

Nutritional inequalities among under-5 children: An analysis of cross-country and within-country hotspots and cold spots in the developing world

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Research Article

Keywords: undernutrition, stunting, wasting, underweight, LISA, Moran's I

Posted Date: February 19th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-256225/v1>

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Nutritional inequalities among under-5 children: An analysis of cross-country and within-country hotspots and cold spots in the developing world

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Abstract

Undernutrition of under-five children is a severe public health issue of the developing world. Around 45% of deaths among children under five years are linked to undernutrition. According to 2019 global estimates, 21% of under-five children were stunted, 7% were wasted, and 13% were underweight in 2019. However, there are wide disparities in the distribution of undernutrition within countries and across countries. As an illustration, 38% of under-five children in Pakistan are stunted. However, the stunting rate in Islamabad Capital Territory is 24% but 52% in FATA, according to Demographic and Health Surveys (DHS) data. Such disparities in undernutrition may reflect policy failures or the genetic vulnerabilities of population subgroups. To the best of our knowledge, very few studies have analyzed the geography of the undernutrition inequalities among under-five children.

We analyzed the geographical patterns in child undernutrition in developing countries. First, we mapped the prevalence of undernutrition in the developing world. Secondly, using the LISA (local indicator of spatial association) technique, we analyzed the geographical patterns in the distribution of undernutrition to highlight the localized hotspots (regions with high undernutrition prevalence surrounded by similar other regions), cold spots (regions with low undernutrition prevalence surrounded by similar other regions), and outliers (regions with high undernutrition surrounded by low undernutrition and vice versa showing inequalities in the distribution in undernutrition). Additionally, we used Moran's *I* to find global patterns in malnutrition.

We used data from Demographic and Health Surveys (DHS) data from 73 developing countries for our study.

The Global Moran's *I* and LISA techniques used to estimate the global and within-country malnutrition patterns, respectively, confirm significant spatial clustering of malnutrition among under-five children. South Asia and Sub-Saharan Africa are global hotspots of child malnutrition, and Latin America and the Caribbean, and Europe and Central Asia are global cold spots of child malnutrition. There are few outliers: areas of low child malnutrition surrounded by high malnutrition and vice versa.

One important policy implication of this study is that it will help identify the areas with i) high undernutrition and ii) high nutritional inequalities and help targeted health interventions in the geographical areas with a high need population.

Keywords: undernutrition; stunting; wasting; underweight; LISA; Moran's *I*

Introduction

According to the recent global estimates, 156 million under-five children were stunted, 50 million under-five children were wasted, and 192 million under-five children were moderately or severely underweight ([WHO & Mathers, 2016](#)). Out of 156 stunted children worldwide, around 145 million children lived in Asia, and 48 million children lived in Africa ([WHO & Mathers, 2016](#)). In Pakistan, around 44% of under-five children were stunted, 11% were wasted, and 29% were underweight ([Khan et al., 2019](#)).

Child malnutrition is a severe issue for developing nations. In 2016, childhood malnutrition, i.e., stunting, wasting, and underweight, caused one million deaths globally ([Ssentongo et al., 2019](#)). Even if the developing world faces serious child malnutrition issues, there is a wide discrepancy in the presence of child malnutrition over the developing world and the within developing countries. In 2017, the prevalence of undernourishment in Africa was 20.4%, under-5 children suffered from undernourishment in Africa, 11.4% in some regions of Asia, and 6.1% in Latin America and ([Organization, 2018](#)). Though many studies have analyzed the factors associated with child malnutrition, not many studies have analyzed the geography of the inequality in the level of child malnutrition. This study, therefore, fills in this important gap by analyzing the geographic patterns of child malnutrition both across the developing world as well as within the developing countries.

A wide range of studies have analysed the factors contributing to the child malnutrition. A study in Egypt found that characteristics like child's age, gender, birth order and being twin were significant determinants of malnutrition ([Rashad & Sharaf, 2018](#)). Malnutrition results from disorders in the nutrient assimilation and defects in the immune system which are generally associated with the nutritional status of parents ([Bourke et al., 2016](#)). Some other

predictors of child malnutrition are household wealth, educational and nutritional profile of mother, food security, geography, and sewerage conditions are significantly associated with malnutrition among children ([Akseer et al., 2018](#)). Nutritional supplements consumed by mothers like folic acid, vitamins, and minerals could also explain nutritional differences among children ([Miranda et al., 2019](#)). In India, gender biases are deep-rooted and lead to disproportionately worse nutritional outcomes for women and children ([Sinha et al., 2017](#)). Children from poor households bear a disproportionately larger burden of malnourishment than the rich households ([Pulok et al., 2016](#)).

Malnutrition has lasting adverse consequences. Micronutrient insufficiencies affect the hematopoietic and lymphoid organs and undermine innate and adaptive immune functions ([Ibrahim et al., 2017](#)). Stroke, interminable obstructive pulmonary illness, coronary and cardiovascular breakdown, breast cancer, dementia, musculoskeletal issues, depression, and colorectal diseases are mainly caused by nutritional deficiencies ([Goates et al., 2016](#)). In countries where obesity and overweight are higher among women, the prevalence of child malnutrition is high ([Anik et al., 2019](#)).

While the incidence and presence of various types of child malnutrition are well-established in the existing literature, few studies have estimated the geographic location of child malnutrition in developing countries. One consequence of incomplete information regarding the geographic distribution of malnutrition is that policy interventions are generally not targeted and may be concentrated in the areas which require the least intervention. This study's objective was to analyze the geographic patterns of child malnutrition both within and across the countries in the developing world.

Theoretical reflections on health inequalities

Why are inequalities bad in the first place?

[Woodward and Kawachi \(2000\)](#) examine four arguments that see health inequalities as intrinsically undesirable whose reduction should be the primary focus of the policymakers. First, inequalities are unfair. Inequalities in health are undesirable to the extent that they are unfair or unjust. Distinguishing between health inequalities and health inequities can be contentious. Our view is that inequalities become “unfair” when poor health is itself the consequence of an unjust distribution of the underlying social determinants of health (for example, unequal opportunities in education or employment).

Secondly, inequalities affect everyone. Conditions that lead to marked health disparities are detrimental to all members of society. Some types of health inequalities have apparent spillover effects on the rest of society, for example, the spread of infectious diseases, the consequences of alcohol and drug misuse, or the occurrence of violence and crime.

Thirdly, inequalities are avoidable. Health disparities are avoidable to the extent that they stem from identifiable policy options exercised by governments, such as tax policy, regulation of business and labor, welfare benefits, and healthcare funding. It follows that health inequalities are, in principle, amenable to policy interventions. Therefore, a government that cares about improving the population’s health should incorporate alternative options’ health impact in its policy-setting process.

Fourthly, interventions to reduce health inequalities are cost-effective. Public health programs that reduce health inequalities can also be cost-effective. The case can be made to prioritize such programs (for example, improving access to cervical cancer screening in low-

income women) on efficiency grounds. On the other hand, few programmes designed to reduce health inequalities have been formally evaluated using cost-effectiveness analysis.

[Woodward and Kawachi \(2000\)](#) concluded that fairness is likely to be the most compelling argument favoring action to reduce health disparities. Still, the concept of equity is contested and susceptible to different interpretations. There is persuasive evidence for some outcomes that reducing inequalities will diminish “spillover” effects on the health of society at large. In principle, you would expect that differences in health status that are not biologically determined are avoidable. However, the mechanisms giving rise to inequalities are still imperfectly understood, and the evidence remains to be gathered on the effectiveness of interventions to reduce such inequalities.

Mechanisms generating health inequalities

According to the evidence on the impact of social determinants on health equity ([Solar & Irwin, 2010](#)), increasing social inequality and poverty, greater job insecurity, rising unemployment, and privatization of public goods and services ([Laparra et al., 2012](#)) can explain the increase in social inequalities in health during crises ([Bacigalupe & Escolar-Pujolar, 2014](#)).

Researchers have examined individual-level inequalities in health within a single society, frequently the United Kingdom and the United States ([Goesling, 2007](#)), establishing social factors, such as income, education, gender, race/ethnicity, or immigration status, as predictors of various health outcomes ([Beckfield et al., 2013](#)). The relationship between aggregate indicators of income inequality and aggregate health outcomes across multiple, but usually advanced, industrialized nations have been explored, finding mixed support for the relationship between income inequality and population-health indicators, such as life expectancy and infant mortality ([Babones, 2008](#); [Beckfield et al., 2013](#)).

The “fundamental-cause” perspective interprets the health gradient as a relationship between social position and health that reproduces itself through multiple mechanisms. Link and Phelan (1995) have directed health scholarship back to societal-level social inequality by arguing that social standing will always be linked to health because it represents a fundamental cause of disease, in that the impact of social standing on health cannot be eliminated by intervening on the mechanisms that link social standing to health disparities. The inverse relationship persists because access to resources (such as money, knowledge, power, and social networks) can be used to avoid health risks and to minimize the consequences of illness. This implies that mortality-reducing technologies and knowledge should steepen the health gradient because the better off can take advantage of them faster ([Cutler et al., 2006](#)).

We argue that societies establish systems for the distribution of resources, social hierarchies that generate relative social comparisons, and institutional mechanisms for translating social and individual resources into health. This opens up a new question: How much (and why) do health inequalities vary across societies? Following the logic of the fundamental-cause approach, one would expect to observe substantial cross-national variation in health inequalities, such that one finds steeper health gradients in richer, healthier societies than in poorer, less-healthy societies, as people higher up the social hierarchy take disproportionate advantage of health-improving knowledge and technologies ([Beckfield et al., 2013](#)). Conversely, a case can be made that if social inequality translates into health inequality through mechanisms that vary in different social contexts, one would expect to observe constant health gradients across societies— primarily if, as we do below for income and education, one measures social standing on relative scales. That is, in addition to reproducing itself over time, an extension of the

fundamental-cause perspective might anticipate that the health gradient is a constant across a heterogeneous set of places.

According to the World Health Organization (WHO), health and well-being disparities are attributable to the specific circumstances in which “people are born, grow, live, work, and age.” Collectively, these circumstances are known as the “Social Determinants of Health” (SDH) and include laws, policies, economics, livelihood, education, living conditions, etc. ([Reap et al., 2020](#)). Within each society, those who hold power and resources determine which specific circumstances are valued and which are not. Most typically, the decisions made by power yielders protect the values, interests, and well-being of themselves and their constituents. Meanwhile, marginalized populations’ values and interests tend to suffer across various domains, compromising their health. Thus, personal health is not solely influenced by genetics and lifestyle but also by systemic societal inequities ([Organization, 2010](#)).

Traditionally, most Western models of health viewed sickness and disease as a product of individual factors such as personal behaviors and genetic predisposition; consequently, healthcare interventions were focused mainly on fixing the individual, with little attention placed on contributing external factors. The WHO’s “Social Determinants of Health” (SDH) framework, however, takes a broader ecological perspective that suggests that interventions must occur at multiple levels to achieve good health on an equitable basis. This model views health as a function of many circumstantial and environmental factors that are continuously and simultaneously interacting across multiple domains. These factors include structural mechanisms, such as laws and policies; socio-economic conditions, such as education and occupation; and intermediary circumstances, such as living and working conditions ([Reap et al., 2020](#)).

As the framework in Fig. 0 illustrates, contextual factors such as social, economic, and political mechanisms play a key role in determining a population's socio-economic position, stratified according to livelihood, income, and education level. These structural determinants then give shape to intermediary determinants, including living and working conditions, behaviors, biological factors, etc. In tandem with the available health care system, the intermediary determinants then directly determine health and health outcomes. Due to its proximal relationship to health, health care policy has traditionally focused on prevention activities at the intermediary level prior to the onset of poor health and treatment after. However, as Fig. 0 demonstrates, this myopic approach fails to address the real root of the problem – the structural inequities that gave rise to such conditions in the first place. Because a person's health is the result of the complex convergence of multiple factors that are mostly out of their control, it becomes apparent that the best way to achieve equitable and sustainable good health is by expanding the focus of healthcare interventions from the individual level to include the system itself (i.e., society).

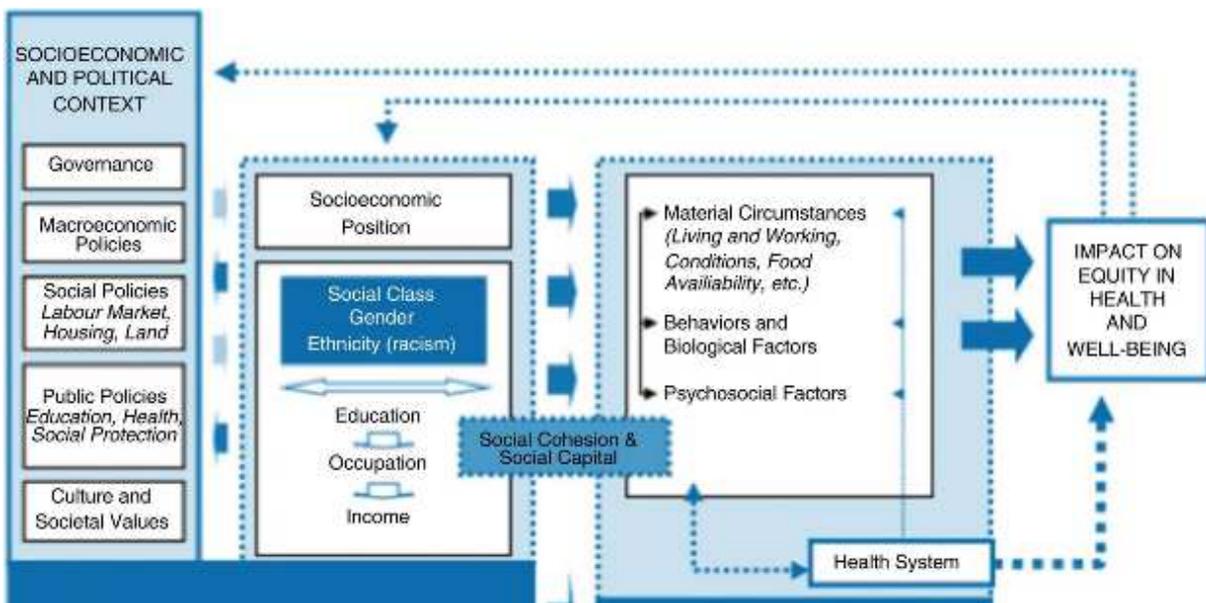


Figure 0: Pathways of health inequalities

The WHO SDH framework is a human rights-based model that precisely endorses such an approach. To make this shift, however, it is necessary first to consider the main driver behind how societies evolve: power. According to this framework, those that possess the most power and resources within a given society determine the prevailing priorities, values, and beliefs. In most cases, these power wielders' decisions in terms of laws, policies, and other determinants disproportionately benefit themselves and those that share their priorities. Unfortunately, however, these decisions often have negative consequences for marginalized groups - such as indigenous peoples - that hold divergent priorities and values. In contrast, with the powerful, such decisions serve only to further constrict their options across various domains such as livelihood, education, and living conditions. The collective and synergistic consequences of these reduced options are often poorer health and health outcomes ([Organization, 2010](#)).

The following example illustrates how this interdependent, power-driven process unfolds: at the structural level, a decision is made about labor policy that expands job opportunities for one portion of the population (i.e., those with power) while simultaneously reducing opportunities for another portion with less power. This reduction in job opportunities may result in lower income potential, thereby reducing the ability to make choices regarding living conditions and nutrition. With fewer options available, the marginalized population may have to settle for inferior housing or unhealthy foods, resulting in serious health consequences ([Reap et al., 2020](#)).

The SDH model is quite logical and provides a very compelling model to explain the large disparity between indigenous populations' health and others living within the same vicinity. It also provides a clear roadmap about where health policy and healthcare interventions

should be targeted to achieve better outcomes - especially for vulnerable and marginalized populations such as the Urak Lawoi' and other indigenous groups.

Some works do not see health inequalities as the direct result of the income inequality approach to health inequalities. They try to understand health inequalities within the framework of the class-based model by focusing on the causes and not only the consequences of income inequalities ([Coburn, 2004](#)). In this model, the relationship between income inequality and health appears as a special case within a broader causal chain. It is argued that global and national socio-political-economic trends have increased the power of business classes and lowered that of working classes. The neo-liberal policies accompanying these trends led to increased income inequality but also poverty and unequal access to many other health-relevant resources. But international pressures towards neo-liberal doctrines and policies are differentially resisted by various nations because of historically embedded variation in class and institutional structures. Data presented indicate that neoliberalism is associated with greater poverty and income inequalities and greater health inequalities within nations. Furthermore, countries with Social Democratic forms of welfare regimes (i.e., those that are less neo-liberal) have better health than do those that are more neo-liberal.

The link between per capita income and health status shows a clear gradient. [Wilkinson \(2002\)](#) argued that GNP/capita is the most important correlate of average levels of health status amongst the less developed nations. However, above about \$5–\$10,000 GNP/capita, the point at which chronic diseases begin to displace acute illness as the chief causes of death, Wilkinson contends that it is the degree of income inequality, rather than national wealth which is the most important determinant of national differences in health status. It is worthwhile noting that, even under the \$5–\$10,000 mark, there is a wide distribution of health for any particular GNP/capita

level. Discussion of the health of the less developed nations cannot be dismissed as the simple product of GNP/capita ([Sen, 2000](#)).

Noting that high-level British civil servants show poorer health than those even higher in the hierarchy, income inequality theorists concluded that relative rather than absolute income differences underlie the relationships between income and health ([Coburn, 2004](#)). Hence, they paid less attention to material inequalities, poverty, or absolute income than to psycho-social status hierarchies. Social hierarchies are said to produce disease because of the poor self-esteem associated with lower status, which, in turn, through psycho-neuro-biological pathways, negatively influences health. Wilkinson, Kawachi, and others also contend that income inequality leads to loss of social cohesion, which produces lower health status ([Wilkinson, 2002](#)).

Research Methodology:

Data

The reason for this investigation is to highlight geographic disparities in the indicators of under-5 child malnutrition in the developing world. Our study used data from 73 countries and 699 sub-regions. The data is collected from surveys. The units of investigation utilized for this analysis are DHS regions and sub-regions.

Measurement of the variables

We used the standard definitions of three measures of under-5 child malnutrition (Table 1).

Table 1: Measurement of the under-5 child malnutrition

Indicators	Definitions
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Stunting	Children whose height-for-age z-score is less than minus 2 (-2.0) and from the WHO Child growth standard, standard deviations is below from the mean (hc70 < -200)
Wasting	Children whose weight-for-height z-score is less than minus 2 (2.0) and from the WHO Child growth standard, standard deviations is below from the mean (hc72 < -200)
Underweight	Children whose weight-for-age z-score is less than minus 2 (2.0) and from the WHO Child growth standard, standard deviations is below from the mean (hc71 < -200)

Source: Demographic and Health Surveys

Empirical analysis

We used Demographic and Health Surveys (DHS) data to analyze under-5 child stunting, wasting, and underweight in 73 countries and 699 sub-regions. DHS data are collected repeatedly. So, when multiple DHS data waves are available, we selected the most recent DHS wave. For example, in Pakistan's case, nutritional information is available in three DHS waves corresponding to 1990-91, 2012-13, and 2017-18. We used data only from the most recent wave, 2017-18, to analyze the most recent trends.

There is substantial evidence to suggest that wide within-country disparities in the status of child malnutrition exist. We give a country-level *spectrum of child malnutrition*, with the lowest and highest levels of malnutrition in a country and the national rate of stunting, wasting, and underweight. As an illustration, in Pakistan's case, we chose the province (the DHS sub-region) with the lowest stunting rates and the province with the highest stunting rates, and the national stunting rate. The national stunting rate, by construction, is between the highest and lowest stunting rates.

Geospatial analysis

We used the DHS survey data to compute under-5 child malnutrition three variables: stunting, wasting, and underweight. To map data to geographical regions, we used the Spatial Data Repository (<https://spatialdata.dhsprogram.com>) and joined indicator estimates to the geospatial data using ArcGIS.

We used the exploratory spatial data analysis (ESDA) technique to analyze child malnutrition in the selected countries. ESDA visualizes and measures the spatial autocorrelation between and among regions. We initially saw the spatial trends of child malnutrition measures, both inside and over the national boundaries.

Then we identified the areas with statistically significant clustering of hotspots (high levels of malnutrition) and cold spots (low levels of malnutrition). The latter analysis gave the intra-and within-country information about the high and low-performing areas concerning geographic proximity ([Yourkavitch et al., 2018](#)).

Spatial autocorrelation of child malnutrition indicators

We first constructed thematic maps of childhood malnutrition in ArcGIS ([Tobler, 1970](#)) to assess child malnutrition prevalence, both inside and across national boundaries. The contiguous areas are more likely to be similar than the areas that are away from each other. Therefore, the spatial autocorrelation measures the degree to which a sub-region is similar or dissimilar from the other neighboring sub-regions for a specific indicator of malnutrition.

Spatial autocorrelation can be done at the worldwide level, just as at the local level. The global measure summarizes the spatial autocorrelation over the entire study area. In contrast, the local measure analyses localized spatial autocorrelation inside the study area.

Moran's I statistic was used to measure global spatial autocorrelation or clustering of malnutrition ([Moran, 1950](#)). The Moran's I test result gives a range from -1 to 1, where a value near 0 shows no statistically significant spatial clustering over the study area. The other possibilities are given in the following equation.

Moran's I measurement was initially utilized to quantify worldwide spatial autocorrelation or bunching of ailing health ([Moran, 1950](#)).

$$\text{Moran's } I = \begin{cases} < 0 & \text{Spatial clustering: neighboring regions have different values} \\ 0 & \text{No significant spatial clustering} \\ > 0 & \text{Spatial clustering: neighboring regions have similar values} \end{cases}$$

To measure localized spatial autocorrelation of child malnutrition, a local indicator of spatial association (LISA) for Moran's I was used, which indicated if significant spatial clusters per each location in the sample region exist or do not exist ([Anselin, 1995](#)). The LISA analysis produces a spatial layer that gives five different types of spatial associations and potential outliers ([Burgert-Brucker et al., 2015](#)).

1. Not significant: the areas which have no statistically significant spatial autocorrelation ($p \leq 0.05$).
2. High-high: this type of spatial association shows that the high values are surrounded by the other neighboring high values. It must be noted that the high values are not high in absolute terms but relative terms. In this type of association, the geographical regions with high prevalence rates of child malnutrition are surrounded by other geographical regions with a high prevalence of child malnutrition.
3. Low-low: the low values are surrounded by other low values. In this type of association, the geographical regions with low prevalence rates of child malnutrition are surrounded by similar other geographical regions with a low prevalence of child malnutrition.

4. Low – high: the low values are surrounded by high values. In other words, the areas with a low incidence of child malnutrition are surrounded by other sub-regions with high prevalence rates of child malnutrition. The geographical areas with this type of association reveal nutritional inequality and offer valuable insights about the factors contributing to the low malnutrition levels even when the neighboring regions have high malnutrition levels. How one region could achieve a lower malnutrition level could be necessary from the perspective of policy formulations.
5. High-low: the high values are surrounded by low valleys values. It means that the regions which have high prevalence rates of child malnutrition are surrounded by other sub regions with low levels of child malnutrition. The geographical areas with this type of association are again a measure of nutritional inequality and offer valuable insights about the factors contributing to the high malnutrition levels even when the neighbouring regions have low levels of malnutrition. In high-low clusters, it would be interesting to see how one region failed to reduce malnutrition when other regions in the neighbourhood reduced malnutrition.

Results

Prevalence of under-five child malnutrition

There are wide disparities in under-five child malnutrition indicators across different world regions (Table 2). South Asia has the highest prevalence of under-five child malnutrition indicators, and Europe and Central Asia have the lowest prevalence rates. The highest stunting rates are in South Asia (32.4%), closely followed by East Asia and Pacific and Sub-Saharan Africa. The smallest stunting prevalence is in Europe and Central Asia (17.5%). Wasting prevalence is again highest in South Asia (12.6%) and lowest in Latin America and the Caribbean (1.8%). South Asia again outpaces other regions with respect to underweight (26.9%). Europe and Central Asia region has the lowest underweight prevalence rate (4.95%).

Table 2: Regional prevalence estimates of indicators of under-five child malnutrition

Region	Stunting	Wasting	Underweight
East Asia & Pacific	33.2	11.3	25
Europe & Central Asia	17.5	4.87	4.95
Latin America & Caribbean	19.7	1.8	6.37
Middle East & North Africa	23.6	8.22	15.5
South Asia	32.4	12.6	26.9
Sub-Saharan Africa	33.2	7.51	16.9

Source: DHS (most recent estimates in every country)

Individual indicators

Stunting

Burundi, Madagascar, Guatemala, and Yemen were the topmost countries with respect to stunting prevalence (>46%) (Figure 1). In contrast, Trinidad and the Tobago Dominican Republic, Jordan, and Armenia were at the bottom of countries with stunting prevalence (<10%).

Timor-Leste and Cambodia had the highest prevalence of stunting in East Asia and the Pacific region (>32%). Uzbekistan in Azerbaijan had the highest stunting prevalence in Europe and Central Asia (>25%). Guatemala and Bolivia topped the list of countries with stunting prevalence in the Latin American Caribbean (>27%). Yemen and Morocco had the highest stunting rates in the Middle East and North Africa region (>22%). India and Pakistan had the highest stunting within South Asia (>37%), whereas Burundi and Madagascar had the highest stunting rates in sub-Saharan Africa (>53%). The regional distribution of stunting shows that the countries which had the lowest rates of stunting in East Asia and Pacific region were Thailand and Myanmar (<30%), Armenia in Moldova in Europe and Central Asia region (<11%), Trinidad and Tobago and the Dominican Republic in Latin America and Caribbean region (<7%), Jordan and Tunisia in the Middle East and North Africa region (<21%), Maldives and Sri Lanka in South Asia (<32%) and Gabon and Senegal in sub-Saharan Africa (<17%).

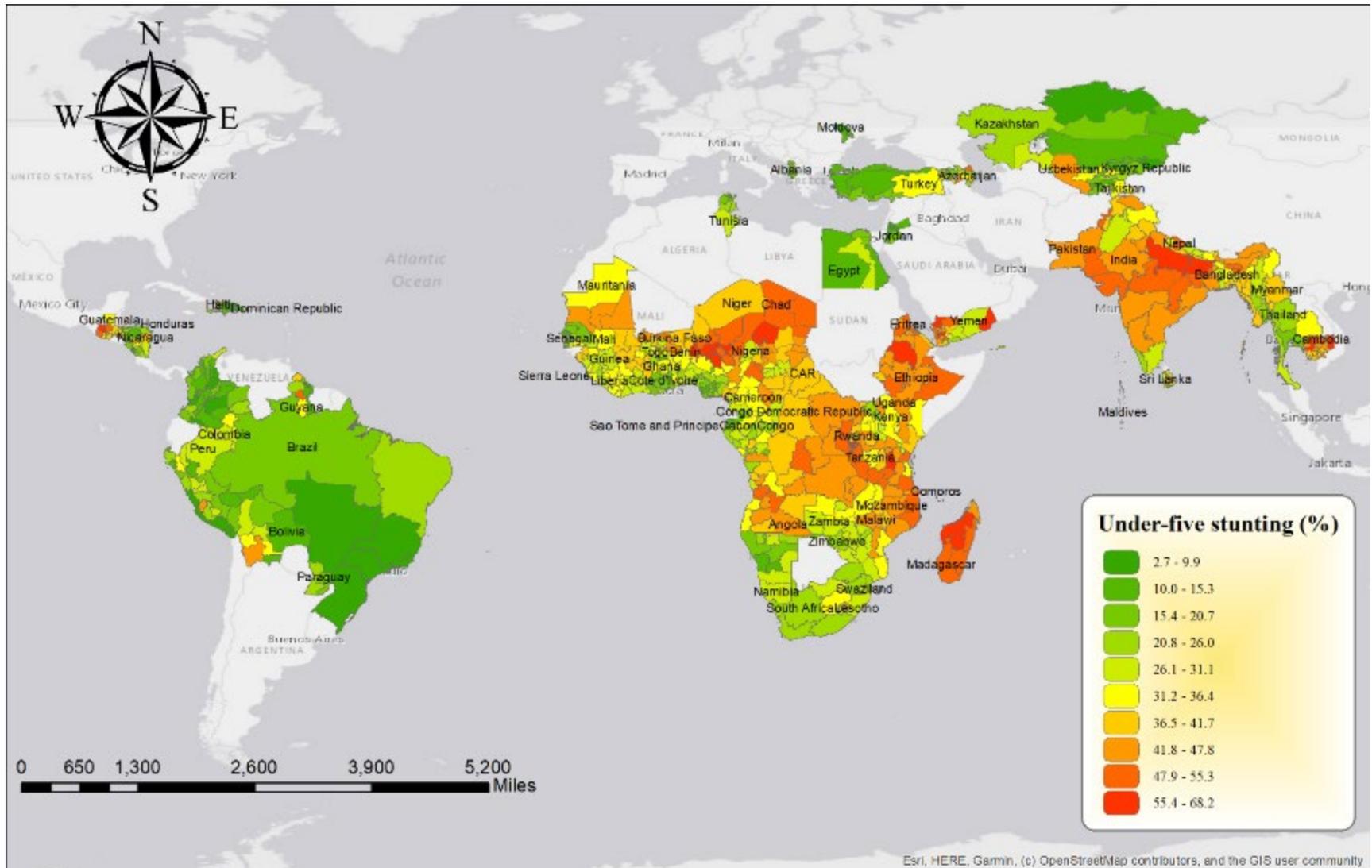


Figure 1: Stunting prevalence rates (Source: Demographic and Health Surveys)

Around 61% of the sample countries had intra-country lowest and highest stunting rate differences of 20% percentage points or more (Figure 2). The highest intra-country stunting differences were found in Burundi (42%), Peru (45%), Guatemala (51%) and Nigeria (52%). The lowest intra-country stunting rates differences were found in Trinidad and Tobago (0%), Swaziland (7.2%), Dominican Republic (7.3%) Moldova (7.5%).

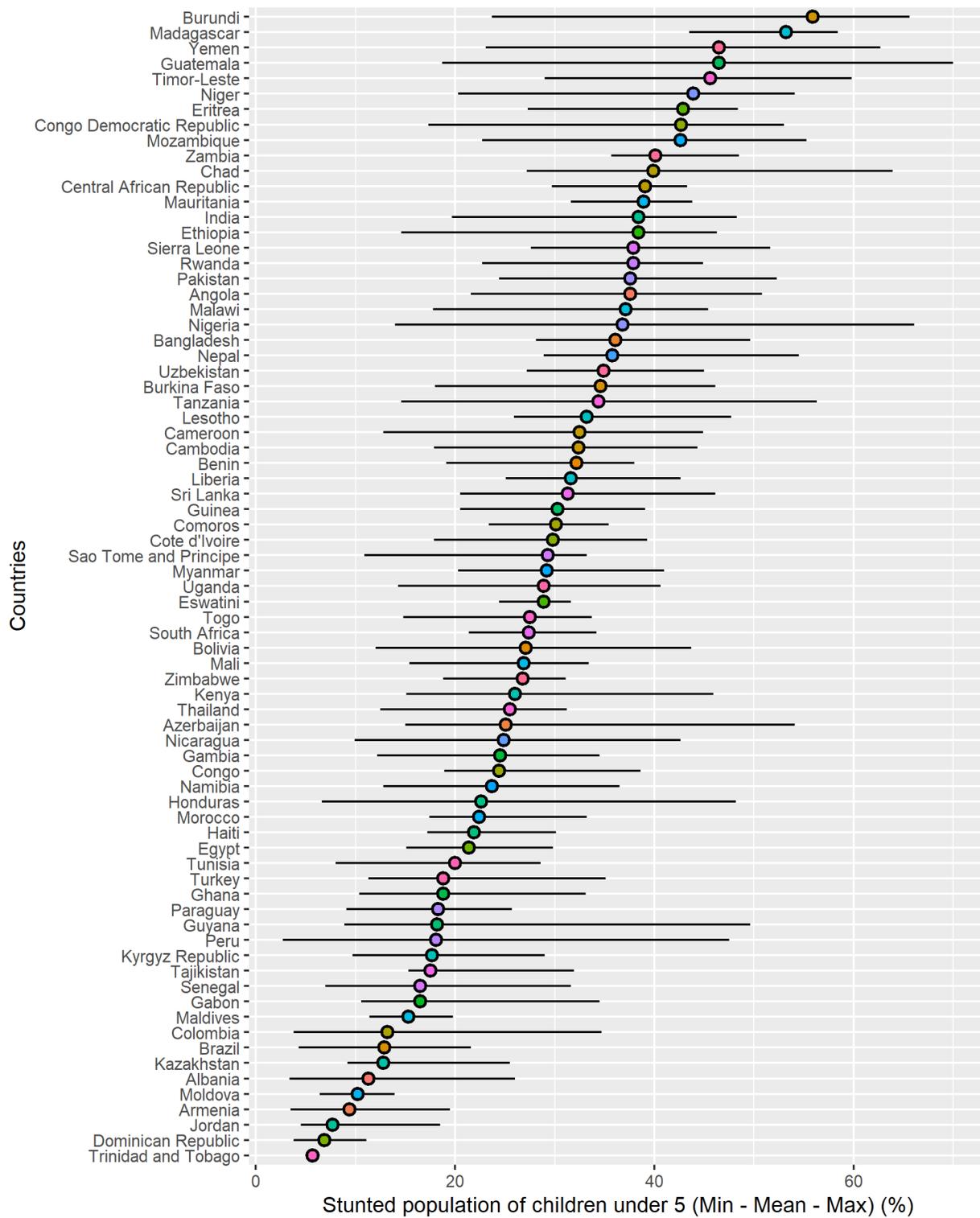


Figure 2: Within country disparities in the stunting rates (Source: DHS)

Wasting

Timor-Leste, India, Niger, and Yemen had the highest wasting rates (>16%). Paraguay, Peru, Guatemala, Colombia, and Bolivia had the lowest wasting rates in our sample countries (<1%) (Figure 3).

At the regional level, the countries with the highest level of wasting rates were Timor-Leste and Cambodia in East Asia and Pacific (> 9%), Uzbekistan and Azerbaijan in Europe and Central Asia (> 6%), Guyana and Haiti in Latin America and the Caribbean (> 3%), Yemen, and Morocco in the Middle East and North Africa (> 9%), India, and Bangladesh in South Asia (> 14%), and Niger and Burkina Faso in sub-Saharan Africa (> 15%). The countries with the lowest level of wasting rates were Thailand and Myanmar in East Asia and Pacific (< 7%), Albania and Kazakhstan in Europe and Central Asia (< 3%), Paraguay and Peru in Latin America and the Caribbean (< 1%), Jordan in Tunisia in the Middle East and North Africa (< 5%), Pakistan and Maldives in South Asia (< 10%), and Rwanda in South Africa in sub-Saharan Africa (< 3%).

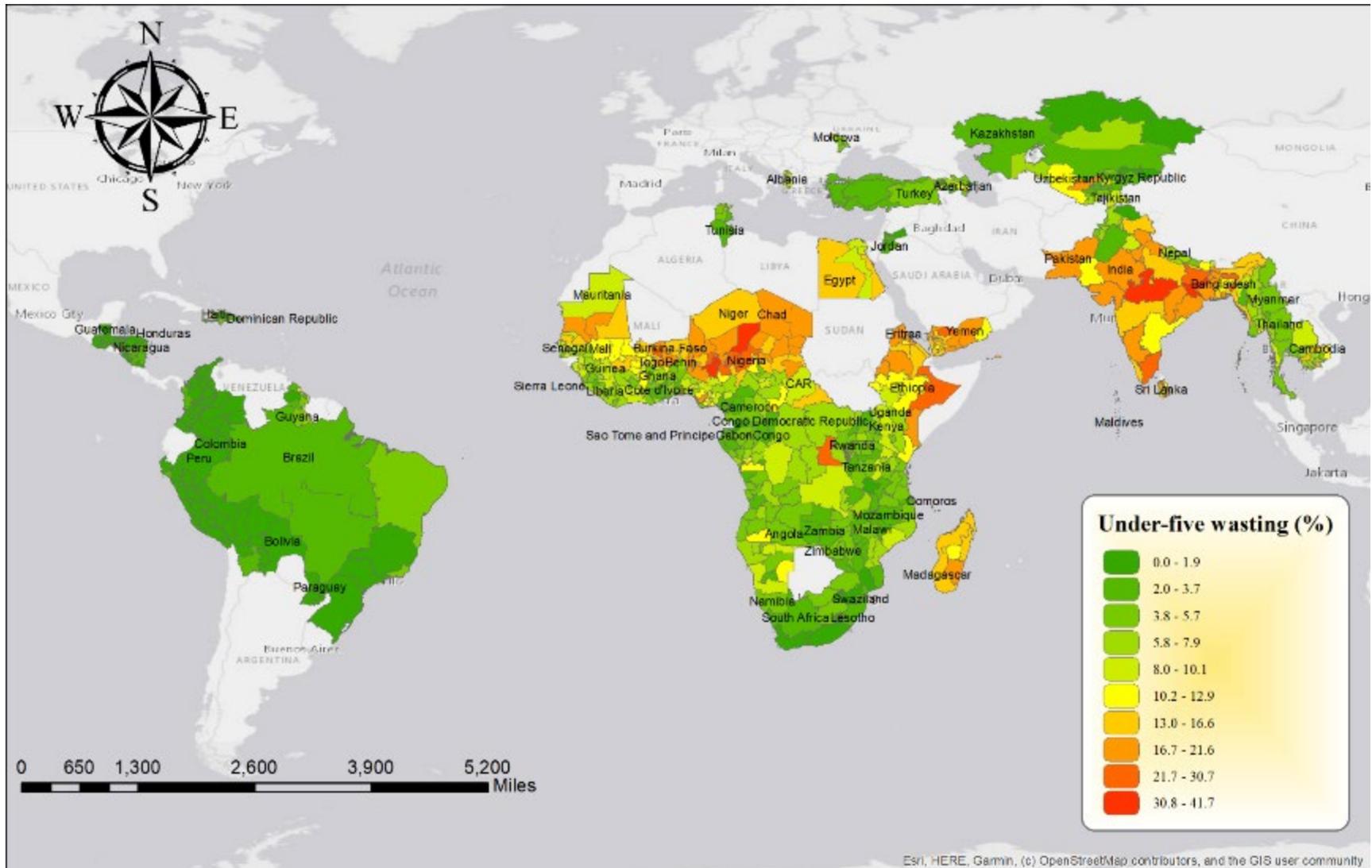


Figure 3: Wasting prevalence rates (Source: Demographic and Health Surveys)

Around 9% of the sample countries had intra-country lowest and highest wasting rate differences of 20% percentage points or more (Figure 4). The highest intra-country wasting differences were found in Kenya (22%), India (23%), Timor-Leste (25%) and Niger (27%). The lowest intra-country wasting rates differences were found in Trinidad and Tobago (0%), Rwanda (0.6%), Paraguay (0.8%) Swaziland (1%).

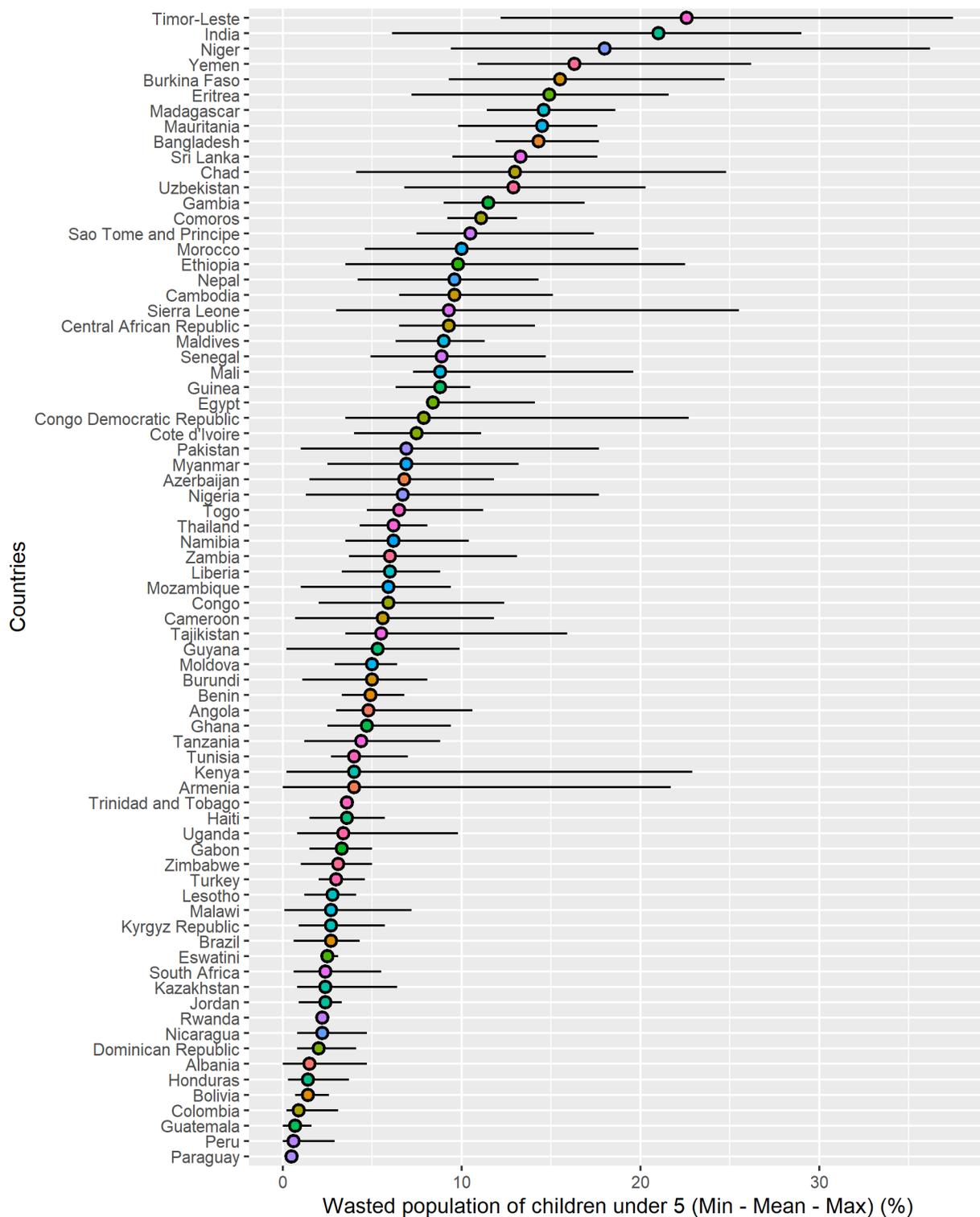


Figure 4: Within country disparities in the wasting rates (Source: DHS)

Underweight

Timor-Leste Yemen, Niger, and Madagascar had the highest underweight rates ($> 36\%$). Albania Armenia Paraguay Jordan and Moldova had the smallest underweight rates ($< 3.5\%$) (Figure 5).

At the regional level, the countries with the highest level of underweight rates were Timor-Leste in Cambodia in East Asia and Pacific ($> 23\%$), Uzbekistan and Azerbaijan in Europe and Central Asia ($> 7\%$), Guatemala and Guyana in Latin America and the Caribbean ($> 10\%$), Yemen, and Morocco in the Middle East and North Africa ($> 8\%$), India, and Bangladesh in South Asia ($> 32\%$), and Niger and Madagascar in sub-Saharan Africa ($> 36\%$). The countries with the lowest level of underweight rates were Thailand and Myanmar in East Asia and Pacific ($< 19\%$), Albania and Armenia in Europe and Central Asia ($< 3\%$), Paraguay and Colombia in Latin America and the Caribbean ($< 4\%$), Jordan and Egypt in the Middle East and North Africa ($< 6\%$), Pakistan and Maldives in South Asia ($< 23\%$), and Swaziland in South Africa in sub-Saharan Africa ($< 6\%$).

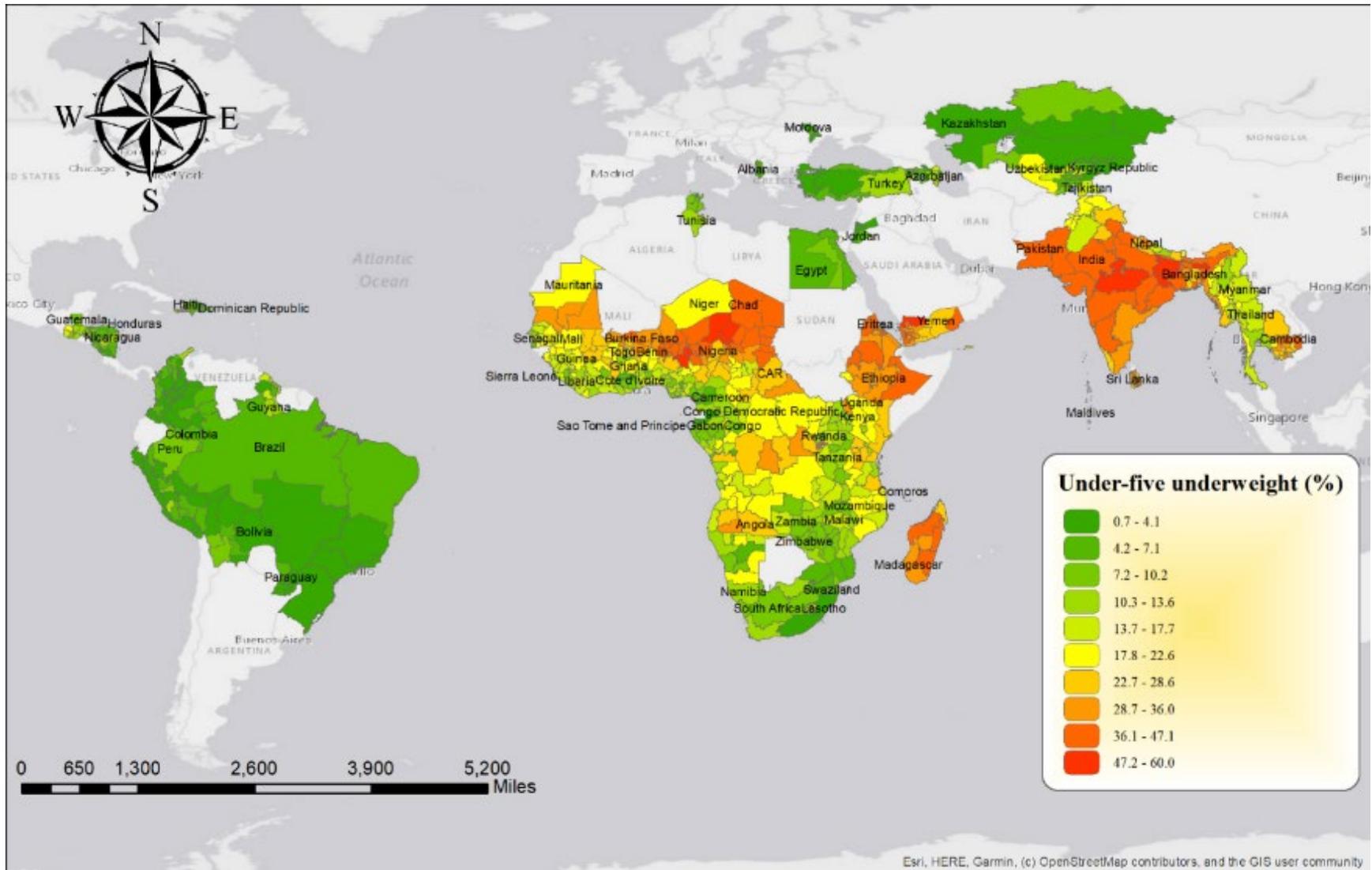


Figure 5: Underweight prevalence rates (Source: Demographic and Health Surveys)

Around 22% of the sample countries had intra-country lowest and highest underweight rate differences of 20% percentage points or more (Figure 6). The highest intra-country underweight differences were found in Kenya (36%), Nigeria (40%), Chad (43%) and Niger (46%). The lowest intra-country underweight rates differences were found in Trinidad and Tobago (0%), Paraguay (2.4%), Moldova (2.5%) Swaziland (3%).

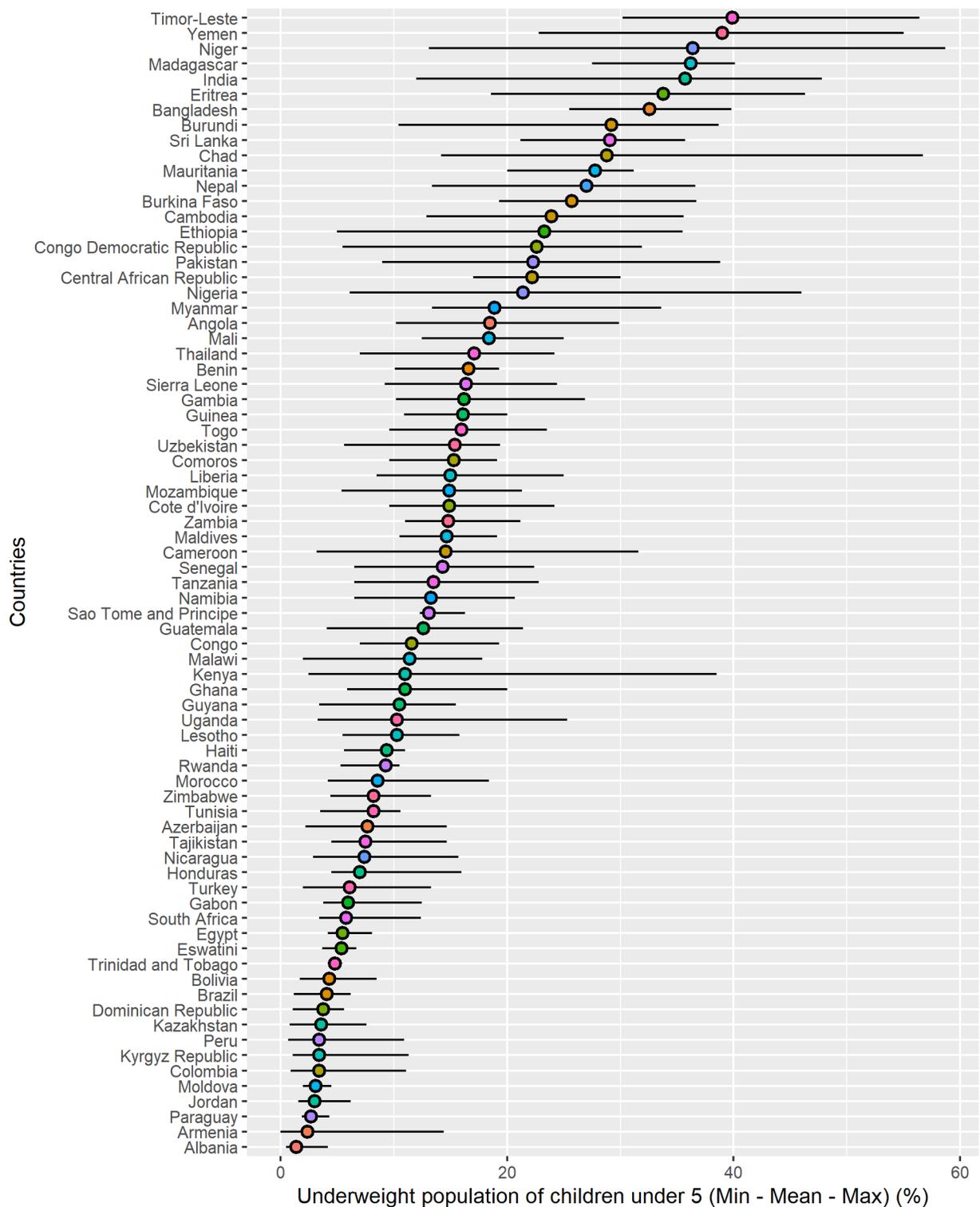


Figure 6: Within country disparities in the underweight rates (Source: DHS)

Multiple indicators

Stunting and wasting

Dominican Republic, Albania, Colombia, Jordan were in the bottom of stunting and wasting indicators (least prevalence), while Madagascar, Niger, Yemen, and Timor-Leste were at the top of stunting and wasting indicators (highest prevalence). Armenia, Albania, Jordan, and Moldova were at the bottom of stunting and underweight indicators (least prevalence). Madagascar, Niger, Yemen, and Timor-Leste were again at the top of stunting and underweight indicators (highest prevalence).

Stunting and underweight

Armenia, Albania, Jordan, and Moldova were at the bottom of stunting and underweight indicators (least prevalence). Madagascar, Niger, Yemen, and Timor-Leste were again at the top of stunting and underweight indicators (highest prevalence).

Wasting and underweight

Paraguay, Albania, Peru, and Colombia were at the bottom of wasting and underweight indicators (least prevalence), while India, Niger, Yemen, and Timor-Leste were again at the top of wasting, and underweight indicators (highest prevalence).

Stunting, wasting, and underweight.

When we consider all three malnutrition measures, Albania, Jordan, Colombia, and the Dominican Republic were at the bottom of three indicators (least prevalence), while Madagascar, Niger, Yemen, and Timor-Leste were at the top of all three indicators (highest prevalence).

Local spatial association

the results of Local Indicators of Spatial Association (LISA) for three indicators of malnutrition are given in the Figures 7-9. The LISA maps, alternatively called the thematic maps, are explained based on the following rubric:

The high-high category (called hotspots) indicated in red colour in the legend indicates the areas with spatial clustering of high indicator values, that is, the areas with high stunting rates for example, are surrounded by the areas with high stunting rates. This category shows a positive and significant spatial correlation, that is, the areas with high indicator values are surrounded by the areas with high indicator values.

The low-low category (called cold spots) indicated in green colour in the legend indicates areas with spatial clustering of low indicator values, areas with low stunting rates for example, are surrounded by areas of low stunting rates. This category shows a positive and significant spatial correlation, that is, the areas with low indicator values are surrounded by the areas with low indicator values.

The high-low category indicated in blue-collar in the legend indicates the spatial clustering of areas which have high indicator value, for example high stunting rates, are surrounded by the areas with low indicator values. This category shows a negative and significant spatial correlation, that is, the areas with high indicator values are surrounded by the areas with low indicator values.

The low-high category indicated in pink colour in the legend indicates the spatial clustering of areas which have low indicator value, for example high stunting rates, are surrounded by the areas with high indicator values. This category shows a negative and

significant spatial correlation, that is, the areas with low indicator values are surrounded by the areas with high indicator values.

The insignificant category which is indicated in white colour in the legend shows that there is no systematic pattern in the high low indicator values. This category does not show a significant spatial correlation.

The LISA maps are of significant policy -related value because they make the identification of the hotspots and cold spots easier. Additionally, the outliers, alternatively called low high and high low categories are of immense policy related value because they indicate disparities in the individual indicator of malnutrition. Sometimes the LISA maps may show disconnected from the prevalence maps, that is, the high prevalence rate in the prevalence map (Figures 1, 3, 5) may not be reflected in the LISA map. This is because the continuous data in the prevalence map is categorised in the LISA map. So it is possible that some high-value in the prevalence map does not show up as a hotspot in the LISA map because that area is not surrounded by a significant number of other areas with high indicator value.

Individual indicators

Stunting

The stunting hotspots in the sample are Bangladesh and India in South Asia, Cambodia in East Asia and Pacific, Guatemala in Latin America and the Caribbean, Yemen in the MENA region and Angola, Benin, Chad, Congo, Eritrea, Madagascar, Malawi, Mozambique, Niger, Tanzania, CAR, Ethiopia, and Rwanda in Sub-Saharan Africa (Figure 7). The stunting cold spots are Albania, Armenia, Kazakhstan, Kyrgyz Republic, and Moldova in Europe and Central Asia, Brazil, Colombia, Dominican Republic, Haiti, Nicaragua, Paraguay, Peru and Guyana in Latin

America and the Caribbean, Egypt and Jordan in MENA region and Cote d'Ivoire and Senegal in Sub-Saharan Africa.

Colombia, Guyana, Turkey, and Uzbekistan high-low outliers which means that these countries have low prevalence, but they are surrounded by high-prevalence regions. Nepal, Nigeria, Pakistan, and Yemen are low-high outliers, suggesting that these countries have low stunting prevalence, but they are surrounded by high-prevalence countries.

Wasting

Wasting hotspots are Bangladesh and India in South Asia, Benin, Burkina Faso, Chad, Eritrea, Ethiopia, Madagascar, Mali, Mauritania, Nigeria, Senegal and Niger in Sub-Saharan Africa and Yemen in MENA region (Figure 8). Wasting cold spots are Kazakhstan and Kyrgyz Republic in Europe and Central Asia, Peru, Bolivia, Brazil, Colombia, Dominican Republic, Guatemala, Guyana, Haiti, Nicaragua and Paraguay in Latin America and the Caribbean. Other wasting cold spots are Jordan in MENA, Sri Lanka in South Asia, and Cameroon, Congo, Gabon, Lesotho, Mozambique, Rwanda, Sao Tome and Principe, South Africa, and Swaziland in Sub-Saharan Africa.

Nepal is the only low-high outlier.

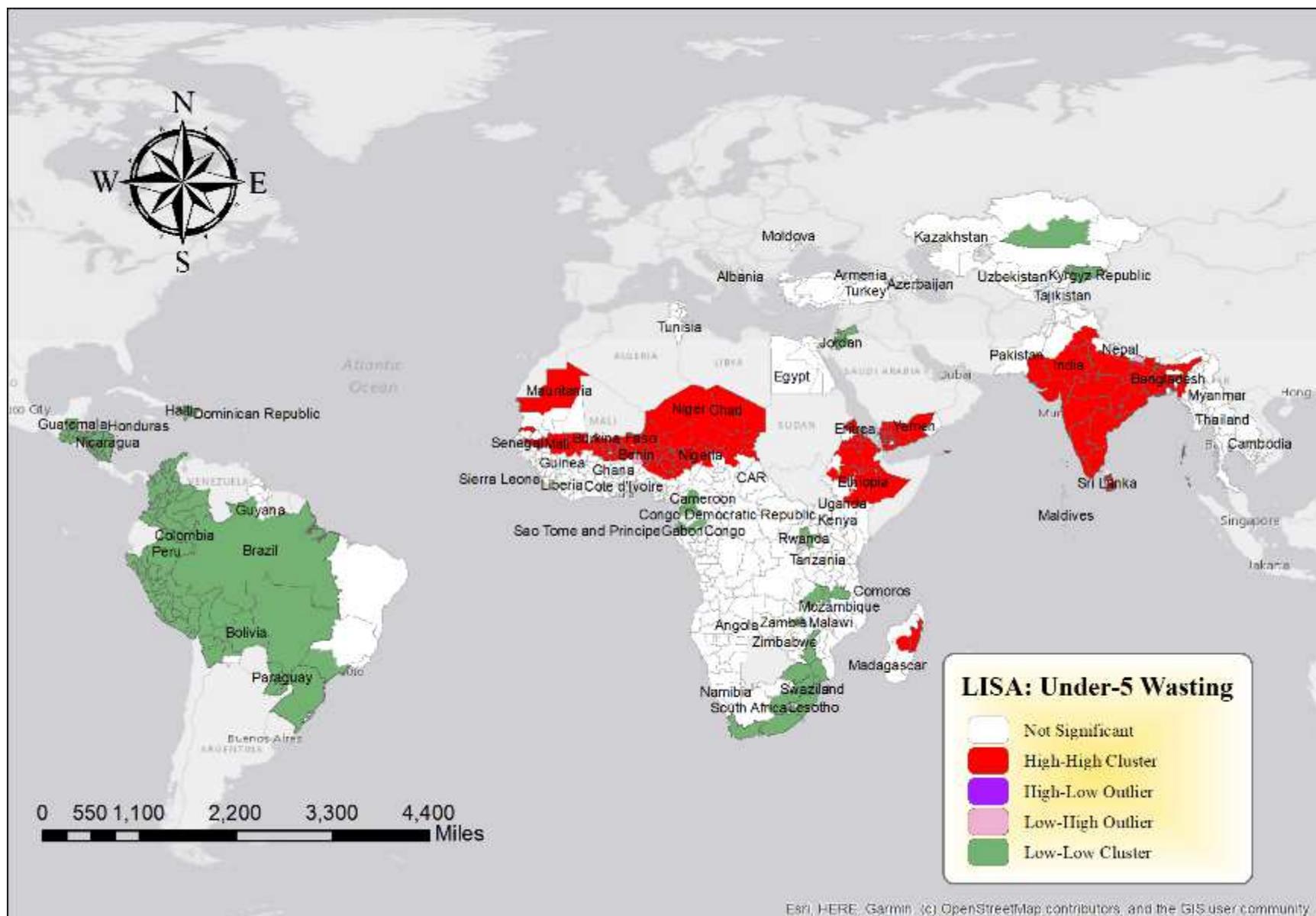


Figure 8: Local Indicators of Spatial Association (LISA): Wasting (Source: DHS)

Underweight

Underweight hotspots are Bangladesh, India, and Sri Lanka in South Asia, Benin, Burkina Faso, Chad, Eritrea, Madagascar, Mali, Mauritania, Niger, Nigeria, CAR and Ethiopia in Sub-Saharan Africa, Cambodia in East Asia and Pacific and Yemen in MENA region (Figure 9). Underweight cold spots are Kazakhstan, the Kyrgyz Republic in Europe and Central Asia, Peru, Bolivia, Brazil, Colombia, Dominican Republic, Guatemala, Guyana, Haiti, Nicaragua, and Paraguay in Latin America and the Caribbean, and Jordan in MENA region and Sri Lanka in South Asia. Other underweight cold spots are Cameroon, Congo, Gabon, Lesotho, Mozambique, Rwanda, Sao Tome and Principe, South Africa, and Swaziland.

Uzbekistan is the only high-low outlier, and Pakistan is the only low-high outlier in underweight indicator.

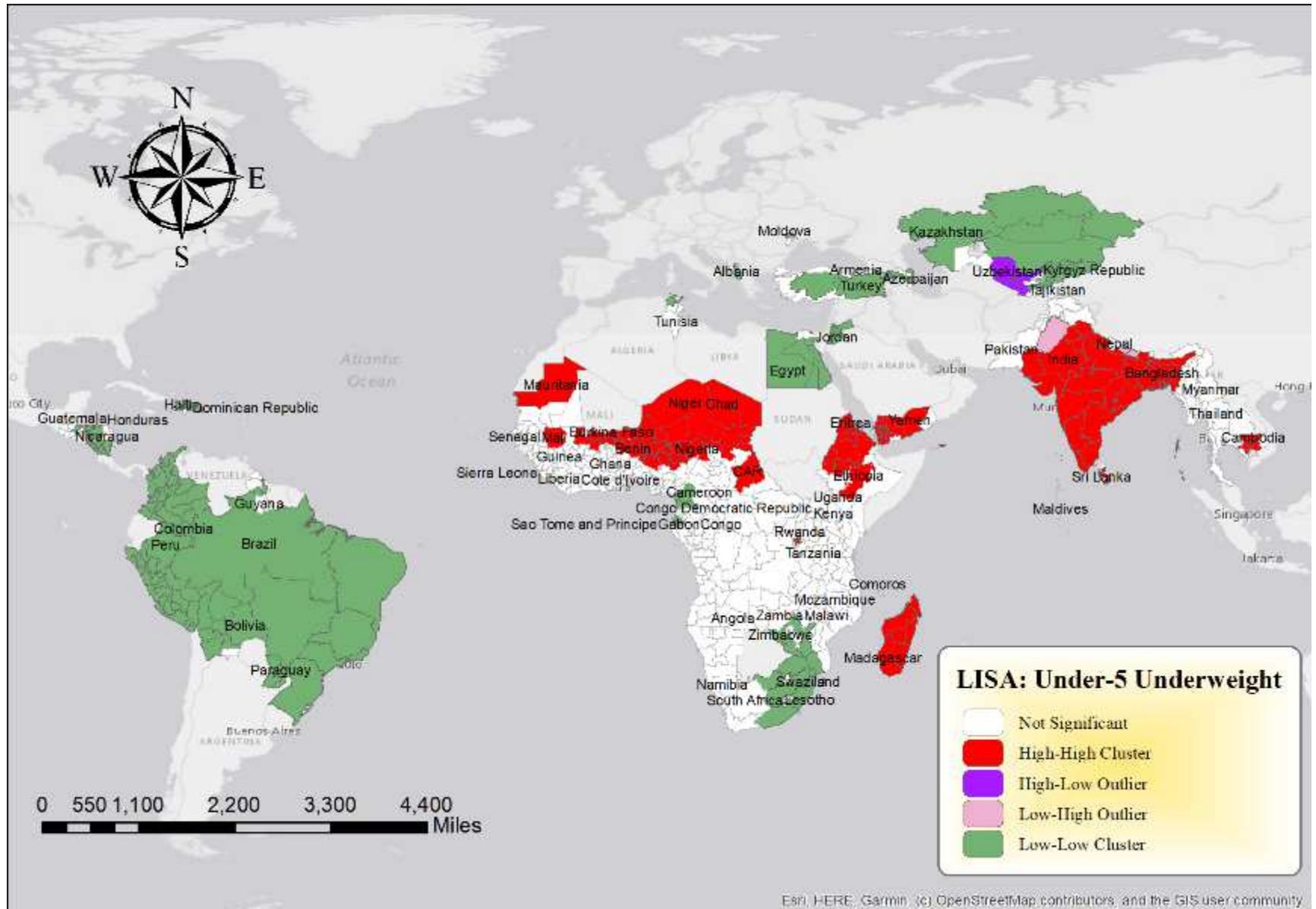


Figure 9: Local Indicators of Spatial Association (LISA): Underweight (Source: DHS)

*Multiple indicators**Hotspots (high-high clusters)*

Some countries are more consistently concentrated in one LISA clustering category across multiple indicators. For example, Bangladesh and India in South Asia, Benin, Chad, Eritrea, Madagascar in Sub-Saharan Africa, and Yemen in the MENA region are hotspots of stunting and wasting. Bangladesh, India in South Asia, Cambodia in East Asia and Pacific, Central African Republic, Chad, Eritrea, Ethiopia, Madagascar and Niger in sub-Saharan Africa and Yemen in the MENA region are hotspots of stunting and underweight. Bangladesh and India in South Asia, Benin, Burkina Faso, Chad, Eritrea, Madagascar, Mali, Mauritania, and Nigeria in Sub-Saharan Africa and Yemen in the MENA region are hotspots of wasting and underweight. Finally, Bangladesh and India in South Asia, Benin, Chad, Eritrea and Madagascar in Sub-Saharan Africa and Yemen in the MENA region are stunting, wasting, and underweight hotspots.

Cold spots (low-low clusters)

Brazil, Colombia, Dominican Republic, Haiti, Nicaragua, Paraguay and Peru in Latin America and Caribbean region, Jordan in MENA region and Kazakhstan and the Kyrgyz Republic in Europe and Central Asia are stunting and wasting cold spots. Armenia, Kazakhstan and the Kyrgyz Republic in Europe and Central Asia, Brazil, Colombia, Dominican Republic, Haiti, Nicaragua, Paraguay and Peru in Latin America and the Caribbean and Egypt and Jordan in MENA region are stunting and underweight cold spots. Peru, Bolivia, Brazil, Colombia, Dominican Republic, Guyana, Haiti, Nicaragua, Paraguay in Latin America and Caribbean, Cameroon, Congo, Gabon, Lesotho, and Swaziland in Sub-Saharan Africa, Jordan in MENA region, and Kazakhstan, Kyrgyz in Europe and Central Asia are wasting and underweight cold

spots of the world. Finally, Brazil, Colombia, Dominican Republic, Haiti, Nicaragua, Paraguay and Peru in Latin America and the Caribbean, Jordan in MENA and Kazakhstan and the Kyrgyz Republic in Europe and Central Asia region are global cold spots of stunting, wasting and underweight.

Outliers

Uzbekistan is the high-low outlier in stunting and underweight indicators. Nepal is the low-high outlier in stunting and wasting indicators, and Pakistan is the low-high indicator of stunting and underweight indicators.

Global spatial association

Significant positive global spatial autocorrelation exists across the study area, suggesting that adjacent countries in our analysis have similar stunting rates (Global Moran's I : 0.72, p -value <0.01) (Table 3). The probability distribution of the Global Moran's I is given in Figure 10.

Similarly, a significant positive global spatial autocorrelation exists across the study area, suggesting that adjacent countries in our analysis have similar wasting rates (Global Moran's I : 0.71, p -value <0.01) and underweight rates (Global Moran's I : 0.78, p -value <0.01).

Table 3: Global spatial autocorrelation (Global Moran's I)

	Global Moran's I	Z-Score	P
Stunting	0.721525	29.291339	0.000
Wasting	0.712945	28.998321	0.000
Underweight	0.782262	31.77604	0.000

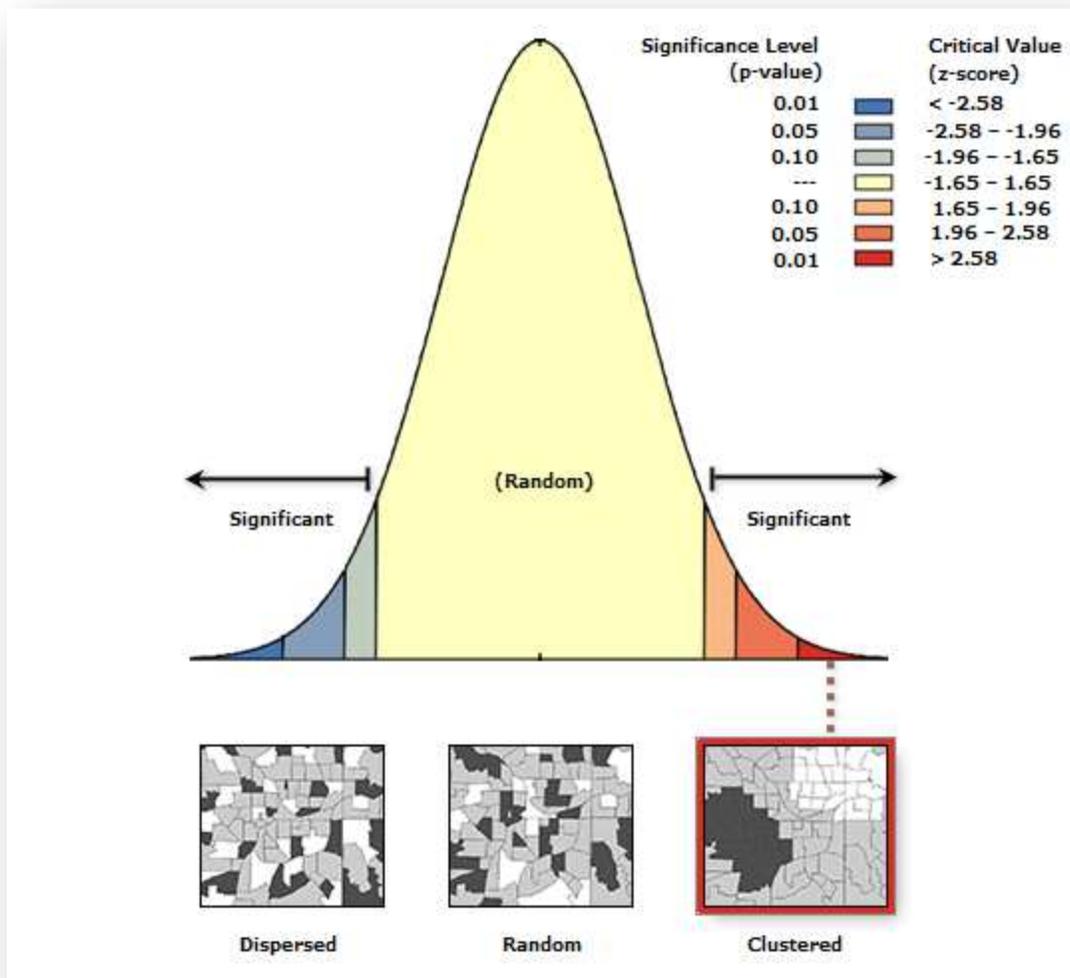


Figure 10: Probability distribution of the Global Moran's I (stunting, wasting, and underweight)

Discussion

The geospatial distribution of three indicators of under-five child malnutrition were analysed in this study. We found a significant within and across country variation in stunting wasting and underweight rates among under five children's population. The geospatial analysis also suggested that stunting wasting, and underweight patterns show clear regional patterns.

The stunting, wasting and underweight hotspots in the sample were mostly in in South Asia and Sub-Saharan Africa. The stunting, wasting and underweight cold spots were mostly concentrated in Europe and Central Asia and Latin America and the Caribbean.

Some countries are more consistently concentrated in one LISA clustering category across multiple indicators. Bangladesh and India in South Asia, Benin, Chad, Eritrea and Madagascar in Sub-Saharan Africa and Yemen in the MENA region are stunting, wasting, and underweight hotspots. Brazil, Colombia, Dominican Republic, Haiti, Nicaragua, Paraguay and Peru in Latin America and the Caribbean, Jordan in MENA and Kazakhstan and the Kyrgyz Republic in Europe and Central Asia region are global cold spots of stunting, wasting and underweight.

An analysis of the spatial distribution of key health indicators helps identify the patterns of malnutrition in addition to identifying the areas where the prevalence of malnutrition is extraordinarily high. The geospatial analysis also identifies the areas with extreme inequalities. A cross-country geospatial analysis helps the policymakers to tailor coordinated policies for better results. Reducing the health-related inequalities is an essential component of sustainable development goals, SDGs. While it is extremely important to identify the determinants of child malnutrition, the geographic location has not been analyzed as a correlate of child malnutrition quite often.

Health inequalities can be observed by the patterns of health outcomes ([Lee et al., 2011](#); [Whitehead, 1991](#)). Sometimes health inequality is analyzed as a function of wealth status ([Barros et al., 2012](#); [Gwatkin et al., 2007](#)). However, large cross-country clusters of malnutrition indicators may reflect similar life circumstances. Cultures often transcend national boundaries. Historically, many homogenous ethnic groups were divided into independent nation-states at the end of the colonial system. Consequently, population groups in the neighbouring areas share many cultural traits, even though they are located in different independent countries ([Michalopoulos & Papaioannou, 2016](#)). Since child malnutrition indicators, such as stunting wasting underweight are both a function of food intake and genetic and hereditary characteristics, it is entirely plausible to see similar patterns within and across countries.

The hotspots and cold spots dominate the malnutrition patterns in the developing world, with very few outliers with high low clusters of low high clusters. However, the wide disparities in the child malnutrition within the countries may indicate the varying levels of quality and quantity of government health interventions, or the differential impact of the government interventions on different population subgroups.

Existing evidence shows that stunting is closely associated with culturally defined patterns of food consumption ([Kavle et al., 2015](#)). Early initiation of breastfeeding is extremely low in developing countries and a significant correlate of stunting and other types of malnutrition ([Muldiasman et al., 2018](#)). The balanced diet, with adequate intake of fruit and vegetables and poultry products, is not accessible for most people in developing countries. There has been a growing shift in the patterns of food consumption favouring readily available processed food ([Monteiro et al., 2013](#)). Food security is a critical issue in the developing world that is only exacerbated by the violent swings in the climatic patterns ([Hellin et al., 2012](#)). But the more

severe issue is the inequitable distribution of food and other productive resources, which subjects—some sections of society- into a vicious cycle of poverty ([Hasegawa et al., 2019](#)).

Developing countries generally have a low productive capacity, which barely leaves enough funds for productive investment ([Peter-Cookey & Janyam, 2017](#)). Consequently, they can hardly go beyond satisfying their basic needs. Since the per capita income is very little, the governments cannot raise sufficient revenue through taxes to put an industrial base, which generally jumpstarts the economy on a higher growth trajectory. Consequently, governments have little to adequately invest in the health and education sector to promote human capital. Such countries have to labour under enormous foreign debts. The aid and grants and official development assistance often come with strings attached. Therefore, there is not much space for manoeuvring for the governments in developing countries.

Maternal health also contributes in a significant way to the nutritional profile of the children ([Shinsugi et al., 2019](#)). Child marriage practices in the developing world are rife. Consequently, the child mothers are not adequately developed physically to feed their children. Additionally, the women in the developing world often have a loyal status within the household. They have limited autonomy in the decision-making related to the health and the health of the child. In some extreme examples, women are not allowed to venture out to receive medical care without the presence of male relative. They often are discriminated against, with respect to the distribution of food within the household. They often are denied their right to education. They often are subjected to domestic violence with profound health implications for themselves as well as their children. A combination of all these factors contributes to inadequate food intake, who adverse effects can transmit to the foetus, and the children leading to child malnutrition.

The average height of the mother is also a significant predictor of stunting ([Addo et al., 2013](#)). With an average maternal height in the developing countries significantly less than the average maternal height in the developed world, stunting can also be explained in terms of genetic characteristics.

A substantial disease burden in the developing countries can be attributed to the health conditions which have been generally addressed in the developed world. For example, malaria, which has been contained mainly in the developed world is a major killer in developing countries ([Dabaro et al., 2020](#)) Apart from that, the chronic diarrhoeal diseases, and other infectious diseases, some of which are avoidable through effective vaccination, also contribute to inaccessibility of balanced diet and in turn, leads to stunting. HIV AIDS in Africa poses a significant disease burden on the population ([Gona et al., 2020](#)). Similarly, South Asia also has a fragile public healthcare system, which cannot effectively satisfy a massive population size's health need. Therefore, the disease burden can translate into disastrous out-of-pocket investment in many households and lead to child malnutrition as a result ([Adeosun & Faboya, 2020](#)).

Conclusion

The geospatial distribution of three indicators of under-five child malnutrition were analysed in this study. We found a significant within and across country variation in stunting wasting and underweight rates among under five children's population. The geospatial analysis also suggested that stunting wasting, and underweight patterns show clear regional patterns.

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Some countries are more consistently concentrated in one LISA clustering category across multiple indicators. Bangladesh and India in South Asia, Benin, Chad, Eritrea and Madagascar in Sub-Saharan Africa and Yemen in the MENA region are stunting, wasting, and underweight hotspots. Brazil, Colombia, Dominican Republic, Haiti, Nicaragua, Paraguay and Peru in Latin America and the Caribbean, Jordan in MENA and Kazakhstan and the Kyrgyz Republic in Europe and Central Asia region are global cold spots of stunting, wasting and underweight.

Colombia, Guyana, Turkey, and Uzbekistan **high-low stunting** outliers which means that these countries have low prevalence, but they are surrounded by high-prevalence regions. Nepal, Nigeria, Pakistan, and Yemen are **low-high outliers**, suggesting that these countries have low stunting prevalence, but they are surrounded by high-prevalence countries. Nepal is the only **low-high wasting** outlier. Uzbekistan is the only underweight **high-low outlier**, and Pakistan is the only **low-high outlier** in underweight indicator.

Significant positive global spatial autocorrelation exists across the study area, suggesting that adjacent countries in our analysis have similar stunting rates.

There are wide inequalities within the countries. This makes the case for prioritisation of the population groups located in distant geographical areas from the centre. However, the bigger catch is that the geographical inequalities within countries areas are matched by cross-country homogeneity. We can see that the wide swathes of regions consisting of multiple countries are hotspots. For example, India and Bangladesh make up one of the largest hotspots of stunting wasting and underweight in the world. Similarly, wide swathes of land in sub-Saharan Africa also hotspots of stunting wasting and underweight. This situation indicates that even if national policies to combat child malnutrition are important, it is the regional policies that hold the key to the solution of the problem of child malnutrition.

As the situation stands now, many of the neighbouring countries in the developing world have regional conflicts, and therefore are coordinated strategy to fight child malnutrition at the regional basis seems extremely challenging. The decades long enmity between nuclear India and Pakistan is one such example of animosity among the neighbours. Similarly, many countries in sub-Saharan Africa have been the sworn enemies of their neighbours and have remained engaged in bloody conflicts. While the national policies have to address the within country nutritional inequalities, any global initiative to alleviate child malnutrition may need to keep the angularity is in the international relations into account for a successful policy intervention.

References

- Addo, O. Y., Stein, A. D., Fall, C. H., Gigante, D. P., Guntupalli, A. M., Horta, B. L., Kuzawa, C. W., Lee, N., Norris, S. A., & Prabhakaran, P. (2013). Maternal height and child growth patterns. *The Journal of pediatrics*, *163*(2), 549-554. e541.
- Adeosun, O. T., & Faboya, O. M. (2020). Health care expenditure and child mortality in Nigeria. *International Journal of Health Care Quality Assurance*.
- Akseer, N., Bhatti, Z., Mashal, T., Soofi, S., Moineddin, R., Black, R. E., & Bhutta, Z. A. (2018). Geospatial inequalities and determinants of nutritional status among women and children in Afghanistan: an observational study. *The Lancet Global Health*, *6*(4), e447-e459.
- Alemayehu Azeze, A., & Huang, W.-c. (2014). Maternal education, linkages and child nutrition in the long and short-run: Evidence from the Ethiopia Demographic and Health Surveys. *International Journal of African Development*, *1*(2), 3.
- Anik, A. I., Rahman, M. M., Rahman, M. M., Tareque, M. I., Khan, M. N., & Alam, M. M. (2019). Double burden of malnutrition at household level: A comparative study among Bangladesh, Nepal, Pakistan, and Myanmar. *PloS one*, *14*(8).
- Babones, S. J. (2008). Income inequality and population health: correlation and causality. *Social science & medicine*, *66*(7), 1614-1626.
- Bacigalupe, A., & Escolar-Pujolar, A. (2014). The impact of economic crises on social inequalities in health: what do we know so far? *International journal for equity in health*, *13*(1), 1-6.
- Barros, A. J., Ronsmans, C., Axelson, H., Loaiza, E., Bertoldi, A. D., França, G. V., Bryce, J., Boerma, J. T., & Victora, C. G. (2012). Equity in maternal, newborn, and child health interventions in Countdown to 2015: a retrospective review of survey data from 54 countries. *The Lancet*, *379*(9822), 1225-1233.
- Beckfield, J., Olafsdottir, S., & Bakhtiari, E. (2013). Health inequalities in global context. *American Behavioral Scientist*, *57*(8), 1014-1039.
- Blanford, J. I., Kumar, S., Luo, W., & MacEachren, A. M. (2012). It's a long, long walk: accessibility to hospitals, maternity and integrated health centers in Niger. *International journal of health geographics*, *11*(1), 24.
- Bourke, C. D., Berkley, J. A., & Prendergast, A. J. (2016). Immune dysfunction as a cause and consequence of malnutrition. *Trends in immunology*, *37*(6), 386-398.
- Burgert-Brucker, C. R., Yourkavitch, J., Assaf, S., & Delgado, S. (2015). Geographic variation in key indicators of maternal and child health across 27 countries in sub-Saharan Africa.
- Coburn, D. (2004). Beyond the income inequality hypothesis: class, neo-liberalism, and health inequalities. *Social science & medicine*, *58*(1), 41-56.
- Cutler, D., Deaton, A., & Lleras-Muney, A. (2006). The determinants of mortality. *Journal of economic perspectives*, *20*(3), 97-120.
- Dabaro, D., Birhanu, Z., & Yewhalaw, D. (2020). Analysis of trends of malaria from 2010 to 2017 in Boricha District, Southern Ethiopia. *Malaria Journal*, *19*(1), 1-10.
- Ebener, S., Guerra-Arias, M., Campbell, J., Tatem, A. J., Moran, A. C., Johnson, F. A., Fogstad, H., Stenberg, K., Neal, S., & Bailey, P. (2015). The geography of maternal and newborn health: the state of the art. *International journal of health geographics*, *14*(1), 19.
- Goates, S., Du, K., Braunschweig, C. A., & Arensberg, M. B. (2016). Economic burden of disease-associated malnutrition at the state level. *PloS one*, *11*(9), e0161833.
- Goesling, B. (2007). The rising significance of education for health? *Social Forces*, *85*(4), 1621-1644.

- Gona, P. N., Gona, C. M., Ballout, S., Rao, S. R., Kimokoti, R., Mapoma, C. C., & Mokdad, A. H. (2020). Burden and changes in HIV/AIDS morbidity and mortality in Southern Africa Development Community Countries, 1990–2017. *BMC public health*, *20*(1), 1-14.
- Gwatkin, D. R., Rutstein, S., Johnson, K., Suliman, E., Wagstaff, A., & Amouzou, A. (2007). Socio-economic differences in health, nutrition, and population within developing countries: an overview. *Socio-economic differences in health, nutrition, and population within developing countries: an overview*.
- Hasegawa, T., Havlík, P., Frank, S., Palazzo, A., & Valin, H. (2019). Tackling food consumption inequality to fight hunger without pressuring the environment. *Nature Sustainability*, *2*(9), 826-833.
- Hellin, J., Shiferaw, B., Cairns, J. E., Reynolds, M., Ortiz-Monasterio, I., Bänziger, M., Sonder, K., & La Rovere, R. (2012). Climate change and food security in the developing world: Potential of maize and wheat research to expand options for adaptation and mitigation. *Journal of Development and Agricultural Economics*.
- Ibrahim, M. K., Zambruni, M., Melby, C. L., & Melby, P. C. (2017). Impact of childhood malnutrition on host defense and infection. *Clinical microbiology reviews*, *30*(4), 919-971.
- Kandala, N.-B., Madungu, T. P., Emina, J. B., Nzita, K. P., & Cappuccio, F. P. (2011). Malnutrition among children under the age of five in the Democratic Republic of Congo (DRC): does geographic location matter? *BMC public health*, *11*(1), 261.
- Kavle, J. A., El-Zanaty, F., Landry, M., & Galloway, R. (2015). The rise in stunting in relation to avian influenza and food consumption patterns in Lower Egypt in comparison to Upper Egypt: results from 2005 and 2008 Demographic and Health Surveys. *BMC public health*, *15*(1), 285.
- Khan, S., Zaheer, S., & Safdar, N. F. (2019). Determinants of stunting, underweight and wasting among children < 5 years of age: evidence from 2012-2013 Pakistan demographic and health survey. *BMC public health*, *19*(1), 358.
- Laparra, M., Eransus, B. P., Lasheras, R., Gamundí, M. A. C., Guinea-Martín, D., Zugasti, N., Cañón, L. A., Virto, L. M., Sarasa, S., & García, Á. (2012). Crisis and social fracture in Europe. *Barcelona: Colección Estudios Sociales*, *35*, 1-206.
- Lee, J. H., Sadana, R., & Health, C. o. S. D. o. (2011). *Improving equity in health by addressing social determinants*. World Health Organization.
- Michalopoulos, S., & Papaioannou, E. (2016). The long-run effects of the scramble for Africa. *American Economic Review*, *106*(7), 1802-1848.
- Miranda, V. I. A., Dal Pizzol, T. d. S., Silveira, M. P. T., Mengue, S. S., da Silveira, M. F., Lutz, B. H., & Bertoldi, A. D. (2019). The use of folic acid, iron salts and other vitamins by pregnant women in the 2015 Pelotas birth cohort: is there socio-economic inequality? *BMC public health*, *19*(1), 889.
- Monteiro, C. A., Moubarac, J. C., Cannon, G., Ng, S. W., & Popkin, B. (2013). Ultra-processed products are becoming dominant in the global food system. *Obesity reviews*, *14*, 21-28.
- Moran, P. A. (1950). Notes on continuous stochastic phenomena. *Biometrika*, *37*(1/2), 17-23.
- Muldiasman, M., Kusharisupeni, K., Laksminingsih, E., & Besral, B. (2018). Can early initiation to breastfeeding prevent stunting in 6–59 months old children? *Journal of Health Research*.

- Organization, W. H. (2010). A conceptual framework for action on the social determinants of health: debates, policy and practice. *A conceptual framework for action on the social determinants of health: debates, policy and practice*.
- Organization, W. H. (2018). *The state of food security and nutrition in the world 2018: building climate resilience for food security and nutrition*. Food & Agriculture Org.
- Peter-Cookey, M. A., & Janyam, K. (2017). Reaping just what is sown: Low-skills and low-productivity of informal economy workers and the skill acquisition process in developing countries. *International Journal of Educational Development*, 56, 11-27.
- Pulok, M. H., Sabah, M. N.-U., & Enemark, U. (2016). Socio-economic inequalities of child malnutrition in Bangladesh. *International Journal of Social Economics*, 43(12), 1439-1459.
- Rashad, A. S., & Sharaf, M. F. (2018). Economic growth and child malnutrition in Egypt: new evidence from national demographic and health survey. *Social Indicators Research*, 135(2), 769-795.
- Reap, M., Pornwattanavate, S., Thame, C., & Van der Putten, M. (2020). The social determinants of health of the Urak Lawoi' of southern Thailand. *BMC public health*, 20(1), 1-14.
- Sen, A. (2000). Social justice and the distribution of income. *Handbook of income distribution*, 1, 59-85.
- Shinsugi, C., Gunasekara, D., Gunawardena, N., Subasinghe, W., Miyoshi, M., Kaneko, S., & Takimoto, H. (2019). Double burden of maternal and child malnutrition and socio-economic status in urban Sri Lanka. *PloS one*, 14(10), e0224222.
- Sinha, A., McRoy, R. G., Berkman, B., & Sutherland, M. (2017). Drivers of change: Examining the effects of gender equality on child nutrition. *Children and Youth Services Review*, 76, 203-212.
- Solar, O., & Irwin, A. (2010). *A conceptual framework for action on the social determinants of health*.
- Ssentongo, P., Ssentongo, A. E., Ba, D. M., Ericson, J. E., Na, M., Gao, X., Chinchilli, V. M., & Schiff, S. (2019). Pooled Analysis of Global, Regional and Country-Level Prevalence of Childhood Stunting, Wasting and Underweight in 62 Low-and Middle-Income Countries, 2006-2018. *Regional and Country-Level Prevalence of Childhood Stunting, Wasting and Underweight in*, 62, 2006-2018.
- Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic geography*, 46(sup1), 234-240.
- Whitehead, M. (1991). The concepts and principles of equity and health. *Health promotion international*, 6(3), 217-228.
- WHO, U., & Mathers, C. (2016). Global strategy for women's, children's and adolescents' health (2016-2030). *Organization*.
- Wilkinson, R. G. (2002). *Unhealthy societies: the afflictions of inequality*. Routledge.
- Woodward, A., & Kawachi, I. (2000). Why reduce health inequalities? *Journal of Epidemiology & Community Health*, 54(12), 923-929.
- Yourkavitch, J., Burgert-Brucker, C., Assaf, S., & Delgado, S. (2018). Using geographical analysis to identify child health inequality in sub-Saharan Africa. *PLoS One*, 13(8).

Figures

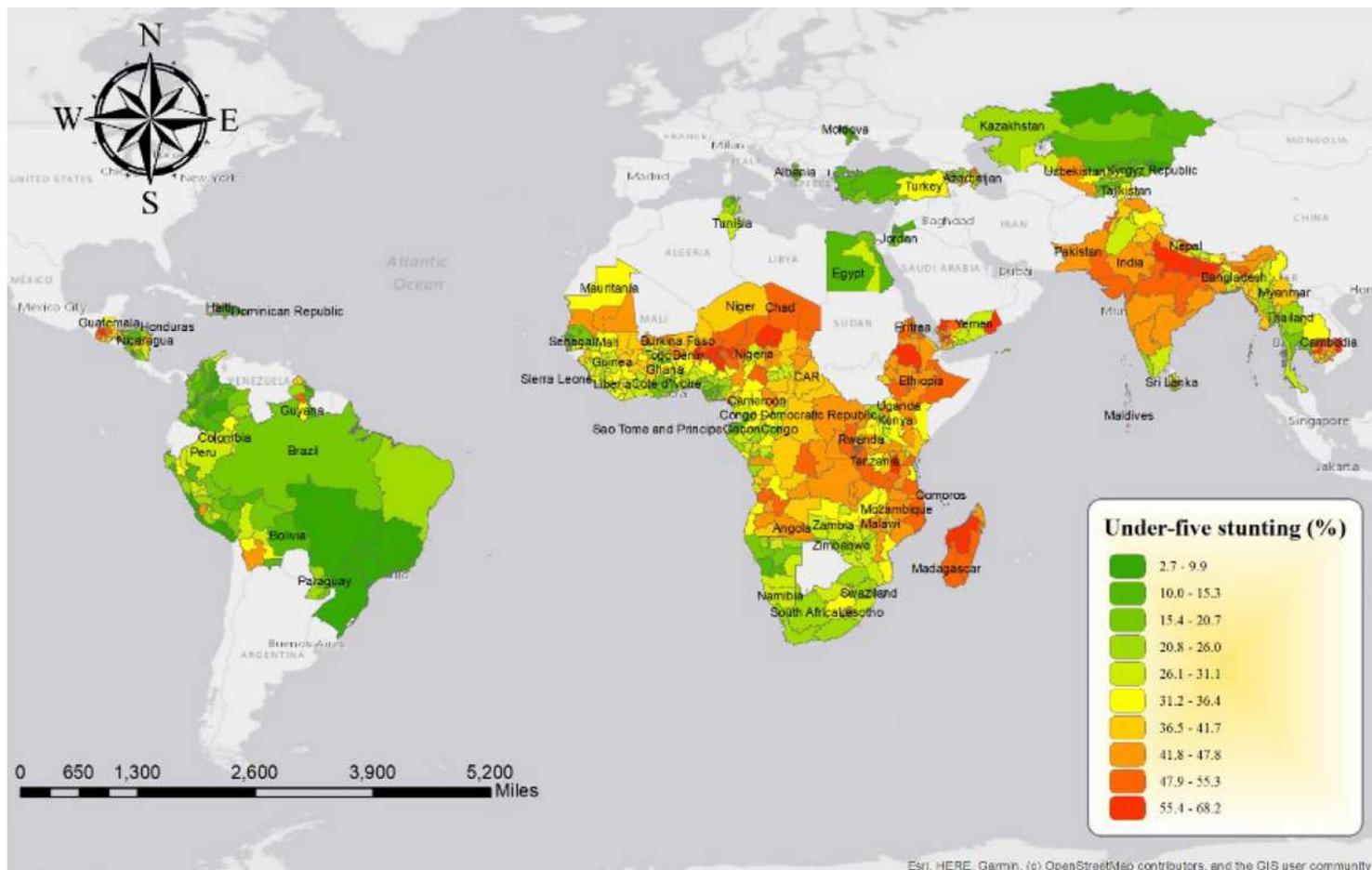


Figure 1

Stunting prevalence rates (Source: Demographic and Health Surveys). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

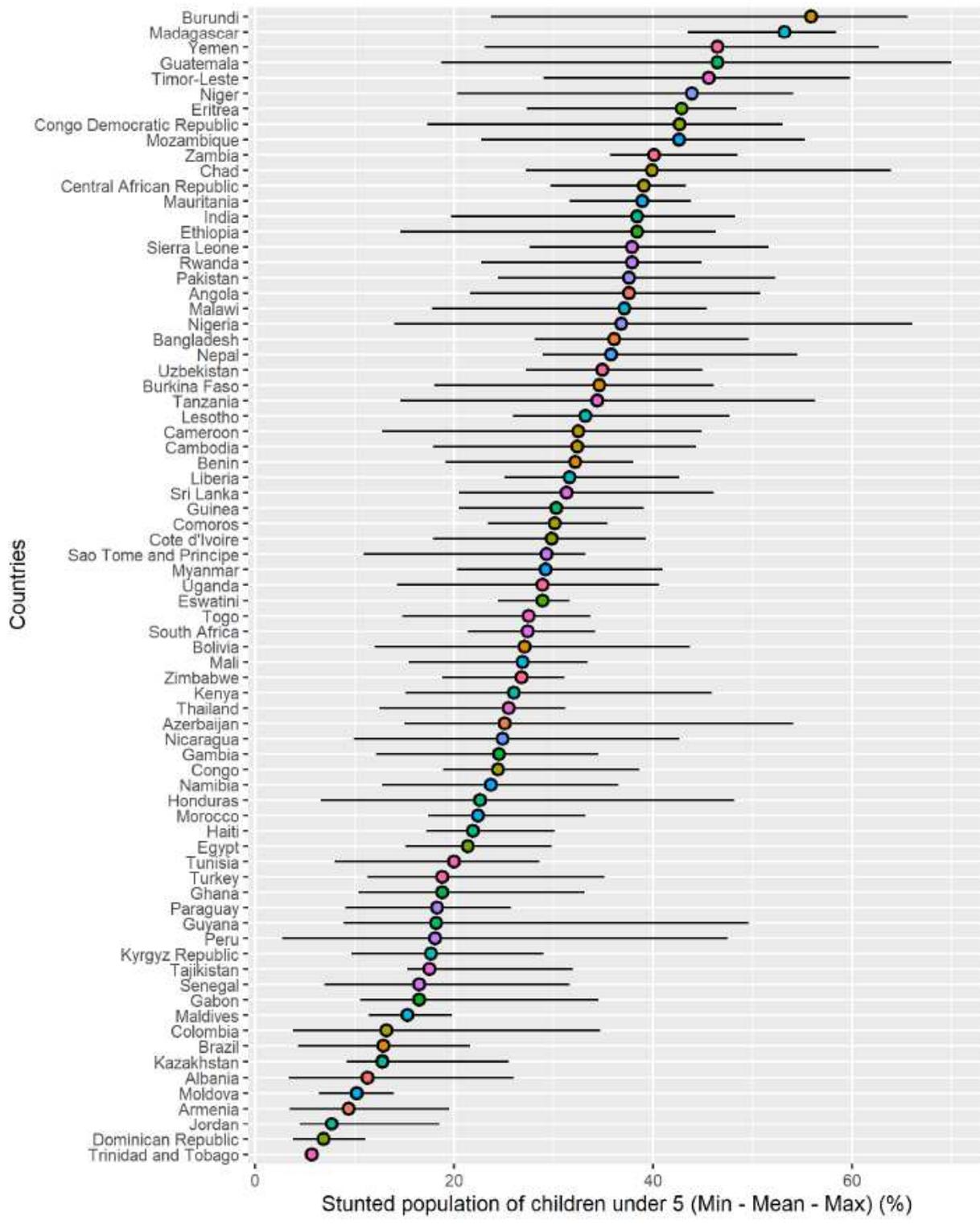


Figure 2

Within country disparities in the stunting rates (Source: DHS)

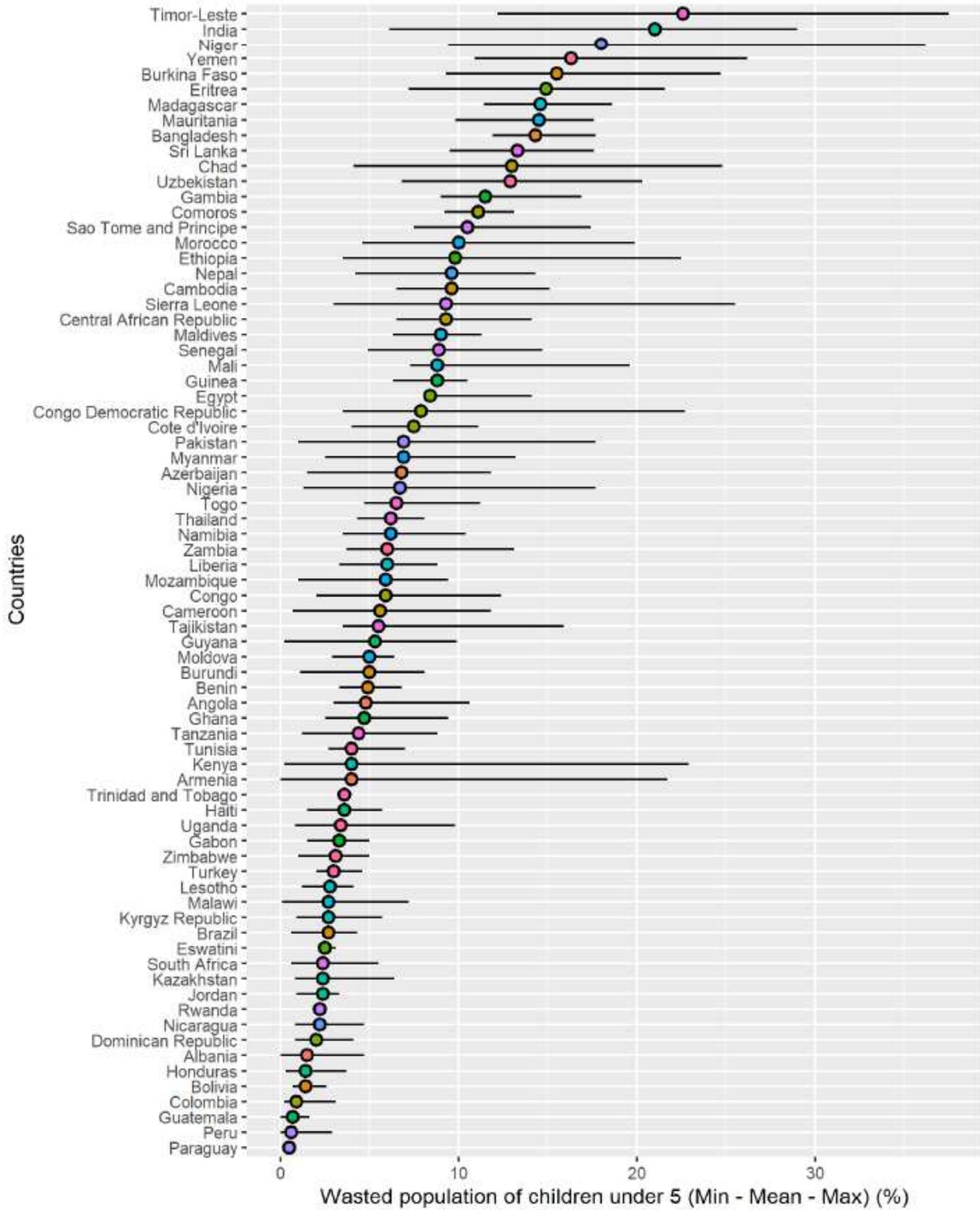


Figure 4

Within country disparities in the wasting rates (Source: DHS)

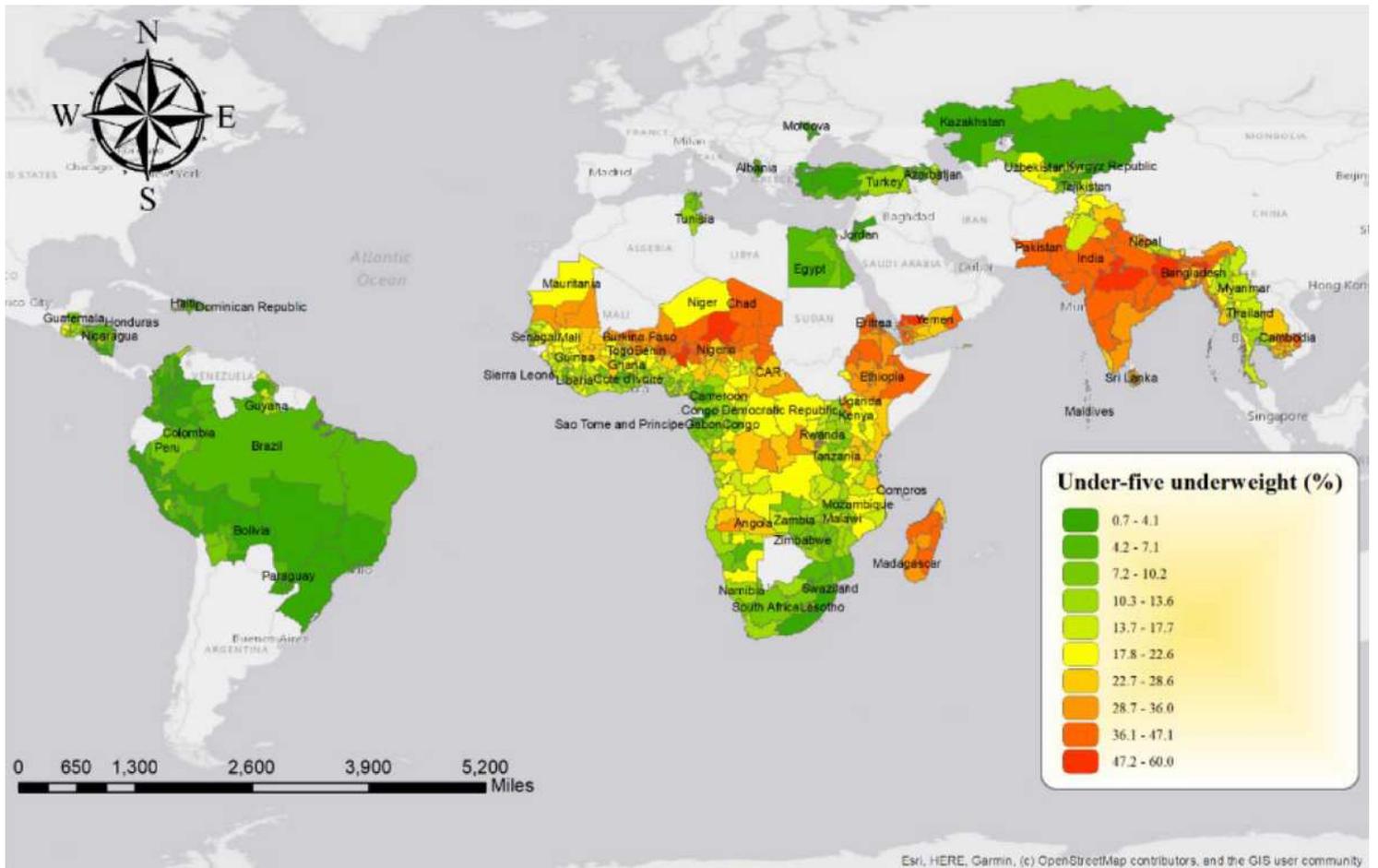


Figure 5

Underweight prevalence rates (Source: Demographic and Health Surveys). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

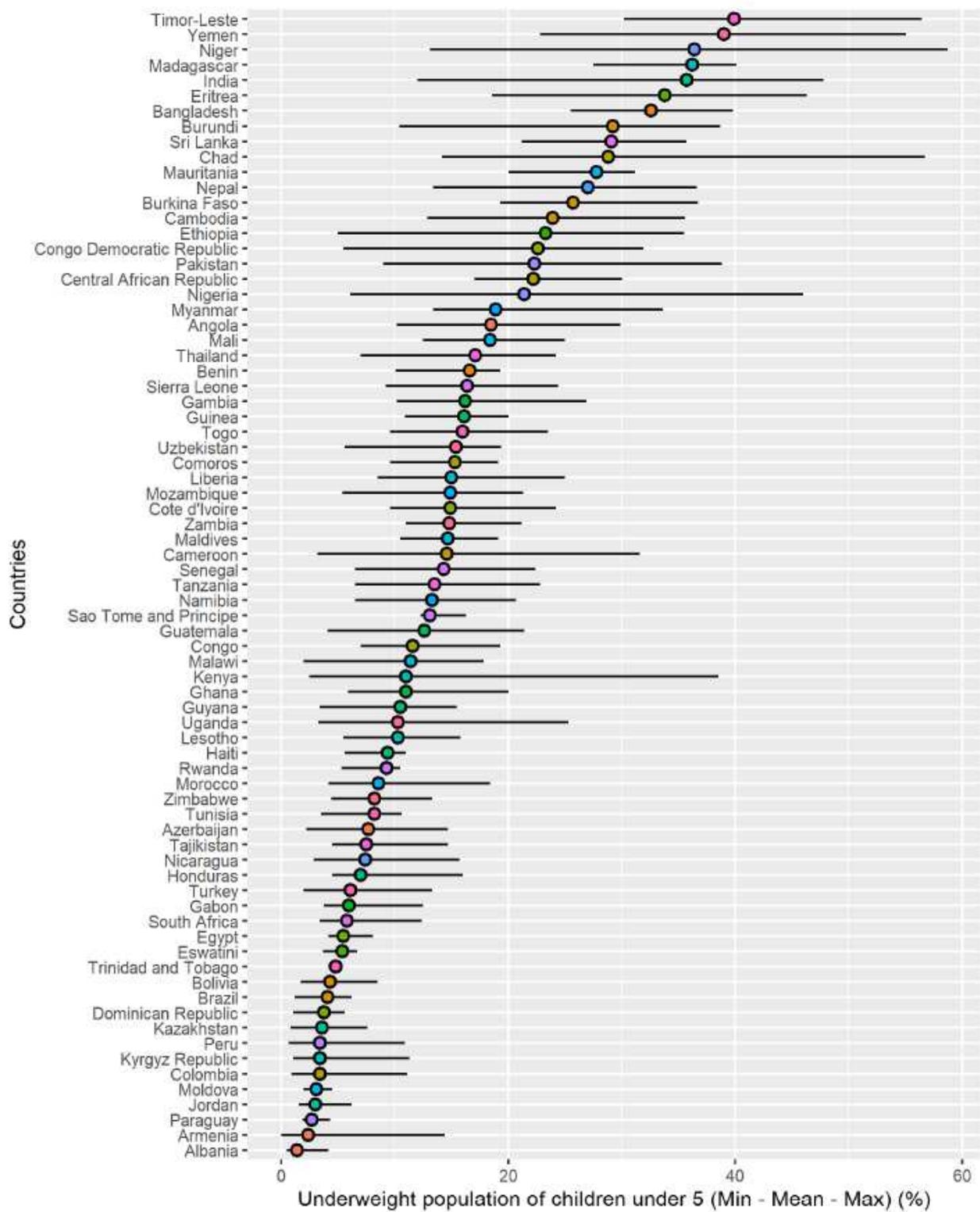


Figure 6

Within country disparities in the underweight rates (Source: DHS)

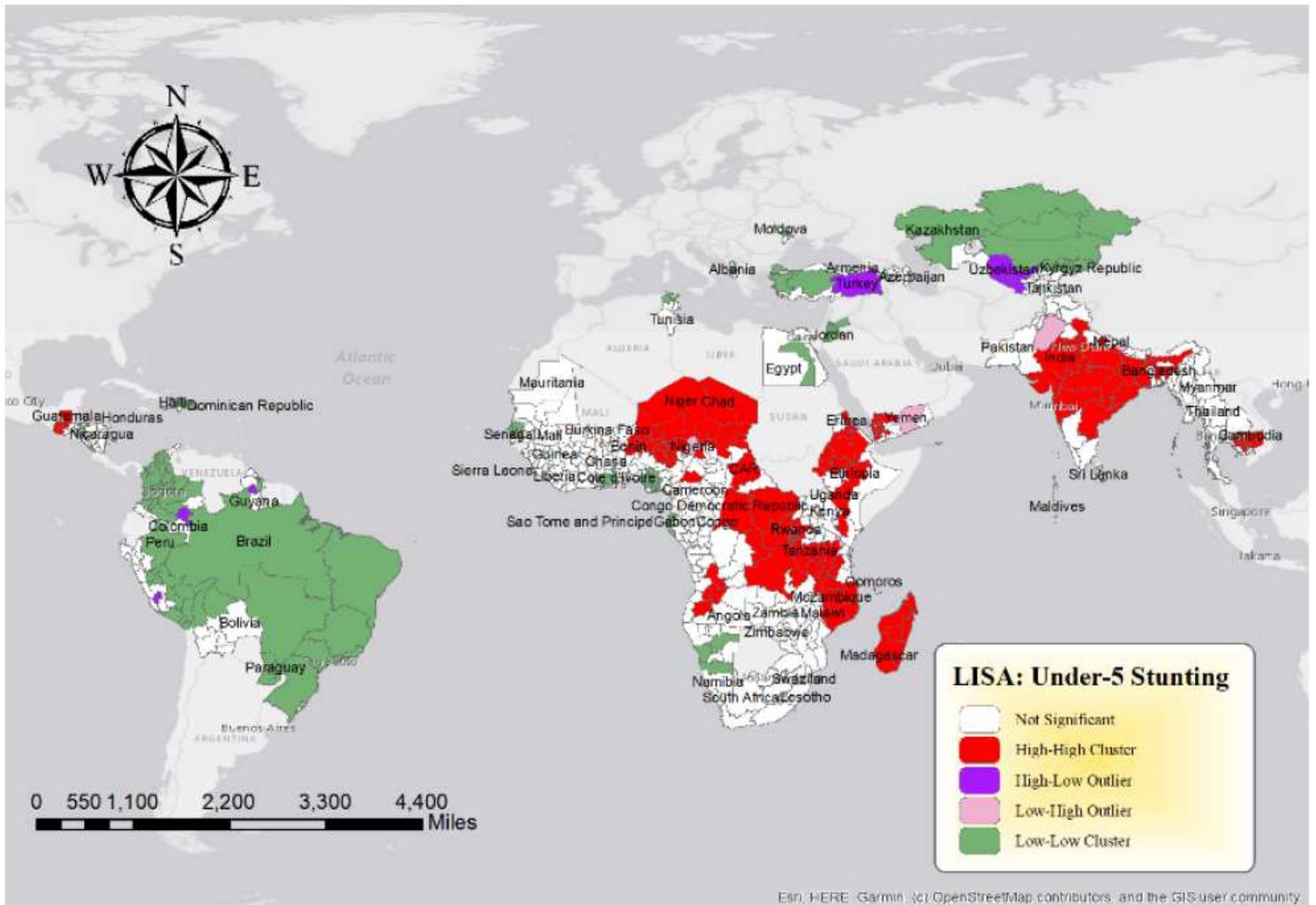


Figure 7

Local Indicators of Spatial Association (LISA): Stunting (Source: DHS). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

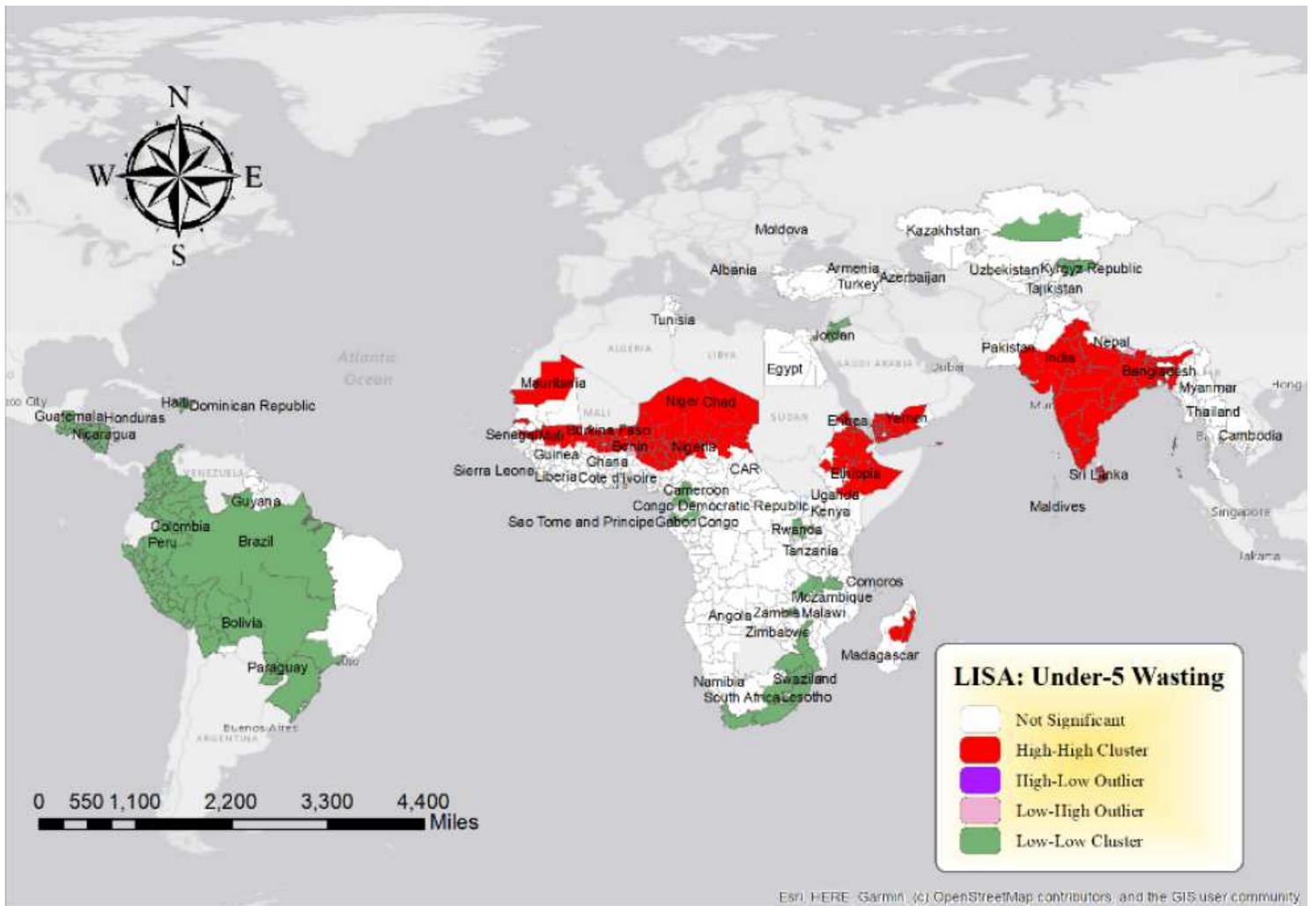


Figure 8

Local Indicators of Spatial Association (LISA): Wasting (Source: DHS). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

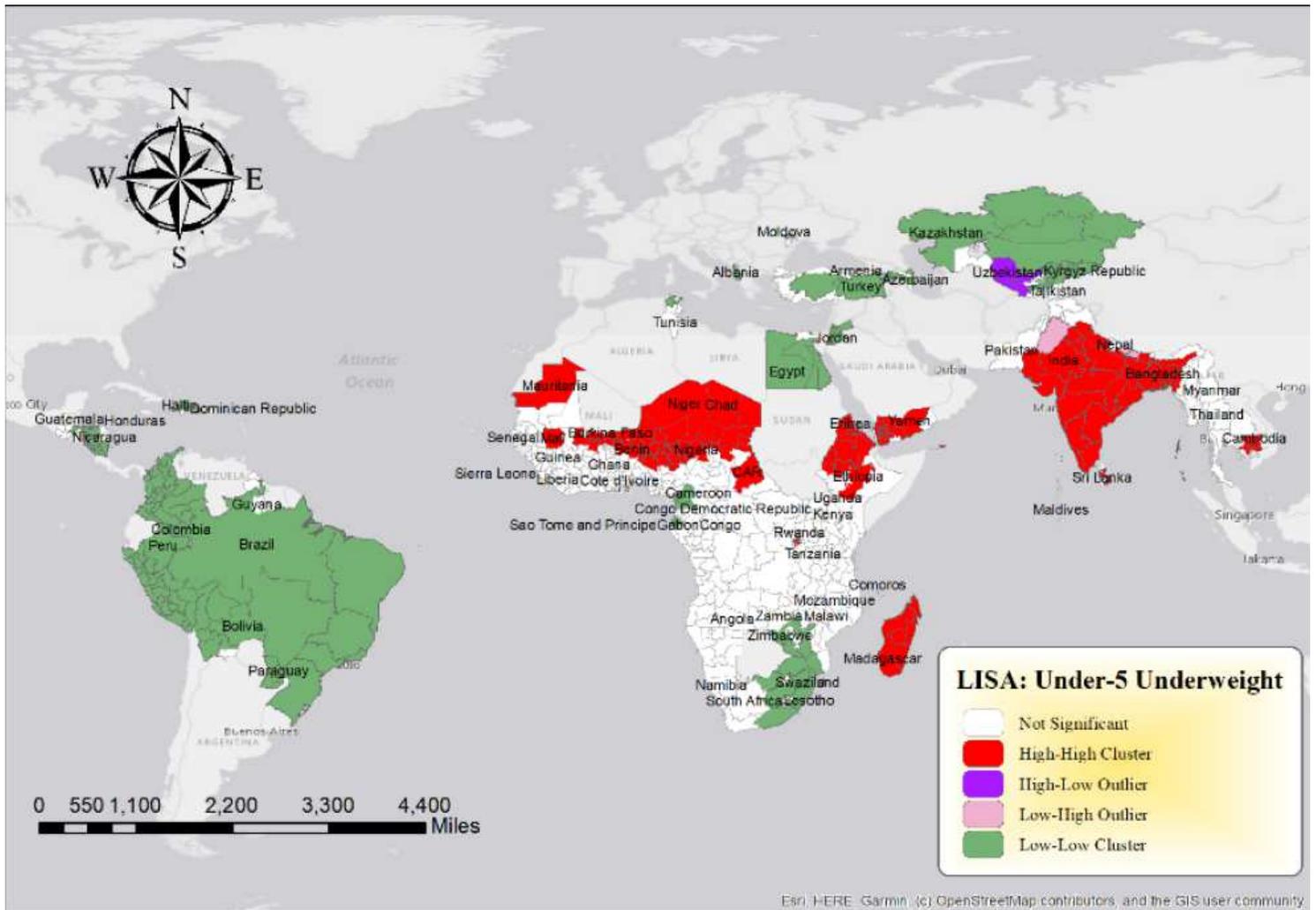


Figure 9

Local Indicators of Spatial Association (LISA): Underweight (Source: DHS. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

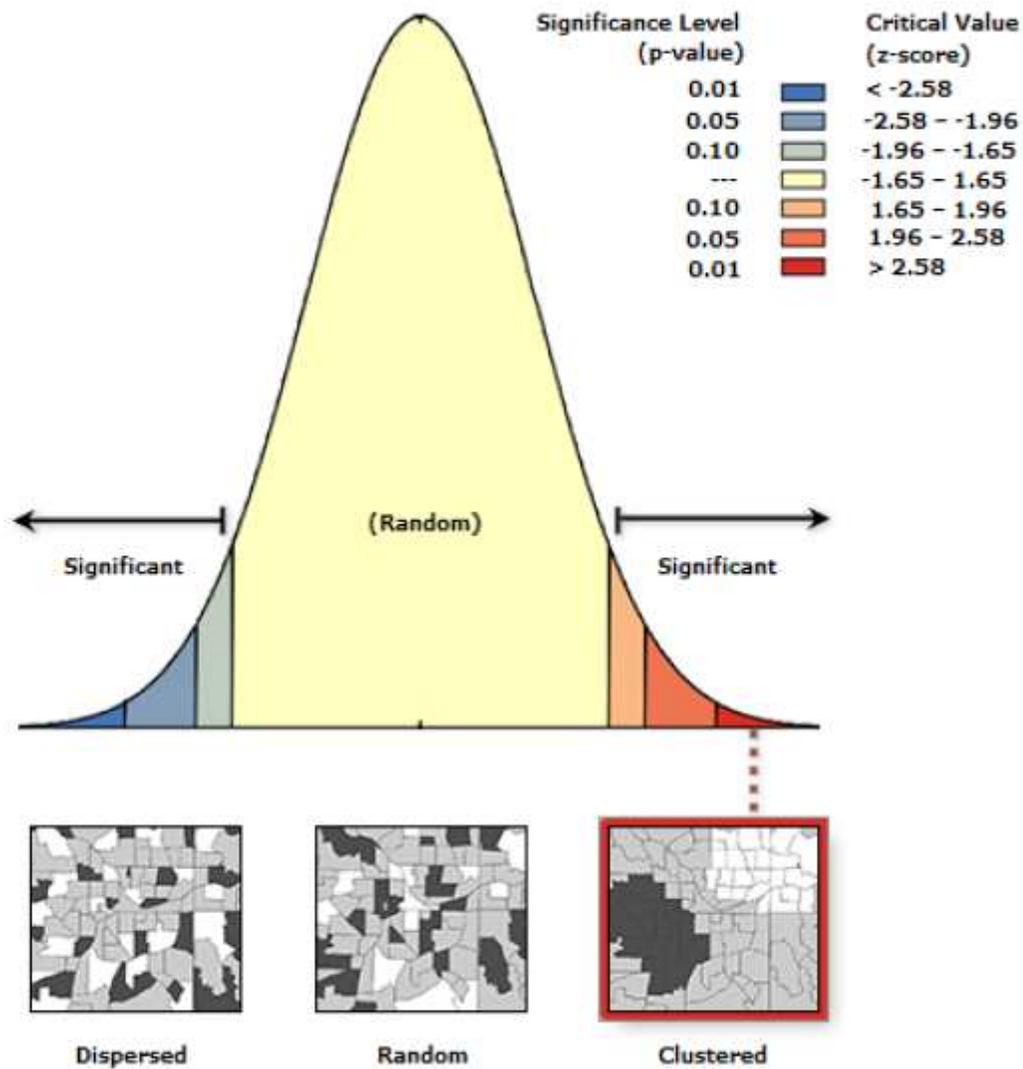


Figure 10

Probability distribution of the Global Moran's I (stunting, wasting, and underweight)

Supplementary Files

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- [Figure0.png](#)