Small Area Estimation of Poverty in Bhutan

Poverty Mapping Report 2017

National Statistics Bureau, Bhutan

Poverty and Equity Global Practice, The World Bank

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Abbreviations

BIC	Bayesian Information Criterion
BLSS	Bhutan Living Standards Survey
PHCB	Population and Housing Census of Bhutan
CI	Confidence Interval
GNHC	Gross National Happiness Commission
NSB	National Statistics Bureau
SE	Standard Error
SD	Standard Deviation

I. Introduction

Bhutan has made great strides in reducing poverty over the last decade. The official national poverty rate declined from 23.2 percent in 2007 to 8.2 percent in 2017; most of this improvement came from rural areas with rural poverty decreasing from 30.9 to 11.9 percent during this period. This is particularly remarkable given a largely agrarian economy and the challenges arising from sparse population settlement patterns. However, there are large differences in poverty levels across Dzongkhags. A good understanding of the geographic distribution of poverty is of great importance to guide policies to realize Gross National Happiness – Bhutan's development philosophy that emphasizes a holistic and inclusive approach to sustainable development.

As part of Bhutan's evidence-based poverty reduction agenda, the Royal Government of Bhutan has made great efforts in measuring and monitoring poverty. The National Statistics Bureau (NSB) has published a wide range of statistics and reports on poverty and other welfare indicators, all of which are based on the Bhutan Living Standard Survey (BLSS), which contains household consumption data, and thus, allows for a direct measure of poverty.

The BLSS, like all household surveys internationally, however, do not enumerate enough households to reliably estimate statistics below a certain administrative level. Bhutan is administratively divided into 20 districts ("Dzongkhag"), which consist of 205 blocks ("Gewogs"), 4 larger towns ("Thromdes"), 18 Dzongkhag towns and 42 satellite towns. However, the sample of the BLSS is only representative at the Dzongkhag level; that is, it cannot provide reliable poverty estimates at below Dzongkhag level due to its small sample size. This poses important challenges to understanding poverty conditions and designing policies to tackle poverty at a grass-roots level because variations in poverty might exist even within the same Dzongkhag.

Poverty mapping can address this issue by providing reliable estimates of poverty statistics, such as poverty headcount ratio, number of poor households and number of poor people, at Gewog/town level. In collaboration with The World Bank, NSB published the Bhutan Poverty Map 2010 which was produced using data from the BLSS 2007 and the Population and Housing Census of Bhutan 2005. The 2010 map, however, most likely no longer reflects Bhutan's current poverty conditions. Since the last poverty map was produced in 2010, Bhutan's economy has grown steadily at an annual rate of nearly 7 percent per year. Moreover, the country has also become more urbanized, with about 38.7 percent of the country's population living in urban areas as of 2017 as compared to only 30.9 percent in 2005[1]. Living standards as well as the spatial distribution of poverty are likely to have changed as a result of economic growth and urbanization.

It is critical, hence, to update the map to capture a more contemporary picture of the extent and geographical concentration of poverty in Bhutan. The updated map complements the Dzongkhag-level results of the 2017 Poverty Analysis Report and could be a useful input for

[1] Source: Population and Housing Census of Bhutan 2005 (p. 17)

Bhutan's 12thFive-Year Plan by helping to direct more resources towards gewogs with a higher concentration of poverty.

In 2017, NSB fielded both the BLSS and PHCB, providing suitable data for a new poverty mapping exercise. In June 2019, NSB and The World Bank collaborated to organize a training workshop on poverty mapping for Bhutan and conducted an estimation of Bhutan 2017 poverty map, with advisory and technical assistance from an external consultant. This report documents the results of that collaboration.

II. Building a poverty map for Bhutan: methodology and challenges

2.1.Poverty mapping methodology

Several poverty mapping methods have been proposed in the literature, each with their strengths and shortcomings. Since 2003, the small-area estimation method developed by Elbers, Lanjouw, and Lanjouw (2003), henceforth the "ELL" method, has been the de facto poverty mapping method used by the World Bank and widely adopted by international researchers to obtain small area estimates of poverty. It was used to estimate the Bhutan 2010 poverty map, as well as poverty maps in many other countries, such as India, Indonesia, Malawi, Mauritius, Nicaragua, Sri Lanka, Pakistan, Tajikistan, and Vietnam.

In response to ongoing scrutiny from researchers, poverty mapping methodology has since evolved to address a wider range of statistical challenges when estimating poverty for small administrative areas. Notably, Molina and Rao (2010) and van der Weide (2014) separately proposed two alternative methods to estimate poverty at disaggregate levels. The key differences among these approaches lie in how they estimate the error components in the small-area estimates, and each method has their strengths and weaknesses[2]. Research and recent applications of poverty mapping have shown that all three methods are acceptable.

[2] The key strength of the ELL method is that it controls for both heteroskedasticity and the cluster effect, i.e. the variation in poverty across small areas. The ELL method decomposes the uncertainty in small-area estimates into two components, one at the household level, which varies across households and one at the local level, which is the same for all households within the same locality. The locality or "cluster" is based on sampling design and does not necessarily correspond to the level at which the small-area estimates are estimated. A key concern over the ELL method, therefore, is that if the uncertainty has more than one level of clusters, the ELL estimates may not fully capture the variation in poverty across disaggregate levels and may overstate the prediction accuracy. In particular, it may lead to considerable standard errors of the final point estimates.

van der Weide (2014) implements the Henderson's Method III (Henderson, 1953) decomposition of the variance components and includes empirical Bayes through the estimated values of the cluster effect. The Henderson's Method 3 decomposition yields different variance components from the ones estimated using the ELL approach. The method by van der Weide (2014) makes use of the estimated cluster effects from survey data in order to improve the point estimates and their standard errors.

Molina and Rao (2010) propose an alternative way to estimate the nested errors via restricted max likelihood method and obtain the empirical best predictors through Monte Carlo approximation. Their approach, unlike ELL and van der Weide, does not incorporate sample weights in the modelling of the errors and thus does not control for the cluster effect. However, it tends to generate smaller SEs for the point estimates than the ELL method.

Which method best suits Bhutan is ultimately an empirical question; it depends on statistical characteristics of the estimation data as well as performance of the estimation models.

It is important to note that despite their differences, these three approaches follow the same principle. They combine information from a household survey and a population census to estimate household consumption and subsequently poverty statistics for disaggregate administrative areas. In the case of Bhutan, this exercise uses data from the Bhutan Living Standards Survey (BLSS) 2017 and the Population and Housing Census of Bhutan (PHCB) 2017 to estimate poverty headcount ratio and number of poor people at the Gewog/town level.

The estimation process involves three main steps as follows.

i. Identify potential covariates of household consumption per capita

The first step is to identify a set of local, household and individual characteristics that are potentially correlated with household consumption per capita and present in both the BLSS and the PHCB. The covariates are grouped into five main groups: location variables, characteristics of household head, demographic characteristics of the household, durable asset ownership, and dwelling conditions. They form the pool of potential explanatory variables to be used in the second and third steps below.

ii. Model selection

In the second step of SAE, data from the household survey are used to develop a set of models that can predict household consumption per capita. In this exercise, three separate models were estimated based on the BLSS data for three different regions of the country to better capture geographical differences in consumption patterns. The model specifications are selected based on their statistical performance, economic rationale with respect to the potential relationship between the explanatory variables and consumption per capita, and prediction accuracy. A model is deemed to have satisfactory prediction accuracy if its estimated poverty rates at the Dzongkhag level are closely similar to the Dzongkhag poverty rates derived directly from the BLSS. Appendix 2 provides a more detailed description of the estimation and simulation processes, as well as additional information on the explanatory variables and model specifications. The goodness-of-fit of the selected models are reported in Appendix 3. Details of the estimated models are shown in Appendix 4.

iii. Simulation

The selected models and the common explanatory variables in the census data are used to predict consumption per capita for every household in the census. Poverty statistics, including poverty headcount ratio and the number of poor people, are then estimated for each gewog.

According to Bhutan's official national poverty line, a person is identified as being poor in 2017 if his or her real consumption per capita is lower than Nu. 2,195.947 per month. Bhutan's national poverty line is obtained using the Cost of Basic Needs (CBN) approach which uses information on household food consumption to estimate the cost of a food bundle that provides a minimum required level of food energy. A non-food allowance is then added to the food component to obtain the total poverty line. This methodology is commonly used in many countries.

The World Bank's small-area estimation packages in Stata, namely *-sae-* and *-sae_mc_bs-*, are used to carry out the model estimation and simulation. The next two sections describe in more detail the technical challenges of this poverty mapping exercise and the steps taken to mitigate the issue.

2.2.Data Challenges

The small-area estimation, which applies the relationships between consumption per capita and the explanatory variables from the household survey to the census, relies on an important underlying assumption that such relationships are the same between the two data sources. For this assumption to hold, it is essential that (i) the survey data and the census data were collected not too long apart, and (ii) the statistical distributions of the explanatory variables are closely similar between the two data sources.

The first requirement is met in this poverty mapping exercise since the BLSS 2017 and PHCB 2017 were conducted in the same year. Social and economic development might change the relationships between consumption and the explanatory variables over time. Thus, when the two data sources are several years apart, it is likely that the relationships estimated from the household survey, as represented by the estimation models, are not applicable to the census. The further apart the two data sources or the more drastic social and economic conditions change during the time period that the two data sets are collected, the higher the risk. This is fortunately not the case for Bhutan.

With respect to the second requirement, this poverty mapping exercise faced some challenges. There are significant discrepancies between the BLSS and PHCB in the mean, standard deviation and frequency of various common explanatory variables that are typically considered in poverty mapping exercises. Table 4 in Appendix 1 displays the more notable discrepancies at the national level; the discrepancies are even more acute when only rural data are considered. For example, household size which is typically highly correlated with household per capita consumption averages 4.2 in the BLSS and 3.6 in the PHCB. Since common variables are included in the model selection process only if they have highly similar summary statistics between the two data sources, this restricts the number of potential explanatory variables that can be used in the modelling process and, consequently, limits the performance of the final models.

Another noteworthy issue is that in the PHCB dataset 4.5 percent of households (equivalent to 3.8 percent of the population) do not have household head information – no member in those households was identified as the head. This is because the household head was absent during Census night and thus absent from these households' roster. In order to keep these households in the estimation of poverty rates, the modelling exercise does not use any variables related to household head's characteristics. A trade-off of this decision is that, since household head's characteristics, such as age, gender, education attainment and employment status, are often strong indicators of household's economic wellbeing and poverty status, excluding them from the modelling process undermines the model's prediction power.

2.3.The poverty mapping challenges of a small population and relatively low poverty headcount

While poverty mapping allows for the estimation of poverty indicators at disaggregate administrative levels, there is an important trade-off: the more disaggregate the estimate, the larger its standard error (SE), which in turn means that the estimate has wider confidence internals and hence could be far from the unobserved actual poverty. A rough rule of thumb is that poverty map estimates could be unreliable for communities of less than 1,000 households (Elbers *et al.* 2004, p. 20).

This statistical requirement poses a critical issue for poverty mapping for Bhutan. About two thirds of Gewogs/towns have a population of less than 500 households and only 27 have 1,000 or more. As a result, regardless of the estimation models the SEs of poverty estimates at this level are likely to be substantial. While grouping Gewogs/towns to form more populous areas for estimation purpose could help address the issue technically, it is impractical from a public policy perspective. Because Bhutan's budget allocation and poverty reduction programs are targeted at either the Dzongkhag or Gewog/town level, estimating poverty for a group of Gewogs/towns, be it within a certain Dzongkhag or across multiple Dzongkhags, would not be useful. Moreover, given the large number of Gewogs/towns any grouping could be arbitrary and controversial.

The issue that arises from Bhutan's small population is related to another challenge: estimating urban poverty. The team initially estimated poverty indicators for both urban towns and rural Gewogs, yet the urban SEs turned out to be too large relative to their point estimates for the urban estimates to be deem reliable. The ratio of SE over estimated poverty rate was equal to or exceeded 100 percent for 45 out of 64 urban towns. Also, the average of the ratio across urban towns was 2.6 times larger than the average across rural Gewogs. Part of this could be attributed to the small population issue.

Another factor that contributes to the substantial SEs among urban towns is mechanical. Urban poverty in Bhutan is exceptionally low at 0.78 percent in 2017.As the point estimates are too small, even a small SE in absolute term could lead to a large SE/estimate ratio. This leads to the decision to estimate and report only rural poverty in this poverty map exercise. All figures reported in Section 3 and Section 4 below, unless otherwise stated, are for rural Bhutan. The decision to estimate a rural only poverty map and the use of alternative small area estimation methods do help mitigate the issue of large SEs in terms of the average ratio of SE over point estimate and the number of Gewogs with a ratio higher than 100 percent.

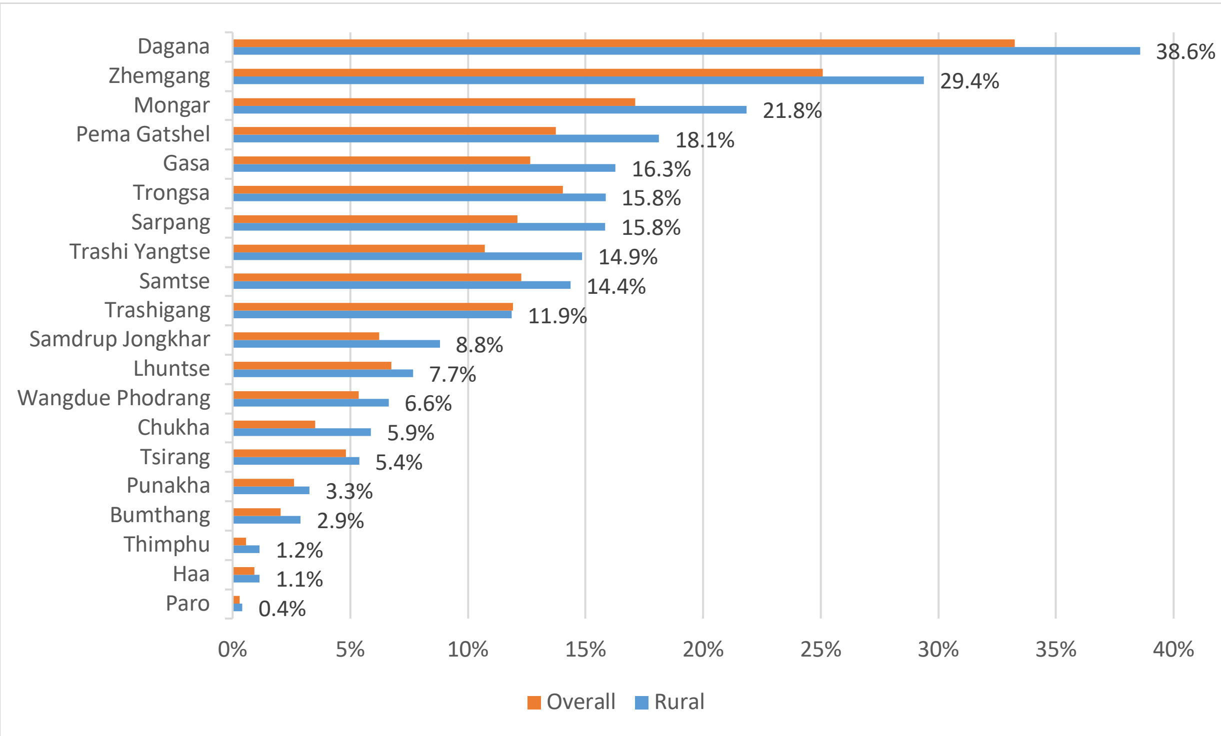
However, the issue remains to some extent and the results include some outliers with particularly large SE relative to the poverty ratewhich should be interpreted with great care. Overall, the SEs tend to be larger among Gewogs with smaller population and/or smaller estimated headcount ratios.While this does not invalidate the poverty map estimates, the point estimates should be considered together with their SEs and caution is needed when the SE is large. It is also important to acknowledge that this issue arises from the combination of the three challenges discussed above – the statistical discrepancies between the BLSS 2017 and PHCB 2017, Bhutan's uniquely small population and relatively low poverty rate.

III. Poverty at Dzongkhag level

3.1. Poverty rate at Dzongkhag level

Before analysing the estimated poverty statistics at the Gewog level, it is worth examining the geographical variation in rural poverty at the Dzongkhag level. Bhutan's moderate rural poverty rate of 11.9 percent marks substantial disparity across Dzongkhags, with the headcount ratio[3], i.e. the proportion of people living below the national poverty line, in 2017 ranging from merely 0.4 percent in Paro to 38.6 percent in Dagana (see Figure 1). More intuitively, in Dagana, the poorest Dzongkhag, more than one in every three persons live in poverty. Zhemgang has the second highest poverty rate of 29.4 percent, considerably higher than that in the next Dzongkhag on the list –Monggar with 21.8 percent. On the contrary, the incidence of poverty in the five least poor Dzongkhags, namely Paro, Haa, Thimphu, Bumthang and Punakha, is marginal at well below 3.5 percent. This pattern of spatial inequality is also largely preserved when urban poverty is taken into account, as shown in Figure 1.

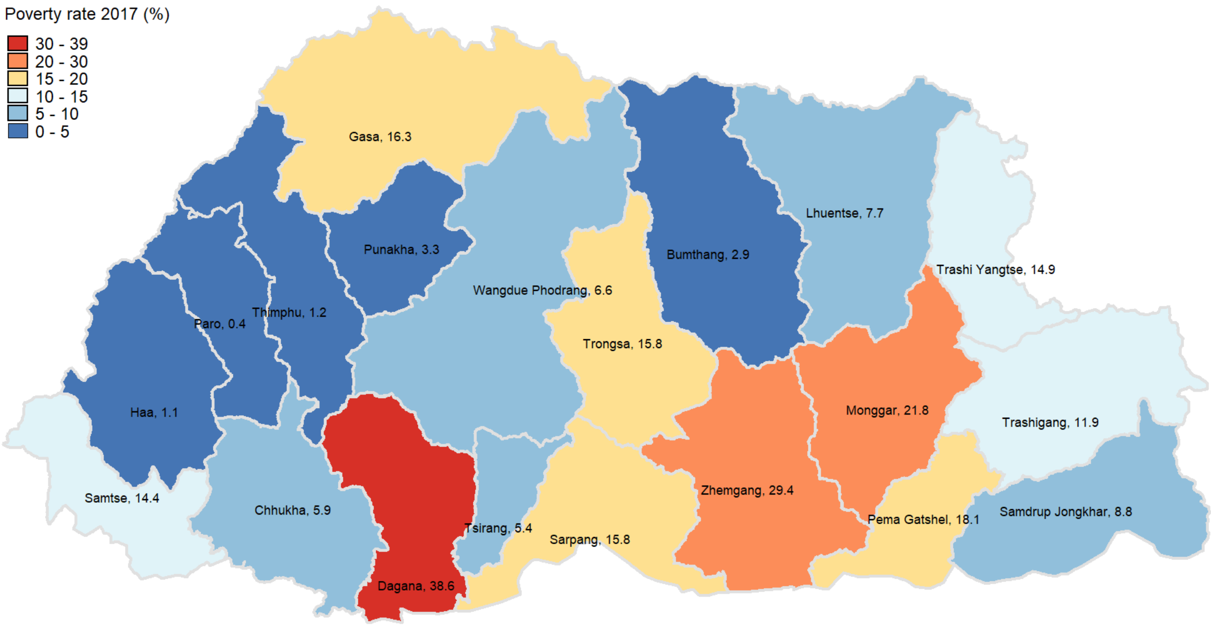
Figure 1: Dzongkhag poverty headcount ratio in 2017 (%)



Note: These figures are calculated directly from the BLSS 2017 consumption data.

[3] In this report, the term "poverty rate", "poverty headcount ratio" and "poverty incidence" are used interchangeably.

Figure 2: Map of rural poverty rate at Dzongkhag level



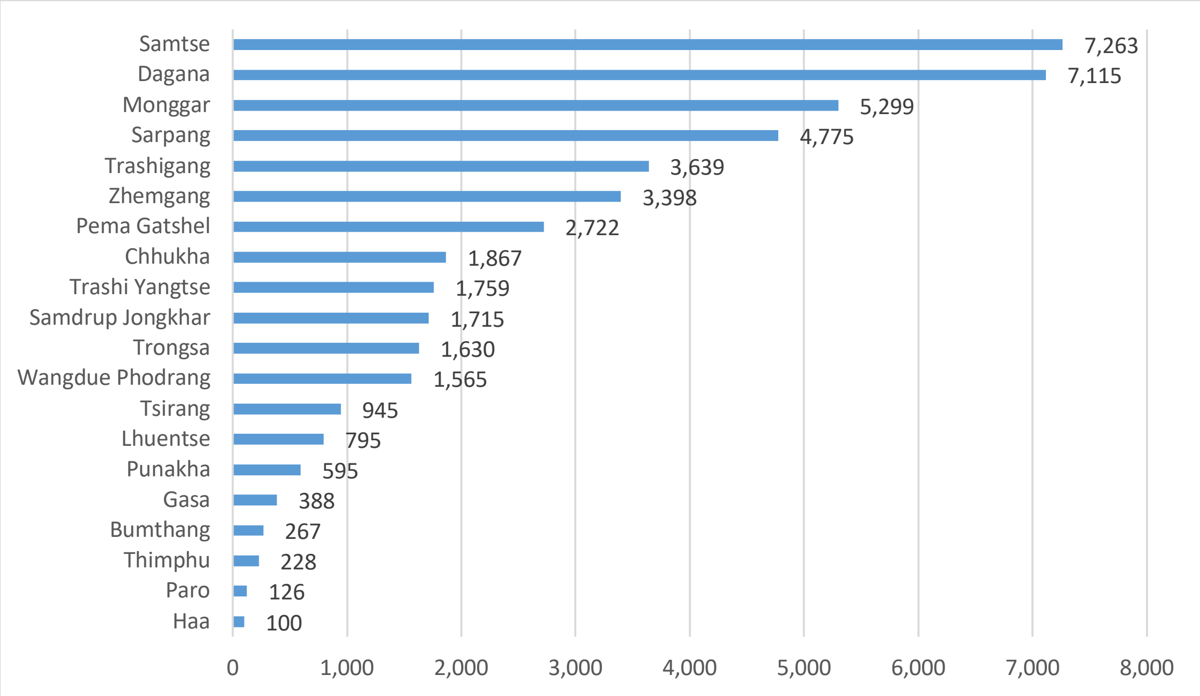
Source: Calculated based on consumption data from the BLSS 2017.

3.2. Distribution of the poor at Dzongkhag level

The headcount ratio, however, is only one aspect of poverty. Areas with the highest poverty rates do not necessarily contain the largest number of poor people because the number of the poor residing in an area depends on not only its poverty rate but also its population.

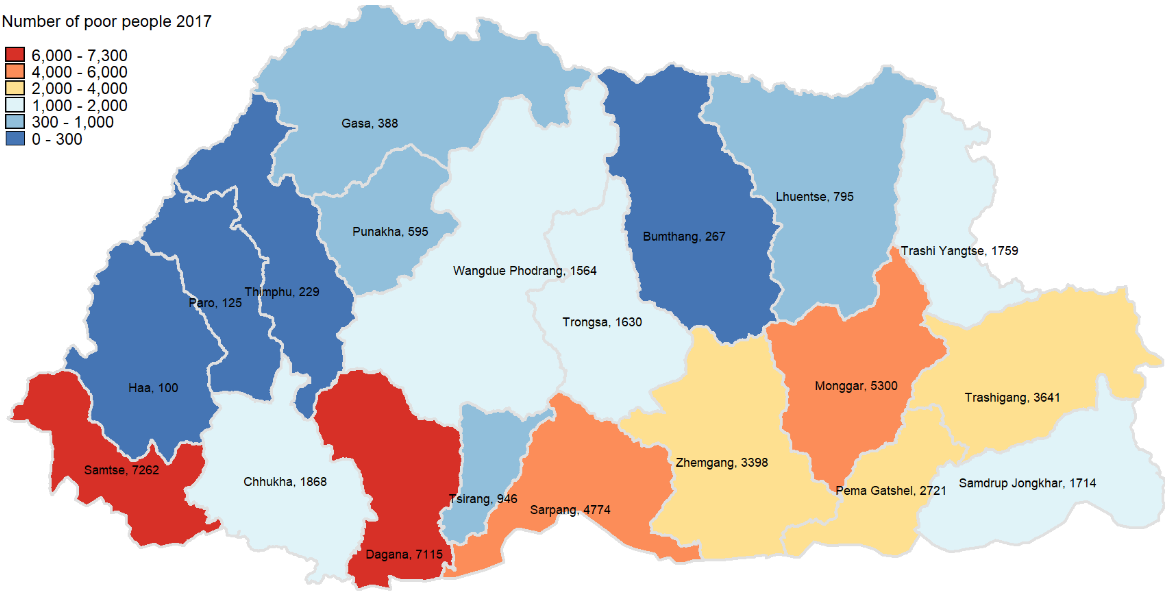
Figure 3 displays the number of poor rural people by Dzongkhag in descending order. Samtse, having a moderate poverty rate of 14.4 percent, hosts the largest number of the poor due to its large population, followed closely by Dagana. Together, these two Dzongkhags account for 31 percent of the rural poor in Bhutan. Zhemgang, the second poorest Dzongkhag, only comes in the 6th position in terms of the number of the poor. Gasa, in contrast, has the 5th smallest population of the poor despite its moderate poverty rate of 16.3 percent. Paro, Haa and Thimphu are home to the smallest shares of poor rural Bhutanese thanks to their low poverty rates.

Figure 3: Number of rural poor people by Dzongkhag



Note: Calculated based on district poverty rate and NSB official population by Dzongkhag

Figure 4: Map of number of poor rural people at Dzongkhag level



Several important points arise from these figures. One is that Dagana stands out as being the most disadvantaged Dzongkhags, while Paro, Haa and Thimphu are the most well-off in terms of both poverty rate and number of the poor. For the majority of the Dzongkhags, however, their relative rankings in these two aspects of poverty can differ considerably. The headcount ratio and the number of poor people therefore should be used as complementary statistics to inform policy decisions; ignoring either of them could mislead poverty analysis and policies that aim to alleviate poverty and reduce inequality.

Moreover, although poverty as measured by both the headcount ratio and the number of the poor is more concentrated in the South and Southeast regions of the country, as displayed in Figure 2 and Figure 4, neighboring Dzongkhags in the same region might have significantly different poverty conditions. For example, wedged between Dagana (the poorest Dzongkhag by headcount ratio with poverty rate of 38.6 percent) and Sarpang (poverty rate of 15.8 percent), Tsirang has a modest poverty rate of only 5.4 percent. This wide disparity across Dzongkhags highlights the need to understand living conditions and consequently to target policy interventions at disaggregate levels.

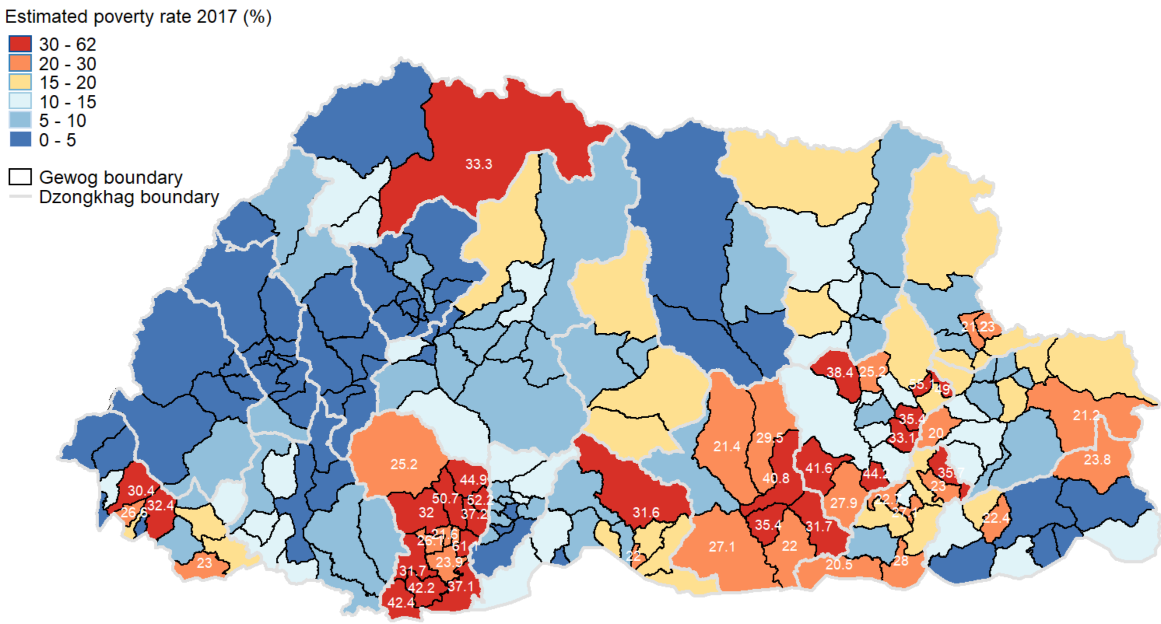
IV. Poverty at Gewog level

4.1. Poverty rate at Gewog level

The estimated poverty rates by Gewog provide a more detailed picture of rural poverty in Bhutan, with significant geographical inequality both between and within Dzongkhag. On the one hand, there are some pockets of poverty within relatively well-off Dzongkhags, such as Wangphu (poverty rate of 22.4 percent) and Lauri (23.8 percent) in Samdrup Jongkhar, which has an average poverty rate across Gewogs of10.4 percent, and Lunana (33.3 percent[4]) in Gasa, whose average poverty rate across Gewogs is 14.7 percent. On the other hand, there are Gewogs with low poverty incidence within relatively poor Dzongkhags, such as Dechhenling (5.5 percent) in Pema Gatshel (average poverty rate across Gewogs 20.6 percent) and Monggar Gewog (6.9 percent) in Monggar Dzongkhag (average poverty rate across gewogs 27 percent).Figure 5 presents the poverty map at the Gewog level. Appendix 5 lists the full set of results, including gewog-level poverty estimates and standard errors.

[4] It should be noted that the estimated poverty rate for Lunana has a SE of 13.3 percent. While this SE amounts to only 40 percent of the point estimate, its large value in absolute terms leads to a very wide 95% CI of [7.2 percent; 59.5 percent]. The poverty rate that is derived directly from the BLSS 2017 for Gasa also has the widest 95% CI among all Dzongkhags (from 7.7 percent to 24.9 percent).

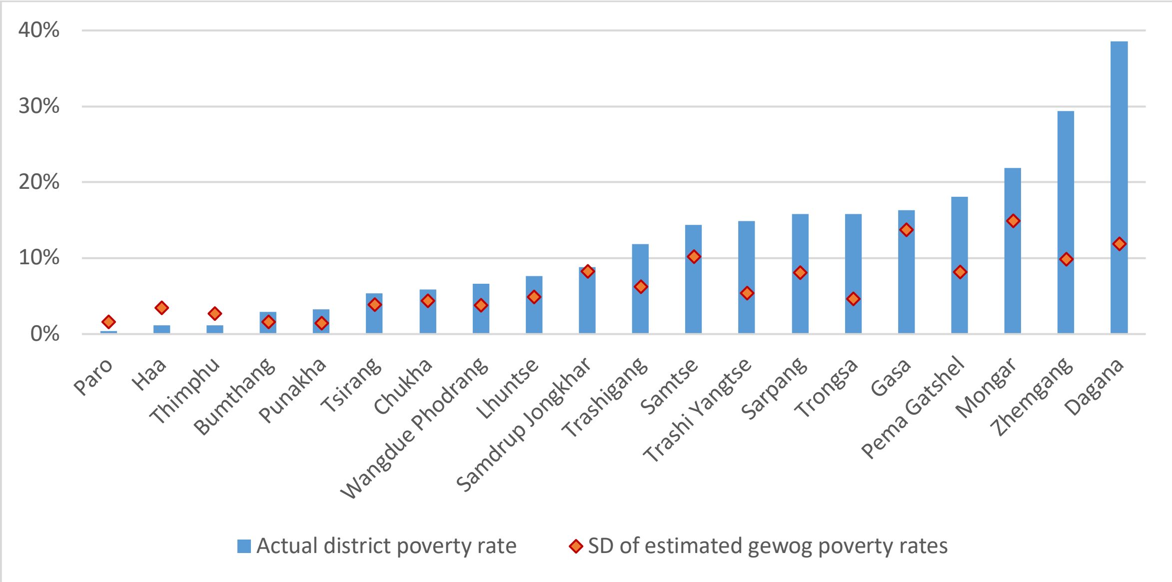
Figure 5: Poverty map at Gewog level



As discussed previously, some outliers remain in terms of their ratio of SE over poverty estimate. While the ratio is below 50 percent for the vast majority of the Gewogs (136 out of 205) it exceeds 100 percent for 17 Gewogs (Appendix 5). All of these 17 Gewogs have fewer than 1,000 households and the estimated headcount ratio is below 2 percent for 11 of them. Notably, there are five outliers with the ratio exceeding 300 percent, all of which have extremely low estimated poverty rates and population of fewer than 500 households. They are Samrang (0.8 percent, 55 households) and Serthig (1.1 percent, 436 households) in Samdrup Jongkhar, Laya (0.2 percent, 240 households) in Gasa, Samar (0.5 percent, 217 households) in Haa, and Hoongrel (0.7 percent, 45 households) in Paro. The use such outliers for policy purpose is strongly discouraged.

The within-Dzongkhag variation in poverty is generally larger in Dzongkhags that have higher poverty rates. Some Dzongkhags, however, have notably higher degrees of spatial disparity relative to their poverty levels. For instance, among Dzongkhags with poverty rates between 14 and 16 percent Gasa stands out; the standard deviation of poverty rate among its Gewogs is 13.7 percent, much higher than that in Samtse, Trashi Yangtse, Sarpang, and Trongsa (see Figure 6). However, the relatively large variation in Gewog poverty rate in Gasa should be treated with care since the 95% CI of the estimated poverty rate for Lunana is very wide. Among the three poorest Dzongkhags, Monggar also displays a larger extent of disparity despite having a markedly lower poverty rate than Zhemgang and Dagana – the standard deviation of their Gewog poverty rates are 14.9 percent, 9.9 percent and 11.9 percent, respectively. Spatial disparity in the three richest Dzongkhags – Paro, Haa and Thimphu – appears relatively large as compared to their poverty rates but is not critical from a policy perspective given their extremely low levels of poverty.

Figure 6: Variation in poverty rate within Dzongkhag



Despite such spatial disparity within Dzongkhags, however, the poorest/richest Gewogs are still concentrated in the poorest/richest Dzongkhags. Given that Dagana is significantly poorer than the rest of the country and Monggar not only is the third poorest Dzongkhag but also has the highest extent of disparity across Gewogs, it is no surprise that all of the 10 poorest Gewogs are in these two areas – six in Dagana and four in Monggar (Table 1). These Gewogs have staggering poverty rates above 40 percent, with Tashiding in Danaga topping the list at 61.2 percent; that is, more than half of the population their lives in poverty. In stark contrast, poverty rates in the 10 least poor Gewogs are negligible at below 1 percent Half of them are located in Paro, the richest Dzongkhag, whilst the remaining five spread across Haa, Chhukha, Gasa and Samdrup Jongkhar. Yet for some of these Gewogs, particularly Laya and Samrang, the SEs are very large relative to the point estimates so these estimates should be interpreted with care. The issue of large SEs among Gewogs with low poverty estimates are further discussed in Appendix 3.

Table 1: Estimated poverty rates of the 10 poorest and 10 richest Gewogs

Ranking	Gewog	Dzongkhag	Estimated Poverty Rate (%)
Poorest	Tashiding	Dagana	61.15
2	Balam	Monggar	55.14
3	Tsangkha	Dagana	52.18
4	Khebisa	Dagana	50.73
5	Na-Rang	Monggar	48.97
6	Largyab	Dagana	44.95
7	Jurmed	Monggar	44.18
8	Lhamoi Dzingkha	Dagana	42.39
9	Karmaling	Dagana	42.24
10	Silambi	Monggar	41.63

10	Dopshar-ri	Paro	0.89
9	Samrang	Samdrup Jongkhar	0.78
8	Hoongrel	Paro	0.71
7	Chapchha	Chhukha	0.69
6	Kar-tshog	Haa	0.54
5	Samar	Haa	0.50
4	Tsento	Paro	0.28
3	Lamgong	Paro	0.28
2	Laya	Gasa	0.18
Richest	Wangchang	Paro	0.11

The Gewog poverty estimates reveal that spatial inequality in Bhutan is more acute than previously reflected by the Dzongkhag poverty rates in Figure 1**Error! Reference source not found.**. Not only is the range of the headcount ratio considerably wider at the Gewog level, but the standard deviation of Gewog poverty rate is also slightly larger (12.3 percent as compared to 9.7 percent at the Dzongkhag level). This further reinforces the need to target poverty reduction and social protection interventions at the Gewog level.

4.2. Distribution of the poor at Gewog level

The distribution of the poor across Gewogs is mostly consistent with the distribution across Dzongkhags (Figure 7). Five out of 10 Gewogs with the largest number of poor people are in Samtse, the other five are in Dagana, Monggar, and Sarpang, as shown in Table 2 below. Together, these 10 Gewogs account for 19 percent of the rural poor. Due to the large number of Gewogs in Bhutan, however, no Gewog accounts for a considerable share of the total poor.

Figure 7: Map of estimated number of poor people at Gewog level

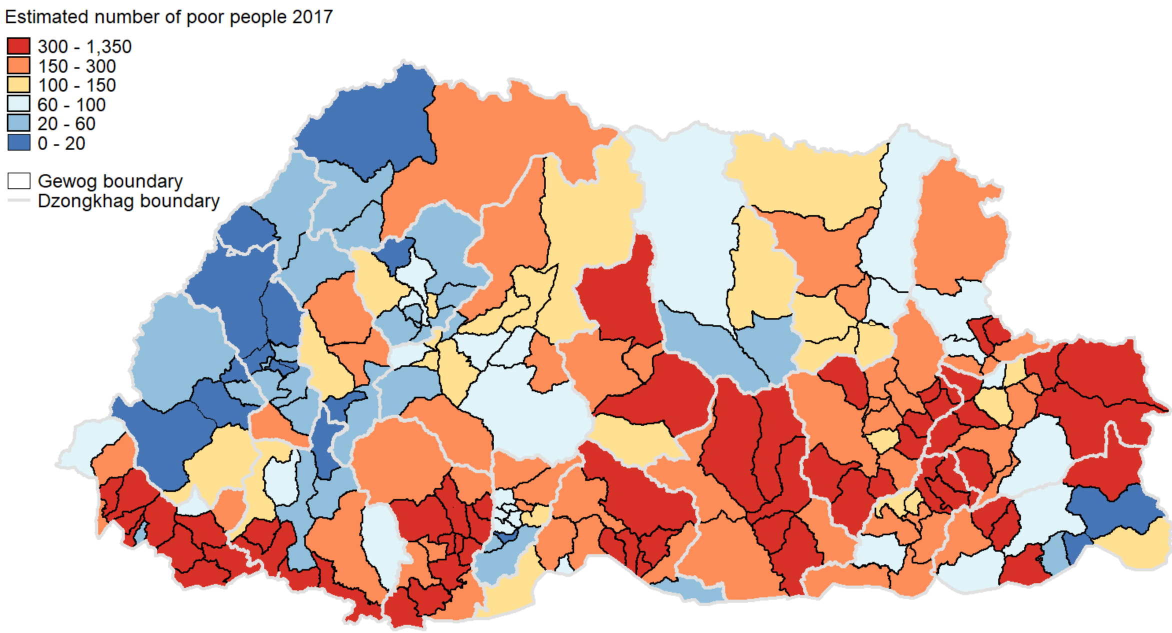


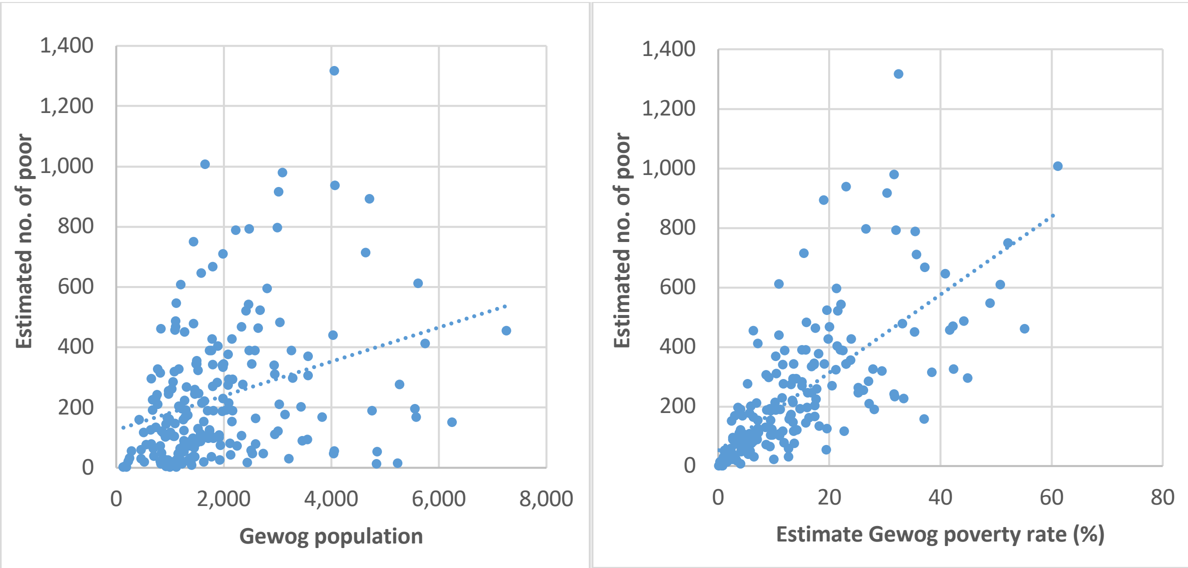
Table 2: Top 10 Gewogs with the largest number of poor people

Ranking	Gewog	Dzongkhag	Number of poor people
1	Norboogang	Samtse	1,316
2	Tashiding	Dagana	1,007
3	Jigme Chhoeling	Sarpang	978
4	Phuentshogpelri	Samtse	937
5	Namgyal chhoeling	Samtse	916
6	Tading	Samtse	892
7	Sang-Ngag-Chhoelin	Samtse	796
8	Karna	Dagana	792
9	Chagsakhar	Monggar	788
10	Tsangkha	Dagana	749

Note: Each of the10 smallest Gewogs in terms of the number of the poor has fewer than 20 people living in poverty. It is, therefore, trivial to display them.

It is also observed that there exists a stronger positive link between the estimated poverty rate and the estimated number of poor people across Gewogs than between the Gewog population and the estimated number of poor (Figure 8). The correlation between the estimated poverty rate and the estimated number of poor is 0.72, as compared to 0.31 between the Gewog population and the estimated number of poor. In other words, the number of poor people is more strongly driven by the estimated poverty rate than the Gewog population.

Figure 8: Correlation between estimated number of poor, estimated poverty rate and population at Gewog level



The estimated poverty incidence and number of poor people reported above are both useful for budget allocation and policy targeting purposes. Yet a relevant policy question is, should policy interventions prioritize areas with high poverty rates or areas with large numbers of poor people? While the answer depends on various factors, such as the intervention's design, objectives, and budget, the cost-effectiveness of targeting the poor depends on how the intervention benefits them.

On the one hand, if the intervention provides mainly private benefits for poor households and/or poor individuals the number of beneficiaries is a key factor determining the total cost of the program. An example of this type of interventions is cash transfer programs. In such cases, the intervention is likely to have lower targeting errors and be more cost-effective if targeted to areas with higher poverty rates, i.e. where a large share of the population is poor.

On the other hand, for policy interventions that create public goods that can be shared by all residents of an area at little or no additional cost, such as improving roads or expanding access to health clinics, the majority of the cost is fixed. In such cases, targeting areas with a large number of the poor will benefit more poor people.

The policy making process when using poverty map estimates in practice, however, is often more complex as policy interventions often have multiple components that target beneficiaries differently. In addition, as the standard errors on poverty map estimates becomes progressively larger as poverty is being measured over progressively smaller groups, poverty map cannot be viewed as a tool to identify very small groups of poor households or a specific poor household (Elbers *et al.* 2007).Based on evidence from Cambodia, Ecuador and Madagascar, Elbers and colleagues suggest that a useful way forward might be to combine fine geographic targeting using a poverty map with within-community targeting mechanisms.

V. Conclusion

The poverty map presented in this report provides an updated picture of rural poverty in Bhutan. The estimated poverty rate and number of poor Bhutanese can be used to locate the poor and inform policy decisions that aim to reduce poverty and spatial inequality in the country. The prominent geographical disparity at Gewog level suggests the need for policies to boost economic growth in poor areas and narrow the income gap. In order to do so, identifying determinants of their lagging performance should be on top of the poverty and inequality reduction agenda.

While a poverty map is a useful and intuitive tool to understand poverty and geographical inequality at disaggregated levels, which cannot be done using only household consumption surveys, it is worth pointing out the shortcomings of poverty maps in general and what their implications are for the Bhutan 2017 poverty map.

First, a poverty map should be interpreted as an approximation of well-being. The estimates are derived from predictions based on household and local characteristics such as demographics and dwelling conditions. These characteristics often change slowly over time and may not fully reflect the impact of economic shocks on the contemporary wellbeing of the households. Therefore, in comparison to poverty statistics that are directly derived from consumption or income data, poverty map estimates might not capture the impacts of economic shocks on poverty. In the case of the map reported above, the fact that the BLSS 2017 and PHCB 2017 were conducted in the same year helps mitigate this issue.

Second, beside income or consumption poverty, a poverty map does not cover other aspects of economic well-being and opportunities, such as access to health clinics and schools, and distance to main roads and major markets. Nor does poverty map measure factors that potentially correlate with poverty incidence, such as labor market outcomes and health status. A potential extension to this poverty mapping exercise that might help pinpoint the reasons pockets of poverty remain economically stagnant and potential solutions to improve their living standards is overlaying the poverty map with geographical information on social services, infrastructure, and social conditions.

Finally and specifically for this exercise, Bhutan’s small population at the Gewog/town level combined with considerable statistical discrepancies in various household-related variables between the BLSS 2017 and PHCB 2017 lead to large SEs for several Gewogs. While this does not invalidate the poverty map estimates, the point estimates should be considered together with their SEs and caution is needed when the SE is large.

Appendix 1: Samples

In order to reliably predict household consumption per capita, this poverty mapping exercise only considers regular households and excludes institutional and transient households, such as dormitories, hospitals and religious boarding institutions, from the PHCB dataset.This is also consistent with the target population for whom national poverty is estimated using the BLSS as consumption data is only collected for regular households. Urban households, as explained in Section 2, are also excluded. After the data cleaning process, the BLSS sample contains 6,714 households, whereas the PHCB contains 102,473 households. The distributions of households across Dzongkhag in the PHCB and the BLSS sample are closely similar, as shown in Table 3.

In datasets, visitors, domestic servants and household members who had been absent for more than 12 months are excluded. This is to ensure that the household size and other household demographic characteristics, such as dependency ratio, sex ratio, and proportion of household members with a certain level of education attainment, reflect the household's consumption per capita.

Table 3: Geographical distribution of the PHCB and the BLSS sample

	PHCB 2017		BLSS 2017	
Dzongkhag	**Number of households**	**Share of population (%)**	**Number of households**	**Share of sample (%)**
Bumthang	2,252	2.20	144	2.15
Chhukha	7,539	7.36	499	7.44
Dagana	4,817	4.70	317	4.71
Gasa	627	0.61	40	0.60
Haa	2,350	2.29	142	2.11
Lhuentse	2,749	2.68	209	3.11
Monggar	6,747	6.58	436	6.50
Paro	7,564	7.38	427	6.36
Pema Gatshel	4,333	4.23	285	4.25
Punakha	4,824	4.71	323	4.82
Samdrup Jongkhar	5,372	5.24	356	5.31
Samtse	12,082	11.79	765	11.40
Sarpang	7,354	7.18	470	7.00
Thimphu	5,019	4.90	362	5.39
Trashi Yangtse	8,927	8.71	593	8.83
Trashigang	3,262	3.18	212	3.15
Trongsa	2,915	2.84	205	3.05
Tsirang	4,417	4.31	284	4.23
Wangdue Phodrang	6,260	6.11	441	6.57
Zhemgang	3,063	2.99	204	3.03
Total	**102,473**	**100.00**	**6,714**	**100.00**

Table 4: Discrepancies in summary statistics between BLSS and PHCB

		BLSS 2017 (weighted by household weight)			PHCB 2017		
Variable group	**Variable**	**Obs.**	**Mean**	**Std. Dev.**	**Obs.**	**Mean**	**Std. Dev.**
Household Demographics	Household size	11,660	4.2	1.9	162,759	3.6	1.9
	Ratio of adults (aged 18-60) working/household size	11,660	0.4	0.3	162,759	0.3	0.3
	Highest education attainment in the household	**Obs.**	**Percent**	**Cumulative Percent**	**Obs.**	**Percent**	**Cumulative Percent**
	Pre-primary/ No schooling/ BLC/PLC	1,821	15.6	15.6	34,310	21.1	21.1
	Primary school	2,368	20.3	35.9	34,226	21.0	42.1
	Middle School	1,376	11.8	47.7	14,789	9.1	51.2
	Lower Secondary	2,137	18.3	66.1	22,996	14.1	65.3
	Upper Secondary	2,321	19.9	86.0	25,205	15.5	80.8
	Diploma/Vocational	334	2.9	88.8	5,899	3.6	84.4
	Bachelor and above	1,303	11.2	100.0	25,291	15.5	100.0
	missing	0	0.0	100.0	43	0.0	100.0
Household's head characteristics	**Marital status**						
	Never Married	515	4.4	4.4	12,382	8.0	8.0
	Living together	41	0.4	4.8	1,560	1.0	9.0
	Married	9,601	82.3	87.1	126,438	81.3	90.3
	Divorced	509	4.4	91.5	6,749	4.3	94.7
	Separated	53	0.5	91.9	949	0.6	95.3
	Widowed	942	8.1	100.0	7,358	4.7	100.0
	missing	0	0.0	100.0	16	0.0	100.0
	Education attainment						
	Pre-primary/ No schooling	6,840	58.7	58.7	83,105	53.5	53.5
	Primary school	1,637	14.0	72.7	22,679	14.6	68.1
	Middle School	615	5.3	78.0	7,605	4.9	72.9
	Lower Secondary	880	7.6	85.5	11,878	7.6	80.6
	Upper Secondary	664	5.7	91.2	10,054	6.5	87.1
	Diploma/Vocational	267	2.3	93.5	5,521	3.6	90.6
	Bachelor and above	758	6.5	100.0	14,528	9.4	100.0
	missing	0	0.0	100.0	82	0.1	100.0
	Employment status						
	Employed	9,878	84.7	84.7	99,688	64.1	64.1

	Unemployed	104	0.9	85.6	3,077	2.0	66.1
	Not in labor force	1,678	14.4	100.0	52,602	33.8	100.0
	missing	0	0.0	100.0	85	0.1	100.0
	Working status						
	Unemployed/Not in labor force	1,782	15.3	15.3	55,679	35.8	35.8
	Working	9,878	84.7	100.0	99,688	64.1	100.0
	missing	0	0.0	100.0	85	0.1	100.0
Housing infrastructure	**Ownership**						
	No	4,368	37.5	37.5	80,147	49.2	49.2
	Yes	7,292	62.5	100.0	82,612	50.8	100.0
	Roof						
	Others	615	5.3	5.3	15,499	9.5	9.5
	Metal sheet	11,045	94.7	100.0	147,260	90.5	100.0
	Floor						
	Wood	4,942	42.4	42.4	9,285	5.7	5.7
	Cement/ Tile	3,573	30.6	73.0	6,978	4.3	10.0
	Concrete	835	7.2	80.2	63,792	39.2	49.2
	Plank/ Shingles	1,413	12.1	92.3	67,675	41.6	90.8
	Clay/ Earthen floor	898	7.7	100.0	15,029	9.2	100.0
	Wall						
	Mud-bonded bricks/stones	4,182	35.9	35.9	40,310	24.8	24.8
	Cement-bonded bricks/stones	2,870	24.6	60.5	24,904	15.3	40.1
	Concrete	1,618	13.9	74.4	45,729	28.1	68.2
	Mud	1,025	8.8	83.2	23,355	14.4	82.5
	Wood / Branches	1,503	12.9	96.1	19,182	11.8	94.3
	Others	461	4.0	100.0	9,279	5.7	100.0
	Cooking fuel (either gas or electricity)						
	No	414	3.6	3.6	1,226	0.8	0.8
	Yes	11,246	96.5	100.0	156,982	96.5	97.2
	missing	0	0.0	100.0	4,551	2.8	100.0
	Toilet						
	Flush	9,603	82.4	82.4	126,649	77.8	77.8
	VIP/Pit Latrine with slab/ Composting	1,117	9.6	91.9	17,179	10.6	88.4
	Pit latrine without slab/open pit	769	6.6	98.5	12,695	7.8	96.2
	Others	171	1.5	100.0	6,236	3.8	100.0
	Sharing Toilet						
	No	10,710	91.9	91.9	137,167	84.3	84.3

	Yes	868	7.5	99.3	25,450	15.6	99.9
	missing	82	0.7	100.0	142	0.1	100.0
	Distance to water source (minutes)	458	7.8	15.2	162,651	3.0	16.8
	Internet connection - overall						
	No	4,887	41.9	41.9	90,550	55.6	55.6
	Yes	6,773	58.1	100.0	72,144	44.3	100.0
	missing	0	0.0	100.0	65	0.0	100.0
	Internet connection -mobile						
	No	4,916	42.2	42.2	91,507	56.2	56.2
	Yes	6,744	57.8	100.0	71,187	43.7	100.0
	missing	0	0.0	100.0	65	0.0	100.0
Assets	land	11,660	71.0%		162,759	56.6%	
	foreign bow	11,660	7.3%		162,695	5.7%	
	bicycle	11,660	3.0%		162,695	5.8%	
	jewellery	11,660	33.4%		162,695	29.4%	
	sofa set	11,660	39.1%		162,695	37.4%	
	motorbike/scooter	11,660	1.9%		162,695	2.7%	
	rice cooker	11,660	95.2%		162,695	87.4%	
	Seshu gho kira	11,660	18.6%		162,696	21.9%	
	computer/laptop	11,660	17.7%		162,694	22.6%	
	fridge	11,660	56.7%		162,695	51.2%	
	camera	11,660	6.6%		162,695	15.6%	
	wristwatch	11,660	26.5%		162,695	43.6%	
	tablet	11,660	4.1%		162,694	5.8%	
	other mobile phones	11,660	55.8%		162,694	50.8%	

Appendix 2: Estimation and simulation process

In addition to the discussion in Section 2, this Appendix describes in more detail the three steps of this poverty mapping exercise.

Step 1: Identify potential covariates of household consumption per capita

Before estimating the consumption model and imputing household consumption into the census data, a set of potential explanatory variables were identified. This was first done by comparing the questionnaires of the household survey and the census to find variables that (i) are likely to be highly correlated with consumption and (ii) exist in or can be constructed from both the BLSS and the PHCB. Five groups of potential explanatory variables were generated; they are location dummies, household characteristics, household head's characteristics, dwelling conditions, and durable assets.

Once the potential explanatory variables were constructed, their summary statistics, including mean, SD, minimum, maximum (for continuous variables) and frequency (for categorical variables) are compared between the BLSS and the PHCB. Only those whose distributions were similar between the two datasets are shortlisted to be used in the modelling step. As described below, there are three regional models to be estimated in Step 2 as adopting one national model for all households did not yield good predictions. Summary statistics, therefore, are compared between the BLSS and the PHCB for each region separately and the list of independent variables selected for each regional model varies, depending on model section criteria. For brevity, descriptive statistics of only the selected variables based on the BLSS sample are presented in Table 5 below.

Table 5: Summary statistics of the BLSS sample (weighted by household weight)

Variable	Obs.	Mean	SD	Min	Max	Definition
Location						
District						Dzongkhag dummies
Bumthang	144	2.15	2.15			
Chhukha	499	7.44	9.59			
Dagana	317	4.71	14.30			
Gasa	40	0.60	14.90			
Haa	142	2.11	17.01			
Lhuentse	209	3.11	20.12			
Monggar	436	6.50	26.62			
Paro	427	6.36	32.98			
Pema Gatshel	285	4.25	37.23			
Punakha	323	4.82	42.04			
Samdrup Jongkhar	356	5.31	47.35			
Samtse	765	11.40	58.75			
Sarpang	470	7.00	65.75			
Thimphu	362	5.39	71.14			
Trashigang	593	8.83	79.96			
Trashi Yangtse	212	3.15	83.12			
Trongsa	205	3.05	86.17			
Tsirang	284	4.23	90.39			
Wangdue Phodrang	441	6.57	96.97			
Zhemgang	204	3.03	100.00			

Demographics						
Household size	6,714	4.35	2.06	1.00	17.00	
Economic dependency ratio	6,714	0.32	0.25	0.00	1.00	Number of members aged below 15 or above 65 divided by household size
Work ratio	6,714	0.43	0.26	0.00	1.00	Number of adults (aged 18-60) who were working divided by household size
English literacy ratio	6,714	0.23	0.25	0.00	1.00	Number of adults (aged 18+) who can read and write in English divided by household size
eduratio_3	6,714	0.06	0.13	0.00	1.00	Number of members with Lower Secondary divided by household size
eduratio_5	6,714	0.01	0.06	0.00	1.00	Number of members with Diploma or Vocational divided by household size
eduratio_6	6,714	0.02	0.10	0.00	1.00	No. of members with Bachelor and above divided by household size
Housing condition						
Number of rooms	6,714	3.32	1.89	1.00	19.00	
Room per capita	6,714	0.96	0.79	0.08	10.00	
Lighting						
Others	112	1.68	1.68			
Electricity	6,602	98.32	100.00			
Water source						
Pipe in Dwelling	1,913	28.50	28.50			
Pipe in Compound	4,495	66.95	95.45			
Others	306	4.55	100.00			
Assets						
Jewellery	6,714	0.31	0.46	0.00	1.00	dummy variable: 1= HH owns jewellery, 0=otherwise
Sofa set	6,714	0.22	0.41	0.00	1.00	dummy variable: 1= HH owns sofa set(s), 0=otherwise
Motor bikes/ Scooters	6,714	0.01	0.11	0.00	1.00	dummy variable: 1= HH owns motorbike/scooter(s), 0=otherwise
Rice cooker	6,714	0.93	0.26	0.00	1.00	dummy variable: 1= HH owns rice cooker(s), 0=otherwise
Seshu gho/kira	6,714	0.12	0.33	0.00	1.00	dummy variable: 1= HH owns Seshu gho/kira(s), 0=otherwise
Computer/ Laptop	6,714	0.08	0.27	0.00	1.00	dummy variable: 1= HH owns other computer/laptop(s), 0=otherwise

Refrigerator	6,714	0.43	0.49	0.00	1.00	dummy variable: 1= HH owns refrigerator(s), 0=otherwise
Washing machine	6,714	0.10	0.30	0.00	1.00	dummy variable: 1= HH owns washing machine(s), 0=otherwise
Smart phone	6,714	0.51	0.50	0.00	1.00	dummy variable: 1= HH owns smart phone(s), 0=otherwise
DVD/VCR	6,714	0.13	0.34	0.00	1.00	dummy variable: 1= HH owns DVD/VCR(s), 0=otherwise

Step 2: Select models to estimate consumption per capita from the BLSS data

<u>Econometric approach</u>

Step 2 aims to find a consumption model that reliably predicts household consumption per capita. The estimation model is:

$$\ln(exp_{ic}) = \beta X_{ic} + u_{ic} \qquad (1)$$

where $ln(exp_{ic})$ is the logarithm of consumption per capita of household i in geographical cluster c, X_{ic} is a vector of explanatory variables, and u_{ic} is the error term.

A technical challenge in estimating equation (1) is controlling for heteroskedasticity in the error term u_{ic}, which is often prominent in household consumption data. This is addressed by breaking the error term into two components, one at the cluster level and the other at the household level:

$$u_{ic}=\eta_c+\varepsilon_{ic} \qquad (2)$$

In this exercise, we define a cluster as a Gewog. Both components in Equation (2) are assumed to be independent of the explanatory variables X_{ic} and independent of each other. However, the variance of the second component is assumed to vary across households. Equation (1) then becomes:

$$\ln(exp_{ic})=\beta X_{ic}+\eta_c+\varepsilon_{ic} \qquad (3)$$

Equation (3) is estimated by the Feasible Generalized Least Square regression method, which takes into account differences in the distribution of errors across households. An important difference between the conventional Ordinary Least Square (OLS) method and the FGLS method is that FGLS estimates not only the coefficients but also the distributions of the coefficients β and errors η_c and ε_{ic}. These estimated distributions will be used to calculate poverty rates in Step 3. More technical discussions on the ELL method can be found in Elbers, Lanjouw, and Lanjouw (2003), World Bank (2005), and Vishwanath and Yoshida (2007).

Tarozzi and Deaton (2009) highlight several concerns over the ELL method. Most notably, the ELL method relies on models of the average relationships between consumption per capita and explanatory variables, which are assumed to be the same for all regional areas within a model's sample. If these relationships in fact vary considerably across areas within the model's sample, that is, if the structure of Equation (2) is mis-specified, the poverty map estimates may not fully capture the variation in poverty across disaggregate levels and may overstate the prediction accuracy.

More recently, Molina and Rao (2010) propose an alternative way to estimate Equation (2)via restricted max likelihood method and obtain the empirical best predictors through Monte Carlo approximation. Later in 2014, van der Weide (2014) present yet another approach that implements the Henderson

's Method III (Henderson, 1953) decomposition of the variance components and includes empirical Bayes through the estimated values of the cluster effect (η_c). The method is different from the ELL approach since the Henderson's Method 3 decomposition yields different variance components from the ones estimated using the ELL approach.

Due to the challenges that arises from the small population at Gewog level as well as the discrepancies in summary statistics between the BLSS and PHCB, all three estimation approaches, namely the ELL, the Henderson's Method 3 with EB, and the approach by Molina and Rao (2010), were explored for all estimation models. Recent applications of poverty mapping have shown that all three approaches are acceptable. Which approach among the three was ultimately selected was determined by the following two criteria: (i) Dzongkhag estimates are closely similar to the actual poverty rates that are derived directly from consumption data and (ii) the SE of Gewog estimates are minimal. As a result, the Henderson's Method 3 with EB was selected for Region 1 and the approach proposed by Molina and Rao (2010)was selected for Regions 2 and 3.

Creating sub-samples

Aside from the heteroskedasticity issue, national household surveys like the BLSS typically contain complex geographical heterogeneity. Differences in lifestyles, preferences, and consumption patterns are likely to be significant across urban and rural areas, as well as across regions within a country. For example, owning a tractor might be a good indicator of economic wellbeing and high consumption in rural areas. Tractor ownership, however, may explain much less of the variation in consumption in urban areas, where most of the population work outside agriculture and thus do not need a tractor at home. Thus, estimating separate consumption models for smaller and relatively homogenous geographical areas is likely to produce more accurate results than estimating a single model for the entire country.

This empirical exercise confirms this by testing various national models and showing that none of the tested national model produces satisfactory estimates at the Dzongkhag level for all of the Dzongkhag. An intuitive reaction to this would be to estimate one consumption model for each Dzongkhag separately. However, given the BLSS's small sample size, that option is not viable since the number of households in some Dzongkhag, notably Bumthang, Gasa and Haa, is too small to generate reliable estimates.

Consequently, three regional models were estimated. Dzongkhags were grouped into regions based on whether (i) the best national model overestimates, underestimates or satisfactorily estimates the poverty rates of all Dzongkhags within a region and (ii) the sample size of a region is sufficiently large. The resulting region groupings are as follows: Region 1 includes Bumthang, Chhukha, Paro, Punakha; Region 2 includes Monggar, Trashi Yangtse, Wangdue Phodrang; and Region 3 includes Gasa, Samtse, Thimphu, Dagana, Haa, Lhuentse, Pema Gatshel, Samdrup Jongkhar, Trashigang, Trongsa, and Tsirang, Sarpang, and Zhemgang.

Model selection criteria

Since this step aims to predict consumption, model specifications were selected based on their fit with the actual BLSS data. The adjusted R-squared measure is a common metric for assessing the ability of a model to explain variation in the sample. However, relying solely on adjusted R-squared favors larger models because adjusted R-squared tends to increase as the number of explanatory variables increases. In other words, adding more regressors can improve adjusted R-squared but not necessarily improve the model's prediction power. In order to avoid over-fitting, we used the Bayesian Information Criterion (BIC)[5], which institutes a penalty for model complexity, and thus, is a more parsimonious model selection criterion than adjusted R-squared. Among the tested models, the one with the smallest BIC was preferred.

For each region, various model specifications were compared in terms of adjusted R-squared, BIC, sign and statistics significance of coefficients. It was observed that once a sufficient set of relevant and statistically significant explanatory variables was added to the model, adding more regressors did not considerably improve adjusted R-squared but lowered BIC. Table 2below presents the final model specification for each of the three regions.

Table 2: Selected model specifications

Explanatory Variables	Model 1	Model 2	Model 3
Location			
District	x	x	x
Demographics			
Economic dependency ratio	x		
Work ratio		x	x
English literacy ratio	x		x
Eduratio_6	x		x
Log of household size			x
Household size squared	x		
Housing condition			
Number of rooms		x	
Number of rooms per capita	x		x
Water sources	x		x
Durable assets			
DVD/VCR			x
Computer/laptop	x		
Sofa set			x
Rice cooker			x
Seshu gho/kira	x		

[5]The BIC is calculated as follows:

$$BIC = kln(N) - 2\ln(\hat{L})$$

where k is the number of parameters estimated in the regression, N is the number of observations, and $\hat{L}$ is the maximized likelihood function. Under the assumption that the errors are normally distributed, the log-likelihood function in a regression model has the form

$$\ln(L) = -\left(\frac{N}{2}\right)\ln(2\pi\sigma^2) - \frac{ESS}{2\sigma^2}$$

where ESS is the sum of squared residuals, π=3.1415, and σ is the standard deviation of the error term in the regression.

Refrigerator		x	x
Washing machine			x
Smart phone	x	x	x
Other mobile phones			x

Step 3: Simulate consumption per capita on PHCB data

After obtaining the estimated distributions of coefficients and errors from Step 2, the small-area estimation packages (-*sae*- and -*sae_mc_bs*-) in Stata randomly draw coefficients and errors from these estimated distributions to simulate household consumption for each household in the census. The software repeats the simulation 500 times and computes the poverty headcount ratios using the simulated household consumptions for each round. Finally, the estimated poverty rates are calculated as the average poverty rates over the 500 simulation rounds, and their standard errors as the standard deviations of the 500 simulation rounds. The final estimated number of poor people was calculated based on the estimated poverty rates and NSB's official population count at the Dzongkhag and Gewog levels. In practice, the process of model selection and simulation was repeated until a model that produces satisfactory results is found.

Appendix 3: Goodness of fit of estimated models

A critical aspect of the estimation's performance is its prediction power. This is evaluated mainly based on how well the models fit the actual BLSS data and how close the estimated Dzongkhag poverty rates are to the poverty rates derived directly from the BLSS consumption data.

The three models fit the actual data reasonably well; with adjusted R-squared ranging from 0.33 to 0.45 (see Table 3). This performance is reasonable as compared to poverty mapping exercises in other countries. For example, the adjusted R-squared was 0.34 in Papua New Guinea, ranges from 0.24 to 0.64 in Madagascar, from 0.46 to 0.74 in Ecuador (Vishwanath and Yoshida 2007) and from 0.39 to 0.61 in Sri Lanka (Doan 2015).

Table 3: Model statistics

Model No.	Included Dzongkhag	No. of Observations	No. of explanatory variables	Adjusted R-squared	F-value (p<F)
1	Bumthang Chhukha Paro Punakha Tsirang	1,630	11	0.45	113.2
2	Monggar Trashi Yangtse Wangdue Phodrang	1,174	5	0.33	117.2
3	Dagana Gasa Haa Lhuentse Pema Gatshel Samdrup Jongkhar Samtse Sarpang Thimphu Trashigang Trongsa Zhemgang	3,909	13	0.45	176.4

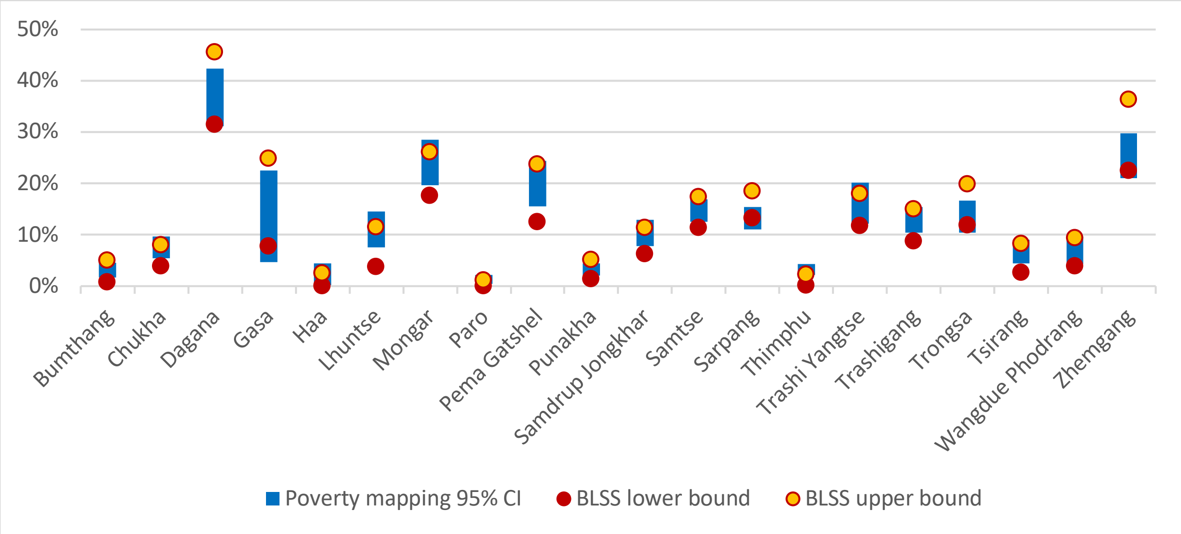
It is important to note that due to the discrepancies in the statistical distribution of many household variables, the pool of potential poverty covariates used in the model selection process and subsequently the number of explanatory variables included in the final models are quite small. The Sri Lanka poverty mapping exercise, for instance, includes between 17 and 30 explanatory variables in its estimation models. This is a key constraint that undermines our models' performance.

The selected models, nevertheless, performs satisfactorily in predicting poverty in Bhutan, given this data constraint. The predicted poverty rates at the Dzongkhag level all fall within the 95% confidence interval (CI) of the BLSS poverty rates, except for Paro and Thimphu, two districts with exceptionally low rural poverty (0.4 percent and 1.2 percent, respectively) – see Table 8. However, even in these Dzongkhags the 95% CI of the estimates largely overlap with the 95% CI of the BLSS rates, as shown in Figure 9.

Table 4: Actual and estimated poverty rates by Dzongkhag

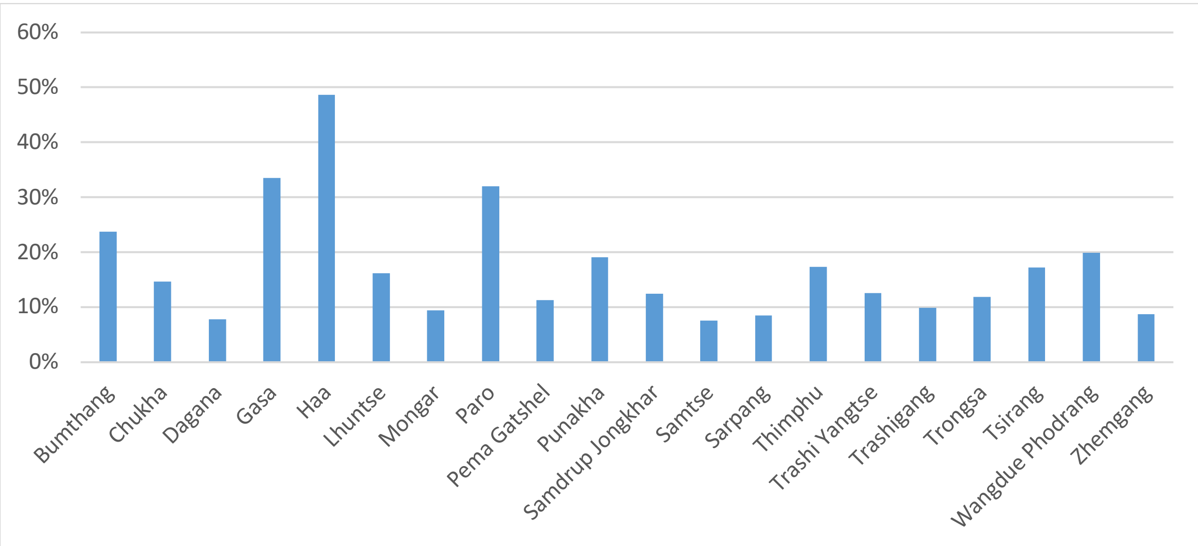
Dzongkhag	Actual poverty rate	SE	95% CI		Estimated poverty rate	SE	Absolute difference (pp)
			Lower bound	Upper bound			
Bumthang	2.9%	1.1%	0.8%	5.0%	3.1%	0.7%	0.21
Chhukha	5.9%	1.1%	3.8%	7.9%	7.6%	1.1%	1.68
Dagana	38.6%	3.6%	31.5%	45.6%	36.8%	2.9%	1.82
Gasa	16.3%	4.4%	7.7%	24.9%	13.6%	4.6%	2.69
Haa	1.2%	0.7%	0.0%	2.5%	2.3%	1.1%	1.14
Lhuentse	7.7%	2.0%	3.8%	11.5%	11.0%	1.8%	3.37
Monggar	21.8%	2.2%	17.6%	26.1%	24.1%	2.3%	2.26
Paro	0.4%	0.4%	0.0%	1.2%	1.3%	0.4%	0.90
Pema Gatshel	18.1%	2.9%	12.6%	23.7%	20.%	2.3%	1.82
Punakha	3.3%	1.0%	1.4%	5.2%	3.3%	0.6%	0.01
Samdrup Jongkhar	8.81%	1.30%	6.3%	11.3%	10.4%	1.3%	1.60
Samtse	14.36%	1.54%	11.3%	17.4%	14.8%	1.1%	0.39
Sarpang	15.84%	1.34%	13.2%	18.5%	13.2%	1.1%	2.60
Thimphu	1.15%	0.53%	0.1%	2.2%	3.2%	0.6%	2.07
Trashi Yangtse	14.86%	1.61%	11.7%	18.0%	16.2%	2.0%	1.34
Trashigang	11.86%	1.57%	8.8%	15.0%	13.0%	1.3%	1.10
Trongsa	15.85%	2.04%	11.8%	19.9%	13.5%	1.6%	2.30
Tsirang	5.38%	1.44%	2.6%	8.2%	6.8%	1.2%	1.40
Wangdue Phodrang	6.63%	1.38%	3.9%	9.3%	7.0%	1.4%	0.37
Zhemgang	29.38%	3.52%	22.5%	36.3%	25.4%	2.2%	3.98
Average	**12.01%**	**1.77%**	**n.a.**	**n.a.**	**12.32%**	**1.58%**	**1.65**

Figure 9: 95% Confidence Interval of estimated poverty rates by Dzongkhag



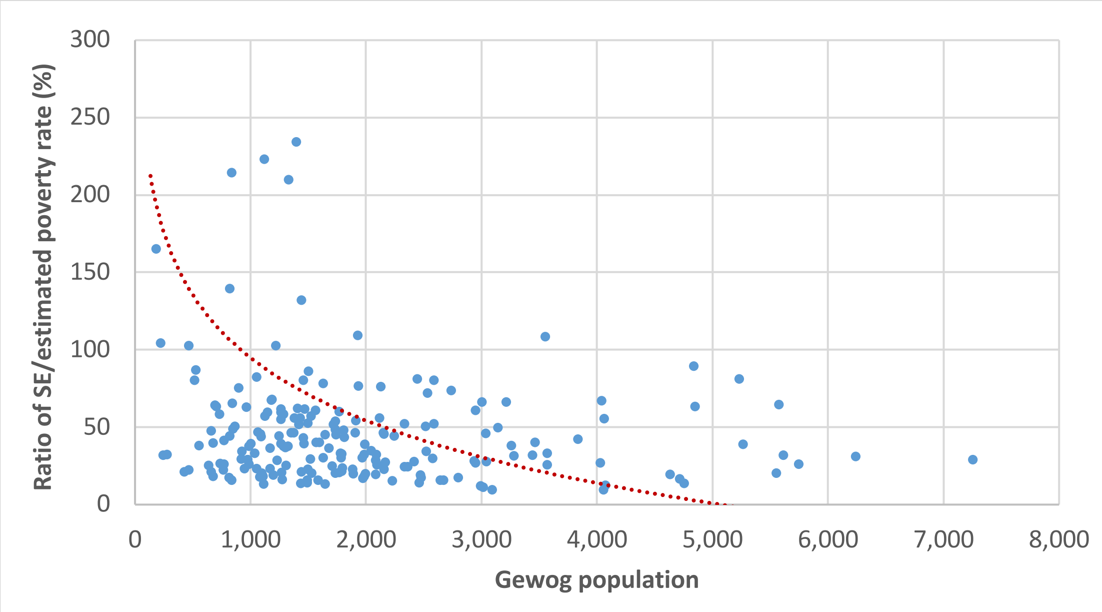
Another indicator of the models' prediction performance is how the SE compares to the estimated poverty rate. The smaller the SE relative to the estimate, the narrower the CI. Since the CI is the range within which the unobserved real poverty rate is likely to fall into, with the point estimate being the middle point of the range, a narrower CI means that the estimated poverty rate is likely to be closer to the real value. As displayed in Figure 10, the SE is less than 25 percent of the point estimates for most Dzongkhags, except Gasa, Haa and Paro; and even for these three, the ratio is well below 50 percent. This again indicates that the models perform well in predicting poverty at least at the Dzongkhag level.

Figure 10: Standard Error as a proportion of estimated poverty rate at Dzongkhag level



The results are more diverse at the Gewoglevel. The pattern of the ratio of SE over estimated poverty rate across Gewogs further reinforces the presence of this issue. The ratio, as shown in Figure 11, tends to be larger among those with smaller population. The 17 Gewogs for which the ratio exceeds 100 percent all have much fewer than 1,000 households; in fact 15 of them have fewer than 500 households.

Figure 11: Gewog population and Ratio of SE to estimated poverty rate



Note: The ratio exceeds 300% in five Gewogs, all of which have extremely low poverty rates: Samrang (0.8 percent) and Serthig (1.1 percent) in Samdrup Jongkhar, Laya (0.2) in Gasa, Samar (0.5 percent) in Haa, and Hoongrel (0.7 percent) in Paro. They are,therefore, considered as outliers and excluded from the figure for presentation purpose.

Another noteworthy pattern is that the ratio is consistently higher among richer Gewogs (see Figure 12). Among the 17 Gewogs with the ratio above 100 percent, for instance, seven have an estimated poverty below 1 percent and seven others have an estimated poverty rate between 1 and 2.7 percent. This suggests that the high ratio in those Gewogs is partly mechanical: as the estimates are too small, even a small SE in absolute term could lead to a large SE/estimate ratio. (The average SE in those Gewogs is 3.9 percent). Excluding this minority group, the average ratio across Gewogs drops significantly from 68.4 percent to 45.9.

From a policy perspective, however, this is arguably not a pressing issue. A key application of the poverty map estimates is that small administrative areas can be ranked in terms of poverty level for budget allocation and policy targeting purposes. The more reliable the estimates, the closer the ranking of the estimates to the ranking of the real and unobserved poverty incidence. Yet because the estimates in those Gewogs are extremely low, their relatively large SEs are unlikely to influence their rankings among all Gewogs to a considerable extent.

Figure 12 displays the ratio of SE to estimated poverty rate across Gewogs, showing a wide range. The ratio is below 50 percent for 136 out of 205 Gewogs and exceeds 100 percent for 17 Gewogs. Although on average it is markedly larger than that at the Dzongkhag level (68.4 percent as compared to 25 percent), this finding is not unusual. As discussed in Section 2.3, since SE tends to increase as poverty is estimated for smaller groups of households, much of these large SEs could be attributed to Bhutan's uniquely small population at the Gewog level.

The pattern of the ratio of SE over estimated poverty rate across Gewogs further reinforces the presence of this issue. The ratio, as shown in Figure 11, tends to be larger among those with smaller population. The 17 Gewogs for which the ratio exceeds 100 percent all have much fewer than 1,000 households; in fact 15 of them have fewer than 500 households.

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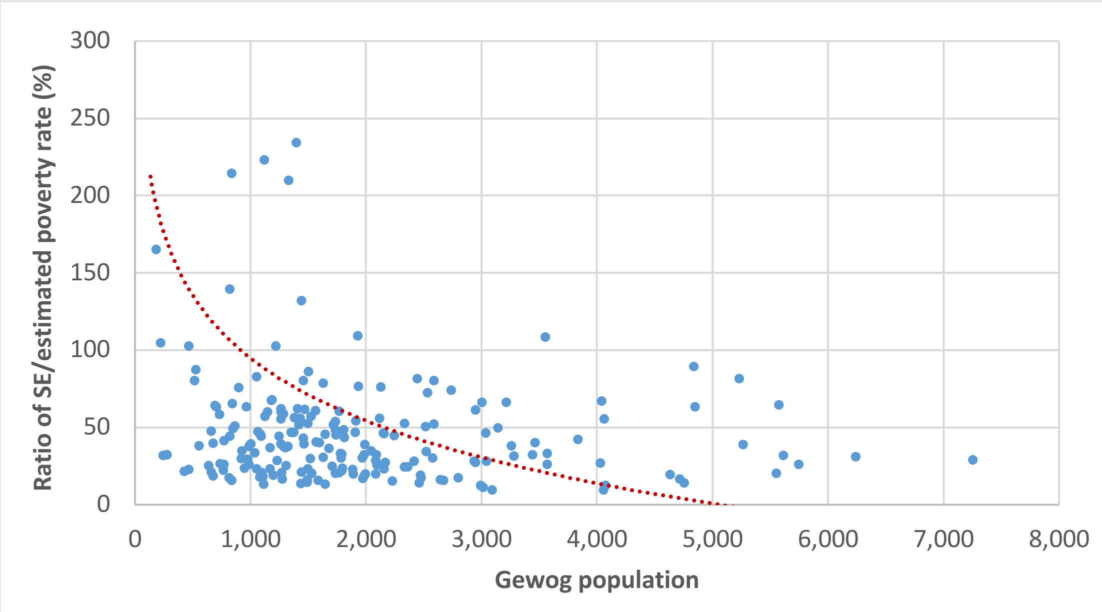

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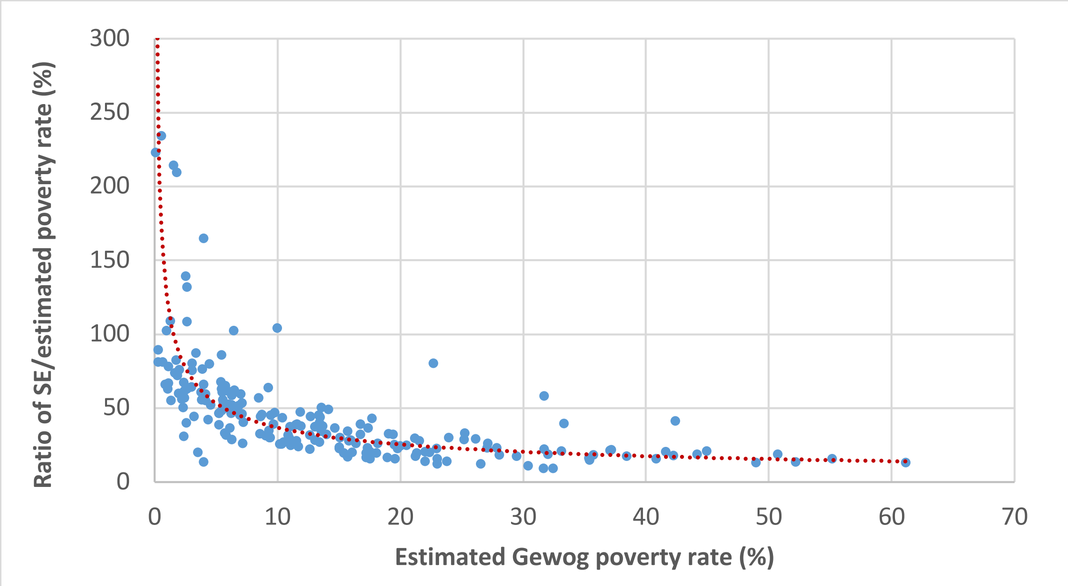
Figure 12: Ratio of SE to estimated poverty rate at Gewog/town level



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Appendix 4: Estimated models

Regional Model 1

	OLS	GLS
DzongkhagParo	.1448083***	.138499**
	(0.03238)	(0.05477)
Water source: Pipe to Compound	-.113316***	-.1220885***
	(0.02698)	(0.02724)
Water source: Other	-.2622167***	-.2624855***
	(0.05496)	(0.05343)
Computer/ Laptop	.1143204**	.1048145**
	(0.04570)	(0.04761)
Economic dependency ratio	-.1680654***	-.1896149***
	(0.05694)	(0.05378)
eduratio_6	.3021778***	.3326882***
	(0.11718)	(0.12387)
Household size squared, divided by 10	-.0469683***	-.0483746***
	(0.00638)	(0.00629)
English literacy ratio	.2711285***	.2728577***
	(0.05709)	(0.05582)
Room per capita	.2225195***	.2097921***
	(0.01592)	(0.01524)
Seshu gho/kira	.2393001***	.2162738***
	(0.03325)	(0.03394)
Smart phone	.101358***	.0965493***
	(0.02812)	(0.02683)
Sofa set	.121816***	.1035095***
	(0.02920)	(0.02910)
_cons	8.351286***	8.392327***
	(0.04478)	(0.04630)
N	1630	
F	113.1862	
adj-R2	0.4525	
RMSE	0.4140	
Eta ratio	0.0650	

Note. Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Regional Model 2

	OLS	GLS
Dzongkhag Monggar	-.2104661***	-.2550778***
	(0.04136)	(0.07093)
Refrigerator	.3826765***	.309431***
	(0.04631)	(0.04234)
Number of rooms	.0453116***	.0454426***
	(0.01344)	(0.01133)
Smart phone	.2433658***	.2123912***
	(0.04296)	(0.03937)
Work ratio	.4868788***	.5387053***
	(0.08059)	(0.06631)
_cons	7.856753***	7.918435***
	(0.06010)	(0.07249)
N	1,174	
F	117.2319	
adj-R2	0.3313	
RMSE	0.5086	
Eta ratio	0.1086	

Regional Model 3

	OLS	GLS
Dzongkhag Dagana	-.4824884***	-.4836573***
	(0.04110)	(0.07265)
Dzongkhag Pema Gatshel	-.2474487***	-.2796495***
	(0.04072)	(0.07320)
Dzongkhag Sarpang	-.2402257***	-.2460325***
	(0.02395)	(0.06527)
Dzongkhag Thimphu	.2125582***	.308533***
	(0.03128)	(0.08507)
Dzongkhag Trongsa	-.2190128***	-.2308147**
	(0.03252)	(0.09213)
Dzongkhag Zhemgang	-.3055441***	-.3157544***
	(0.04372)	(0.08107)
Water source: Pipe to Compound	-.0900731***	-.0866698***
	(0.02125)	(0.01972)
DVD/VCR	.1019727***	.1190254***
	(0.02959)	(0.02698)

eduratio_6	.3514636***	.3683913***
	(0.10477)	(0.10209)
Refrigerator	.0966918***	.0950941***
	(0.02209)	(0.01956)
English literacy ratio	.1268028***	.1345771***
	(0.04258)	(0.03804)
Ln of household size	-.4652813***	-.4662299***
	(0.02642)	(0.02308)
Rice cooker	.1122631***	.180199***
	(0.03498)	(0.03062)
Room per capita	.1246134***	.1394085***
	(0.01691)	(0.01646)
Smart phone	.1732304***	.1453791***
	(0.02063)	(0.01781)
Sofa set	.1683247***	.1819403***
	(0.02676)	(0.02468)
Washing machine	.1725699***	.20842***
	(0.03511)	(0.03488)
Work ratio	.2212537***	.160892***
	(0.03961)	(0.03501)
_cons	8.682374***	8.639394***
	(0.05775)	(0.05987)
N	3,909	
F	176.4403	
adj-R2	0.4469	
RMSE	0.4549	
Eta ratio	0.1652	

Appendix 5: Estimated poverty rate and standard error by Gewog

Figure 13: Estimated poverty rate and 95% CI by Gewog

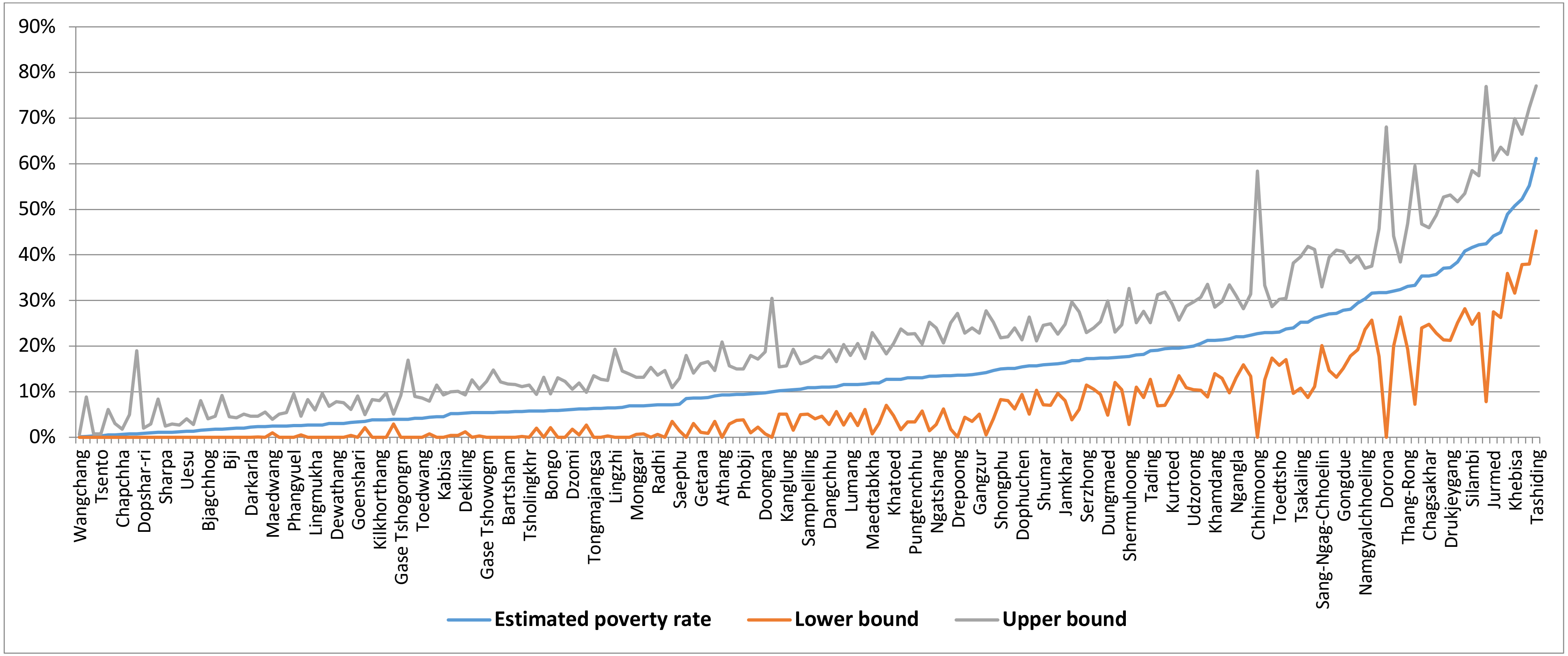

Table 5: Estimated poverty rate, standard error and number of poor by Gewog

District	Gewog code	Gewog name	Estimated poverty rate (%)	SE (%)	Ratio of SE/estimated poverty rate (%)	Gewog population	Estimated number of poor people
Bumthang	101	Chhoekhor	2.58	1.04	40.4	3,465	89
Bumthang	102	Tang	5.72	1.90	33.2	1,779	102
Bumthang	103	Chhumig	2.32	1.17	50.5	2,514	58
Bumthang	104	Ura	2.46	1.52	61.8	1,467	36
Chhukha	201	Bjagchhog	1.67	1.23	74	2,735	46
Chhukha	202	Bongo	5.83	1.88	32.2	3,439	201
Chhukha	203	Chapchha	0.69	0.56	81.5	2,442	20 or fewer
Chhukha	204	Darla	6.27	1.82	29	7,256	455
Chhukha	205	Getana	8.61	3.83	44.5	820	71
Chhukha	206	Doongna	9.76	4.60	47.1	1,064	104
Chhukha	207	Geling	2.39	1.62	67.7	1,182	28
Chhukha	208	Loggchina	13.60	4.69	34.5	2,521	343
Chhukha	209	Maedtabkha	11.87	5.66	47.7	657	78
Chhukha	210	Phuentshogling	10.90	3.47	31.9	5,615	612
Chhukha	211	Samphelling	10.90	2.96	27.1	4,029	439
Dagana	301	Drukjeygang	37.20	8.14	21.9	1,790	666
Dagana	302	Gozhi	21.55	6.05	28.1	2,417	521
Dagana	303	Karna	32.04	6.17	19.2	2,473	792
Dagana	304	Khebisa	50.73	9.74	19.2	1,198	608
Dagana	305	Largyab	44.95	9.53	21.2	657	295
Dagana	306	Tseza	25.25	8.45	33.5	1,038	262
Dagana	307	Tsangkha	52.18	7.27	13.9	1,435	749
Dagana	308	Karmaling	42.24	7.70	18.2	1,109	468
Dagana	309	Dorona	31.72	18.51	58.4	731	232
Dagana	310	Gesarling	26.14	7.66	29.3	976	255
Dagana	311	Lhamoi Dzingkha	42.39	17.62	41.6	769	326
Dagana	312	Nichula	37.07	7.99	21.5	425	158
Dagana	313	Tashiding	61.15	8.11	13.3	1,647	1,007
Dagana	314	Tsenda-Gang	23.93	7.28	30.4	1,782	427
Gasa	401	Khamaed	12.65	2.87	22.7	467	59
Gasa	402	Lunana	33.35	13.34	40	676	225
Gasa	403	Khatoed	12.67	4.04	31.9	245	31
Gasa	404	Laya	0.18	4.43	2447.3	994	20 or fewer
Haa	501	Bji	1.85	1.34	72.4	2,532	47

Haa	502	Kar-tshog	0.54	1.26	234.3	1,398	20 or fewer
Haa	503	Uesu	1.27	1.39	109.3	1,926	25
Haa	504	Gakiling	9.48	4.32	45.6	1,086	103
Haa	505	Samar	0.50	2.84	564.9	925	20 or fewer
Haa	506	Sangbay	1.55	3.33	214.6	836	20 or fewer
Lhuentse	601	Gangzur	13.98	4.54	32.5	2,089	292
Lhuentse	602	Khoma	7.03	4.21	59.9	1,265	89
Lhuentse	603	Kurtoed	19.50	4.96	25.4	635	124
Lhuentse	604	Minjey	5.39	3.67	68.1	1,184	64
Lhuentse	605	Jarey	14.15	6.96	49.2	845	120
Lhuentse	606	Maenbi	11.10	2.79	25.1	1,705	189
Lhuentse	607	Maedtsho	15.72	5.45	34.7	925	145
Lhuentse	608	Tsaenkhar	7.14	3.85	53.9	1,733	124
Monggar	701	Balam	55.14	8.73	15.8	834	460
Monggar	702	Chagsakhar	35.41	5.40	15.3	2,225	788
Monggar	703	Dramedtse	19.08	6.23	32.7	1,791	342
Monggar	704	Na-Rang	48.97	6.63	13.5	1,116	546
Monggar	705	Ngatshang	13.41	5.41	40.3	1,595	214
Monggar	706	Shermuhoong	17.72	7.63	43.1	1,456	258
Monggar	707	Thang-Rong	33.12	7.02	21.2	1,441	477
Monggar	708	Gongdue	27.87	6.53	23.4	1,168	326
Monggar	709	Jurmed	44.18	8.48	19.2	1,100	486
Monggar	710	Kengkhar	13.35	6.07	45.4	1,644	220
Monggar	711	Saling	10.40	4.54	43.7	1,810	188
Monggar	712	Silambi	41.63	8.58	20.6	1,096	456
Monggar	713	Chhaling	14.68	5.41	36.9	1,300	191
Monggar	714	Drepoong	13.58	6.90	50.8	862	117
Monggar	715	Monggar	6.90	3.19	46.3	3,036	210
Monggar	716	Tsakaling	25.19	7.35	29.2	974	245
Monggar	717	Tsamang	38.43	6.77	17.6	816	314
Paro	801	Dokar	2.02	1.54	76.2	2,129	43
Paro	802	Loong-nyi	1.16	0.78	67.2	4,039	47
Paro	803	Nagya	5.64	2.81	49.8	3,143	177
Paro	804	Sharpa	1.08	0.68	63.4	4,846	52
Paro	805	Dopshar-ri	0.89	0.59	66.4	3,213	29
Paro	806	Doteng	0.98	1.01	102.7	1,221	20 or fewer
Paro	807	Hoongrel	0.71	2.14	302.6	134	20 or fewer
Paro	808	Lamgong	0.28	0.23	81.5	5,233	20 or fewer

Paro	809	Tsento	0.28	0.25	89.6	4,839	20 or fewer
Paro	810	Wangchang	0.11	0.25	223.2	1,119	20 or fewer
Pema Gatshel	901	Chhimoong	22.69	18.23	80.4	515	117
Pema Gatshel	902	Chongshing	27.12	7.10	26.2	771	209
Pema Gatshel	903	Dungmaed	17.40	6.38	36.7	1,169	203
Pema Gatshel	904	Khar	16.76	6.61	39.5	1,460	245
Pema Gatshel	905	Yurung	13.46	5.95	44.2	1,091	147
Pema Gatshel	906	Nanong	35.73	6.60	18.5	1,984	709
Pema Gatshel	907	Shumar	15.85	4.45	28.1	3,040	482
Pema Gatshel	908	Zobel	22.96	5.29	23.1	1,496	343
Pema Gatshel	909	Chhoekhorling	28.05	5.22	18.6	678	190
Pema Gatshel	910	Dechhenling	5.47	4.72	86.2	1,502	82
Pema Gatshel	911	Norboogang	20.52	5.18	25.3	1,306	268
Punakha	1001	Barp	1.34	0.74	55.6	4,060	54
Punakha	1002	Guma	3.24	1.45	44.6	2,243	73
Punakha	1003	Goenshari	3.35	2.93	87.3	525	20 or fewer
Punakha	1004	Kabisa	4.55	2.39	52.5	2,334	106
Punakha	1005	Talog	2.41	1.38	57.3	1,123	27
Punakha	1006	Toedpaisa	1.97	1.19	60.4	1,769	35
Punakha	1007	Chhubu	5.24	2.45	46.7	1,353	71
Punakha	1008	Dzomi	6.12	2.24	36.6	1,677	103
Punakha	1009	Lingmukha	2.67	1.69	63.2	966	26
Punakha	1010	Shelnga-Bjemi	3.06	2.32	75.7	895	27
Punakha	1011	Toedwang	4.15	2.30	55.4	1,265	52
Samdrup Jongkhar	1101	Dewathang	3.04	2.45	80.4	2,586	79
Samdrup Jongkhar	1102	Gomdar	15.72	2.74	17.4	2,474	389
Samdrup Jongkhar	1103	Orong	11.69	2.85	24.4	2,358	276
Samdrup Jongkhar	1104	Phuentshogthang	10.51	2.85	27.2	2,946	310
Samdrup Jongkhar	1105	Wangphu	22.38	4.59	20.5	1,733	388
Samdrup Jongkhar	1106	Langchenphu	11.01	3.27	29.7	920	101
Samdrup Jongkhar	1107	Lauri	23.78	3.42	14.4	1,493	355
Samdrup Jongkhar	1108	Martshala	3.88	2.98	76.8	1,932	75
Samdrup Jongkhar	1109	Pemathang	2.67	3.53	132.1	1,441	38
Samdrup Jongkhar	1110	Samrang	0.78	9.27	1190.8	191	20 or fewer
Samdrup Jongkhar	1111	Serthig	1.07	3.76	350.1	1,393	20 or fewer
Samtse	1201	Duenchhukha	11.52	4.49	39	1,987	229
Samtse	1202	Dophuchen	15.40	3.04	19.7	4,634	714
Samtse	1203	Doomtoed	6.52	4.06	62.3	1,410	92

Samtse	1204	Tading	18.93	3.17	16.7	4,714	892
Samtse	1205	Norboogang	32.43	3.07	9.5	4,057	1,316
Samtse	1206	Phuentshogpelri	23.00	2.90	12.6	4,072	937
Samtse	1207	Samtse	8.56	2.84	33.1	3,571	306
Samtse	1208	Norgaygang	2.64	2.87	108.6	3,550	94
Samtse	1209	Pemaling	11.92	4.55	38.2	3,260	388
Samtse	1210	Tashichhoeling	4.35	1.85	42.4	3,834	167
Samtse	1211	Tendruk	3.02	1.95	64.7	5,576	168
Samtse	1212	Sang-Ngag-Chhoelin	26.58	3.28	12.3	2,994	796
Samtse	1213	Namgyalchhoeling	30.40	3.42	11.3	3,014	916
Samtse	1214	Ugyentse	1.79	3.77	209.9	1,330	24
Samtse	1215	Yoeseltse	15.08	4.55	30.1	2,577	389
Sarpang	1301	Samtenling	19.57	3.11	15.9	2,670	523
Sarpang	1302	Chhuzanggang	22.04	3.15	14.3	2,459	542
Sarpang	1303	Gelegphu	7.16	1.88	26.3	5,747	411
Sarpang	1304	Jigme Chhoeling	31.64	3.02	9.5	3,091	978
Sarpang	1305	Serzhong	17.21	2.93	17	1,973	340
Sarpang	1306	Tareythang	19.42	6.31	32.5	279	54
Sarpang	1307	Umling	16.10	3.31	20.5	1,527	246
Sarpang	1308	Dekiling	5.25	2.04	38.9	5,264	276
Sarpang	1309	Chhudzom	6.30	3.29	52.3	2,589	163
Sarpang	1310	Gakiling	13.08	3.75	28.7	2,085	273
Sarpang	1311	Senggey	11.61	4.58	39.5	1,004	117
Sarpang	1312	Shompangkha	4.46	3.58	80.3	1,455	65
Thimphu	1401	Kawang	3.98	0.56	14	4,756	189
Thimphu	1402	Lingzhi	6.42	6.60	102.7	468	30
Thimphu	1403	Naro	10.00	10.46	104.6	221	22
Thimphu	1404	Soe	3.99	6.59	165.2	182	20 or fewer
Thimphu	1405	Chang	3.53	0.72	20.4	5,553	196
Thimphu	1406	Darkarla	2.22	1.25	56.2	1,380	31
Thimphu	1407	Ge-nyen	1.77	1.46	82.7	1,052	20 or fewer
Thimphu	1408	Maedwang	2.41	0.75	31.3	6,241	150
Trashigang	1501	Bartsham	5.57	3.12	56	1,431	80
Trashigang	1502	Bidoong	9.68	3.82	39.5	1,265	122
Trashigang	1503	Yangnyer	18.06	3.58	19.8	2,084	376
Trashigang	1504	Shongphu	15.04	3.44	22.9	1,882	283
Trashigang	1505	Kanglung	10.35	2.69	26	3,570	369

Trashigang	1506	Samkhar	6.95	3.15	45.3	1,738	121
Trashigang	1507	Udzorong	20.01	4.90	24.5	2,335	467
Trashigang	1508	Merag	21.20	6.30	29.7	1,519	322
Trashigang	1509	Phongmed	19.81	4.58	23.1	2,154	427
Trashigang	1510	Radhi	7.12	3.31	46.5	2,152	153
Trashigang	1511	Sagteng	16.78	5.45	32.5	1,985	333
Trashigang	1512	Kangpar	6.85	3.56	52	1,420	97
Trashigang	1513	Thrimshing	9.34	3.26	34.9	2,045	191
Trashigang	1514	Khaling	13.45	3.68	27.4	2,167	292
Trashigang	1515	Lumang	11.58	3.27	28.3	2,939	340
Trashi Yangtse	1601	Boomdeling	15.04	3.59	23.8	1,796	270
Trashi Yangtse	1602	Jamkhar	16.38	4.28	26.2	986	162
Trashi Yangtse	1603	Tongmajangsa	6.30	3.70	58.7	1,284	81
Trashi Yangtse	1604	Yangtse	5.91	3.67	62	1,261	75
Trashi Yangtse	1605	Ramjar	17.36	4.07	23.5	950	165
Trashi Yangtse	1606	Khamdang	21.24	3.72	17.5	2,800	595
Trashi Yangtse	1607	Toedtsho	23.01	3.71	16.1	1,490	343
Trashi Yangtse	1608	Yalang	17.57	3.64	20.7	1,271	223
Trongsa	1701	Draagteng	9.08	2.86	31.5	3,280	298
Trongsa	1702	Korphu	18.16	4.82	26.5	739	134
Trongsa	1703	Langthil	17.53	2.82	16.1	2,642	463
Trongsa	1704	Nubi	17.25	3.45	20	1,996	344
Trongsa	1705	Tangsibji	9.38	2.87	30.5	1,627	153
Tsirang	1801	Barshong	5.78	3.79	65.5	842	49
Tsirang	1802	Patshaling	4.14	2.48	59.9	1,147	47
Tsirang	1803	Kilkhorthang	3.84	2.15	56	2,114	81
Tsirang	1804	Mendrelgang	1.15	0.90	78.6	1,629	20 or fewer
Tsirang	1805	Rangthangling	5.52	3.36	61	1,563	86
Tsirang	1806	Tsholingkhr	5.71	2.95	51.8	1,716	98
Tsirang	1807	Doonglagang	8.48	4.84	57.1	1,521	129
Tsirang	1808	Gosarling	5.44	2.63	48.4	1,808	98
Tsirang	1809	Sergithang	13.04	4.91	37.7	1,287	168
Tsirang	1810	Pungtenchhu	13.07	4.94	37.8	1,325	173
Tsirang	1811	Semjong	12.71	5.65	44.4	1,246	158
Tsirang	1812	Tsirang Toed	6.24	2.91	46.7	1,373	86
Wangdue Phodrang	1901	Athang	9.26	5.95	64.2	690	64
Wangdue Phodrang	1902	Bjenag	6.03	3.17	52.7	1,495	90
Wangdue Phodrang	1903	Darkar	10.22	2.65	25.9	2,092	214

Wangdue Phodrang	1904	GaseTshogongm	3.99	2.64	66.2	3,004	120
Wangdue Phodrang	1905	GaseTshowogm	5.45	3.46	63.4	701	38
Wangdue Phodrang	1906	Nahi	13.70	5.24	38.3	552	76
Wangdue Phodrang	1907	Thedtsho	3.78	2.31	61.2	2,949	111
Wangdue Phodrang	1908	Ruebisa	6.41	3.11	48.5	1,735	111
Wangdue Phodrang	1909	Dangchhu	11.02	4.17	37.8	984	108
Wangdue Phodrang	1910	Gangteng	5.23	2.44	46.7	1,908	100
Wangdue Phodrang	1911	Kazhi	15.97	4.58	28.7	1,229	196
Wangdue Phodrang	1912	Nyishog	5.59	3.03	54.2	1,909	107
Wangdue Phodrang	1913	Phangyuel	2.56	3.57	139.5	820	21
Wangdue Phodrang	1914	Phobji	9.43	2.85	30.2	1,967	186
Wangdue Phodrang	1915	Saephu	7.21	2.92	40.5	1,568	113
Zhemgang	2001	Bardo	40.82	6.44	15.8	1,583	646
Zhemgang	2002	Nangkor	21.36	4.29	20.1	1,888	403
Zhemgang	2003	Shingkhar	29.46	5.25	17.8	1,079	318
Zhemgang	2004	Trong	8.72	3.99	45.8	2,158	188
Zhemgang	2005	Bjoka	31.70	7.14	22.5	764	242
Zhemgang	2006	Goshing	35.37	5.83	16.5	1,272	450
Zhemgang	2007	Ngangla	22.02	4.60	20.9	1,768	389
Zhemgang	2008	Phangkhar	27.07	6.34	23.4	1,053	285

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