Chronic Child Undernutrition in Kenya: A Multilevel and High-Resolution Spatial Modelling Approach

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Undernutrition remains a significant obstacle to children under five years old in Kenya. One in four children under five are stunted, meaning that they have z-scores for height-for-age below two standard deviations from the median of the reference population. By compromising their immune systems, undernutrition may result in a higher risk of disease and mortality. While child stunting in Kenya varies within and between various geographical scales, no high-resolution and multilevel analyses have been conducted to identify and analyze independent predictors. The paper aims to quantify socioeconomic, demographic, cultural, climatic and environmental factors associated with childhood stunting in Kenya using a multilevel multivariate logistic regression and high-resolution spatial modelling approach. We anticipate that the results of this study will elucidate high resolution undernutrition 'hotspots' that are in critical need of, and can respond well to, prioritized policy interventions.

Keywords: Kenya, stunting, spatial statistics, hot-spot

I. INTRODUCTION

Despite valiant efforts towards addressing food insecurity that have seen undernutrition decline globally, many sub-Saharan countries still struggle to feed their people. Undernutrition, a global health problem with effects particularly devastating in Sub-Saharan Africa, causes those affected to suffer from weakened immune systems, increased susceptibility to diseases, and higher mortality rates [1]. Chronic undernutrition remains a significant obstacle to children under five years old in Kenya, where approximately 1 in 4 children are stunted, meaning that they have height-for-age Z-scores less than minus two standard deviations below the median of a reference height-for-age standard [2]. Chronic child undernutrition in the form of stunting varies within and between various regional scales [3], [4]. As such, there are several studies that have examined stunting prevalence by conducting trend analyses [5] and analyzing socioeconomic, demographic and cultural factors associated with childhood stunting by using standard logistic regressions [6], [7]. However, no high-resolution spatial analysis has been conducted to identify hotspots of stunting in Kenya. Furthermore, no multilevel analyses have been conducted to identify and analyze independent predictors of stunting in Kenya. Only one study has conducted spatial analysis of climate-related child undernutrition in the portion of Kenya contained in the Lake Victoria Basin [8]. The objective of this paper is to identify and quantify socioeconomic, demographic, cultural, climatic and environmental factors associated with childhood stunting in Kenya using a multilevel multivariate logistic regression and high-resolution spatial modelling approach.

II. DATA AND METHODS

To achieve our objectives, we will conduct an in-depth secondary data analysis of individual and cluster-level variables using the Kenya Demographic and Health Survey (KDHS) from 2014. Individual-level variables to be included in this multi-level study would consist of child factors (e.g. age of child, sex of child, birth-weight, type of birth, immunization and anemia) and maternal factors (e.g. maternal age, mother's education level, mother's body mass index, birth interval, number of under-five children, head of household and wealth index) [4]. Cluster-level variables would include poverty rate, latrine facility type, drinking water sources, precipitation and Normalized Difference Vegetation Index (NDVI) [4], [8]. We will obtain the precipitation data from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) web database, which reports monthly rainfall in millimeters at a 5km resolution. Next, we will obtain NDVI datasets from the National Aeronautics and Space Administration (NASA) Earth Observations web database at a 10km resolution, to represent

the ‘greenness’ of the country as estimated from data captured by multiple satellites.

We will employ multivariate multilevel logistic regression to analyze and quantify socioeconomic, demographic, cultural, climatic and environmental factors associated with childhood stunting in Kenya at two levels: individual and cluster levels. We will construct four models to do so. The first model will be a baseline model without any explanatory variables, to investigate the extent of cluster variation on stunting. The second model will be adjusted for individual-level variables, the third model adjusted for cluster-level variables while the fourth model will be adjusted for both the individual and community-level variables simultaneously. Adjusted Odds Ratios (AOR) with their corresponding 95% Confidence Intervals (CI) will be calculated to identify independent contributors to stunting. To measure variation within clusters, we will calculate statistics such as Intra-cluster Correlation (ICC), Median Odds Ratio (MOR) and Proportional Change in Variance (PCV) [9], [10]. Optimized hot spot analysis will be conducted using Getis-Ord Statistics, specifically the Local Getis-Ord G index (LGi) to compute and map the spatial heterogeneity of significant high/low prevalence clusters of stunting [11].

III. EXPECTED FINDINGS

From this study, we expect to determine if either individual and cluster-level factors, or both, are significant determinants of child stunting. Where significant, we will to quantify the effect of individual and/or cluster-level factors on the variation of child stunting across the country. Moreover, following the hotspot analysis, we will explicate and map measures of statistically significant hotspots and/or coldspots of child stunting at a high-resolution pixel level. These results will be the output of rigorous multilevel multivariate and spatial modelling efforts that account for spatial heterogeneity among socioeconomic, demographic, cultural, climatic and environmental factors associated with childhood stunting in Kenya. All in all, we anticipate that the results of this study will elucidate high resolution undernutrition 'hotspots' such as urban slum areas and rural areas that are in critical need of, and can respond well to, prioritized policy interventions.

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