The Republic of the Union of Myanmar

MAPPING MYANMAR'S NUTRITION IN 2015

A Small Area Estimation

MARCH 2020

The 2014 Myanmar Population and Housing Census

Department of Population
Ministry of Labour, Immigration
and Population

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FOREWORD

The Myanmar Sustainable Development Plan (MSDP) puts an emphasis on the needs to improve access to quality food and nutrition as part of the country's development goals. The MSDP further recommends the expansion of the universal cash allowance to all pregnant women and children as a core strategy to reach this goal. Implementation of such strategy requires quality statistics to inform the design, implementation, and monitoring of programs and reforms. Hence, it is important to have information at granular levels on where malnutrition is high with children being stunted or underweighted. Malnutrition has negative effects in the short term, limiting early-childhood development and learning outcomes, with longer term impacts through a reduced productivity.

This report presents estimates of malnutrition among children under 5 years old at the township level applying advanced econometric techniques, on two datasets: the 2015-16 Myanmar Demographic and Health Survey (DHS), and the 2014 Myanmar Population and Housing Census. The DHS is used to infer the predictive relationship between different variables and the malnutrition outcome indicators. The predictive relationship is then used to predict the malnutrition outcome indicators for the Census, for which malnutrition outcome indicators were not collected. Given the granularity of the Census data, it is therefore possible to derive estimates of malnutrition outcome indicators for smaller areas such as townships.

Estimates provided in this report represent the first ever small area estimations of malnutrition outcome indicators for Myanmar. This report shows that large variation in malnutrition status of children exists even between townships in the same state or region. Even within the better-off states and regions, there are townships who exhibit poor nutrition outcomes. This is a real game-changer in the targeting public resources and aid flows toward improving access to quality food and reducing malnutrition. With the available information, it will now be possible to identify those who need it the most, and to design better with interventions.

On behalf of the Government of Myanmar, I would like to give special thanks to the Department of Population for its leading role in the elaboration of this report. I also would like to thank the World Bank for the technical and financial assistance they provided to conduct this analysis. Likewise, I also extend my sincere thanks to the Department of Public Health for their collaboration and contribution to the report. I do believe that the findings of this report will be useful in making development policies for our country. I hope this report will be useful and beneficial not only to government departments but also to other stakeholders.

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EXECUTIVE SUMMARY

According to the Government of Myanmar, the World Bank, UNICEF, and other development partners, malnutrition represents one of Myanmar's direst health and development challenges. One out of three children below the age of 5 is stunted (DHS 2015-2016) and almost 316,000 suffer from acute malnutrition (wasting). Malnutrition has short and long-term impacts on child development, and ultimately will affect Myanmar's human capital accumulation.

To understand the severity and distribution of malnutrition, countries rely on cross-sectional surveys such as Demographic and Health Surveys (DHS), which often have limited granularity in term of coverage. Because of the cost involved, most cross-sectional surveys are designed to be representative at a high geographic level. Thus, in Myanmar, cross-sectional surveys are often designed to be representative at the state/region level.

The problem is that state/region level estimates can hide lot of disparities across townships. A more **granular geographic disaggregation can provide more evidence for the design of programs aimed at curbing malnutrition.** If made available, sub-national level estimates offer unparalleled opportunities to inform geographic targeting of social programs, which are especially critical in a context of limited resources.

The objective of this report is to estimate the prevalence of malnutrition among children under age 5 in Myanmar at the township level using small area estimation techniques. Small area estimation techniques rely primarily on two types of datasets: (i) a survey; and (ii) a census. The survey is used to find a statistical model that provides the predictive relationship between different variables and the outcome of interest. For malnutrition, these outcomes are stunting, wasting, or underweight indicators. The predictive variables are individual and household characteristics such as gender, age, education level, housing, and health and/or welfare of the children and their family members. When available, GIS information such as night light, temperature, precipitation, land coverage, and travel time to nearest city can be used to improve the predictive power of the statistical model. The model is then used to predict the outcome indicator for a larger dataset that did not assess this outcome, typically a census. It is therefore possible to derive estimates of the outcome indicator for smaller areas such as townships or districts.

The small area technique used in this study is based on the ELL method (Elbers, Lanjouw, and Lanjouw, 2003), which was developed for poverty and inequality estimation, and an extension of this method developed by Fujii (2010) specifically for nutrition. This report attempts to use these methodologies in order to create the first Nutrition Map for Myanmar. The estimation of stunting and underweight at the small area level was first calculated using the Povmap software developed by the World Bank, which uses the ELL methodology. Then, the methodology proposed by Fujii (2010) was implemented in order to acquire a more precise estimation for the nutrition indicators. The results indicate how using the Povmap software yields more optimistic estimates of precision than those associated with Fujii's method, though overall, both methods yield similar average estimates of stunting and underweight. It was not possible to include estimates for wasting because a regression model of weight-for-height with sufficient explanatory power could not be constructed (an empirical problem that is not limited to Myanmar).

The two main datasets used in this report are the 2014 Myanmar Population and Housing Census and the 2015/2016 Demographic and Health Survey for Myanmar. The latter collected anthropometric information for children below the age of 5, as well as other characteristics on individuals and their households. The Census did not collect information on the nutritional status of the population, but it gathered a wealth of information on individuals and their households. Estimations were done for the three main child nutrition anthropometric indices (stunting, underweight, and wasting). But only two passed robustness checks. The analysis in this report then focused on stunting and underweight.

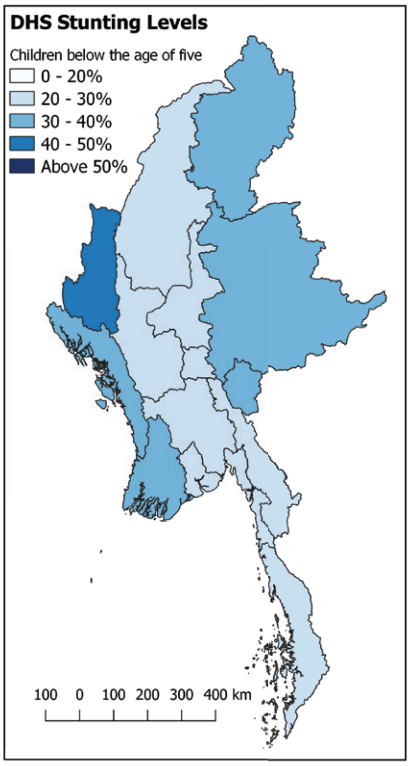
This report's most important contribution is, at last, a picture of malnutrition within different areas of the country, down to district and township levels. Since the two methodologies[1] provide the same overall picture and only differ in respect to the precision, the results used for this report are the ones calculated with Fujii's method, which presented less conservative estimates. ES Figure 1 displays the nutrition maps for stunting and underweight in Myanmar, which clearly show that stunting levels are relatively higher in the North-East area of the country, while underweight seems to be more critical in the West-Coastal area.

Large variation in the nutritional status of children exists even between townships in the same state or region. For instance, even within the better-off states/regions, there are townships that exhibit poor nutrition outcomes. The spatial difference across townships within the same state or region is illustrated in ES Figure 2. For instance, Yangon Region is a relatively better-off state, with 20.3 percent of children who are stunted. But four townships in Yangon Region have a stunting rate that is equal or higher than the national average, which is 29%. These are Hmawby, Htantabin, Taikkyi, and Thongwa with stunting rates between 29% and 31%. On the other hand, several townships in the city of Yangon have a very low stunting rate: Seikkan and Dagon townships, for example, have the lowest stunting rate in the country (5%). The same regional disparities do exist for all states/regions, consequently, it is important to build on small-area estimations to inform the design of programs to curb malnutrition in an efficient way.

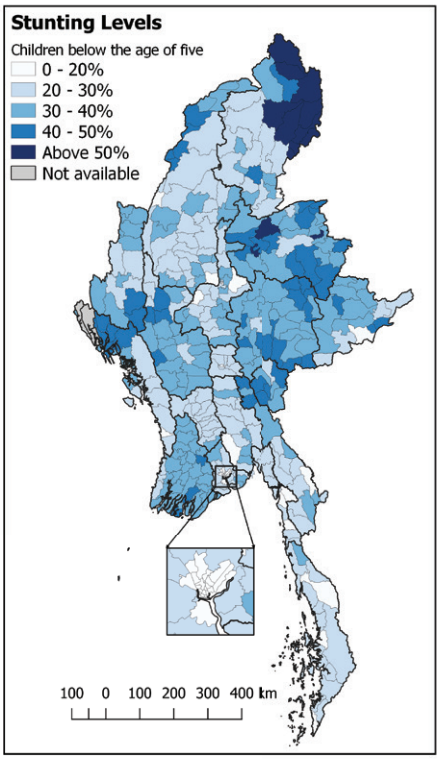
1 Elbers, Lanjouw, and Lanjouw (2003) and Fujii (2010).

ES Figure 1 | Nutrition outcomes at state/region and township-level

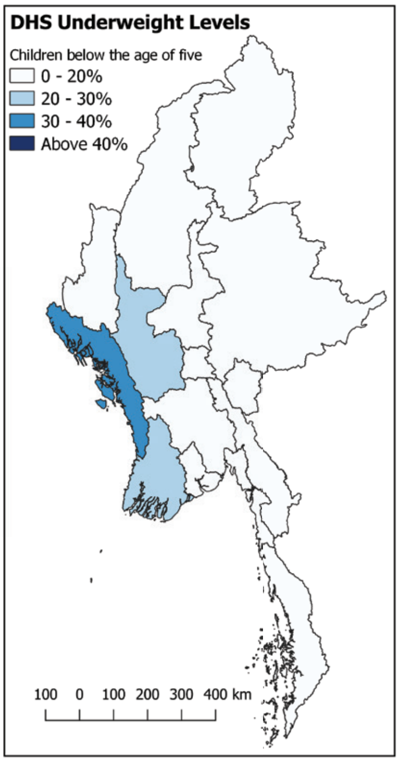
Stunting levels by state/region



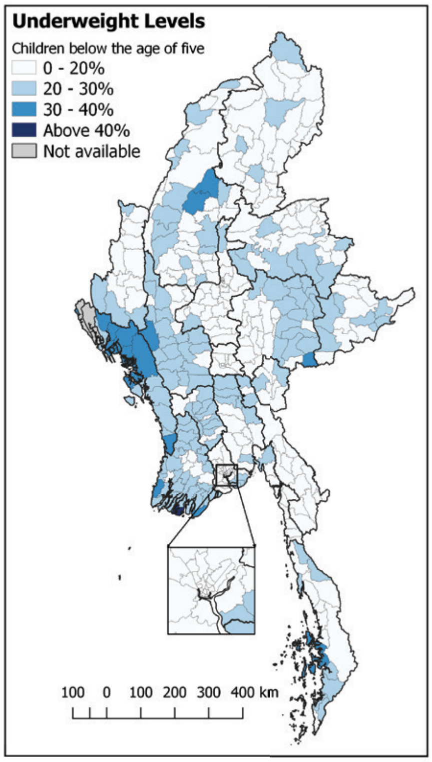
Stunting levels by township



Underweight levels by state/region



Underweight levels by township



Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

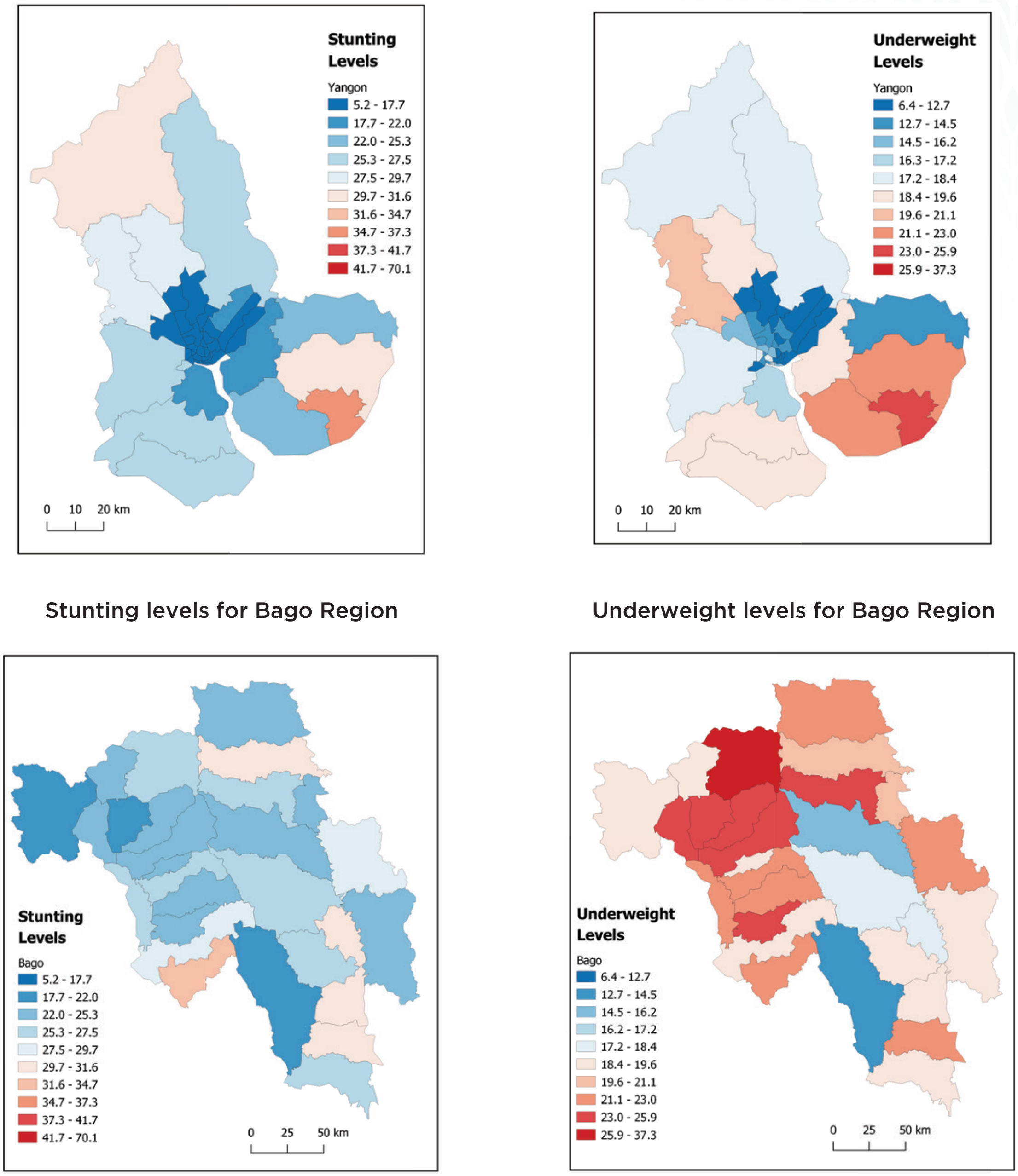
ES Figure 2 | Nutrition outcomes at state/region and township-level

Stunting levels for Yangon Region

Underweight levels for Yangon Region

Stunting levels for Bago Region

Underweight levels for Bago Region



These estimates reveal a more detailed picture of malnutrition in Myanmar than what was possible before this report. On one hand, the stunting and underweight estimates calculated with the Demographic and Health Survey were only representative at the state level. On the other hand, not only do these estimates not differ as much as the ones calculated with the small area estimation technique, but the results presented in this report have lower confidence intervals and are therefore more precise at the state level.

The report provides robust estimates of nutrition outcomes at township level. It is therefore possible to determine which townships are in more need of assistance than others. Programs aiming at overcoming stunting and underweight should redirect attention to these small areas in order to be more efficient when trying to achieve nutritional targets.

CHAPTER 1

INTRODUCTION

According to the World Health Organization (WHO), malnutrition refers to deficiencies, excesses, or imbalances in a person's intake of energy and/or nutrients. Malnutrition is among the main challenges in developing countries. Malnutrition has long-lasting impacts on child development, and ultimately affects human capital accumulation.

Currently, a great deal of attention is directed at the measurement of the prevalence of malnutrition around the world and the steps required to reach the Global Nutrition Targets. For example, the WHO sets two global undernourishment targets for children below the age of 5: (i) by 2025, the levels of stunting need to be reduced by 40%[2]; and (ii) the level of wasting to be reduced and maintained at less than 5%. The Sustainable Development Goals (SDGs) state a commitment to achieve Zero Hunger Goal by ending all forms of malnutrition altogether by 2030. Further, one of the targets to eradicate extreme poverty and hunger - goal number one of the Millennium Development Goals (MDGs) - was to reduce the prevalence of underweight in children under five.

Levels of undernourishment in different populations are usually measured based on international child growth standards established by the WHO. Among these standards, Z-scores are primarily used in the analysis and presentation of anthropometric data when assessing undernourishment for a specific population. For instance, children that suffer from stunting, or who are abnormally short for their age, are conventionally defined as having heights more than two standard deviations below the WHO child growth standards median, resulting in a Z-score of less than -2. Similarly, underweight, which is defined as having a lower weight for their respective age, and wasting, which is defined as having lower weight for their respective height, exists if the specific child is also below two standard deviations from the reference population median. This reference population was established by the WHO Multicenter Growth Reference Study (MGRS). The MGRS collected primary growth data and related information from approximately 8,500 children of different ethnic and cultural backgrounds.[3] Thus, if child anthropometric information is available for a specific population, Z-scores can be calculated and a level of undernourishment, that is, the percentage of stunted or underweight children, can be estimated.

These three measures of undernourishment are generally selected because they present a spectrum of the severity of children's malnutrition. Stunting (height-for-age) represents chronic, or long-term, undernutrition, because children cannot lose height and growth in height takes a longer time. In contrast, wasting (weight-for-height) represents acute, or short-term, undernutrition. Underweight (weight-for-age) is somewhere in between these two measures and is normally used when a measure of wasting cannot be reliably calculated. All three measures are calculated with the available anthropometric data (i.e. height and weight), for children below the age of 5.

In most countries, particularly developing countries, children's anthropometric data are not usually collected for everyone in the population of interest. Instead, a representative sample of children is measured in a survey and the level of undernourishment is then extrapolated to the whole population of children. Often, such surveys are representative only for large groups of individuals, which is problematic if the purpose is to finely target policies to decrease malnutrition. Countries with high prevalence of malnutrition frequently lack the resources to assist the whole population and policies must be designed to target the most vulnerable groups. It is thus useful to be able to determine prevalence of malnutrition at a more granular geographic level. Policymakers can then identify the most vulnerable small areas and design policy accordingly. Statistical techniques, such as small area

2 By 2025, projections indicate that 127 million children under 5 years will be stunted. The target is to reduce this number to 100 million children.
3 For more information, go to http://www.who.int/childgrowth/mgrs/en/

estimation (SAE) methods, were developed to help attain this goal.

The objective of the present report is to use this statistical technique to estimate prevalence of malnutrition among children in Myanmar at the township level, or in other words, to produce a nutrition map.

In essence, SAE techniques typically use one dataset to find a statistical model which provides the predictive relationship between different variables and the outcome of interest. In the case of malnutrition, for example, the outcome indicators could be the z-scores for stunting, wasting, or underweight, and the predictive variables are characteristics such as age, gender, health, welfare, etc., of the child and its family members. This model is then used to predict the outcome indicator for another larger dataset in which that outcome indicator was not collected. Since the second dataset is larger than the first dataset, possibly including the whole population, estimation for smaller areas can be performed. In a typical small area estimation of welfare indicators, the first dataset is the survey, which collects information on the outcome indicator, while the second dataset is the census collected for the population that the survey represents.

The SAE statistical techniques used in this report are based on a method introduced by Elbers et al. (2003) and an extension of this method developed by Fujii in Cambodia (Fujii, 2010). The ELL method (Elbers, Lanjouw, and Lanjouw, 2003) has been widely used in the estimation of poverty and inequality indicators at the local level in a number of developing countries. The final output of this exercise is referred to as a Poverty Map because, once the small area estimation is achieved, the estimates can be conveniently presented on a map. Recently, several studies have used this technique to determine levels of malnutrition as well. This report uses this approach to create the first Nutrition Map for Myanmar.

According to the Government of Myanmar, the World Bank, UNICEF, and other Development Partners, malnutrition represents one of Myanmar's biggest health and development challenges. One out of three children below the age of 5 is stunted (DHS 2015/2016) and almost 316,000 suffer from acute malnutrition (wasting). These statistics reveal that Myanmar has one of the highest prevalence of malnutrition in the Southeast Asian region.

Despite improvement in recent years,[4] there is still a lot of work to do in reducing child undernutrition. The last known data on child anthropometric outcomes was collected in the 2015/2016 Myanmar Demographic and Health Survey (MDHS), which constitutes one of the main data sources for this report. Findings from the MDHS reveals that 29% of children nationwide are stunted, with a wasting level of 7% and an underweight level of 19%. Since this information is only representative at the state/ region level, where populations range from approximately 150 thousand people (Shan State) to almost 7 million people (Yangon Region), it is difficult to determine which specific populations across the country should be prioritized in nutrition programs. Hence, in order to design more focused policy interventions, it is helpful to identify levels of malnutrition for smaller sub-populations.

This report has five sections. The next section provides a detailed description of the methodology (ELL and Fujii methods). Section three discusses the data sources and the data preparation process, including variables selection. Section four shows the results, including the outcome of the validation exercises. The last section gives a brief conclusion.

4 For example, stunting levels decreased significantly from 55% in 1985 to 35% in 2011 (UNICEF/WHO/World Bank group, 2017).

CHAPTER 2

METHODOLOGY

The methodology used for the construction of Myanmar's Nutrition Map is based on the small area estimation method developed by Elbers, Lanjouw, and Lanjouw (2003), commonly known as the ELL method. The method was constructed to provide poverty and inequality estimates at the small area level. The method has been successfully tested, including through actual experimentation, and it has been used to construct poverty maps worldwide, especially in developing countries.

Usually, welfare information is collected through national surveys, which are only representative at highly aggregated levels, such as states/regions. However, using information with a national coverage, such as census data, makes it possible to estimate welfare levels for small areas like districts, townships, or even village tracts/wards. The method uses common variables collected in both survey and census to estimate a statistical model that is then used to predict each household's welfare in the census. Once this prediction is made, welfare levels for small areas can be estimated and their precision assessed on the basis of Monte Carlo simulations.

As mentioned above, the ELL method can also be used to estimate child malnutrition for small areas. This has been implemented in countries like Nepal, Tanzania, Ethiopia, and Cambodia. In the latter, Fujii (2010) adapted and refined the ELL methodology in order to include specifications more closely related to child malnutrition estimation. These specifications are applied in this report and are discussed below.

Following the ELL method, the first step is to fit a statistical model using the survey data that collects anthropometric information for children below the age of 5. The linear model form is presented in equation 1, where X refers to a n-by-k matrix of k candidate variables, which are correlated with the z-scores of n individuals represented by the n-by-1 vector y. Thus, the k-by-1 vector β represents the coefficients and the n-by-1 vector u the error term.

$$y = X\beta + u \tag{1}$$

The left-hand-side variables used in this study are height-for-age z-score, for stunting, and weight-for-age z-score, for underweight, as defined in section 1. Once this model is estimated, the coefficient estimates and residual term, as well as its distribution, can be used to predict a z-score for each child under five in the census dataset. It is therefore possible to estimate the prevalence of stunting and underweight at the small area level, such as townships or districts. The assumption behind this procedure is that the relationship found by equation 1 in the survey sample data also applies for the whole population. This is why it is important that candidate variables are defined and distributed identically in the survey and census data.

One of the attractions of the ELL method is the way the disturbances are treated. They are assumed to be a combination of a cluster-level effect and a household-level effect unobserved with the model. Since welfare indicators, such as income per capita, are usually observed at household level in standard poverty applications, this is considered to be the lowest relevant disturbance effect in the model. Therefore, the decomposition of the disturbance term when estimating poverty is assumed to be as presented in equation 2, where η_c is the cluster-level effect and ϵ_{ch} is the household-level effect.

$$\mu_{ch} = \eta_c + \epsilon_{ch} \tag{2}$$

Now, in case of malnutrition, it would be reasonable to assume that the disturbances u_{chi} can be decomposed not only into cluster-level effect η_c and household-level effect μ_{ch}, but also into individual-level effect ϵ_{chi} as shown in equation 3. This specification is used by Fujii (2010) when estimating levels of malnutrition for Cambodia.

$$u_{chi} = \eta_c + \mu_{ch} + \epsilon_{chi} \tag{3}$$

In both cases, the cluster-level effect captures the within-cluster correlation that could be found on the error term, while the household-level effect captures the similarities among the disturbances that correspond to one specific household. Thus, the decomposition presented by Fujii allows for the effect of an individual belonging to a specific household, or cluster, to be independent of any other unobserved effect on his/her anthropometric indicator. One of the implications of not using a correct decomposition of the error term is that it can lead to biased estimates of precision. If the residuals are mostly composed of a cluster effect η_c, for example, the aggregation over individuals might lead to underestimated standard errors since a greater part of the disturbances are common in the specific cluster. In an effort to mitigate this effect, location means can be calculated with census data, as well as additional GIS information[5] at the locality level (Elbers et al., 2003, Fujii, 2010). It is important to take this effect into consideration when reviewing the final estimates, since the selection of the cluster level might affect the precision of these estimates.

The ELL method, as well as the refined methodology by Fujii, accounts for heteroskedasticity in the household-level effect. The authors relax the assumption that the variance of this component is the same across households. Once the statistical model is estimated, this variance can be calculated from the household-effect component and a prediction model for the variance can be formulated. The authors propose a logistic functional form,[6] which is shown in equation 4.

$$ln\left[\frac{\hat{\sigma}^2_{\mu,ch}}{A-\hat{\sigma}^2_{\mu,ch}}\right] = z'_{ch}\alpha + r_{ch} \tag{4}$$

Here, z_{ch} represents a set of variables that determine this variability, α the coefficient and r_{ch} an error term. A is considered to be the upper bound of $\hat{\sigma}_{\mu,ch}^2$.[7] Once these parameters are determined, an estimate of the variance for the household-level effect can be found using the delta method, as presented in equation 5.

$$\hat{\sigma}^2_{\mu,ch} = \max\left(0, \left[\frac{Ae^{z'_{ch}\hat{\alpha}}}{1+e^{z'_{ch}\hat{\alpha}}}\right] + \frac{1}{2}\hat{\sigma}_r\left[\frac{Ae^{z'_{ch}\hat{\alpha}}(1-e^{z'_{ch}\hat{\alpha}})}{(1+e^{z'_{ch}\hat{\alpha}})^3}\right] - \hat{\sigma}^2_{\delta}\right) \tag{5}$$

Since the number of survey clusters is limited, as well as the number of individuals per household, homoskedasticity must be assumed for the cluster-level and individual-level effect. This indicates that variances $\hat{\sigma}_n^2$ and $\hat{\sigma}_\epsilon^2$ are thus estimated from the cluster-level and individual-level component of the OLS estimated residuals. One important specification on Fujii's methodology is the consideration of correlation between anthropometric indicators for everyone, which he called the intrapersonal correlation. In this case, the correlation between the height-for-age and the weight-for-age indicator is also estimated from the individual-level component of the OLS-estimated residuals for both indicator[8]. Subsequently, with this information, a variance-covariance matrix Σ for the residual term can be constructed so that feasible Generalized Least Squares (GLS) estimation is performed. Once both GLS estimates $\hat{\beta}_{GLS}$ and their respective variance $Var(\hat{\beta}_{GLS})$ are estimated, it is then possible to go for the last step of the method, the simulation.

5 Presented in Appendix A.

6 This logistic functional form is appealing because it can avoid negative and high predicted variances.

7 The authors set this maximum bound to be A = (1.05)max[$\hat{\sigma}_{\mu,ch}^2$]

8 The technical details of this estimation are presented in Appendix G.

The simulation procedure aims to predict not only one, but S z-scores for each individual in the census dataset,[9] so that it is possible not only to estimate levels of malnutrition in small areas, but also to assess the precision of these estimates. Considering this is a frequentist approach, standard errors and confidence intervals can be calculated. These predictions follow the form of equation 6.

$$y^s_{chi} = X_{chi}\beta^s + \eta^s_c\hat{\sigma}^s_\eta + \mu^s_{ch}\hat{\sigma}^s_{\mu,ch} + \epsilon^s_{chi}\hat{\sigma}^s_\delta \tag{6}$$

First, the βs coefficient is the s draw from a multivariate normal distribution with mean $\beta\hat{}$ and variance $Var(\beta\hat{})$. Second, following Fujii's methodology, each component of the disturbance term η^s_c, μ^s_{ch} and ϵ^s_{chi}, is drawn from its specific standardized empirical distributions and the household-specific effect is corrected for heteroskedasticity. The latter means that $\hat{\alpha}s$ is also drawn from a normal distribution with mean $\hat{\alpha}$ and variance $Var(\hat{\alpha})$, and it is used to estimate $\hat{\sigma}_{\mu,ch}{}^2$.[10]

It is important to take into account that the predicted z-scores might reflect three possible types of error. The first type of error is the idiosyncratic component of the model, or the disturbance term, which depends on the deviation of the expected from the actual z score. This error usually is comparatively more important when there are smaller target populations, since it will be more difficult to determine the distribution of the disturbances. The second type is the model error that arises from the incorrect estimation of the model coefficients. The model error does not depend on the size of the population but on the precision of the estimates. This error might increase with the variance of these estimates. Finally, the third type of error corresponds to a computational error, which tends to decrease as more simulations can be performed.

Lastly, the final estimates for small areas are typically calculated using the Foster, Greer, and Thorbecke (1984) headcount measure for malnutrition shown in equation 7. Here, the prevalence of stunting or underweight for an area is defined as P, the number of individuals for a specific area as N, and z is the z-score cut off for malnutrition -2.[11] The predicted values found in each simulation round are aggregated at different geographical levels using this formula. Then, the smallest area chosen to estimate stunting and underweight will depend on the precision of the estimates, or the size of standard errors, found after simulation is completed.

$$P = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}(y_{chi} < z \tag{7}$$

9 S is the number of simulations and $s \in S$.

10 When estimating using only the ELL method, each component was drawn in every round of the simulation semi-parametrically. This means that the specific component was drawn with replacement from all sampled $\hat{}u$ and adjusted for heteroskedasticity.

11 Since the DHS dataset tries to avoid decimal points, the standard deviation was multiplied by a factor of 100, so the cut off is -200 in the calculations.

CHAPTER 3

DATA PREPARATION

There are two principal datasets used in this report. First, the Demographic and Health Survey for Myanmar was used as the source for anthropometric information and for which the statistical models were fitted. Second, the 2014 Myanmar Population and Housing Census was used for the prediction of malnutrition indicators in small areas. Other auxiliary data, like GIS, were also used and their sources can be found in Appendix A.

The 2014 Myanmar's Population and Housing Census (hereinafter, "the Census") is the first nationwide data on the entire population's social and demographic characteristics carried out in the 21th century. After 31 years of only relying on a series of small-coverage surveys, the implementation of the Census has created a much more complete source of information. Although it did not cover the whole population, due to inter-communal tensions and security-related concerns, it collected information for more than 50 million people all around the country.[12]

The Census was conducted in March 30th, 2014 and it was designed under a de-facto approach, so that the census accounts only for people who spent the night before the interview in the surveyed household. The Census data was used for a target population of children under the age of 5 for the estimation of stunting and underweight at township level. This population represents 4,409,928 children in the Census, of which about 24% live in urban areas. The distribution of children under the age of 5 by states/regions, districts, and townships is presented in Table 1.

Table 1 | Census at Geographical Levels

	States/Regions	Districts	Townships
Number of units	15	74	413
Mean No. of children	293,995	59,594	10,678
Max No. of children	590,418	202,960	54,327
Min No. of children	33,244	3,992	136

It is important to note that this report uses the geographical delimitation of Myanmar that was valid at the time of the Census.[13] That is, the country is divided into 413 townships and sub-townships units, for which 330 were named townships and 83 sub-townships. In this document, they will all be referred to as Townships for simplicity. Myanmar's administrative structure also includes a lower geographical level denominated as Ward/Village Tract or EA. However, since an official delimitation for this level is still under construction by the government, this study uses townships as target population. The township level is not ideal for analysis of the malnutrition in urban and rural areas separately, as these are delimited at the Ward/Village Tract level.

The second main source used in this report is the Demographic and Health Survey (DHS) for Myanmar. It was collected between December of 2015 and July of 2016 and its objective was to provide estimates of basic demographic and health indicators. Specifically, it collected anthropometric information for children under 60 months old, from which the estimates of stunting, underweight, and wasting were calculated. These results are only representative at the national and state/region level, as reviewed in section 4.

12 It has been estimated that approximately 1 million people were not interviewed.

13 After 2014, the government reorganized the administrative structure and merged Sub-Townships with Townships, fixing the number to 330 units.

The DHS survey followed a two-stage sample design. First, a total of 439 clusters were selected from a master sample of 4,000 primary sampling units (PSU),[14] and next, 30 households were selected from each selected cluster. In the DHS, the sample comprises 4,656 children of which 20% live in urban areas. The allocation over states/regions, districts, and townships is presented in Table 2.

Table 2 | DHS at Geographical Levels

	States/Regions	Districts	Townships	Clusters
Number of units	15	70	250	439
Mean No. of children	310	66	19	11
Max No. of children	435	293	140	31
Min No. of children	233	4	1	1

The target population for this report needs to be comparable between both main sources, Census and DHS. Therefore, it is important to only take into consideration children that slept in the household the night before the interview. In addition, only children under 60 months old were selected from the DHS because they were the ones eligible for anthropometric measurement.[15] In the Census, it was not possible to identify the months of age for each individual but the age distribution of children under the age of 5 corresponds to the age distribution of children with less than 60 months of age in the DHS. Furthermore, households in the Census that had more members than the maximum of household members in the DHS were ignored. On the one hand, this could be beneficial when comparing the distribution of candidate variables between the Census and DHS. On the other, the number of households ignored is so small that the small area estimates are not affected substantially (Fujii, 2010, Haslett, Jones, and Sefton, 2014).

As mentioned in section 2, the information needed to fit the linear model should be found in both DHS and Census, just as it should be similarly distributed in both sources. Usually, when mapping poverty, this information is related to households' physical and economic status, such as dwelling or goods owned, or to each individual's characteristics, such as education or occupation. However, since the relevant population in this study are children, the information about their parents or relatives should also be included. As an example, malnutrition is known to be correlated with the education of the child's mother (Li et al., 1999; Frongillo, de Onis, and Hanson, 1997; Rahman, Roy, Ali, and Akbar, 1993). Yet, in the Census it was impossible to determine who was the mother of each child in the household. Therefore, information regarding the head, the spouse, or a representative woman inside the child's household was considered as candidate variables as well. In this report, the most educated woman in the household, measured by years of schooling, was chosen to represent a representative woman of the household. Since education of the mother is correlated to malnutrition, it is assumed that education of women inside the child's household should be an important factor in their nutrition. Moreover, this information can be found for all households.

14 The primary sampling units were Enumeration Areas (EA) or Ward/Village Tract.
15 Children that were not measured in both height and weight were not included.

The Census questionnaire contains 41 questions regarding demographic, social, and economic data, as well as information related to identification, migration, and mortality for household members. Similarly, the DHS household questionnaire includes questions about age, sex, education, and marital status, along with information on household dwelling characteristics, such as water source, toilet facilities, and flooring materials, as well as possessions such as durable goods. After an exhaustive selection process, the candidate variables that matched in both DHS and Census are presented in Appendix B.

The process of selecting the candidate variables consisted of four steps. First, a review of the literature to identify important factors related to causes of undernutrition. Second, an examination of both questionnaires was performed, in order to find matching information in both dataset sources that could also potentially correlate with undernutrition as per the literature review. Third, basic statistics were calculated for the data collected in both sources respective to the matching questions in step one. These statistics were compared between the Census and DHS in order to establish if the data matched in distribution, as well as on definition. For the numerical information, such as age of the head of household or the number of household members, the mean, median, and standard deviation were used for comparison, while for the categorical information, it was the proportions for each category.

Fourth, if the distribution of categorical variables from the two data sources did not match, new categories were created because this information might still have been useful in the model. For example, the relationship between the child and the head of the household had three main categories: son/daughter, grandchild, and other. The DHS reports a higher percentage of grandchildren than the Census does, while the Census reports a higher percentage of children as direct offspring. This phenomenon could be related to the Census information having been collected only on one day, specifically a Saturday, while the DHS's was collected in a span of six months. Children might have stayed at their grandparents' house while their parents worked during the week, and then spent the weekend with their parents. To overcome this issue, a new category was created which merged the first two possibilities into one.

Other candidate variables found in both questionnaires, like occupation of the head of household, and activity status of the women with higher education, did not match in distribution. One of the reasons for this mismatch is that DHS information about occupation or activity status was only collected in the questionnaires made exclusively for women and men over the age of 15. Most of the heads of household heads in Myanmar are men, but in the DHS, men were only interviewed in half of the surveyed households[16], which meant that the DHS information on men's occupation was incomplete. In the case of information on women, the definitions of occupation and activity status in each questionnaire were presented differently, causing mismatches in the responses and activity status in both questionnaires.

Important information related to child mortality was also collected for each household in both Census and DHS. Since malnutrition is a contributing factor to child mortality rates (Rice, Sacco, Hyder, and Black, 2000; Black et al., 2013), it could also be set as one of the candidate variables for the model. The information regarding child mortality was: first, the number of children that had died (per woman in the household), and second, whether each woman in the household's most recent child had died. Unfortunately, once compared in distribution these variables did not match, so this information from

16 DHS focus mainly on demographic and health indicators for women and children; while all households with women aged 15 to 49 received the individual level questionnaire for women, individual level questionnaire for men were only done with half of the surveyed households as per DHS sampling design.

the DHS could not be fitted into the model. Nevertheless, the information from the Census regarding child mortality was still relevant and thus included into the model as location means.

The use of location means in the statistical model is beneficial, because it reduces the cluster-level effect on the disturbance term. The Census information used to create location means can be found in Appendix C. These variables were averaged out over the number of individuals at the township level[17] and then merged with the DHS dataset with respect to this localization. This information was also verified to be distributed similarly in both main sources, before it was included as a covariate in the model.

Finally, a set of variables were drawn from GIS data specified in Appendix A. The variables constructed for Myanmar at the township level are: land coverage, nightlights composite, precipitation, predicted travel time to city, temperature, and population density. In addition, information regarding the spatial limits of malaria transmission[18] was also included as candidate variables. The latter is pertinent since malnutrition has been found to be correlated with the presence of infectious diseases.

17 The definition of individuals depends on the type of location mean. For example, mean of individual with agricultural occupation was averaged over individuals that registered any type of occupation.
18 The malaria transmission was considered for two types of parasites: Plasmodium falciparum and Plasmodium vivax

CHAPTER 4

RESULTS

Once the data preparation process was finished, the structure of the models for the estimation of stunting and underweight prevalence in small areas was determined. The Povmap software developed by the World Bank was first employed in this step. One of the advantages of using this software is that all results obtained in this study can be replicated by the team at Myanmar's Department of Population and Ministry of Health and Sports, or any other organization or party who desires to do so.

As indicated in section 2, for each malnutrition indicator, a single model was constructed for the entire child population, thus using the complete target population for Myanmar. Nonetheless, the models captured variables associated with agro-zones,[19] states/regions, urban and rural areas, which could produce an effect to having different models for each type of geographical disaggregation. The pool of variables used to find the best fitted models did not only include pure candidate variables, but also interactions among these, as well as numerical variables transformed into polynomials of second degree.[20]

The variables selection procedure for each model was exhaustive with more than 600 variables under consideration and this procedure consisted of three steps. Step 1 is the selection of the pure candidate variables, listed in Appendix C, which presented high correlation with the dependent variable, and whose contribution to the explanatory power of the model (R^2) was substantial. Second step consists of testing the interactions of all pure variables for significance in the model using stepwise selection and lasso regression; those with a high contribution to the model were also included. The third step relies on tests of multicollinearity to discard variables correlated with each other[21]. Overall, two linear models were fitted: one for the z-scores for height-for-age (stunting) and one for weight-for-age (underweight)[22].

Even though there were different attempts to find a model for the z-score associated with wasting (weight-for-height), most of the tested models were not robust enough. This a problem encountered elsewhere in the literature (Fujii for example).[23] The models for stunting and underweight were more satisfactory. These results are not markedly different from the ones presented in other nutrition mapping studies, as it is shown in Appendix E. The fact that the explanatory power is not too high in this type of models should be kept in mind when the final estimates are considered. Usually, low R^2 levels could lead to elevated standard errors, particularly for small areas, and therefore less precision of these estimates.

19 The five agro-zones delimited by the World Bank for Myanmar are Hills/Mountains, Dry Zone, Delta, Coastal and Yangon.

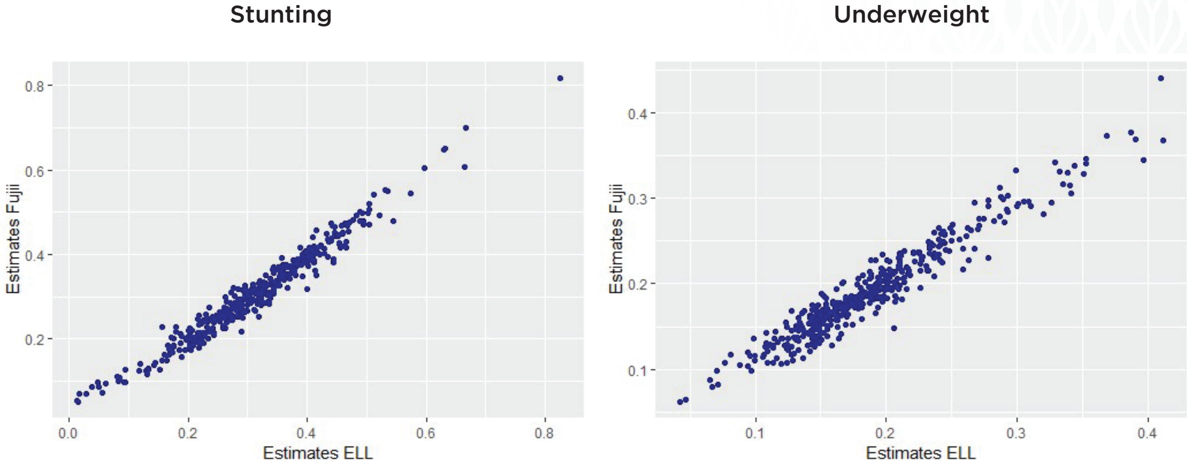
20 The interactions and polynomials were only included if they had similar distributions in both Census and DHS, as with the other candidate variables.

21 The Variance Inflation Factors (VIF) for the variables selected needed to range below 4%.

22 These models are presented in Appendix D.

23 Since small area estimation uses static data, it can be more difficult to measure and predict indicators that depend on changes in the short term.

Figure 1 | Estimation: ELL vs. Fujii method



Note: In the left, the township stunting estimates and in the right, the underweight estimates. On average, the difference between estimates is less than 0.01 in both stunting and underweight.

The final malnutrition estimates were aggregated at township and district levels using first the ELL method, which ignores household-level effect, and then the Fujii method, which factors it in. Both methods indicate similar levels of stunting and underweight as presented in Figure 1. The average standard errors for these results are collected in Tables 3 and 4. These show how the precision of the estimates using the ELL method seem to be overestimated, when compared to the findings using the method from Fujii, 2010.

Table 3 | Average Standard Errors: Stunting Estimates

	Fujii Estimation	ELL Estimation
Township	0.0374	0.0264
District	0.0253	0.0197
State/Region	0.0177	0.0148

Table 4 | Average Standard Errors: Underweight Estimates

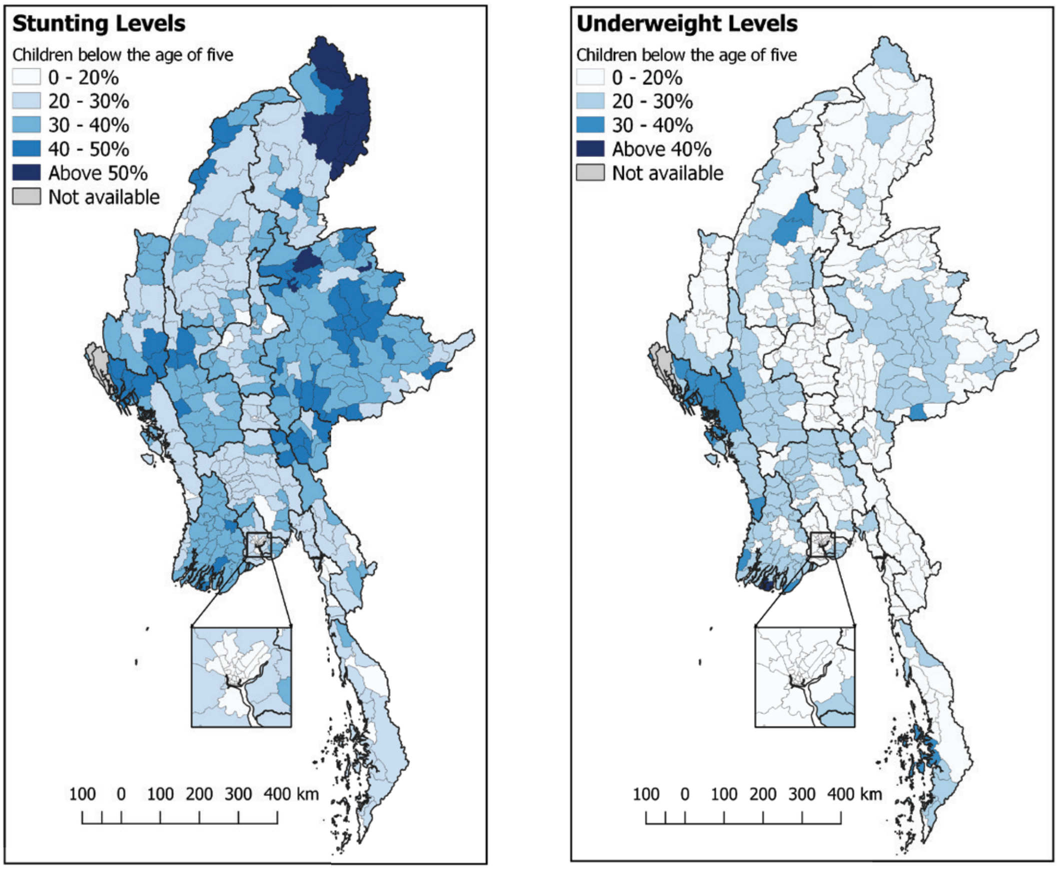
	Fujii Estimation	ELL Estimation
Township	0.0418	0.0386
District	0.0255	0.0243
State	0.0160	0.0159

The precision of the estimates is a function of the size of the calculated standard errors. At the township level, for example, these average around 0.026 and 0.039 using the ELL method and around 0.037 and 0.042 using the Fujii method, for stunting and underweight estimates respectively. Higher standard errors in underweight estimates can be related to a low R^2 presented in the model.[24] Since the estimates from Fujii's method are less conservative, these were the ones selected for this report.[25]

Using these results, maps were drawn to present estimated levels of malnutrition for township levels in Myanmar, as displayed in Figure 2. Some conclusions can be readily drawn by scrutinizing these maps. For instance, levels of stunting are relatively higher in the Northeast of the country and underweight seems to be more critical in the Western coastal area. Other maps are presented in Appendix F, which shows a greater prevalence of malnutrition in rural areas, and particularly among boys.

On one hand, though these maps present a general idea of malnutrition in the country, it is important to study the precision of these estimates. In Figure 3, stunting and underweight levels were ranked from low to high with their respective 90% confidence intervals. At this chosen precision, around 63% of the townships can significantly be differentiated from one another and be classified from lowest to highest, while for underweight it is only 30%.[26] Now, if the confidence interval decreases to 80%, for example, this number increases to 75% for stunting and 51% for underweight, as shown in Figure 4.

Figure 2 | Myanmar Township Estimates



Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

24 Another possibility could be a large ratio σ_c^2 over MSE; however, this seems not to be the issue in this case, as it is shown in Appendix D.

25 Results from ELL method can be presented upon request.

26 This ranking was calculated using a one-tail z test for two independent samples.

Figure 3 | Precision at 90% Confidence Interval

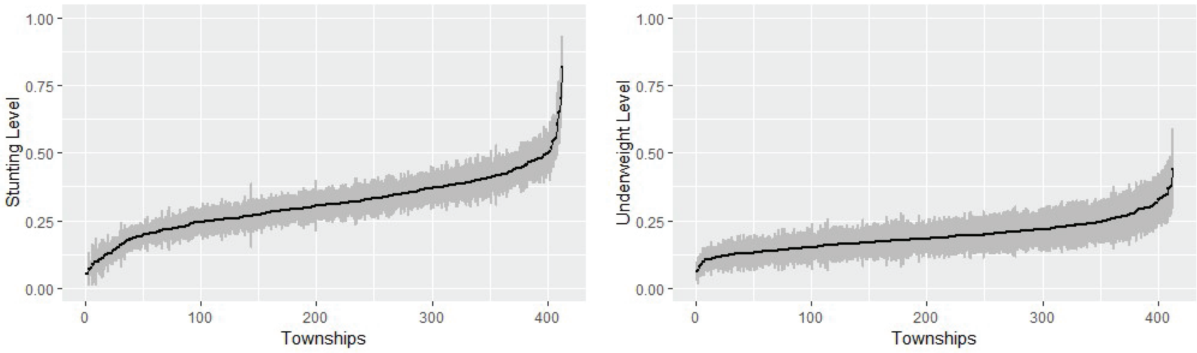
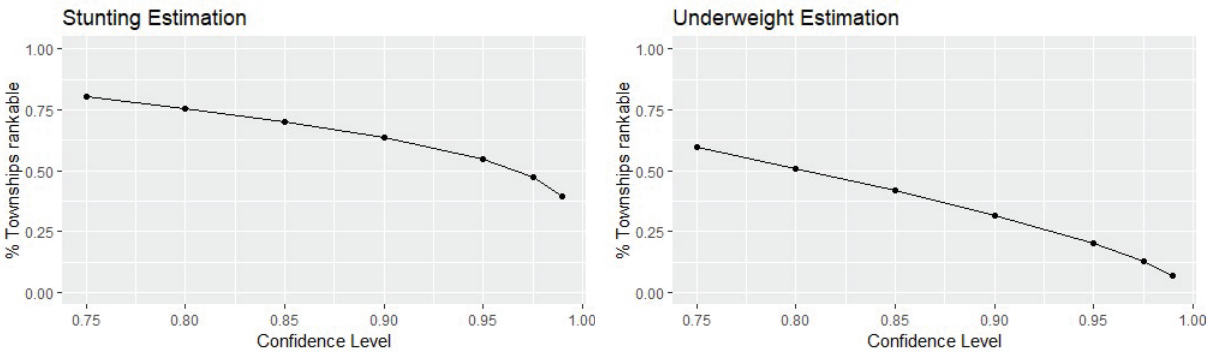


Figure 4 | Ranking at different Confidence Intervals

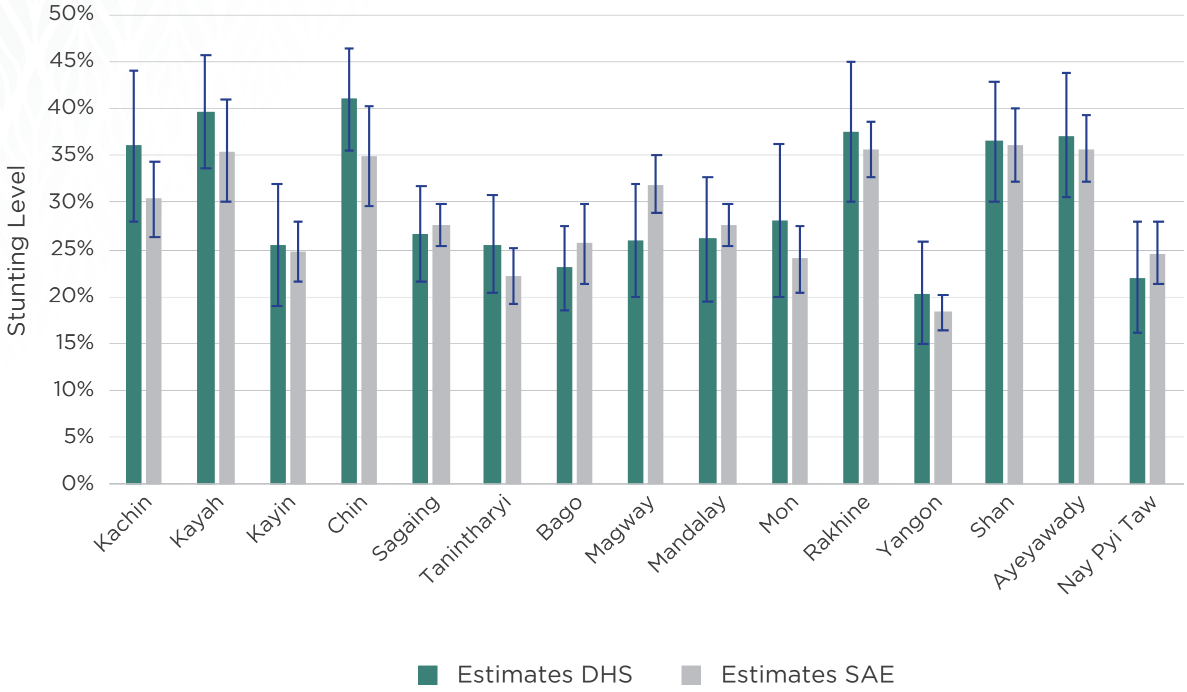


On the other hand, these estimates reveal a more disaggregated picture of malnutrition in Myanmar than what was previously available. The previous DHS stunting and underweight estimates were only representative at the state/region levels and they do not differ as much from the estimates found in this report[27]. Figure 5 indicates not only the similarity,[28] but also how the SAE estimates have lower confidence intervals and therefore are more precise than DHS estimates at that level of aggregation. This result is also found when contrasting the final stunting and underweight national levels: The DHS estimates a 29.2% level of stunting and a 18.9% of underweight for Myanmar, with standard errors 0.010 and 0.008 respectively, while SAE estimates a 28.9% of stunting and a 18.6% of underweight, with 0.007 and 0.006 standard errors respectively.

27 The sampling stratum of the DHS consisted of each state or region separated into urban and rural areas, which represented 30 strata.

28 Only one state, Sagaing, is significantly different when estimating underweight levels.

Figure 5 | **DHS vs. SAE at State/Region Level**



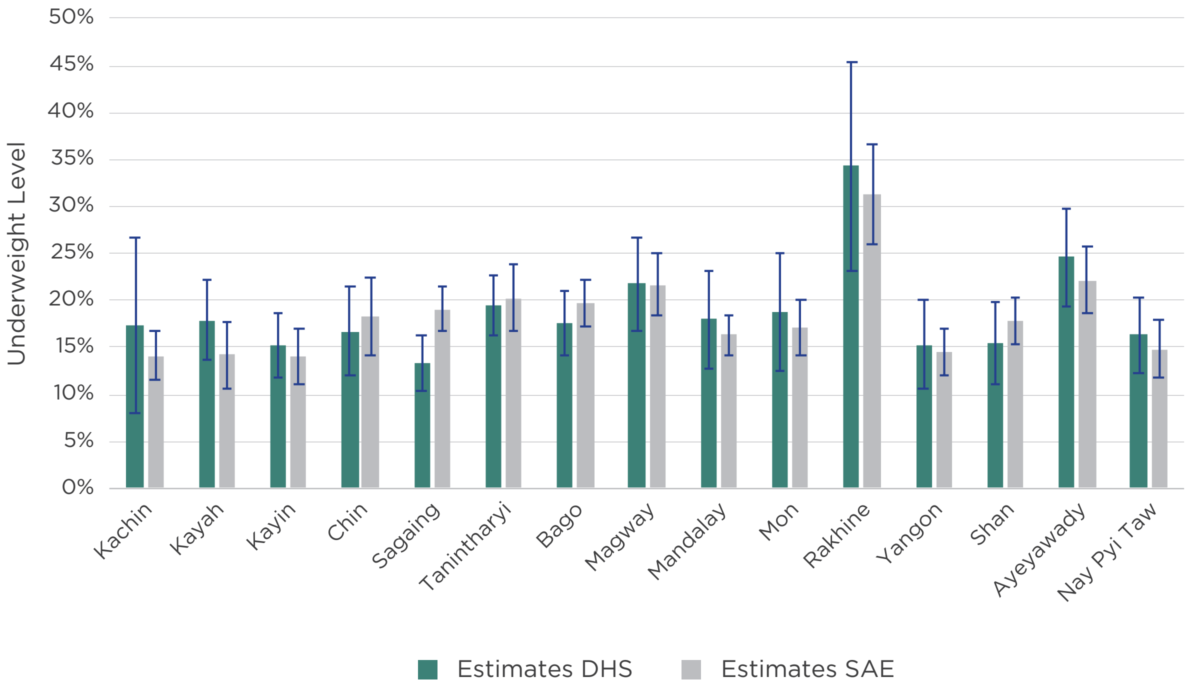
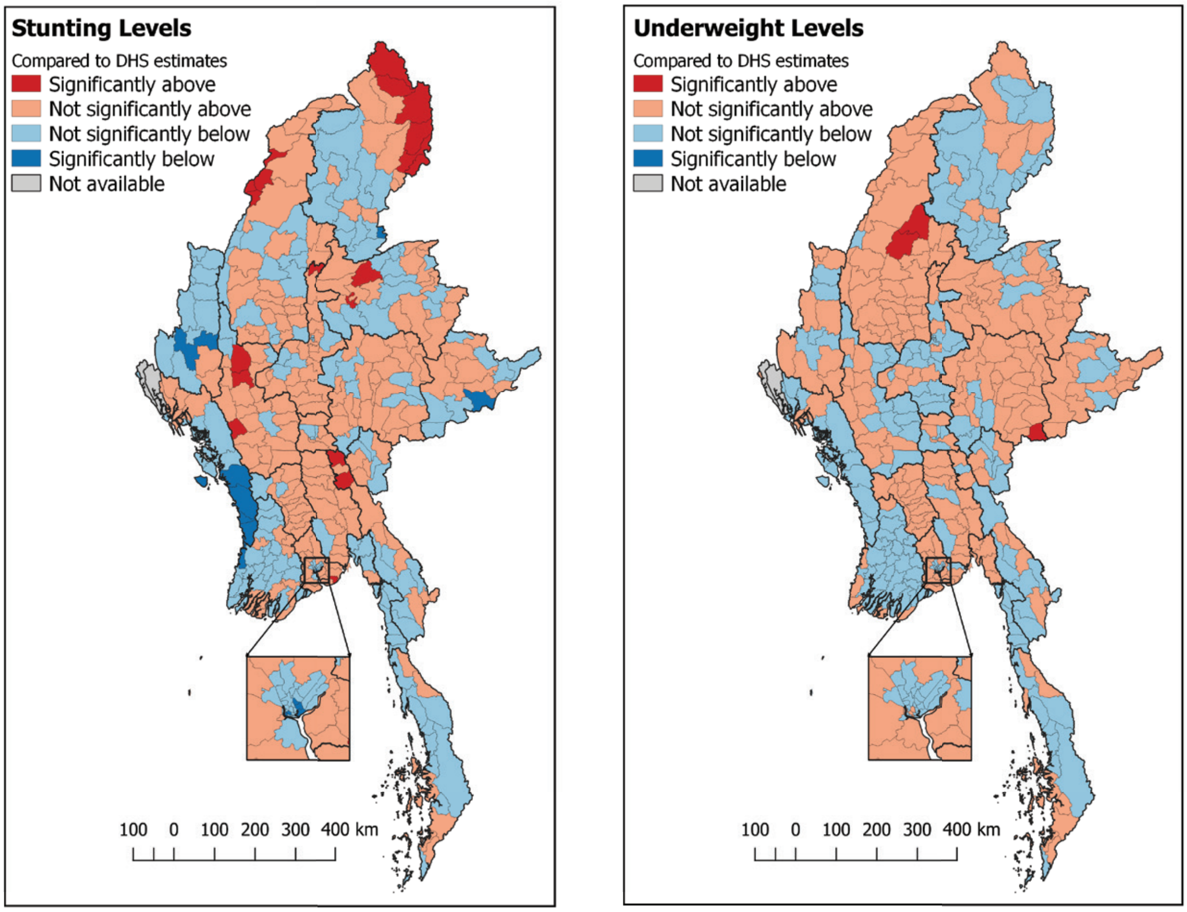


Figure 6 | SAE vs. DHS Estimates



Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

Now, if the only information on malnutrition in Myanmar was taken from the DHS estimation, then the recommendation would be to target the following states: Rakhine State, Chin State, and Kayah State. But in so doing, townships in other states/region would be wrongly overlooked, like the ones shown in Figure 6. Townships in dark red present a higher significant level of stunting or underweight compared to the DHS estimate for their state/region, while those in dark blue present a lower significant level. Thus, this nutrition mapping exercise is a new tool that can be used to help determine where nutrition programs should focus their efforts in Myanmar.

Another interesting way to analyze these results is to adjust the level of the cluster effect in the residuals decomposition from township to district. Using a lower spatial level than the target estimation as cluster-level could lead to underestimation of standard errors. In this case, if the stunting or underweight estimates are calculated at district level, while the decomposition the cluster-effect was set up at township level, the standard errors could be too conservative. In order to test this statement, the results presented before were calculated again using district-level effect in the residuals decomposition. Tables 5 and 6 indicate the average standard errors of this exercise, in contrast to the results using township-level decomposition.

Table 5 | Average Standard Errors: Stunting Estimates Different Cluster Choice

	Township Cluster	District Cluster
Township	0.0374	0.0251
District	0.0253	0.0193
State/Region	0.0177	0.0146

Table 6 | Average Standard Errors: Underweight Estimates Different Cluster Choice

	Township Cluster	District Cluster
Township	0.0418	0.0257
District	0.0255	0.0228
State/Region	0.0160	0.0145

At district level, the standard errors seem to be lower on average when using district cluster level in the error decomposition, though this effect is higher for stunting estimates than underweight. A possible interpretation of these results is that the township-level effect could be larger than the district-level effect, and therefore, the results do not show underestimation of standard errors at the district level when using the township-level effect. However, a better analysis of the data will be necessary to test this statement.

Lastly, for this report, while the estimation of malnutrition indicators was done using a unique statistical model covering the whole country, attempts were also made to obtain agro-zone specific models. These attempts were only successful for two agro-zones (Hill/Mountain and Coastal)[29] and the national rural area. The models and its results are presented in Appendix E, but since little difference was found between the rural and the national models, and those presented by the agro-zone models either have less precision or did not match the DHS estimation, the results from the national model were selected as the most recommended SAE estimation of this study.

29 Myanmar has five Agro-zones: Hills/Mountains, Dry, Delta, Coastal and Yangon

CHAPTER 5

CONCLUSION

The objectives of this report were to obtain estimates of undernutrition prevalence at the township level and to construct a Nutrition Map that could be helpful in the design of public policy. The estimation of stunting and underweight levels was successfully executed using the ELL method and the Fujii (2010) method. Results at the township level are presented in different maps, offering a more disaggregated view of the nutritional situation in Myanmar.

Applying the basic ELL method by using the Povmap software is ideal because it allows for ready replication of the estimate, if more information on stunting and underweight in Myanmar becomes available in the future. However, some restrictive assumptions were applied in order to implement this simple method. Therefore, a more refined estimation of malnutrition was finally done using a more sophisticated methodology developed by Fujii (2010). These results are a benchmark for estimating the landscape of malnutrition in Myanmar.

This report reveals valuable findings on malnutrition in Myanmar. First of all, levels of stunting are generally higher in rural areas and are particularly prevalent in the Northeast corner of the country, which is a mountainous region. Another general finding is that the level of underweight appears to be much higher on the Western Coast, especially in the Rakhine State. However, using small area estimation it is possible to determine which townships within these large areas are in more need of assistance than others.

Last but not least, it is important to be cautious when interpreting or using these results, especially if the purpose is to design public policy. The purpose of this study is to contribute to an estimation of malnutrition indicators at small area level, but it should not be forgotten that these are estimates and nothing more. Such estimation is useful when trying to locate the most vulnerable population groups, particularly if there is no information available that could achieve the same. Nonetheless, it is still recommended that, if possible, a field verification should be performed, as the one carried out by Haslett et al., 2014 in Nepal for poverty estimates, in order to test the results presented in this report.

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ANNEXES

Appendix A: GIS Sources

Table 7 | GIS Information

Name	Source
Myanmar Land Coverage	OneMap Myanmar
Predicted Travel Time (minutes) to nearest city	OpenStreetMap
Spatial limits of malaria transmission (Plasmodium falciparum)	Malaria Atlas Project
Spatial limits of malaria transmission (Plasmodium vivax)	Malaria Atlas Project
Nightlights Composite	NOAA National Centers for Environmental Information
Population per pixel and per hectare (with and without UN-adjustment)	WorldPop Asia
Precipitation (mm)	WorldClim
Temperature	WorldClim

Appendix B: Candidate Variables

Table 8 | Matched Candidate Variables

Name Variable	Description
Age Difference Below	Difference in years with the next youngest household member. (Takes the value 99 if he/she is the youngest)
Age Difference Above	Difference in years with the next oldest household member
Birth order	Position when ordered from the youngest to the oldest member
Age of Spouse	Age of the spouse of the household head
Age of the WHE	Age of the women with highest education (WHE) in the household
Spouse attendance	Spouse attended school at some point
State/Region	Region or state
Urban/Rural	1=Urban area and 2=Rural area
Agro-Zones	Delimitation of 5 zones constructed by the World Bank for Myanmar
Source Drinking Water	1= Tap/Piped, 2= Tube well/Borehole and 3=Well/Spring
Education Spouse	1=primary and 2=secondary or higher,
Education WHE	1=primary and 2=secondary or higher
Electricity	1=Household has electricity
Floor material	1=Bamboo/Earth, 2=Concrete/Tile and 3=other
Marital Status WHE	1=Single, 2=Married, 3=Widow and 4=Divorced
No. 0-5 Children	Number of children under the age of 5 in the household
No. Household	Number of Household Members
No. Men	Number of men in the household
No. Women	Number of women in the household
Sex	Sex of the child
Age	Age of the child
Sex of Head	Sex of the head of the household
Spouse	There is information of the spouse of the head
Toilet	1=Flush, 3=Pit latrine, 4=Bucket, 5=other and 6=none
Wall material	1=Dhani/theke/inleaf, 2=Palm/Bamboo, 4=Wood, and 6=Concrete/Tile
Relationship	Relationship with the head of the household 1=Son/Daughter or Grandchild and 0=other

Appendix C: Census Means

Table 9 | Census Information for Location Means

Name Variable	Description	
Migration	Resident abroad	Household member lives abroad: JK=Japan or Korea MS=Malaysia or Singapore UO=USA or other A30=Age is below 30 years old
	Internal migration	Household member migrated: RR=From rural area to rural area RU=From rural area to urban area UR=From urban area to rural area UU=From urban area to urban area
Education	Attendance	Household member attended school
	Attendance Men	Male household member attended school
	Attendance Women	Female household member attended school
	Pre. Attendance (5-15)	Children between 5 and 15 years old are previously attended school
	Curr. Attendance (5-15)	Children between 5 and 15 years old are currently attending school
	Education High	Household member has a higher level of education
	Education Secondary	Household member has a secondary level of education
	Education Primary	Household member has a primary level of education
	No Education	Household member has no education
Dwelling	Drinking Water	Source of drinking water: Bottle Pond Well
	No Drinking Water	Source of nondrinking water: Pond Well
	Roof	Household member lives under roof material: Rud= Rudimentary (Earth, Bamboo and Wood)
	Toilet	Type of sanitary installation: Improved=Flush and water seal No Improved=Pit latrine and bucket
	Residence	Type of housing: Bamboo Wooden
	Lighting	Source of lighting: Candle or Kerosene

Table 10 | Census Information for Location Means (Cont.)

Name Variable	Description	
Identification	ID	Household member counts with pink, blue or green identification card
Occupation	Occupation Sector	Household member works for occupation sector: Agri= Agriculture Serv= Services Prof= Professional Skill=Skilled Unskill= Unskilled
Mortality	Child mortality per woman	Percentage of children who died for each mother
	Lost child	Woman lost a child
	Last child	Woman's last child deceased
	Total children	Total number of children deceased

Appendix D: National models

Table 11 | OLS Regression for Weight-for-Age

	Coefficient	Standard Errors
Birth order=1	-16.543*	6.450
Age Spouse	0.499***	0.128
Agro_Zone=Hill/Mountain	16.480**	5.297
Land Coverage Majority: Cropland	29.678*	13.542
Mean Migration: Abroad US	-122.083***	32.566
Mean Women Last Child Deceased	-1018.849***	211.069
Age=0	68.154***	5.311
State/Region=Rakhine	-28.128**	6.886
Toilet: Flush	28.835***	5.214
Number Children (0-5)=2	-15.519**	4.879
(Birth order=1*Age=1)	21.195**	6.605
(Birth order=1*Sex Head: Female)	19.656**	7.189
(Age WHE*Mean Occupation: Agric)	-0.660**	0.256
(Agro_Zone: Dry Zone*Sex: Female)	23.715***	6.511
(Education Spouse: Secondary or Higher*No Electricity)	20.765*	8.139
(EducationWHE: Secondary or Higher*Electricity)	21.720***	4.904
(EducationWHE: Primary*Sex: Female)	14.326*	5.818
(Land Coverage Percentage: Cropland*Mean Migration: Rural to Urban)	-1351.777**	503.949
(Land Coverage Percentage: Cropland*Number of Household Members)	-38.121**	12.087
(Land Coverage Percentage: Cropland*Total No. of Children (0-5) Deceased)	2.960***	0.659
(Mean Malaria (PF)*Mean Migration: Urban to Rural)	-37.967**	12.639
(Mean Malaria (PF)*Mean Pre. Attendance (5-15))	-74.005**	23.410
(Marital Status WHE: Married*Sex: Female)	11.884*	5.855
(Marital Status WHE: Single*Spouse)	33.839**	11.118
(Age=1*Sex: Female)	25.300**	8.951
(Age=4*Sex: Female)	-17.642*	6.853
(Sex: Female*Toilet: Flush)	-28.492***	6.509
Intercept	-69.907***	15.947
Observations	4633	
R^2	0.1279	
Adjusted R^2	0.1228	
Ratio σ_c^2 over MSE	0.017	

* p<0.05, ** p<0.01, *** p<0.001

Table 12 | OLS Regression for Height-for-Age

	Coefficient	Standard Errors
Mean Drinking Water: Bottle	81.139**	25.292
Mean No Drinking Water: Well	61.142***	10.888
Mean Occupation: Professional	229.075***	66.683
Mean Pre. Attendance (5-15)	-186.504**	63.927
Mean Women Last Child Deceased	-781.346**	255.430
Nightlights Average	3.69**	1.216
Number Children (5-15)=3	-22.552**	7.523
Number Women=3	16.495*	6.485
Age=0	120.525***	6.041
Urban Area	15.743**	6.101
State/Region=Kayah	-34.076***	7.481
State/Region=Bago	30.324**	9.062
Temperature March	4.078***	1.234
Number Children (0-5)=2	-18.570***	5.414
Wall Material: Dhani/theke/inleaf	-57.107**	21.710
(Age Difference Above*Sex: Female)	0.823**	0.318
(Birth order=1*Age=1)	33.917***	7.849
(Birth order=1*Sex Head: Male)	-17.432**	6.547
(Agro_Zone=Delta*Mean Migration: Urban to Urban)	-89.878**	27.451
(Agro_Zone=Hill/Mountain*Drinking Water: Well Spring)	-18.290**	6.677
(Agro_Zone=Dry Zone*Sex Head: Female)	-33.002**	11.492
(Spouse Attendance*Relationship: Son/Daughter/Grandchild)	17.764*	7.018
(Education WHE: Secondary or Higher*Sex:Male)	23.766***	6.292
(Floor:Bamboo/Earth*Sex:Male)	-20.834***	6.249
(Land Coverage Percentage: Deciduous forest*Mean Malaria (PV)	94.103*	39.924
(Mean Malaria (PV)*Mean Migration: Abroad MS)	20.029*	8.017
(Number Children (5-15)*Sex: Male)	-17.255*	7.386
(Age=1*Sex: Female)	30.346**	10.507
(Age=4*Sex: Male)	23.045**	7.730
(Total Population (per hectare-UN adj.)*Mean Migration: Abroad US)	-0.0005**	0.0002
(Total Population (per pixel-UN unadj.)*Mean Migration: Abroad JK)	0.002***	0.0005
(Sex Head: Male*Wall Material: Dhani/Theke/Inleaf)	72.714**	23.027
(Sex: Male*Toilet: Flush)	16.660**	6.075
(Spouse*Wall Material:Wood)	23.960*	10.342
Intercept	-242.886***	34.572
Observations	4626	
R^2	0.2044	
Adjusted R^2	0.1985	
Ratio σ_c^2 over MSE	0.0011	

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Appendix E: Zonal and Rural models

The agro-zone models for Hill/Mountain, Dry, and Coastal Zones, and the model for rural areas, were the only models with an R^2 higher than 10% for both stunting and underweight and with little risk of overfitting. The models for Hill/Mountain Zone, Coastal Zone, and rural area are presented below.[30]

Table 13 | OLS Regression for Height-for-Age: Hill/Mountain Zone

	Coefficient	Standard Errors
Mean Pre. Attendance (5-15)	-301.641***	65.861
Mean Women Last Child Deceased	-1078.696***	290.902
Age=0	129.560***	16.209
State/Region=Kayah	-39.365***	9.439
Temperature March	4.778**	1.484
Number Children (0-5)=2	-34.460***	10.492
(Age Difference Above*Sex: Female)	1.326*	0.539
(Birth order=1*Age=1)	64.096***	15.450
(Birth order=1*Sex Head: Male)	-37.186*	17.524
(Spouse Attendance*Relationship: Son/Daughter/Grandchild)	34.792**	12.912
(Education WHE: Secondary or Higher*Sex:Male)	38.201***	10.050
(Floor:Bamboo/Earth*Sex:Male)	-41.799**	12.477
(Sex: Male*Toilet: Flush)	39.181***	10.632
Intercept	-210.007***	39.994
Observations	1787	
R^2	0.1826	

* *p*<0.05, ** *p*<0.01, *** *p*<0.001

Table 14 | OLS Regression for Height-for-Age: Coastal Zone

	Coefficient	Standard Errors
Mean No Drinking Water: Well	119.125***	35.090
Age=0	146.624***	11.713
(Age Difference Above*Sex: Female)	2.533**	0.690
(Birth order=1*Age=1)	79.494***	17.518
(Education WHE: Secondary or Higher*Sex:Male)	46.816***	12.028
(Floor:Bamboo/Earth*Sex:Male)	-33.348*	13.693
(Age=4*Sex: Male)	41.181**	14.421
(Total Population (per hectare-UN adj.)*Mean Migration: Abroad US)	-0.001**	0.0004
(Total Population (per pixel-UN unadj.)*Mean Migration: Abroad JK)	0.011***	0.002
Intercept	-237.390***	19.821
Observations	685	
R^2	0.2735	

* *p*<0.05, ** *p*<0.01, *** *p*<0.001

30 The model for Dry area is not presented since it shows similar results from the Coastal Zone model

Table 15 | OLS Regression for Height-for-Age: Rural

	Coefficient	Standard Errors
Mean Drinking Water: Bottle	98.877*	38.693
Mean No Drinking Water: Well	68.162***	13.082
Mean Occupation: Professional	-282.032**	100.852
Mean Pre. Attendance (5-15)	-157.206**	60.611
Mean Women Last Child Deceased	-609.779*	282.668
Age=0	116.663***	8.075
State/Region=Kayah	-26.702*	10.504
State/Region=Bago	36.279***	7.793
(Age Difference Above*Sex: Female)	1.185**	0.424
(Birth order=1*Age=1)	29.249***	9.098
(Agro_Zone=Delta*Mean Migration: Urban to Urban)	-84.770**	26.848
(Agro_Zone=Hill/Mountain*Drinking Water: Well Spring)	-35.800***	7.583
(Spouse Attendance*Relationship: Son/Daughter/Grandchild)	22.028**	7.240
(Education WHE: Secondary or Higher*Sex:Male)	23.934***	6.601
(Floor:Bamboo/Earth*Sex:Male)	-21.315**	7.783
(Age=1*Sex: Female)	31.534*	12.920
(Age=4*Sex: Male)	18.387*	7.344
(Total Population (per pixel-UN unadj.)*Mean Migration: Abroad JK)	0.002***	0.0005
(Sex: Male*Toilet: Flush)	17.893**	6.684
(Spouse*Wall Material:Wood)	25.689*	12.101
Intercept	-161.572***	19.352
Observations	3702	
R^2	0.1711	

* p<0.05, ** p<0.01, *** p<0.001

Table 16 | OLS Regression for Weight-for-Age: Hill/Mountain Zone

	Coefficient	Standard Errors
Mean Women Last Child Deceased	-1040.317***	290.549
Age=0	70.285***	11.039
(Age WHE*Mean Occupation: Agric)	-0.886*	0.348
(EducationWHE: Secondary or Higher*Electricity)	19.997*	8.604
(Mean Malaria (PF)*Mean Pre. Attendance (5-15))	-85.151**	29.654
(Age=1*Sex: Female)	48.145**	12.353
(Sex: Female*Toilet: Flush)	-18.776*	8.568
Intercept	-38.699*	16.143
Observations	1787	
R^2	0.1068	

* p<0.05, ** p<0.01, *** p<0.001

Table 17 | OLS Regression for Weight-for-Age: Coastal Zone

	Coefficient	Standard Errors
Mean Migration: Abroad US	-454.489***	128.214
Age=0	57.133***	9.192
(EducationWHE: Secondary or Higher*Electricity)	42.063***	9.729
(Land Coverage Percentage: Cropland*Number of Household Members)	-177.855**	57.646
(Age=1*Sex: Female)	55.472***	13.493
Intercept	-125.278***	6.594
Observations	685	
R^2	0.1822	

* p<0.05, ** p<0.01, *** p<0.001

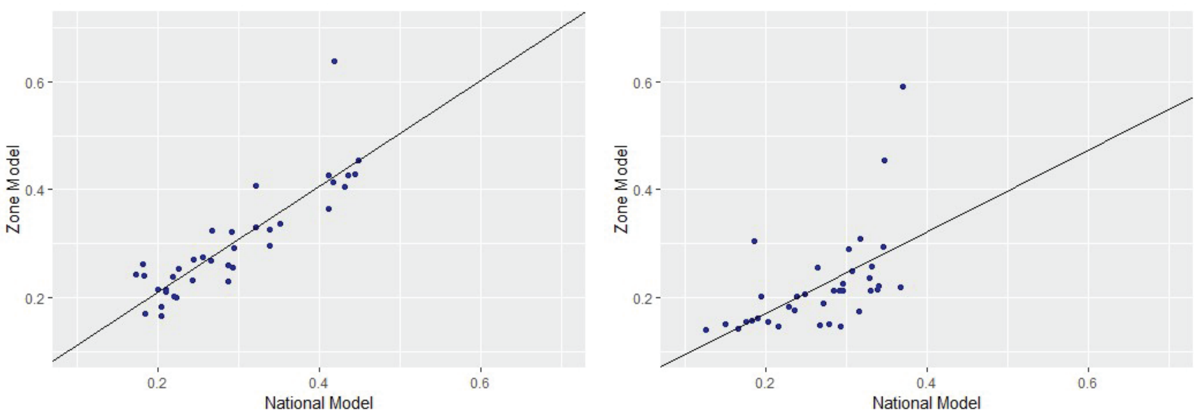
Table 18 | OLS Regression for Weight-for-Age: Rural

	Coefficient	Standard Errors
Agro_Zone=Hill/Mountain	13.994*	5.962
Mean Migration: Abroad US	-155.932**	54.331
Mean Women Last Child Deceased	-1026.662***	225.370
Age=0	66.798***	6.995
State/Region=Rakhine	-29.637**	11.414
Toilet: Flush	16.140***	4.159
(Birth order=1*Age=1)	21.062**	6.608
(Age WHE*Mean Occupation: Agric)	-0.671*	0.269
(Agro_Zone: Dry Zone*Sex: Female)	26.292***	6.992
(Education Spouse: Secondary or Higher*No Electricity)	21.496*	9.567
(EducationWHE: Secondary or Higher*Electricity)	19.688**	6.245
(EducationWHE: Primary*Sex: Female)	10.211*	5.077
(Land Coverage Percentage: Cropland*Mean Migration: Rural to Urban)	-1991.737***	601.083
(Land Coverage Percentage: Cropland*Number of Household Members)	-35.573**	13.454
(Land Coverage Percentage: Cropland*Total No. of Children (0-5) Deceased)	2.907***	0.725
(Mean Malaria (PF)*Mean Migration: Urban to Rural)	-35.327*	15.637
(Mean Malaria (PF)*Mean Pre. Attendance (5-15))	-75.444**	23.719
(Age=1*Sex: Female)	20.997*	10.276
(Age=4*Sex: Female)	-24.059***	6.452
Intercept	-57.954***	14.003
Observations	3702	
R^2	0.1254	

* *p*<0.05, ** *p*<0.01, *** *p*<0.001

The results from the agro-zone models are compared to the national model in Figures 7 and 8, and Tables 19, 20, 21, and 22. For the Coastal Zone, the estimates are similar for stunting, though the standard errors seem to be higher using the zonal model.[31] For underweight, on the other hand, the estimates are higher on average using the national model, with higher standard errors. Nonetheless, it is important to take into account the fact that the underweight estimation using the national model is consistent with the DHS estimation for both states, Rakhine State and Tanintharyi Region, while the agro-zone model presents much lower significance levels. Similar results are found for the Hill/Mountains Zone, though the estimates are more similar for underweight than stunting.

Figure 7 | National vs. Zonal Model: Coastal Zone



31 Although the R2 is higher for the agro-zone model, the existence of larger standard errors could be due to a higher model error.

Table 19 | Average Standard Errors: Stunting Estimates - Coastal Zone

	National Model	Zone Model
Township	0.0319	0.0692
District	0.0219	0.0443
State/Region	0.0150	0.0280

Table 20 | Average Standard Errors: Underweight Estimates - Coastal Zone

	National Model	Zone Model
Township	0.0510	0.0493
District	0.0333	0.0305
State/Region	0.0227	0.0204

Figure 7 | National vs. Zonal Model: Coastal Zone

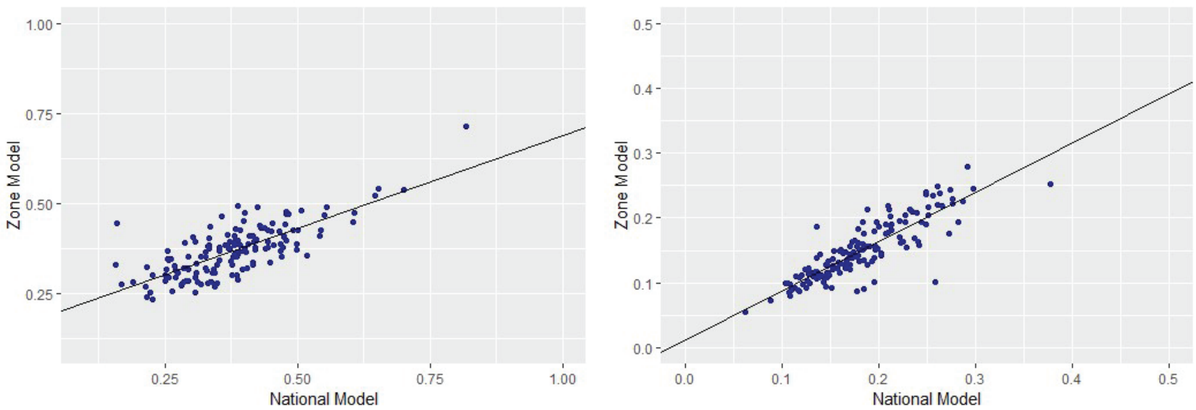


Table 21 | Average Standard Errors: Stunting Estimates- Hills/Mountains Zone

	National Model	Zone Model
Township	0.0433	0.0681
District	0.0308	0.0455
State/Region	0.0224	0.0330

Table 22 | Average Standard Errors: Underweight Estimates - Hills/Mountains Zone

	National Model	Zone Model
Township	0.0390	0.0384
District	0.0256	0.0249
State/Region	0.0153	0.0161

Another example is the distinction between the national model and the rural model. In this case, Figure 9 and Tables 23 and 24 show similar results for both stunting and underweight estimations, with slightly higher standard errors in the rural model.

Figure 9 | National vs. Rural Model

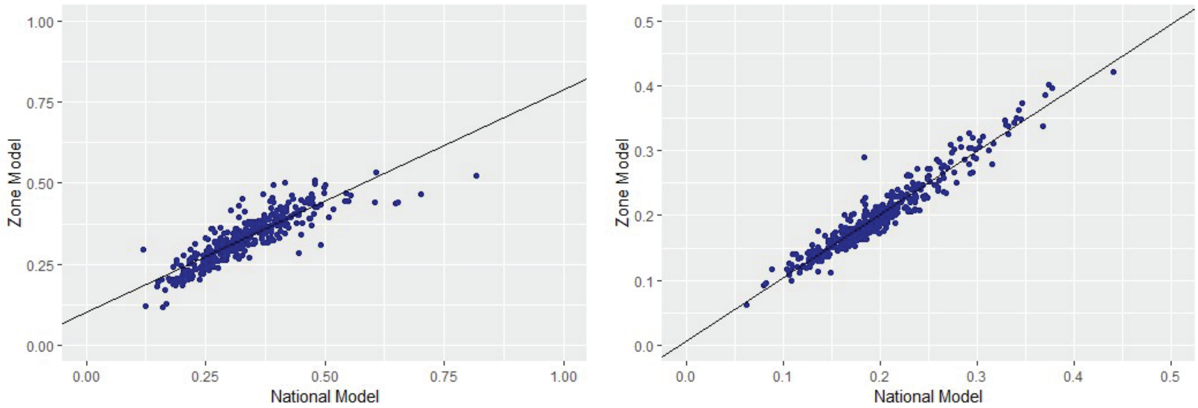


Table 23 | Average Standard Errors: Stunting Estimates - Rural

	National Model	Zone Model
Township	0.0411	0.0571
District	0.0275	0.0349
State/Region	0.0190	0.0234

Table 24 | Average Standard Errors: Underweight Estimates - Rural

	National Model	Zone Model
Township	0.0471	0.0493
District	0.0286	0.0302
State/Region	0.0174	0.0195

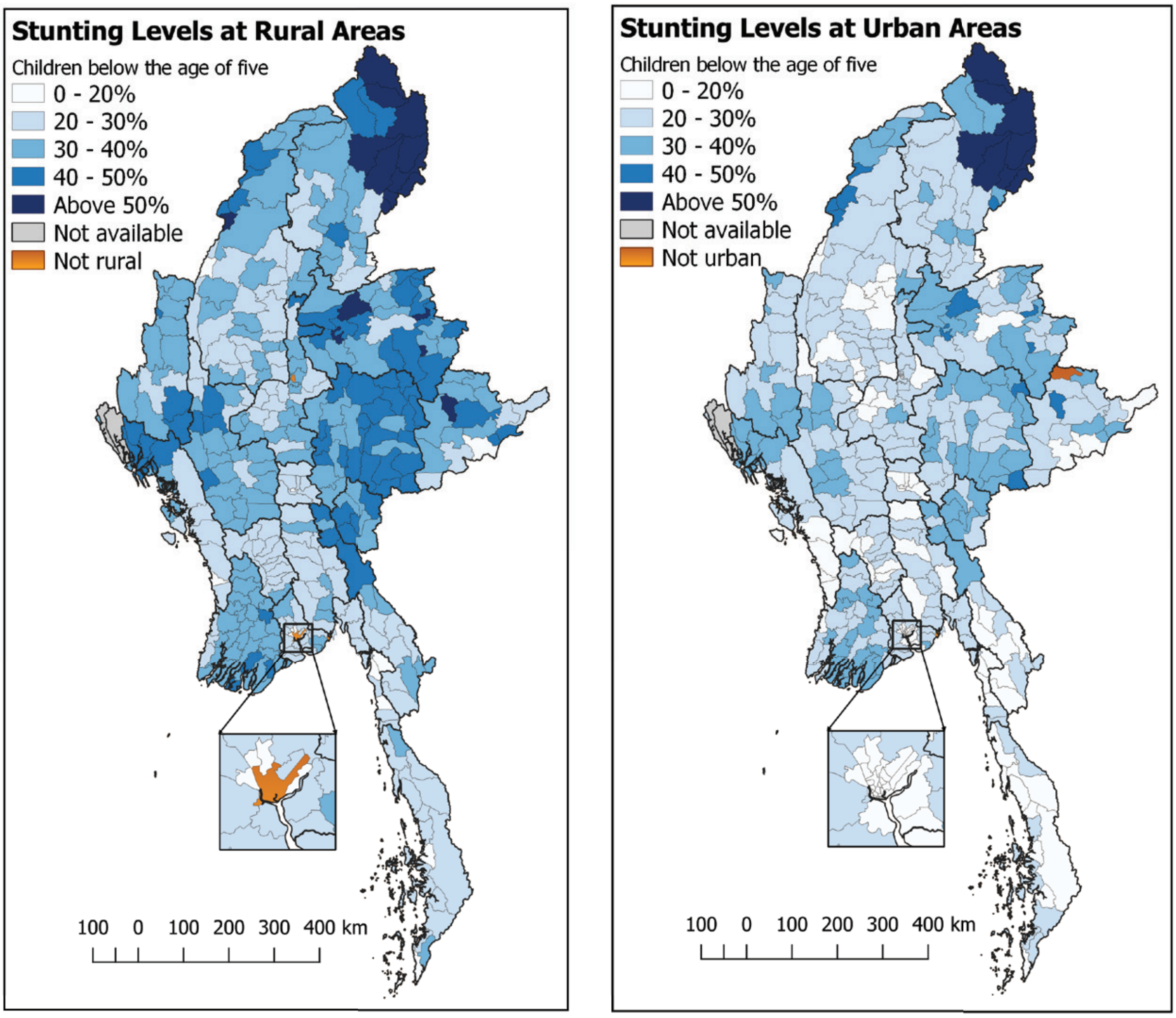
Appendix F: Other Maps

There are different ways malnutrition estimation at small area can be presented. For this report, we chose to separate stunting and underweight estimations for residential areas (rural and urban), states/regions, as well as for each gender (boys and girls). Also, it is possible to present the nutrition maps with respect to the number of stunted and underweight children, and finally make a simple contrast of the small area estimation with the national nutritional levels. The purpose of this appendix is to present the results of this exercise.

As mentioned throughout the report, levels of stunting and underweight are much more predominant in rural areas compared urban ones. This is presented in Figures 10 and 11. If these estimates are transformed into number of children who are stunted or underweighted in each township, the difference between the rural and urban areas is more pronounced. This can be observed when looking at Figures 12, 13 and 14.

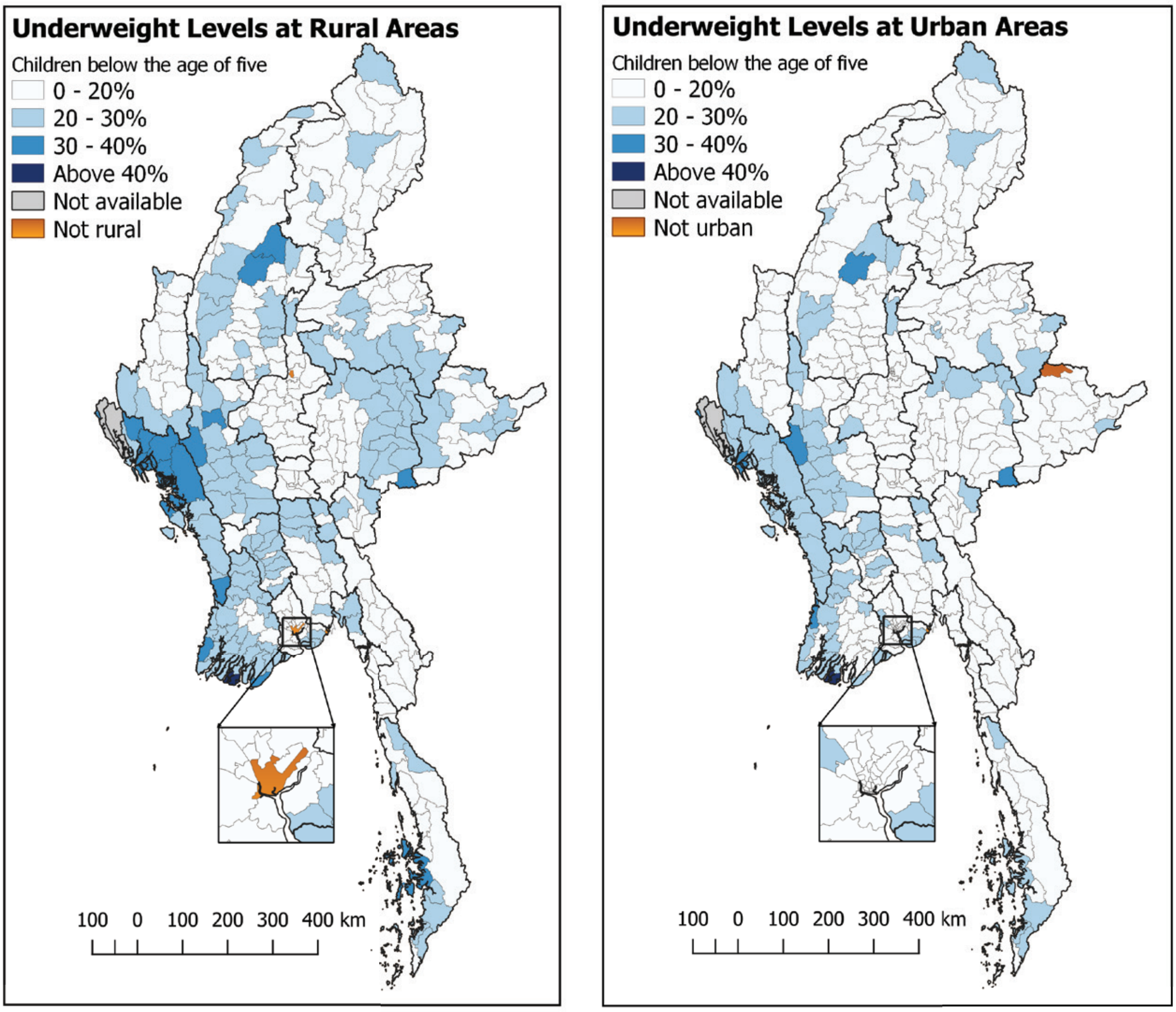
With respect to gender, the picture is slightly more critical for boys than for girls, as shown in Figures 15 and 16. Finally, another type of map designed to attain a better analysis of Myanmar's malnutrition situation is the one presented in Figure 17, in which the levels of stunting and underweight at township level are compared to their respective national estimates.

Figure 10 | Stunting Estimation



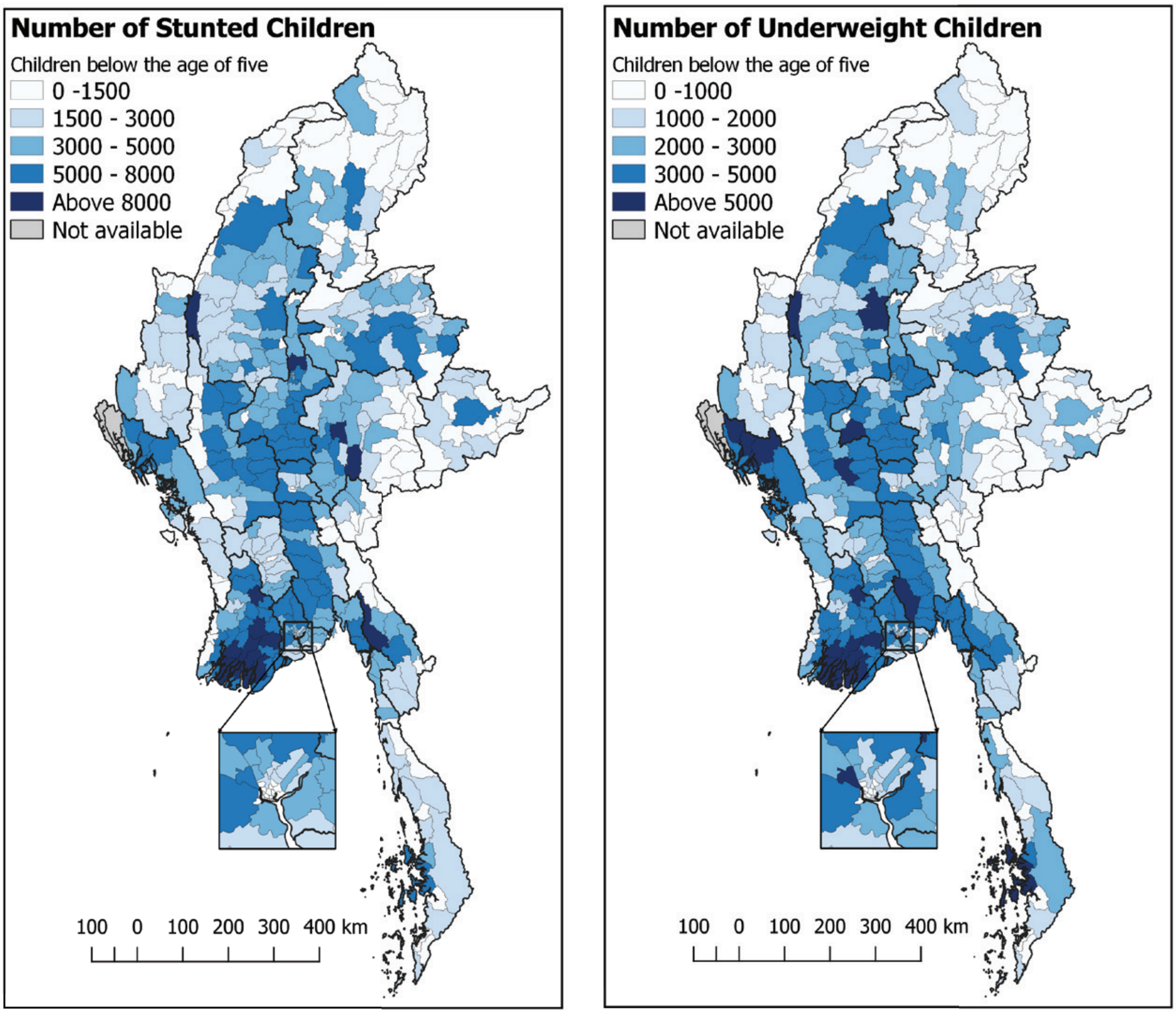
Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

Figure 11 | Underweight Estimation



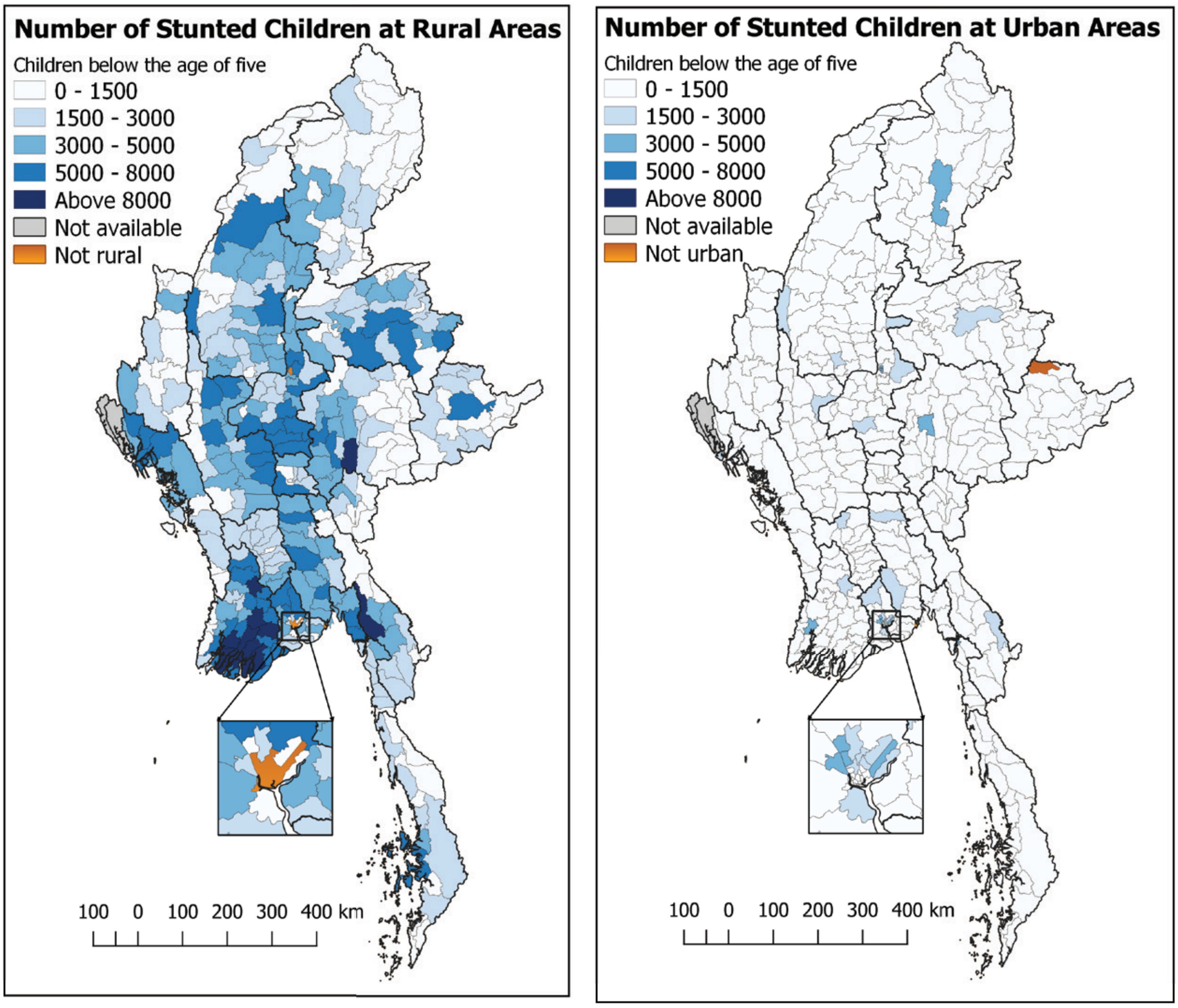
Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

Figure 12 | National Estimation



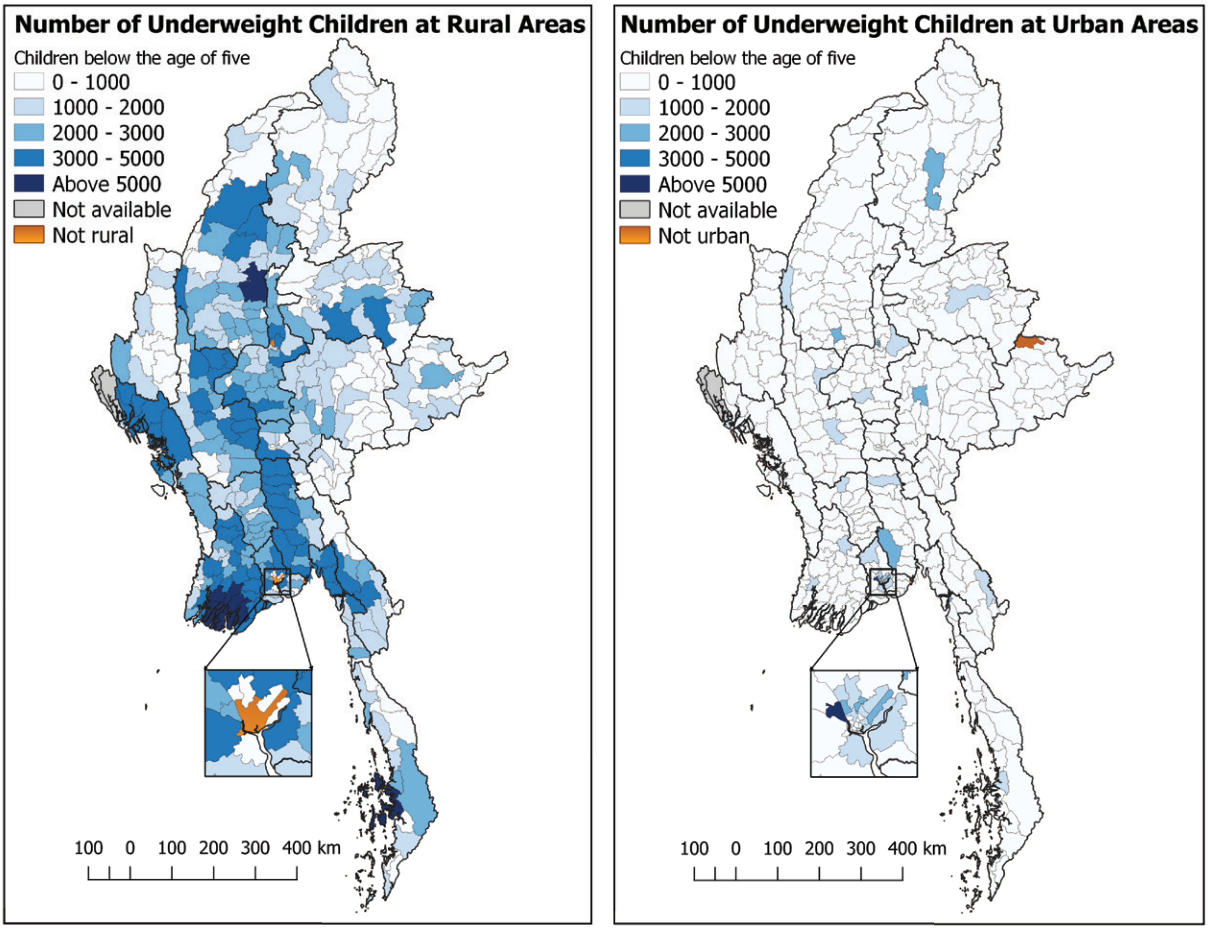
Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

Figure 13 | Stunting Estimation



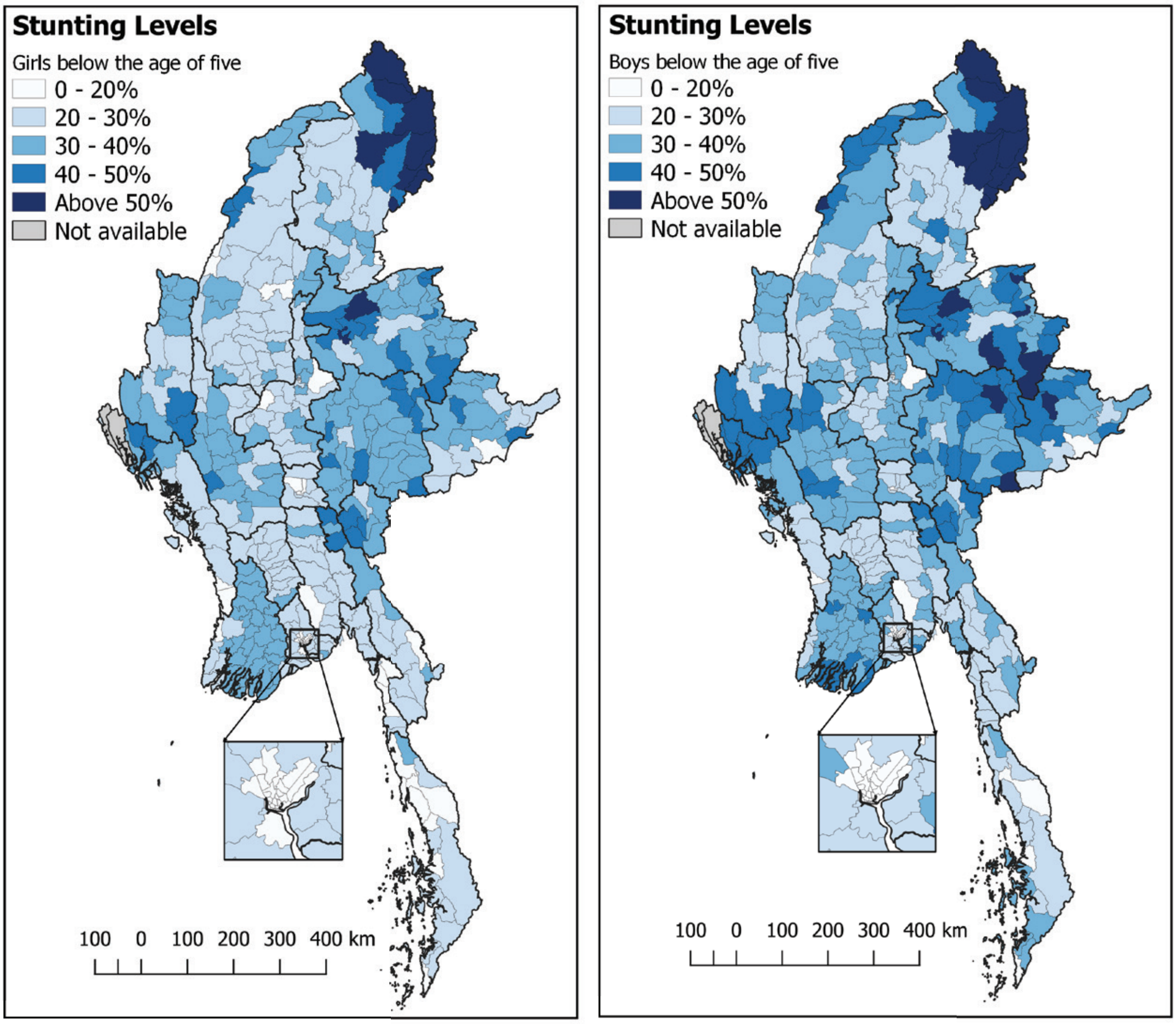
Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

Figure 14 | Underweight Estimation



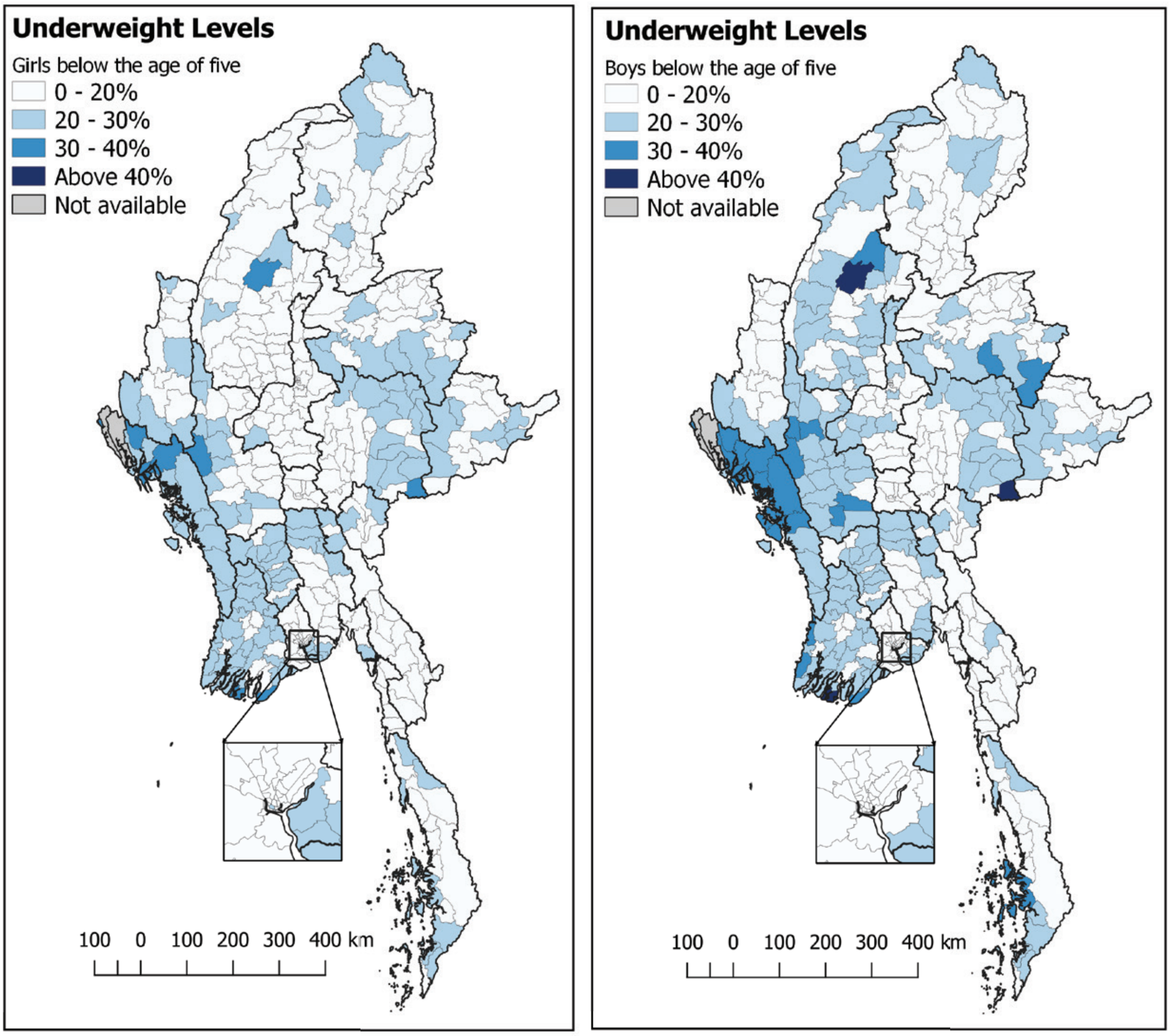
Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

Figure 15 | Stunting Estimation



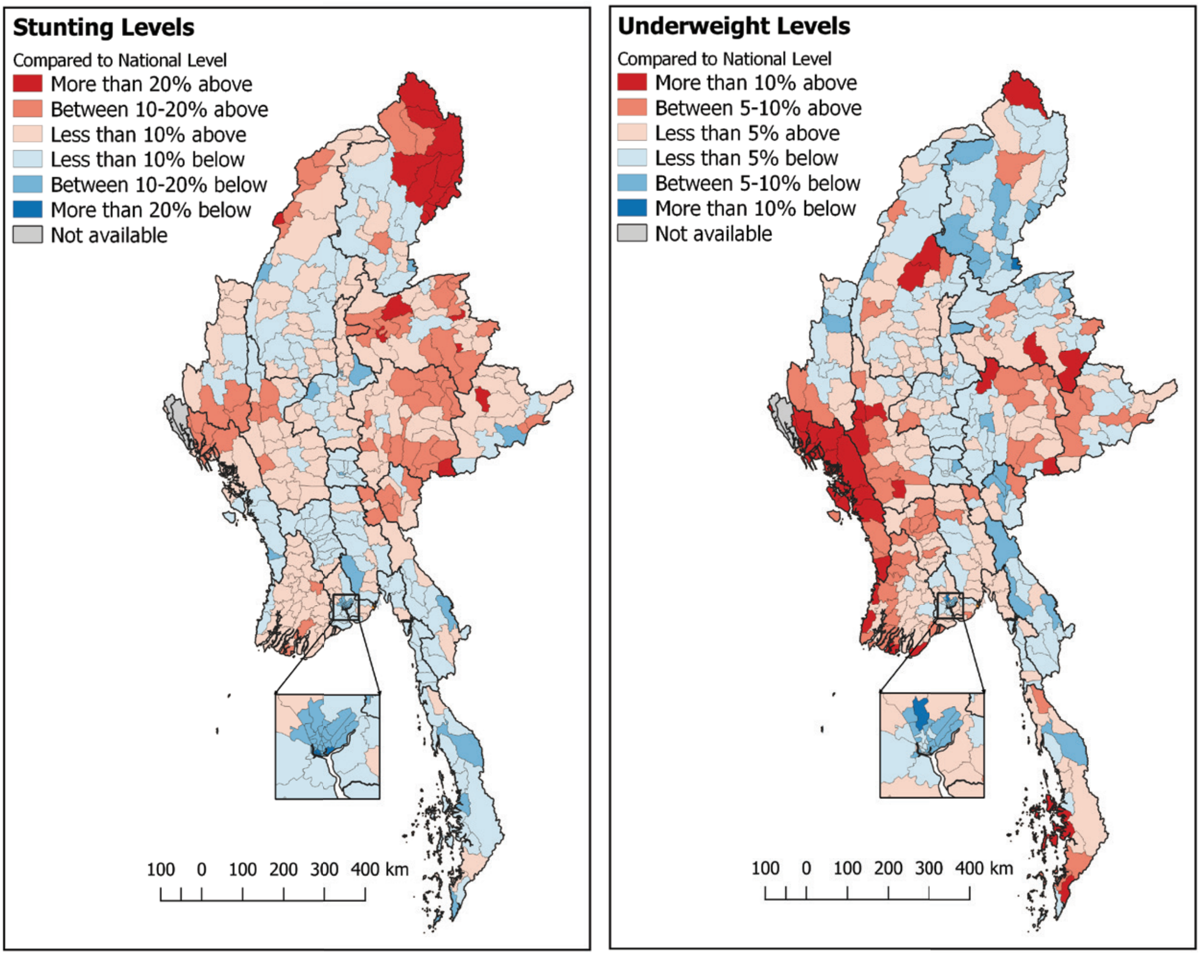
Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

Figure 16 | Underweight Estimation



Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

Figure 17 | National vs. Township



Note: Three townships (Maungtaw, Buthidaung, Yethedaung) in the Northern part of Rakhine State have limited information from census 2014 data preventing the use of small area estimation (SAE) to estimate nutrition outcomes. These are highlighted in gray for every map in this report.

Appendix G: Technical Details

The equation used to estimate the variance of the cluster-effect, $\hat{\sigma}_\eta^2$, is the following:

$$\hat{\sigma}_\eta^2 = E\Big[\frac{\sum_{c\in C} w_c H_c \hat{u}_{c..}^2 - \sum_{c\in C}\frac{w_c}{H_c}\sum_{h\in\mathcal{H}}\hat{u}_{ch.}^2}{\sum_{c\in C} w_c(H_c-1)}\Big]$$

where w_c is cluster c weight and H_c is the number of households in cluster c. Now, the equation for variance of the individual-effect, $\hat{\sigma}_\epsilon^2$, is the following:

$$\hat{\sigma}_\epsilon^2 = E\Big[\sum_{c\in\tilde{C}}\frac{\tilde{w}_c}{\tilde{H}_c}\sum_{h\in\tilde{\mathcal{H}}}\sum_{i\in\mathcal{I}}\frac{(\hat{u}_{chi}-\hat{u}_{ch.})^2}{I_{ch}-1}\Big]$$

where $\tilde{H}_c$ is the number of households with more than one individual in cluster c, $\tilde{w}_c = \frac{w_c}{\sum_{c'\in\tilde{C}} w_{c'}}$ and $\tilde{C}$ are the set of clusters with $\tilde{H}_c$. Finally, the intrapersonal correlation is $\hat{\rho}^{(k,l)} = \frac{\hat{\sigma}_\epsilon^{(k,l)}}{\hat{\sigma}_\epsilon^l \hat{\sigma}_\epsilon^k}$, where k and l represent the height-for-age and the weight-for-age indicator. The equation to estimate $\hat{\sigma}_\epsilon^{(k,l)}$ is the following:

$$\hat{\sigma}_\epsilon^{(k,l)} = E\Big[\sum_{c\in\tilde{C}}\frac{\tilde{w}_c}{\tilde{H}_c}\sum_{h\in\tilde{\mathcal{H}}}\sum_{i\in\mathcal{I}}\frac{(\hat{u}_{chi}^k-\hat{u}_{ch.}^k)(\hat{u}_{chi}^l-\hat{u}_{ch.}^l)}{I_{ch}-1}\Big]$$

More about the derivation of these equations can be found in the technical appendix of Fujii (2010).

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