute Moran's *I*. States with a shared border were considered neighbors. Points were considered to be neighbors if they were within 200 km of each other. *P*-values were obtained with 9999 Monte Carlo simulations.

Table 2. Root mean square error (RMSE) of height-for-age-*Z*-values in Nigeria by year, for all interpolation methods.

Year	National average	Regional average	State average	Spatial TPS	Spatio-temporal TPS
1990	0.74	0.69 (6.8%)	0.67 (9.5%)	0.66 (11%)	0.64 (13%)
2003	1.03	0.89 (14%)	0.89 (14%)	0.87 (15%)	0.86 (16%)
2008	0.89	0.78 (12%)	0.74 (17%)	0.73 (18%)	0.74 (17%)
2013	0.91	0.65 (29%)	0.61 (33%)	0.59 (35%)	0.62 (32%)
Mean	0.89	0.75 (16%)	0.73 (18%)	0.71 (20%)	0.72 (20%)

Values are the mean obtained with five-fold cross validation. Numbers in parenthesis indicate the improvement of the estimates relative to the national average Null model.

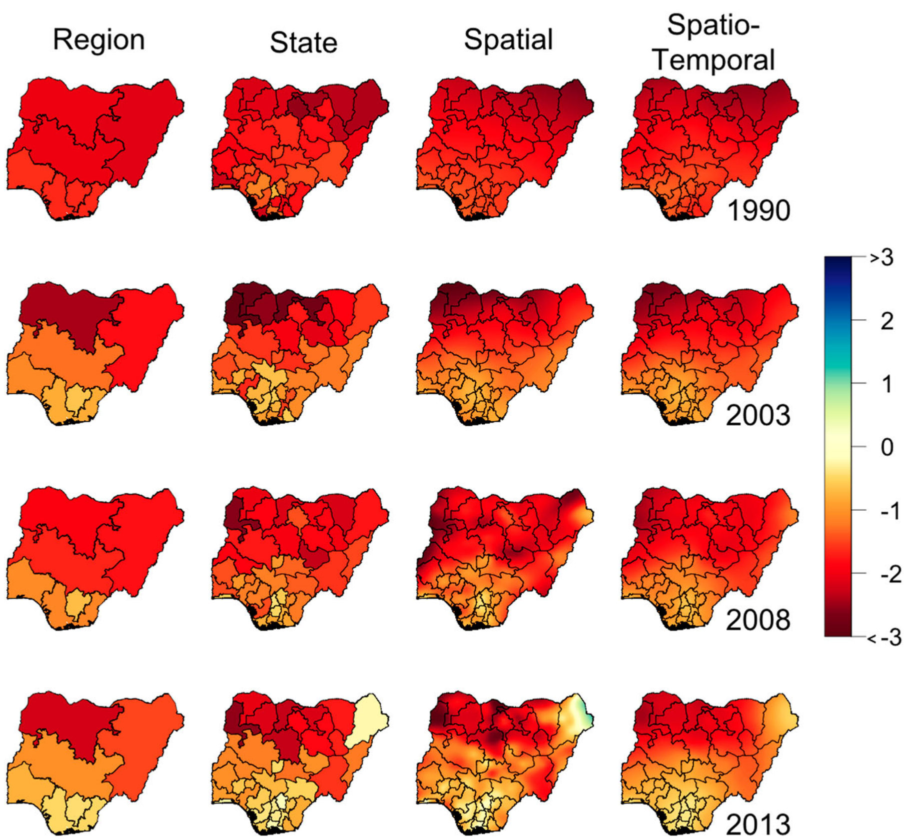

Figure 3. Regional- and state-level averages and spatial and spatio-temporal interpolated of Height for Age *Z*-scores in Nigeria, by year. Black lines identify region or state boundaries.

that there is much additional variation within some states. There are also some marked differences between the results obtained with spatial and spatio-temporal interpolation. For example, the 2013 spatial interpolation results exhibit much higher HAZ values in the northeast corner of Nigeria than the spatio-temporal interpolation, and spatial interpolation estimates of HAZ > 2 in Borno state (the far NE corner) seem spurious (Figure 3). This may be related to edge effects and the relative low sampling density in that area, but it should be noted that sampling density was also low there in previous years.

The spatial interpolations also show striking differences between years (Figure 3). The 2008 and 2013 spatial interpolations have steep spatial gradients, particularly in central Nigeria. In some cases, areas where the average HAZ was estimated to be below −2 in 2008 rose to almost zero over a five year time span. The spatio-temporal interpolations also show major increases in HAZ over time, but the spatial and temporal gradients are not as steep as those in the spatial interpolation. In particular, HAZ values in the northeast corner of Nigeria increased much more in the spatial interpolation than in the spatio-temporal interpolation (Figure 4).

Temporal predictions of HAZ values for years without data (mean RMSE = 0.94; Table 3) were not as good as the spatial predictions (mean RMSE = 0.73; Table 2). Differences between methods

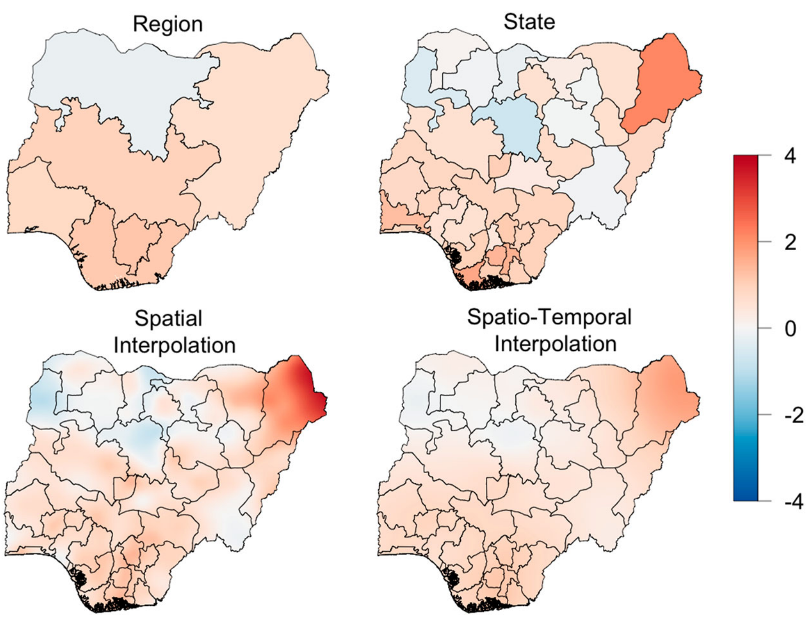

Figure 4. Change in Height for Age *Z*-Scores between 1990 and 2013 in Nigeria, by interpolation method. Estimates were obtained by averaging data at the regional- and state-level, and with spatial and spatio-temporal interpolation. Black lines identify state boundaries.

Table 3. Root mean square error (RMSE) and Pearson's correlation coefficient (*r*) for spatio-temporal cross-validation of all interpolation methods.

Year	Regional average		State average		Spatial TPS		Spatio-temporal TPS	
	RMSE	*r*	RMSE	*r*	RMSE	*r*	RMSE	*r*
1990	1.10	0.30	1.58	0.20	1.38	0.21	0.79	0.36
2003	0.90	0.48	0.88	0.50	0.88	0.51	0.89	0.54
2008	0.83	0.44	0.82	0.49	0.80	0.50	0.79	0.45
2013	0.92	0.38	1.04	0.31	0.97	0.40	0.96	0.62
Mean	0.94	0.40	1.08	0.38	0.98	0.41	0.91	0.49

Values are the mean obtained with five-fold cross validation.

were again generally small, though the spatio-temporal interpolation was better at predicting values for boundary years than the other methods (much lower RMSE than other methods for 1990 and very high correlation coefficient for 2013; Table 3).

The spatial and spatio-temporal interpolation predictions for 2018 differed greatly. Values of mean HAZ for the spatial interpolation ranged from −4.47 to 4.87, while values from the spatio-temporal interpolation were between −2.07 and −0.09 (Figure 5). The extrapolated spatial model predicted that 7% of the area (not the population) of the country would have mean HAZ values below −3, 20% would have mean HAZ values below −2, and 2.3% above 2. In contrast, the spatio-temporal interpolation predicted only 0.5% of Nigeria had mean HAZ values below −2 and no cells had mean HAZ values above 2. The spatial interpolation also had very strong spatial gradients in several places in northern Nigeria. In contrast, the spatio-temporal interpolation predicted a relatively weak gradient from the northwest to the south (Figure 5).

The results obtained with the subsampled data suggested that the spatial changes over time were not an artifact of changing sampling schemes. The spatial patterns obtained with the data subsampled to match the sampling scheme of 1990 correlated more strongly with the values for the year of sampling than with those from 1990 (Table 4). The spatial patterns for the full and subsampled data for a single year were also similar (Figure 6), especially compared with the patterns

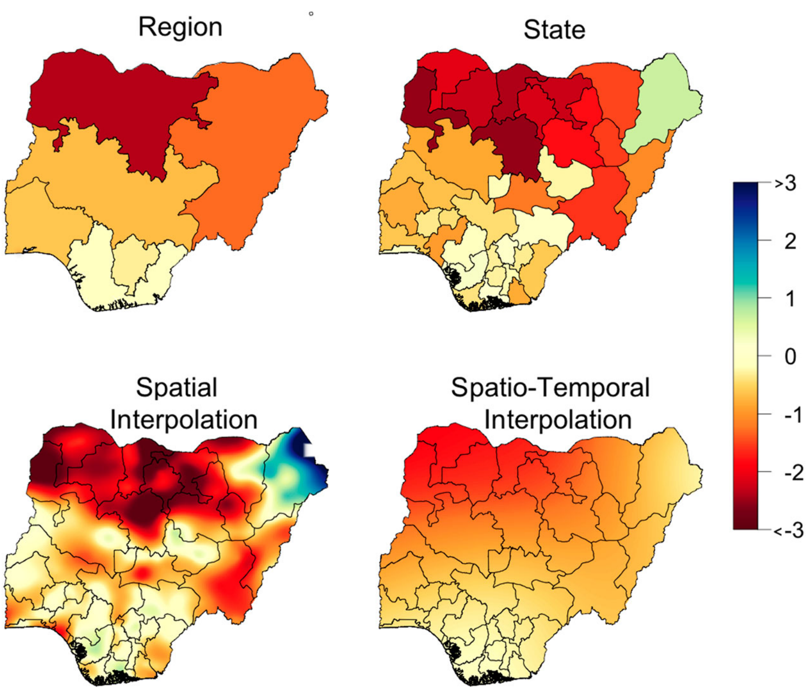

Figure 5. Predicted Height-for-Age *Z*-Score in Nigeria in 2018. Predictions come from the spatio-temporal interpolation and from linear extrapolation of regional- and state-level zonal averages, as well as the spatial interpolation.

Table 4. Correlations between the predictions made with data subsampled to the 1990 data point locations and the predictions made with the full data from 1990, 2008, and 2013.

Subsampled year	2008		2013	
Full data year	1990	2008	1990	2013
Region	0.95	0.98	0.69	0.97
State	0.48	0.89	0.64	0.93
Spatial interpolation	0.59	0.80	0.57	0.87
Space–time interpolation	0.60	0.82	0.39	0.83

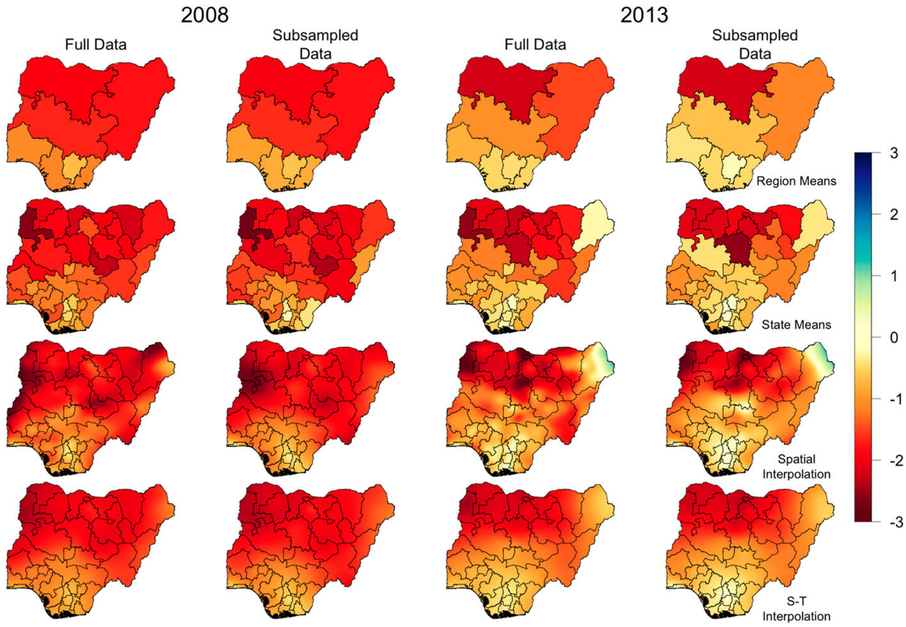

Figure 6. Comparisons of interpolations of full Height-for-Age *Z*-Score datasets and datasets subsampled to the 1990 sample size.

from 1990 (Figures 3 and 6). Additionally, differences between the estimates obtained with the subsampled and the full data sets were small relative to the change in HAZ over time. Given the correlations between the means and interpolations from 1990 and 2008 and 2013 (Table 4), we can say the subsampling successfully recovered the spatial patterns from 2008 and 2013.

4. Discussion

DHS surveys were designed to provide national-level estimates for health indicators like height for age. However, our analysis shows that it may be possible to use some of the survey data for estimating health status for sub-national areas. The approaches used to estimate sub-national HAZ generally performed similarly in terms of RMSE values and spatial patterns. However, predictions varied considerably in some respects. For example, the spatial interpolation results suggest that HAZ in northern Nigeria is highly spatially variable and changes rapidly over time. In contrast, the spatio-temporal interpolation produced patterns that were much more stable over both time and space. Given that low HAZ is caused by extended and repeated periods of deprivation and/or disease, one would expect changes in mean HAZ to happen relatively slowly. This leads us to believe that the spatio-temporal interpolation results are more reliable.

Our interest was primarily in interpolation methods as these can provide estimates at very high-spatial (and temporal) resolution. We also investigated aggregation techniques because this approach is commonly used, very easy to implement, and because site location data (geographic coordinates) may not be available for some surveys. For example, older DHS surveys generally report the sub-national regions that sites fall into, but they do not have site location data. This is also the case for some recent surveys, either because site location data were not collected or because they are not made available. Thus, while aggregation may cause significant information loss it still represents an important basis for comparison with interpolation methods.

The spatial interpolation results can be used to extrapolate future conditions, but the results obtained with that method diverged considerably from those obtained with a single spatio-temporal model for mean HAZ values in 2018 diverged considerably, especially in the north. The spatial interpolation for 2018 predicted rather extreme values and steep gradients in northern Nigeria, which do not appear to be realistic, especially given the on-going violent conflict in that part of the country. Placing some restrictions on the spatial interpolation would produce more conservative estimates, but this would come at the cost of increased model complexity. The spatio-temporal model predictions were much more conservative, and we think, more reasonable. These predictions of future expected values for HAZ can serve as a baseline by which we can assess the success of new projects to further improve height for age values.

Obtaining large samples is important because, everything else being equal, larger samples will yield better, more reliable, results. Nonetheless, large health surveys are often prohibitively costly because of the need for skilled workers and large amounts of travel, among other reasons. Being able to put an upper bound on a required sample size would be quite useful to keep costs down while not sacrificing statistical rigor. The results of our resampling approach indicate that only 297 locations were sufficient to reveal the major sub-national spatial pattern in HAZ in Nigeria. Thus, the observed changes do not appear to be an artifact of changes in sample size and site locations between surveys. However, it may very well be that for other countries and variables, larger sample sizes are necessary.

For this paper, we chose to evaluate the Thin Plate Spline method for interpolation because it can easily implemented for space and space-time modeling and because we had uncertainty (noise) in our measurements. Other methods are available and these could possibly perform better (e.g. general additive models, regression Kriging). Such methods could be based on the site locations only, or constructed as more complex models that use environmental co-variables. The sub-national spatial structure of the data could also be investigated further, with local indicators of spatial association (LISA, Anselin 1995) and for the presence of spatially stratified heterogeneity (Wang, Zhang, and Fu 2016).

Over the past 25 years, HAZ has improved enormously in Nigeria. However, the rate of improvement was much higher in the south than in most of the north, and the northwest region lagged behind the rest of the country. This spatial differentiation suggests that health improvement strategies for Nigeria should vary by region. Subnational health data can facilitate for more efficient program planning to better suit the needs of the people it serves (Brown et al. 2015). The level of spatial detail required will depend on the application. State-level averages of HAZ have been used in a number of analyses (WHO 1995; Grace et al. 2012; Adekanmbi, Uthman, and Mudasiru 2013), but higher spatial resolution interpolated data may be relevant for future geographic analysis and program planning. Moreover, if state or regional averages are required for a specific purpose, they can be easily calculated from high-resolution spatial interpolations. This may be advantageous, as interpolation methods can make use of data in adjacent areas, which state-wide averaging ignores. This is particularly relevant for estimates for (smaller) states with low sample sizes. Whether the interpolated data, or results obtained by other methods, are 'good enough' for a particular purpose is a question we cannot answer in general terms, but using interpolation methods to assess spatial variation in health variables of interest is an important step to take in research or program implementation.

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Disclosure statement

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Appendix. Equations

A.1. Interpolation methods

Aggregation: $y_i \sim \frac{\sum_{i=1}^{N} y_i}{N}$ for all y_i in a given region of interest and year.

Spatial Thin Plate Splines: $y_i \sim \text{longitude} + \text{latitude}$ for all y_i in a given year.

Spatio-temporal Thin Plate Splines: $y_i \sim \text{longitude} + \text{latitude} + \text{time}$ for all y_i.

A.2. Temporal Interpolation and Extrapolation for Aggregation and Spatial Thin Plate Spline methods

Interpolation: $\mathrm{HAZ}_y \sim HAZ_x + \Delta\mathrm{HAZ}\,(y - x)$ where

$$\Delta\mathrm{HAZ} = \frac{\mathrm{HAZ}_z - \mathrm{HAZ}_x}{z - x} \text{ and } x < y < z$$

Extrapolation: $\mathrm{HAZ}_z \sim \mathrm{HAZ}_y + \Delta\mathrm{HAZ}\,(z - y)$ where

$$\Delta\mathrm{HAZ} = \frac{\mathrm{HAZ}_y - \mathrm{HAZ}_x}{y - x} \text{ and } |z - y| < |z - x|$$