Improving targeting of poor and extremely poor families in Georgia:

THE CONSTRUCTION OF POVERTY MAPS AT THE DISTRICT LEVEL

Georgia 2003

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GoG	Government of Georgia
GSIF	Georgian Social Investment Fund
HH	Household Survey
LSMS	Life Style Measurement Survey
NHDR	National Human Development Report
SDS	State Department of Statistics
STC	Save the Children
UNDP	United Nations Development Programme
USAID	United States Agency for International Development
WB	World Bank
WFP	World Food Programme

1. EXECUTIVE SUMMARY

The project applied a method that combines household and census data to estimate poverty for disaggregated geographical units. This is the first time this method has been applied in Georgia and the results are shown in maps of different welfare indicators (poverty headcount; poverty gap, severity of poverty and income inequality) disaggregated at the district level. The project also compared the resulting poverty maps with a selected set of geographical and demographic factors. Finally, the project explored the current targeting methods applied by other organizations and the potential use of poverty maps in assisting the targeting by agencies. A summary of result is as follows:

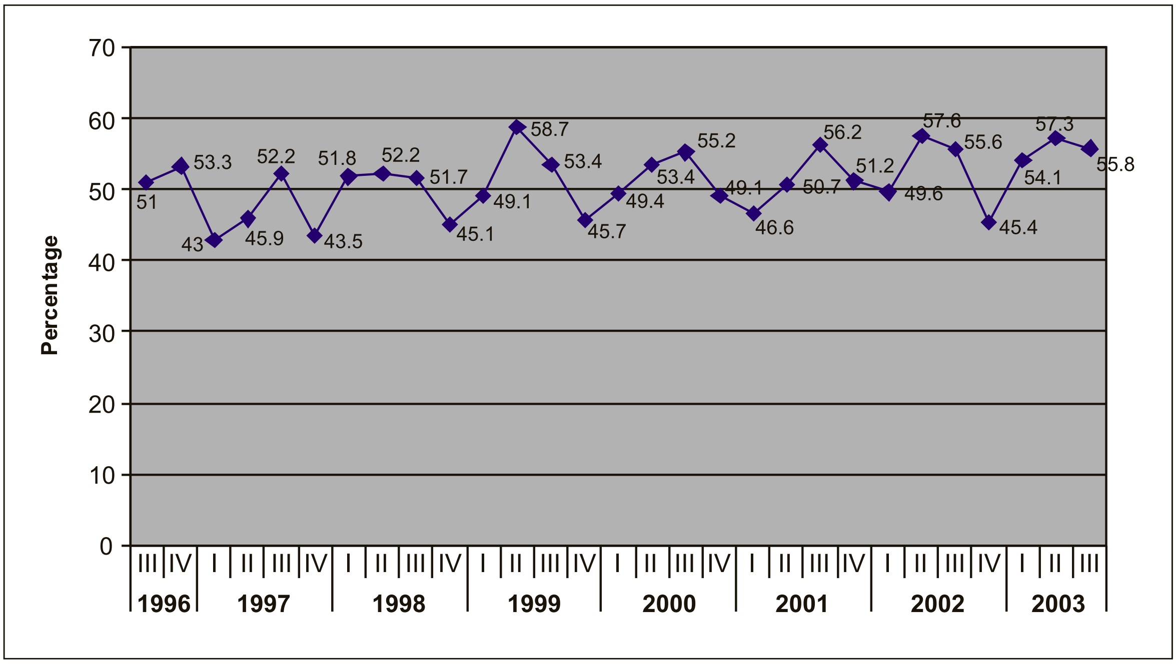
- The poverty maps show a southeast-northwest diagonal of districts with poverty headcounts that are significantly above the national poverty rate (at a 95% confidence level). The most affected regions are Adjara, Samtskhe-Javakheti, Mtskheta-Mtianeti and Shida Kartli.
- The maps show a southeast-northwest diagonal of districts with values of poverty gap and severity of poverty significantly above the national average (95% confidence level). Similarly as observed for poverty headcounts, the most affected regions are Adjara, Samtskhe-Javakheti, Mtskheta-Mtianeti and Shida Kartli.
- This diagonal of districts with poverty headcounts significantly above the national average includes 17 districts and comprises 23.9% of all the poor in Georgia.
- The diagonal of poor districts, however, does not show the greatest concentration of poverty. Rather, poverty is concentrated in the towns of Kutaisi, Batumi and Rustavi, the Tbilisi districts of Isani-Samgori, Gldani-Nadzaladebi, and Vake-Saburtalo, and the districts of Gori and Zugdidi. All together, these locations account for 32.5% of all the poor in Georgia.
- A map of income inequality in Georgia at the district level does not show the same diagonal patterns as seen for headcount and distributional measures of poverty (poverty gap and severity of poverty). In general, higher income inequality appears more frequently in the northern part of the country plus the districts of Vani, Tsalka and Chokhatauri.
- The overlapping of districts with poverty headcounts above national average and main geographical variables seems to indicate a relationship between geographical isolation, low intensity of arable land use and higher poverty levels. However, this picture is not free of distortions as the overlapping does not include districts in Racha and Svaneti, which are also characterized by geographical isolation, poorly developed road networks and scarce arable land.
- The district poverty maps produced by this report are tools that complement others in the targeting of poor families. As such, poverty maps cannot substitute for good project design. Specifically, poverty maps together with census data in GIS format can assist the project designer in fine-tuning (i) project objectives; (ii) the type of poor people the project plans to reach; and (iii) the identification of catalytic and replication strategies.
- Poverty maps can be used as "intermediate" tools between national and local level targeting. Even if the project's priority is reaching the poor and districts have been identified, accurate targeting can require the application of local targeting methods.
- Important follow-up steps to this project are **(i)** to confirm findings using the new sampling design of the SDS household surveys, which will allow for a greater accuracy in the construction of poverty maps. For example, in the winter of 2001, Racha and Svaneti, which are mountainous and isolated regions, failed to show districts significantly poorer than the national average. The development of poverty maps for several quarters of data would allow us to explore whether this finding is only a feature of winter 2001 or whether it remains consistent over time; **(ii)** to explore changes in the distribution of poverty over time. In general, the construction of several poverty maps for different quarters would allow us to explore temporal patterns in the geographical distribution of poverty. These patterns are of importance for multi-year projects because the geographical priority for a project can change over time and, particularly, from winter to summer.

2. INTRODUCTION

2.1 Poverty in Georgia: a summary of current findings

The transition from a planned to a market-based economy has had a great impact on the living standards of the population, an impact that has not been reversed 13 years after independence. Figure 1 shows that poverty rates, as measured by the Official Poverty Line, have been fluctuating at around 50%[1]. Economic growth has not been translated yet into an overall decrease in poverty rates.

Figure 1: poverty headcount – Official Poverty Line



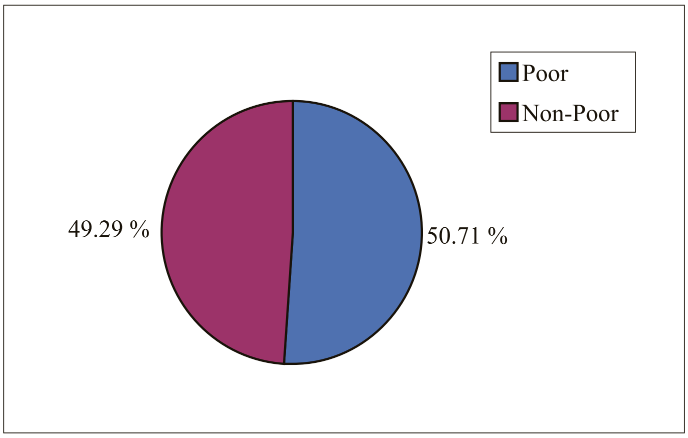
Source: SDS

The poverty headcounts of the State Department of Statistics (SDS) are compatible with those from other surveys. For example, in the winter of 2001, the United Nations Development Programme (UNDP) produced a poverty analysis that showed poverty headcounts compatible with those of the SDS[2]. In March 2001, UNDP estimated that 50.7% of families were in poverty while the SDS put that figure at 46.6%.

[1] The Official Poverty Line is about GEL 115/month for an equivalent adult.

[2] The UNDP's report used a poverty line with a value close to that of the Official Poverty Line. See National Human Development Report 2001/2002. United Nations Development Programme. Tbilisi, Georgia.

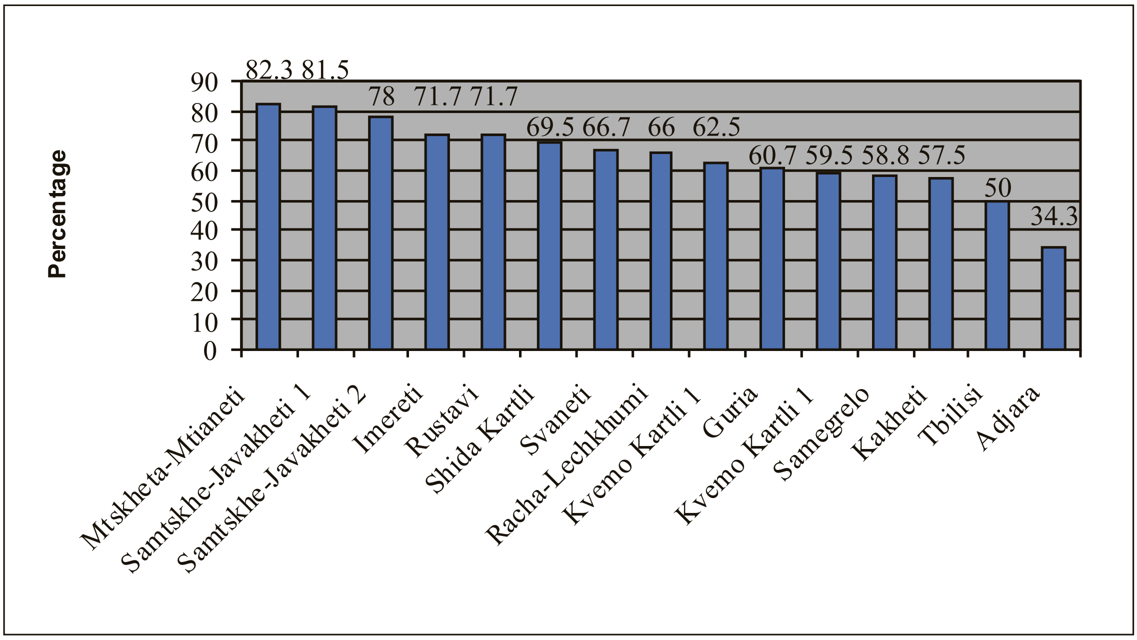
Figure 2: poverty headcount – NHDR Poverty Line – March 2001



Source: NHDR 2001/2002

Another source of comparison originates in an analysis of the situation of Georgian households undertaken by Save the Children (STC) in February 2002. STC applied a modified life style measurement survey (LSMS) that included questions on food security and overall household vulnerability[3]. The report estimates the nationwide poverty headcount based on income figures. Because reported income is usually lower than reported expenditures, the STC results are higher than the SDS's for the same period. Specifically, while the SDS reports 49.6%, STC finds a nationwide poverty rate of 60%.

Figure 3: poverty headcount by region – February 2002



Source: Save the Children

Note: Kvemo Kartli 1 comprises Tetritskaro, Tsalka and Dmanisi.
Kvemo Kartli 2 comprises Bolnisi, Marneuli and Gardabani.
Samtskhe-Javakheti 1 comprises Borjomi, Adigeni, Akhaltsikhe and Aspindza
Samtskhe-Javakheti 2 comprises Akhalkalaki and Ninotsminda.

In summary, the available sources of data show that poverty in Georgia is high and that it has remained high for a long time. The poverty headcounts have been oscillating between the low 40s and the high 50s, with an average of 50.6% for the period 1996-2002.

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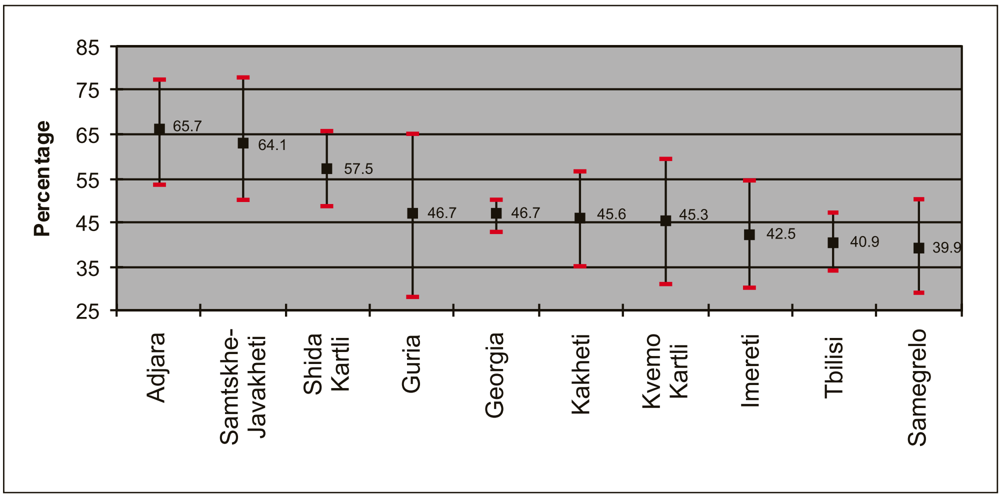
[3] See "The Situation of Households in Georgia - 2002". Save the Children. Tbilisi, Georgia. The report was financed by USAID.

2.2 The problem of regional targeting

Turning attention to poverty headcounts in the regions, the Household Survey of the SDS reported that Adjara, Samtskhe Javakheti, and Shida Kartli were the poorest regions of Georgia in the winter of 2001. In contrast, Samegrelo and Tbilisi were better off. Other regions fell in between with poverty headcounts of around 45%.

Figure 4: SDS poverty headcount - ranking by region - winter 2001

(point estimate and 95% confidence interval)



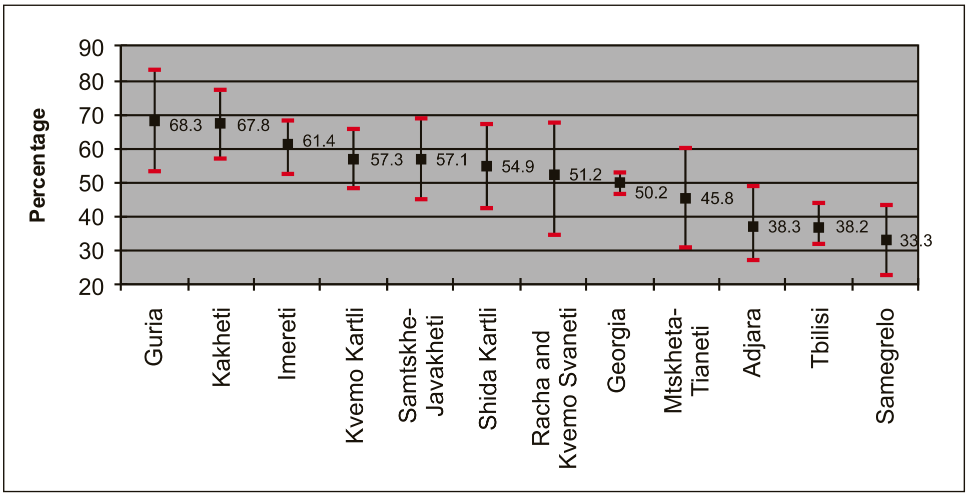
Source: Household survey dataset; SDS

Note: headcount based on Official Poverty Line

A household survey carried out by UNDP at around the same time found a somewhat different ranking of regions by poverty headcounts. For example, Adjara tops the SDS's list but is near the bottom in UNDP's survey. Samtskhe Javakheti is the second poorest in the SDS's survey but the fifth one in UNDP's. On the other hand, Samegrelo and Tbilisi showed the lowest poverty headcounts in both the SDS and UNDP surveys.

Figure 5: NHDR poverty headcount - ranking by region - winter 2001

(point estimate and 95% confidence interval)



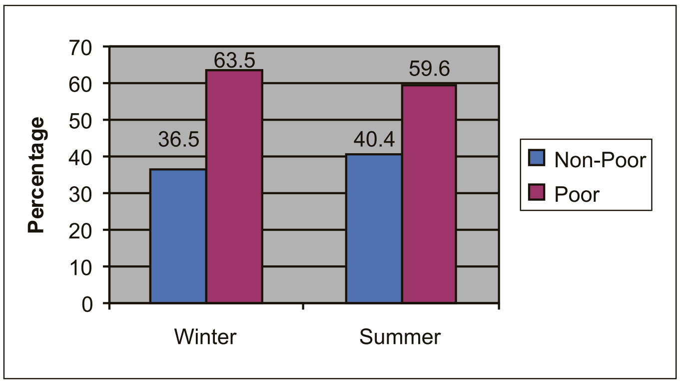
Source: UNDP

Note: based on the NHDR poverty line

However, a closer look at Figures 4 and 5 shows that the differences between regions are not as radical as they may first seem. This can be seen by comparing the confidence intervals of point estimates. For example, in the SDS survey, the confidence intervals for Adjara, Samtskhe Javakheti, Shida Kartli and Guria all overlap implying that their point estimates (poverty headcounts) are not significantly different to the 95% confidence level[4].
The size of the confidence intervals depends on the number of families that participate in the household survey. The larger the number of respondents, the smaller the margin of error. Therefore, a potential way to increase the accuracy of the poverty indicator would simply be to increase the number of respondents in the survey. The problem, of course, is that increasing the number of respondents comes with a cost. The sampling size would have to increase considerably in order to keep regional errors at around 3%. As an example, it could require quadrupling the number of respondents in Adjara. In the current budgetary situation of Georgia, at a time the household survey is being financed by donor sources, such an increase in the number of respondents, and its subsequent cost, is probably not possible.

The work presented in this report attempts to improve the value of information from household surveys for targeting purposes while keeping the current cost of the survey unchanged. The method applied in this report allows the estimation of poverty headcount at the district level, and while the problem of confidence intervals still accrues, the results nevertheless allow inter-district comparisons for purposes of geographical targeting. Better geographical targeting should help improve the efficiency of donor aid, which at present seems to show problems in reaching the correct beneficiaries. In the winter and summer of 2001, a UNDP-financed household survey indicated that between 36.5% and 40.4% of all donor support (mostly in-kind) ended up in the hands of non-poor families.

Figure 6: destination of transfers from international organizations



Source: UNDP

2.3 Poverty maps: current experiences

Available research indicates that countries can show a geographical distribution of poverty. Higher poverty headcounts can be more common in remote areas without access to basic infrastructure and be lower in more favorable environments, like those with connections to markets or endowed with a better supply of public services. Information on the spatial distribution of poverty can be of interest to policymakers because it can pinpoint regional disparities in living standards and identify areas that are worse off and in need of priority attention. An accurate geographical picture of poverty can contribute much to improving the targeting of anti-poverty programs

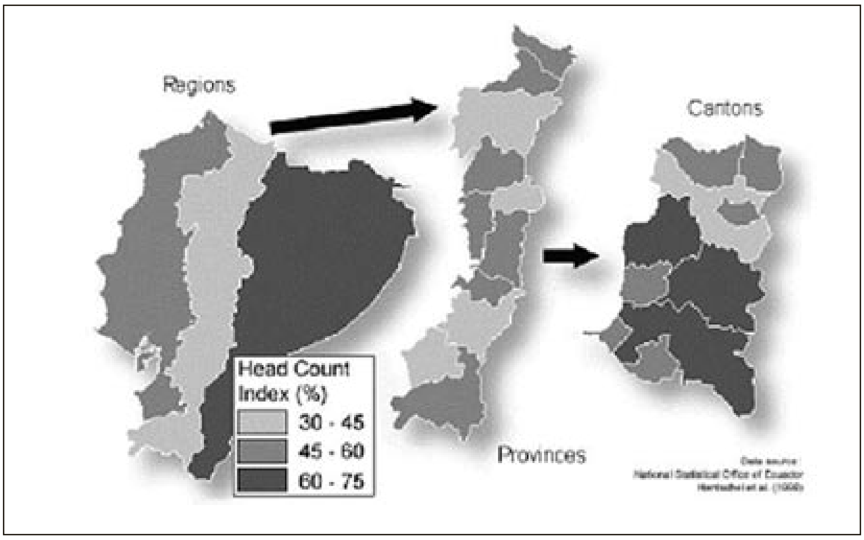
In Georgia, as in many other countries, the data to estimate poverty rates come from household surveys. Usually these surveys, which are often based on the LSMS type developed by the World Bank (WB), allow nationwide estimations of poverty with errors of around 3%. Regional estimations of poverty, however, are subjected to greater

[4] The term "significantly greater" is in the statistical sense of the word. In this report "significance" is taken at the 95% confidence level. For example, if we say that district "A" is significantly poorer than district "B" at the 95% confidence level, we would mean that if we undertake an infinite number of poverty surveys in these two districts, we would expect district "A" to come up poorer than district "B" 95% of the time.

errors, as it has been seen in the previous section. When the interest is at the district level, the only household information usually available is the census data. However, the census is generally limited to family characteristics like number of members, education and employment and rarely includes questions on expenditure. Georgia is not an exception. Its recently completed census provided only general information on household characteristics and none on family income or expenditures.

Recently, a group of researches at the World Bank developed new techniques to combine household and census data to estimate poverty for more disaggregated geographical units (e.g. districts)[5]. Basically, the method uses household survey data to identify family characteristics that can explain variations in family expenditures. The family characteristics used to explain variations in expenditures are restricted to those that appear in the census dataset. The result is the construction of models in which the level of family consumption can be estimated using variables that are present in the census. By inserting the data from the census into the models one can generate estimates of poverty for small geographic areas. Variations of this method have been applied in Vietnam (Minot and Baulch, 2002), Madagascar (Mistiaen *et al*, 2002), South Africa (Alderman *et al*, 2002), Ecuador (Demombynes *et al* 2002) and Brazil (Elbers *et al*, 2001).

Figure 7: an example of applications from disaggregated poverty maps (Ecuador)



Source: World Bank

The results of these efforts are promising. Figure 7 shows the results of combining census and household data to construct poverty maps at higher levels of resolution. In the example above, data from the household survey allowed the estimation of poverty headcounts at the regional level. When combined with census data, the result is the estimation of poverty headcounts at the provincial and canton levels.

For Georgia, this project has applied a variation of the method to estimate several measures of poverty and inequality at the district level. The data originates from the 2002 census and the database of the SDS HH survey for the first quarter of 2001. An explanation of the methodology and data used is presented in Annex A.

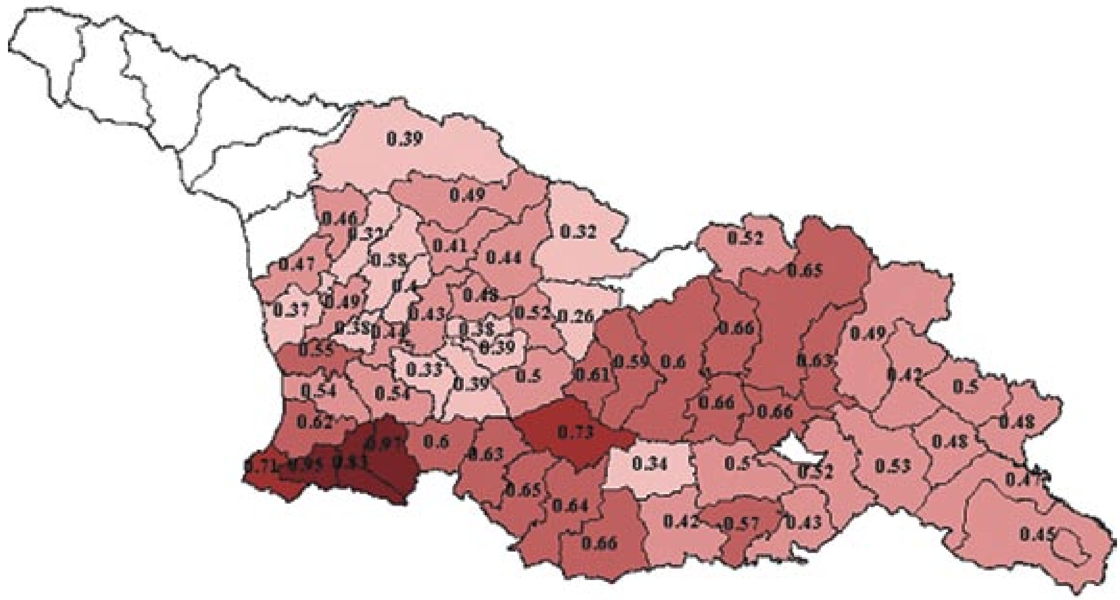
[5] See Annex A.

3. RESULTS

3.1 Poverty headcounts in districts

The poverty headcount measures the share of the population for which consumption or income is less than the poverty line. Poverty headcounts can be based on individual or family income. The results in Figure 8 show district poverty rates for families based on their reported consumption and the official poverty line.

Figure 8: district poverty map (headcount; official poverty line)

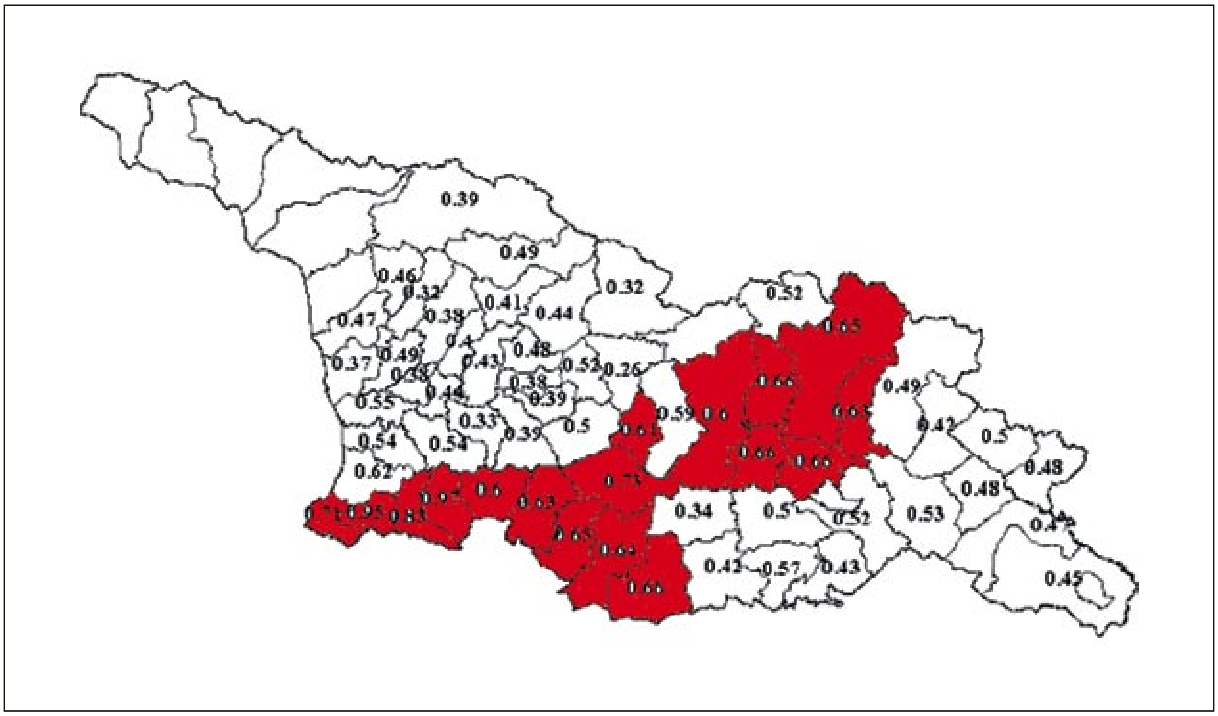


Source: own calculations based on SDS HH survey and census data

The map in Figure 8 shows poorer districts with darker tones. It can be seen that there exists a diagonal of districts, which runs southwest to northeast, which shows larger poverty headcounts. These districts encompass the regions of Adjara, Samtskhe Javakheti, Mtskheta-Mtianeti and Shida Kartli. In addition, though outside the diagonal, districts in Guria and the town of Rustavi also show high poverty headcounts.

It should be remembered, however, that there is an error component affecting all point estimates of poverty headcount. These errors originate in that data and models are not 100% precise. It is therefore necessary to take these errors into account when reading the poverty headcounts in Figure 8. A way to do that is to identify those districts with poverty headcounts that are significantly greater than the average for Georgia.

Figure 9: districts with poverty headcount significantly above the national average



Source: own calculations based on SDS HH survey and census data

Figure 9 shows that the southwest-northeast diagonal contains those districts that are significantly poorer than the national average for Georgia (46.6%). Specifically, these districts are the following:

Table 1: Districts with poverty headcount significantly above the national average

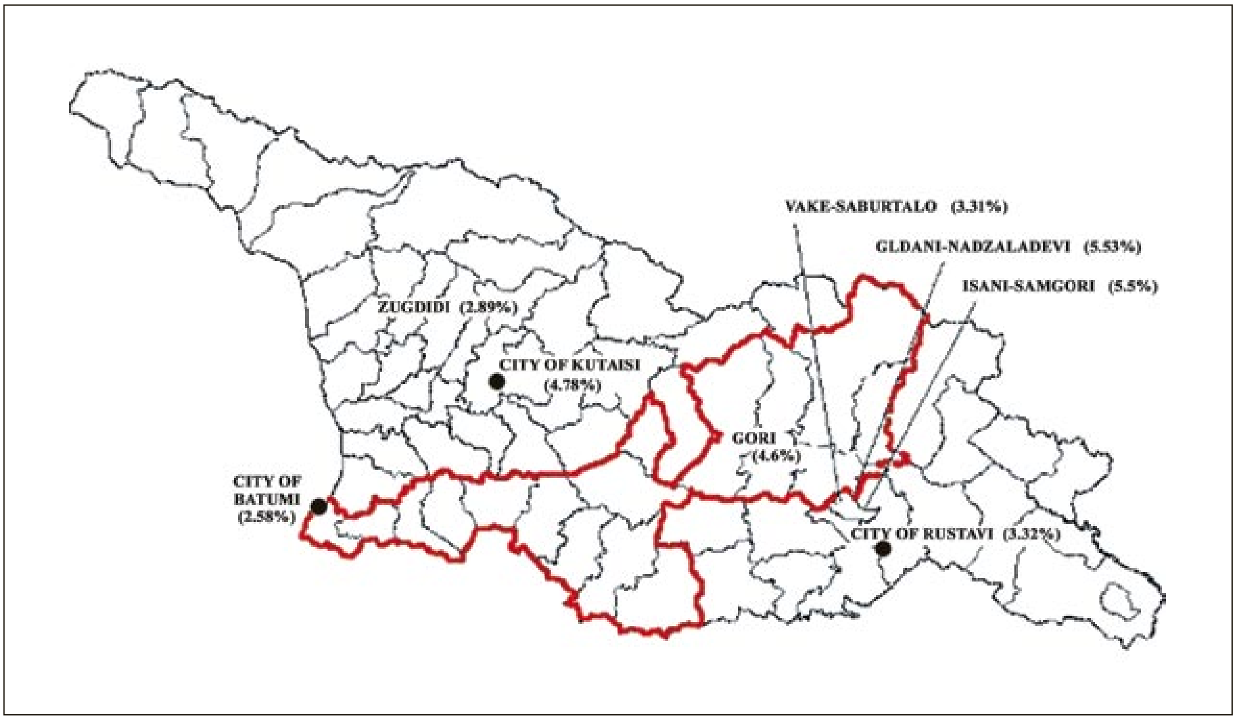
District	Headcount	Confidence Interval		Region
		Low	Upper	
Khulo	0.97	0.905	0.996	Adjara
Keda	0.95	0.848	0.992	Adjara
Shuakhevi	0.83	0.779	0.885	Adjara
Borjomi	0.73	0.684	0.775	Samtskhe Javakheti
Khelvachauri	0.71	0.58	0.812	Adjara
Kaspi	0.66	0.591	0.733	Shida Kartli
Ninotsminda	0.66	0.604	0.723	Samtskhe Javakheti
Mtskheta	0.66	0.589	0.726	Mtskheta-Mtianeti
Akhalgori	0.66	0.575	0.739	Shida Kartli
Dusheti	0.65	0.574	0.73	Mtskheta-Mtianeti
Aspindza	0.65	0.59	0.703	Samtskhe Javakheti
Akhalkalaki	0.64	0.579	0.698	Samtskhe Javakheti
Akhaltsikhe	0.63	0.576	0.68	Samtskhe Javakheti
Tianeti	0.63	0.521	0.723	Mtskheta-Mtianeti
Khashuri	0.61	0.533	0.682	Shida Kartli
Adigeni	0.60	0.54	0.664	Samtskhe Javakheti
Gori	0.60	0.53	0.666	Shida Kartli
Rustavi	0.56	0.5	0.62	Kvemo Kartli
GEORGIA	**0.47**	**0.431**	**0.504**	

Source: own calculations based on SDS HH survey and census data

Some results in Table 1 demand discussion, particularly those for Adjara. The top three districts in Table 1 are from that region and show very high poverty rates. Based on the data from the SDS and the Census, one can see that at least 90% of people in Khulo are below the official poverty line. For Keda, this figure is 85%. Poverty rates of this magnitude are unusual and need further validation. Finally, all districts in Samtskhe-Javakheti show poverty rates significantly above the national average. Shida-Kartli and Mtskheta-Mtianeti account for seven districts in Table 1.

The districts with poverty headcount significantly above the national average do not show the highest concentration of poverty. Together, these 17 districts comprise 23.9% of all poor families. Poverty is particularly concentrated in the cities of Kutaisi (4.78%), Rustavi (3.32%) and Batumi (2.58%), and in the districts of Gldani-Nadzaladebi (5.53%), Isani-Samgori (5.5%), Gori (4.6%), Vake-Saburtalo (3.31%), and Zugdidi (2.89%). Together, these locations account for 32.5% of all the poor.

Figure 10: highest concentration of poverty



Source: own calculations based on SDS HH survey and census data

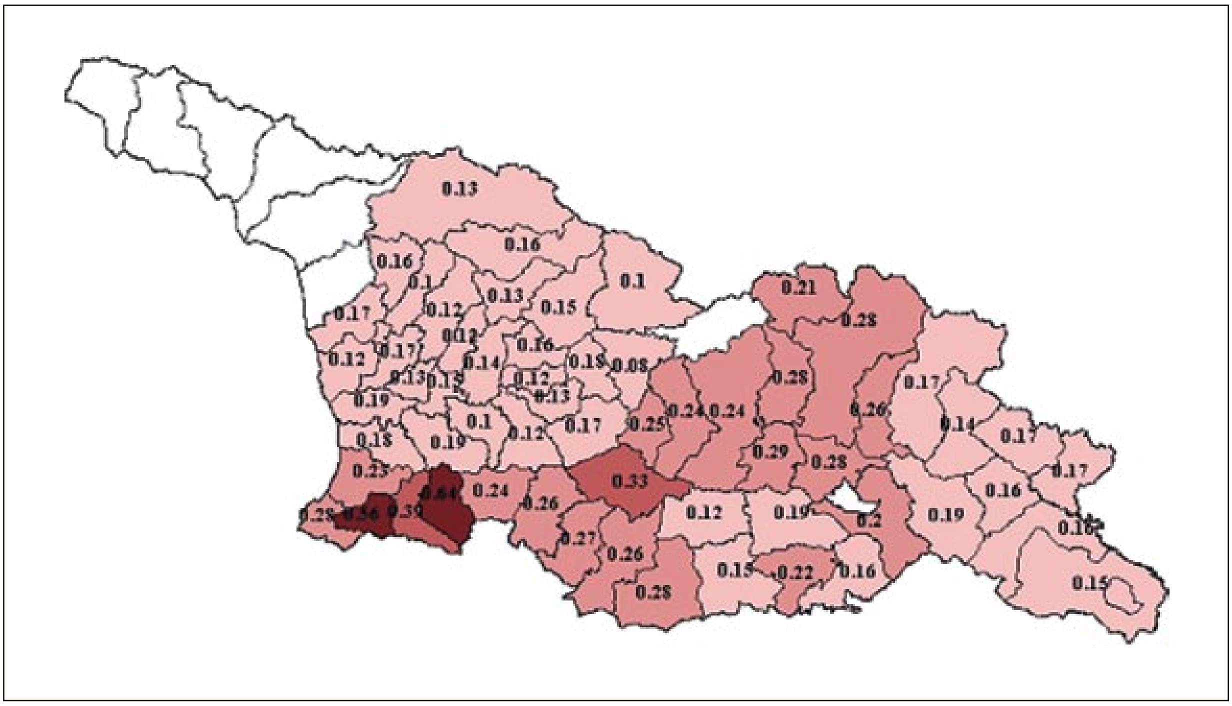
Of all these locations, only the town of Gori falls within a district (Gori) with a poverty headcount significantly higher than the national average. There is little or no relation between the level of poverty and the number of poor families in districts.

3.2 Poverty gap in districts

The poverty gap, which is also called the "depth of poverty", can be understood as a measure of the resources needed to lift all the poor out of poverty through perfectly targeted cash transfers. It is numerically calculated by taking the average distance separating the population from the poverty line with the non-poor being given a distance of zero. The poverty gap is a useful statistic to assess the extent of resources needed to eradicate poverty through cash transfers targeted to the poor[6].

[6] The following example may help one to understand the meaning of the poverty gap. For example, in a situation where the poverty gap is equal to 0.20, the cash transfers needed to lift the poor out of poverty would amount on average to 20 percent of the poverty line. If the mean income in the country is equal to twice the poverty line, the cash transfer required to lift all poor people out of poverty would represent 10% of the country's mean income. In the specific case of Georgia, the national poverty gap is 0.16 and this represents approximately 13% of the country's mean income.

Figure 11: poverty gap in districts

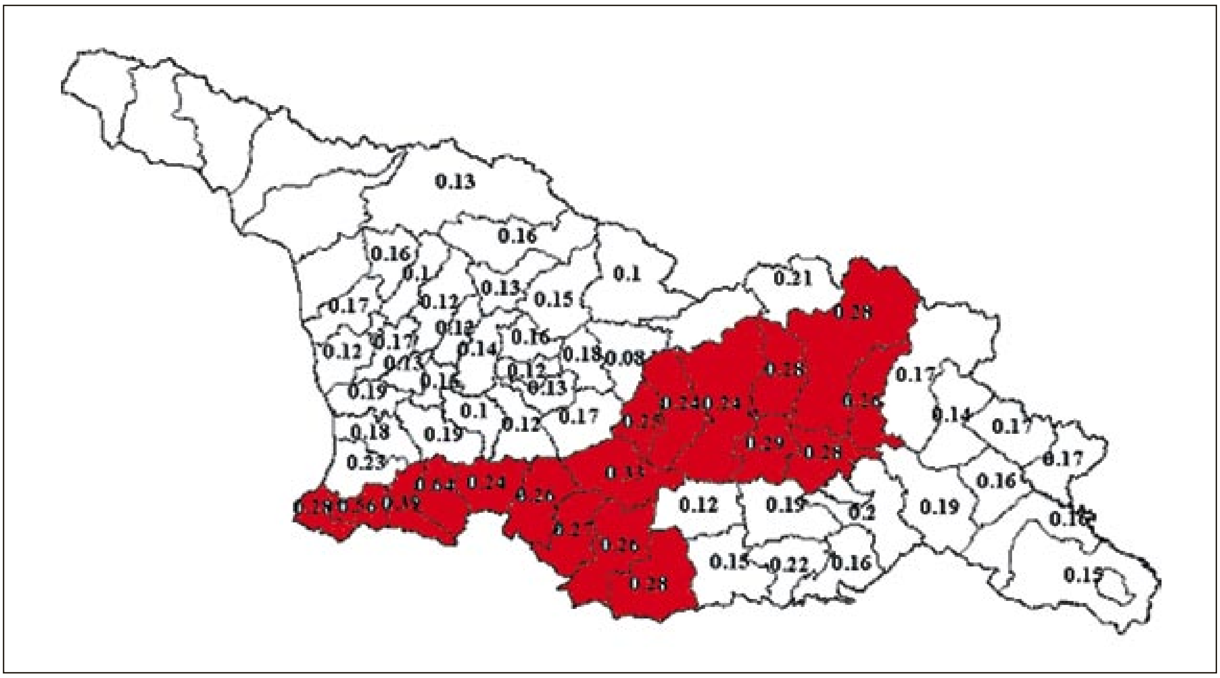


Source: own calculations based on SDS HH survey and census data

Figure 11 shows the estimated values of the poverty gap for districts in Georgia. The greater the poverty gap, the darker the color in the map. The distribution of districts with larger poverty gaps forms a southwest-northeast diagonal similar to that observed for the poverty headcount. The regions of Adjara, Samtskhe Javakheti, Mtskheta-Mtianeti and Shida Kartli comprise the districts with the larger values of the poverty gap. Therefore, this southwest-northeast diagonal not only includes those districts with larger poverty headcounts but also those districts where the poor are on average further away from the poverty line.

The estimations of the poverty gap are subject to the same errors as those described for the poverty headcount. These errors originate in that the data and the models are not perfect. Data is subject to measurement error while the predictive models are just approximations of reality. It is therefore worth identifying those districts whose values of poverty gap are significantly above the national average with a confidence level of 95%.

Figure 12: districts with poverty gap significantly above the national average



Source: own calculations based on SDS HH survey and census data

Figure 12 shows a southwest-northeast diagonal almost identical to that of the poverty headcount. This did not have to happen. There is *a priori* no reason why districts with larger poverty headcounts should also have larger poverty gaps. For example, districts with similar poverty rates can have widely different values for poverty gaps depending on "how poor are the poor". The district in which the poor are farther below the poverty line will have a larger value of poverty gap.

The picture for Georgia shows a significant overlapping of poverty headcount and poverty gaps. The districts with poverty gaps significantly above the national average are shown in Table 2.

Table 2: Districts with poverty headcount significantly above the national average

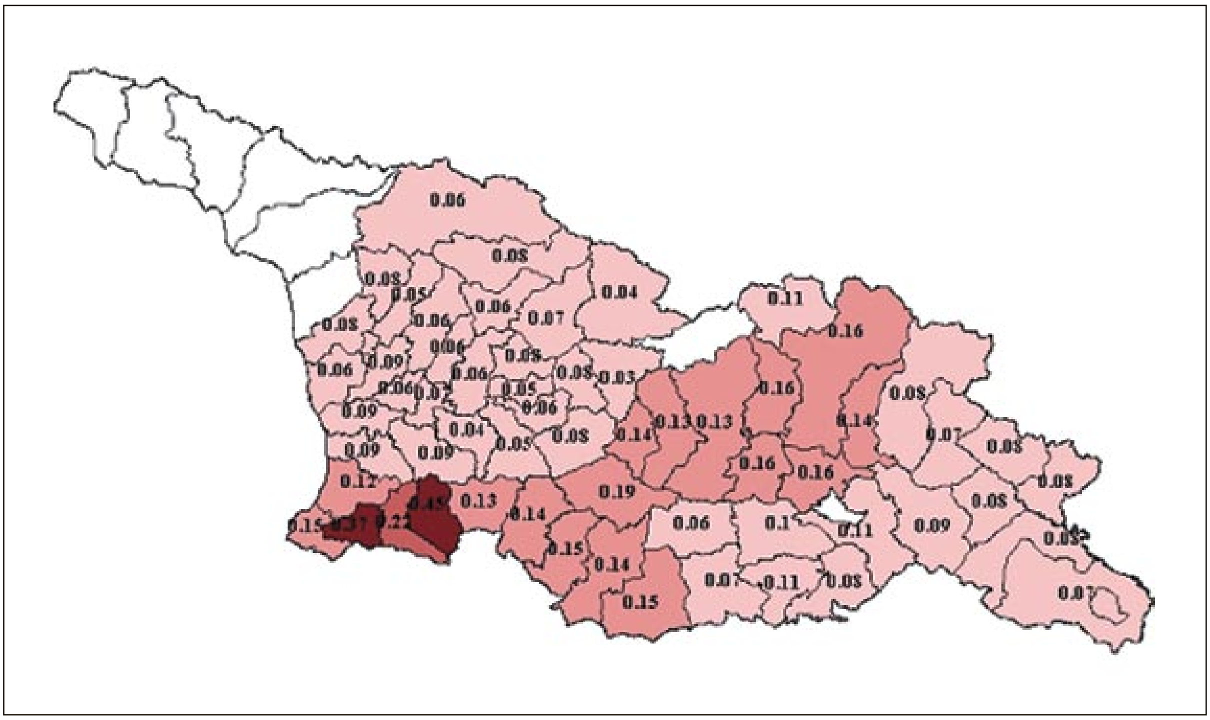
Region	Poverty Gap	Confidence interval		Region
		Low	Upper	
Khulo	0.64	0.49	0.79	Adjara
Keda	0.56	0.41	0.71	Adjara
Shuakhevi	0.39	0.33	0.45	Adjara
Borjomi	0.33	0.29	0.38	Samtskhe Javakheti
Kaspi	0.29	0.24	0.34	Shida Kartli
Mtskheta	0.28	0.24	0.33	Mtskheta-Mtianeti
Akhalgori	0.28	0.23	0.34	Shida Kartli
Khelvachauri	0.28	0.21	0.36	Adjara
Dusheti	0.28	0.23	0.33	Mtskheta-Mtianeti
Ninotsminda	0.28	0.23	0.32	Samtskhe Javakheti
Aspindza	0.27	0.23	0.31	Samtskhe Javakheti
Tianeti	0.26	0.20	0.33	Mtskheta-Mtianeti
Akhaltsikhe	0.26	0.22	0.30	Samtskhe Javakheti
Akhalkalaki	0.26	0.22	0.30	Samtskhe Javakheti
Khashuri	0.25	0.20	0.30	Shida Kartli
Gori	0.24	0.20	0.29	Shida Kartli
Adigeni	0.24	0.20	0.28	Samtskhe Javakheti
Kareli	0.24	0.19	0.28	Shida Kartli
City of Rustavi	0.20	0.16	0.24	Kvemo Kartli
GEORGIA	0.16	0.14	0.18	

Source: own calculations based on SDS HH survey and census data

3.3 Severity of poverty in districts

The severity of poverty can be understood as a measure of inequality among the poor. While the poverty gap takes into account the distance separating the poor from the poverty line, the severity of poverty takes the square of that distance into account. The severity of poverty is simply the poverty gap squared[7].

Figure 13: severity of poverty in districts (official poverty line)

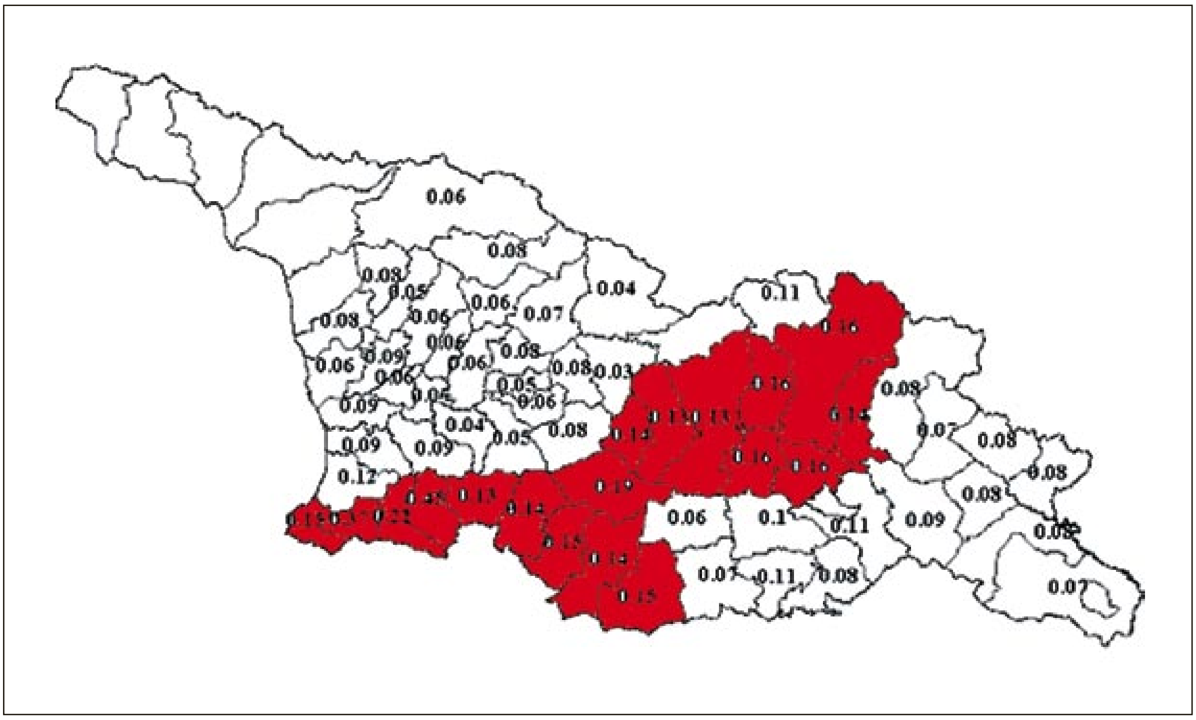


Source: own calculations based on SDS HH survey and census data

The same districts identified with the larger headcounts and poverty gaps are also those with a greater severity of poverty. This is observed when mapping those districts with values of severity of poverty that are significantly above the national average (0.08). A map of those districts shows the same southwest-northeast diagonal observed before.

[7] The severity of poverty is therefore the poverty gap weighted by itself, which in turn gives more weight to the very poor.

Figure 14: districts with severity of poverty significantly above the national average



Source: own calculations based on SDS HH survey and census data

Table 3 shows the values of severity of poverty and their confidence intervals for those districts shown in red in Figure 14 above.

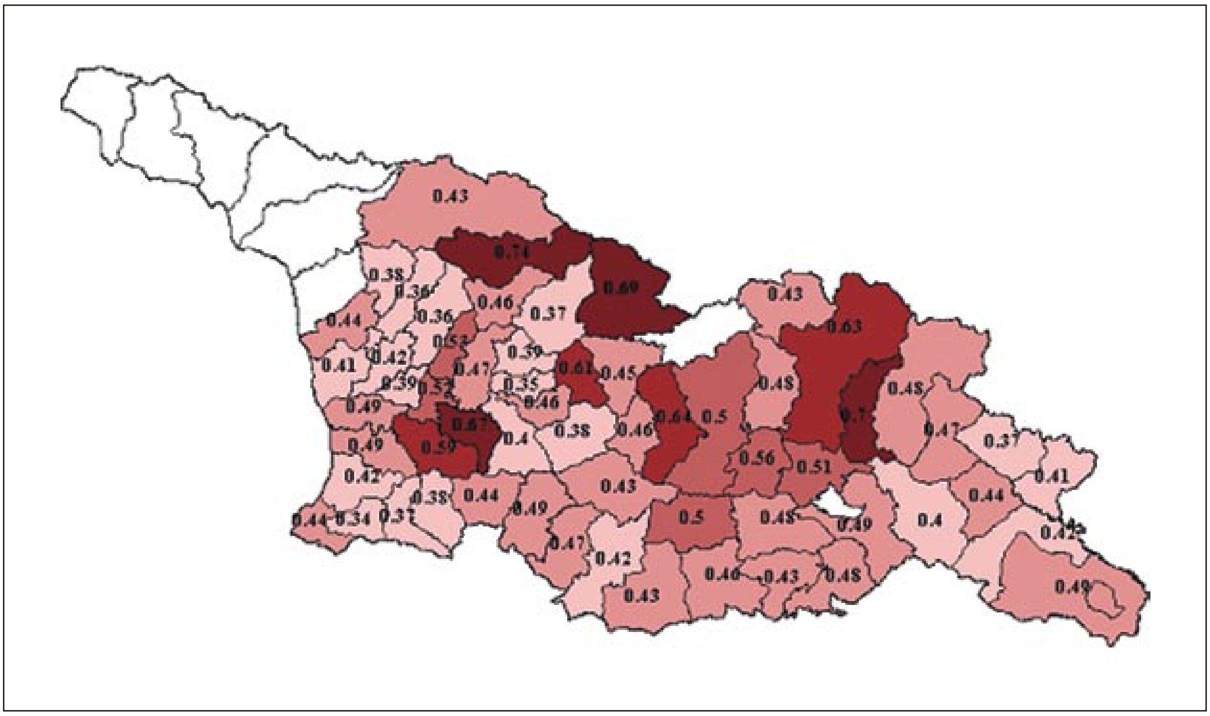
Table 3: Districts with severity of poverty significantly above the national average

Region	Poverty Gap	Confidence interval		Region
		Low	Upper	
Khulo	0.45	0.29	0.62	Adjara
Keda	0.37	0.23	0.52	Adjara
Shuakhevi	0.22	0.17	0.27	Adjara
Borjomi	0.19	0.15	0.22	Samtskhe Javakheti
Kaspi	0.16	0.12	0.20	Shida Kartli
Akhalgori	0.16	0.12	0.20	Shida Kartli
Mtskheta	0.16	0.12	0.19	Mtskheta-Mtianeti
Dusheti	0.16	0.12	0.19	Mtskheta-Mtianeti
Ninotsminda	0.15	0.12	0.18	Samtskhe Javakheti
Khelvachauri	0.15	0.10	0.19	Adjara
Aspindza	0.15	0.12	0.18	Samtskhe Javakheti
Tianeti	0.14	0.10	0.19	Mtskheta-Mtianeti
Akhaltsikhe	0.14	0.11	0.17	Samtskhe Javakheti
Khashuri	0.14	0.10	0.17	Shida Kartli
Akhalkalaki	0.14	0.11	0.17	Samtskhe Javakheti
Gori	0.13	0.10	0.16	Shida Kartli
Kareli	0.13	0.10	0.16	Shida Kartli
Adigeni	0.13	0.10	0.15	Samtskhe Javakheti
Rustavi	0.10	0.08	0.12	Kvemo Kartli
GEORGIA	0.08	0.07	0.09	

Source: own calculations based on SDS HH survey and census data

It should be noticed that those districts with higher inequality among the poor are not those with higher levels of *overall* income inequality (poor and non-poor). Figure 15 shows the estimations of the Gini coefficient for all districts of Georgia[8]. In terms of overall income inequality, that is, not just inequality among the poor, the diagonal pattern previously observed disappears. Now districts in Shida Kartli, Mtskheta-Mtianeti, Guria, Racha and Svaneti are those with the highest levels of overall income inequality.

Figure 15: income inequality in districts (Gini coefficient)



Source: own calculations based on SDS HH survey and census data

[8] The Gini coefficient is a measure of income inequality for the population as a whole (both poor and non-poor). Its value ranges from 0 (total equality) to 1 (total inequality).

4. POVERTY HEADCOUNT AND PHYSICAL VARIABLES

This report explores whether there is overlapping between poverty headcounts and a selected set of physical variables. The first one explored is geographical relief and districts with poverty headcounts significantly above the national average.

Figure 16: geographical relief and poverty headcount

Source: own calculations based on SDS HH survey and census data

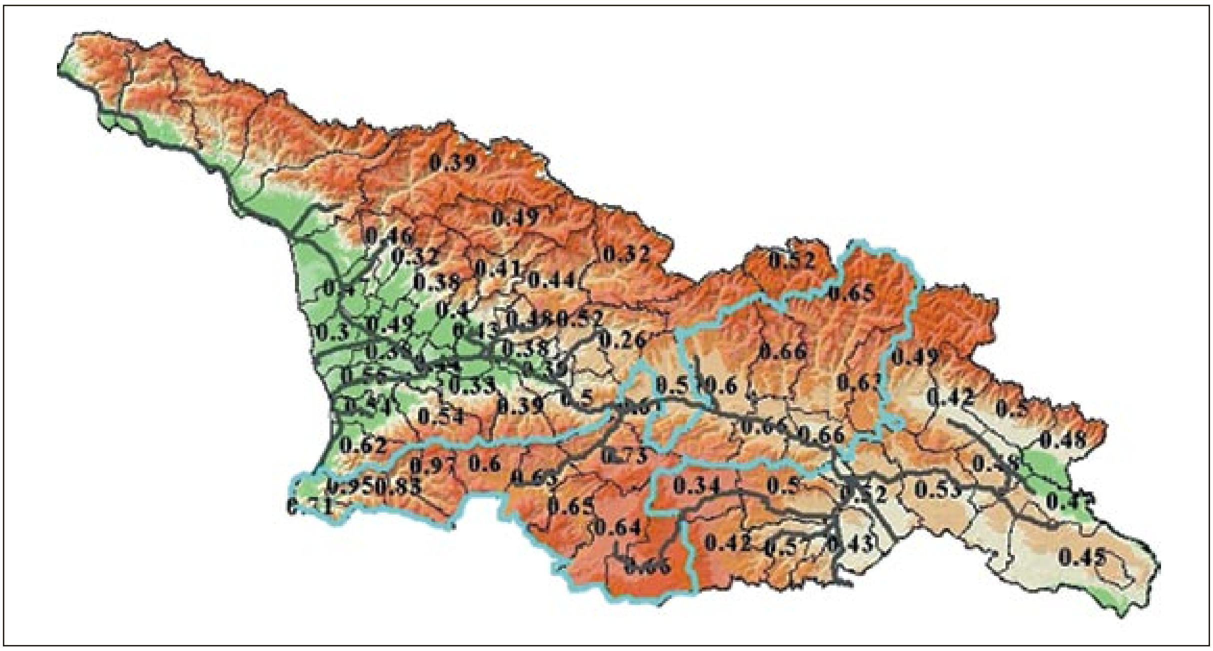
Figure 16 shows the boundary of significantly poor districts in Georgia. It can be seen that all of them are mountainous regions of Georgia. The lowlands of Guria, Samegrelo, western Imereti as well as the relatively low lying areas of Kakheti and southern Kvemo Kartli are outside its area.

The overlapping of relief and poverty headcounts is therefore a partial one. It would have been almost a perfect match had it included the highlands of Racha and Svaneti. The absence of these mountainous regions could be due to the fact that the SDS put data from Imereti together with Racha and data from Samegrelo together with Svaneti. This could have the effect of diluting the poverty headcounts for the highland regions and could affect the estimation of poverty by district. There is a need to validate the poverty readings for Racha and Svaneti so as to confirm whether geographical relief does have a good match with poverty headcounts.

We next overlap the geographical relief with the railroad network and draw the boundary of the diagonal of districts with poverty headcounts significantly above the national average. It can be seen that these districts consistently show a less developed railroad network than other regions, particularly in the east and west of Georgia. Only three railroads cross these districts. One is the main rail link that connects Tbilisi and the Black Sea Coast. The second is a branch line that links Tbilisi and Borjomi and the third is an extension to Ninotsminda. The northern districts in the diagonal have no railroad connection.

However, the northwestern regions of Georgia, Racha and Svaneti, also show a lack of railroad connections, yet they do not form part of the diagonal of the poorest districts. As mentioned before, this may reflect the way the SDS bundles regions in its household survey rather than a lack of impact from an absence of a railroad network.

Figure 17: geographical relief, railroads and poverty headcount

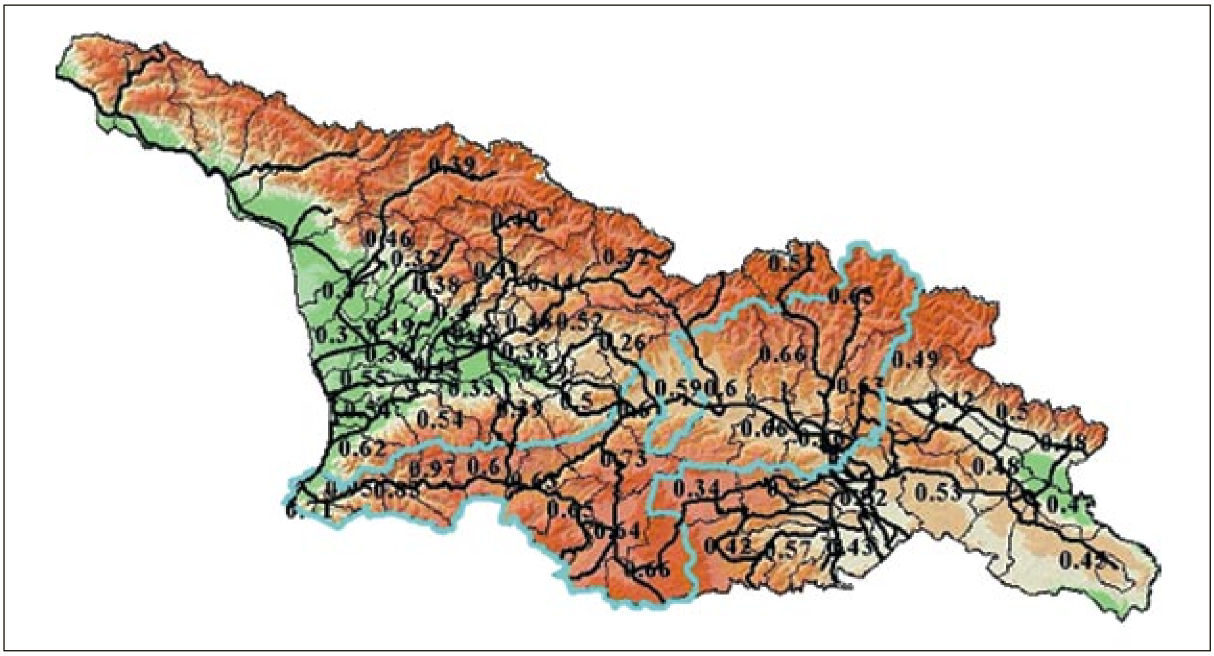


Source: own calculations based on SDS HH survey and census data

Next, we overlap the road network and geographical relief keeping in place the boundaries of districts with poverty headcounts significantly above the national average. The result can be seen in Figure 18. As it could have been expected, the poorest districts also show a relatively low density of roads. However, it should be noted that Racha and Svaneti also show an almost total lack of roads, yet they do not have districts significantly poorer than the national average.

There is also a quality factor in addition to quantity. Only the main roads connecting Tbilisi with Khashuri, Tbilisi with Gudauri, and Khashuri with Akhalkalaki are in relatively acceptable conditions. All others are in very bad shape. For example, the road connecting Samtskhe-Javakheti and Adjara is in a very poor state. The same applies to the one that connects Tbilisi with Dusheti.

Figure 18: geographical relief, road network and poverty headcount

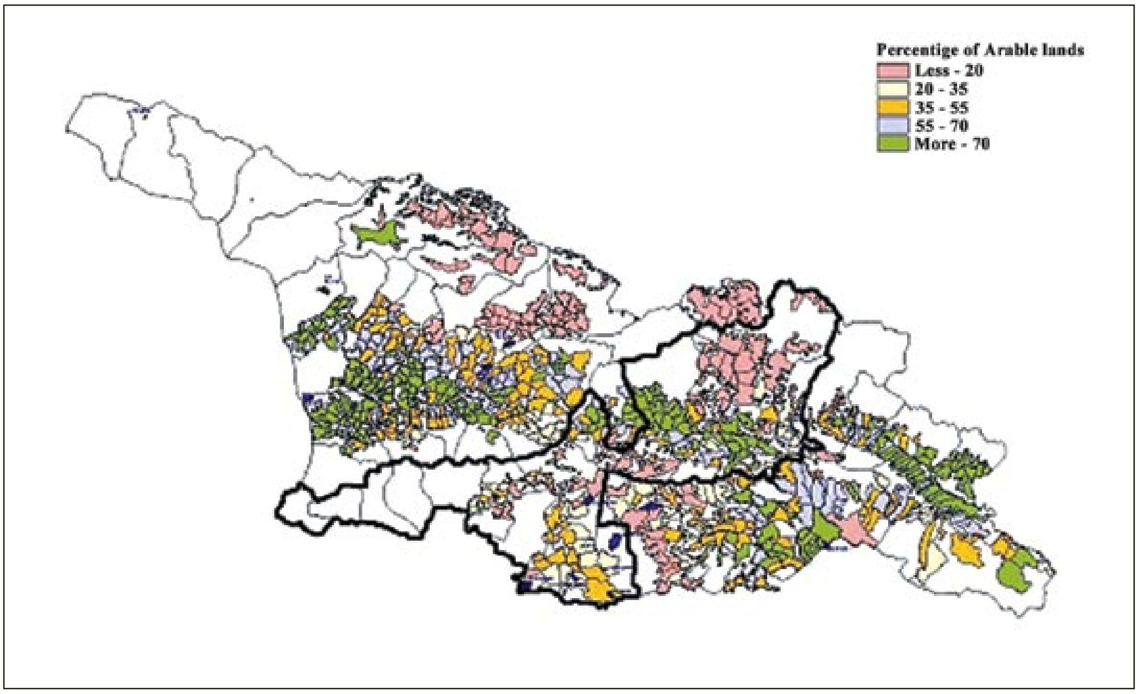


Source: own calculations based on SDS HH survey and census data

Since independence in 1991, Georgia has seen its industrial base decay severely. Today, it has almost totally disappeared. During the transition period, the agricultural sector gained relative weight and became important as a source of income and employment. For a great number of Georgians, farming was the only available option to escape hunger. Farming has been a "sponge" that has absorbed labor during times of crisis when employment in cities and towns has decreased. Therefore, it might be of interest to overlap districts with poverty headcounts above the national average together with a map of agricultural use. This is shown in Figure 19 below.

Figure 19 shows a map with percentages of arable land over total area. For example, areas in pink indicate that arable land constitutes approximately less than 20% of total area for that pixel. No color indicates negligible amounts of arable land or no recent data (e.g. Abkhazia). Figure 19 shows that the southern and northern sections of the diagonal of poorest districts have the lowest percentage of arable land use. Samtskhe-Javakheti possesses some sections with as much as 50% of arable land while Adjara shows little or nothing. Similarly, Dusheti and Akhalgori, on the northern part of the diagonal, show less than 20% of arable land. In the central section of the diagonal, however, land use is intensive with rates of more than 70%. This mainly constitutes a corridor comprising the areas along the sides of the Tbilisi-Khashuri highway.

Figure 19: percentage of arable land and poverty headcount



Source: own calculations based on SDS HH survey and census data

The overlapping of districts with poverty headcounts above the national average and main geographical variables seems to indicate a relationship between geographical isolation, low intensity of arable land use and higher poverty levels. However, this picture is not free of distortions and we highlight below the most obvious ones.

The first is that the northwestern regions of Racha and Svaneti also show a lack of rail and road networks as well as low percentages of arable land, although poverty data there is not worse than in the 'diagonal'. As mentioned before, this can be due to the way the SDS bundles regions in its household survey. Data from Imereti is processed together with that of Racha while that of Samegrelo is put together with Svaneti. This may have the effect of diluting the headcounts in the northwestern mountainous regions. The second distortion is the high use of arable land at the center of the diagonal of the poorest districts. This concentration of arable land takes place in the form of a corridor following the Tbilisi-Khashuri highway in the districts of Mtskheta, Kaspi and Gori. It may be possible that the construction of a poverty map with a higher level of resolution (e.g. *Sakrebulos*) would show this corridor to have lower poverty headcounts.

5. USING POVERTY MAPS

We close this report with a brief incursion into the potential use of poverty maps in the work of government and donors. In doing so, we are interested in how best we can combine poverty maps with other targeting tools usually applied in project design. This section also summarizes the results of consultations with government agencies, donor organizations and NGOs regarding their targeting methods.

Poverty maps are tools that are best put to use when combined with other information. Because they are just tools, they cannot substitute for good project design. Specifically, the use of poverty maps might want to be part of a design process that includes the following questions:

- What are the objectives of the project?
- What type of poor you are looking for?
- Depth of poverty, poverty rate, or the concentration of poor people?
- Will there be a need for local targeting?

Below we explore these issues in more detail.

5.1 Defining the objectives of the project

The work of donor agencies is often shaped by their own priorities, which may or may not be poverty reduction, as well as the donors' main strategies for providing assistance (e.g. capacity building, direct work with communities, budget support, etc). We find that in most cases, donors come with defined areas of expertise and defined methods for delivering assistance. These priorities and delivery strategies may or may not be compatible with the location and characteristics of the poor.

For example, assume a road rehabilitation project for which a feasibility study is being carried out. Deciding on which roads will be rehabilitated will depend on who the ultimate beneficiaries of the project will be. In other words, while "road rehabilitation" is the general objective, the selection of which road to rehabilitate demands further fine-tuning of the project objectives.

In choosing which roads to invest in, a decision-making criterion can be the return on the investment measured by the current and expected traffic after rehabilitation. On this score, the main routes (e.g. Tbilisi-Poti-Batumi; Tbilisi-Telavi) and the connections with main trading partners (Russia; Turkey; Armenia, etc) could become priorities.

A second decision-making criterion could be to improve communications with both the poor and potentially conflictive regions. In this case, Samtskhe-Javakheti could become a priority. Indeed, anyone who has traveled to this region will have witnessed the rough condition of its roads, which tend to increase the isolation of the whole region. The poverty maps also tell us that Samtskhe-Javakheti is home to districts that are significantly poorer than the national average.

The criteria for selection could be further refined. For example, the ultimate objective of the project could be the rehabilitation of roads that will improve connections with trading partners, decrease the isolation of conflict prone regions and facilitate connections with the poorest districts of Georgia. By overlapping poverty maps with the road network of the country we see that the axis Khashuri-Borjomi-Akhalsikhe and Tbilisi-Akhalkalaki-Akhalsikhe would become attractive options.

In general, the definition of the project objectives and target beneficiaries can require some form of multi-criteria evaluation, in which welfare indicators (e.g. poverty rates, poverty gaps, etc) can be used in conjunction with others like the existence of conflict prone zones, ethnic composition, and quality of roads[9]. More often than not,

[9] Multi-criteria evaluation implies the use of more than one indicator in the construction of an indicator or ranking. For example, the construction of the Human Development Index is a multi-criteria indicator in which development is measured along the axis of income, education and health.

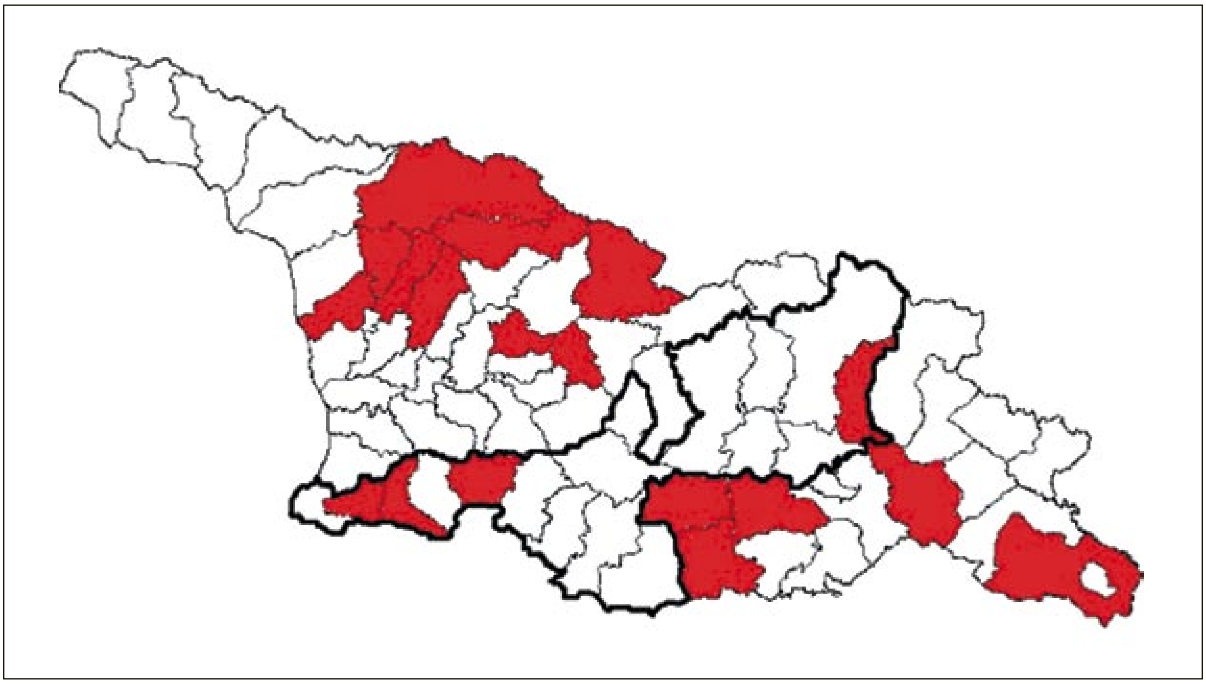
poverty maps will be best put to use in combination with other information once the objectives of the project and its target beneficiaries have been accurately defined.

Most importantly, the geographical location of a project (e.g. ranking of priority districts) can vary much according to the set of indicators used in the identification of target beneficiaries. For example, the Georgian Social Investment Fund (GSIF), a program of infrastructure support that is being financed by the Government of Georgia (GoG) through a loan from the World Bank, uses a combination of the following variables to select its priority districts[10]:

- Geographical relief.
- Changes in production lines in comparison with 1987
- Industrial background
- Highway network
- Quality of roads in the district
- Changes in population numbers
- Share of IDPs among the local population
- District revenues and expenditures on a per capita basis
- Number of educational institutions in the districts and number of pupils and teachers in mountainous districts
- Number of healthcare institutions, beds and personnel by district
- Poverty, including expenditure and revenue indicators
- Employment

All these variables are given a value ranging from one to five and the final score for any district is simply the sum of all values with equal weight given to all of them. Figure 20 shows the 18 priority districts that result from the application of GSIF's multi-criteria evaluation.

Figure 20: GSIF's top 18 priority districts



Source: GSIF

[10] For a more detailed description of the method see "Selection Indicator of Target Districts (according to the State Department of Statistics)". GSIF. Tbilisi, Georgia (mimeo). This document can be obtained by contacting the office of GSIF in Tbilisi.

Figure 20 shows in red the top 18 priority districts for GSIF. It also shows in black the boundaries of the diagonal of the poorest districts as identified in the poverty maps. It can be seen that the overlapping between the two is not substantial and that only four districts (22%) are common to both (Adigeni, Tianeti, Shuakhevi and Keda). With the multi-criteria method of GSIF, Adjara continues to show priority districts but Samtskhe-Javakheti now has only one priority district (Adigeni) and Mtskheta-Mtianeti only retains the district of Tianeti. In contrast, Kvemo Kartli, Kakheti, Racha and Svaneti now present several priority districts for assistance.

Figure 20 indicates that the targeting method varies much depending on the particular objectives of the project and on the choice of a corresponding set of indicators that can highlight priority areas. For GSIF, which has a mandate on financing infrastructure development, the poverty rate is just one variable among many in the definition of priority areas. Whether one prefers to rely exclusively on direct poverty indicators or on a combination of poverty indicators and other variables, is a choice that depends on the type of assistance program and the identified beneficiaries.

5.2 What type of poor is of interest to the project?

The terms "poor families" or "poor individuals" hide the fact that the "poor" can be a highly heterogeneous group with highly different capacities. At the simplest level, not all poor people are equally poor or face similar problems. Some of the poor face serious difficulties to ensure a proper education for their children but others also find it challenging just to have enough to eat. Indeed, while half of the population is poor, about 10% face daily and serious problems in securing a minimum diet[11].

Sex, age, education and other characteristics can be used to define eligibility for projects and to assist in targeting of the poor. For example, the overwhelming majority of single pensioners that have no extended families are poor. Their meager pensions and lack of family support condemn them to live in poverty. On the other hand, couples without children are usually a demographic group with the least incidence of poverty vis-à-vis other groups.

The poverty maps developed by this project can be used in conjunction with the census data, which this project has also put into GIS format, to pinpoint districts in which poverty overlaps with a desired characteristic (e.g. demographic, education, etc). The project designer can also use maps showing the poverty gap to identify those districts in which the poor are further away from the poverty line. Furthermore, the poverty gap maps can also be combined with census data to pinpoint particular districts that show the highest gaps and a particular demographic, education or employment characteristic.

Understanding what type of poor people there are in a given project's target area is of particular importance for good targeting. The poor do not have equal capacities to access donor programs. By ignoring the capacities of the poor, one incurs the risk of negative selection in projects. This can happen when the conditions for participating in a project turn out to be beyond the capacities of the target population, for example, the poorest in a district.

For example, there is a risk that the very poor may fail to access programs such as micro-credit operations and support to the private sector. The reason is simply that people need some minimum level of assets (land; other collateral) to access credit programs and some minimum level of economic activity to access programs directed to private sector support. Community development programs, quite popular at the moment, also face similar risks. The location of these programs is only partially based on poverty levels. Rather, the necessary condition is the capacity of the community to mobilize and maintain its social structure during and after the project termination date[12]. Whether poverty levels affect the capacity of a community to mobilize is something not yet explored in Georgia, but if it does, there would be a risk of a negative self-selection process. The result could be that while the

[11] This percentage (10%) is based on the share of Georgians that on average are expected to fall below the NHDR Extreme Poverty Line or the SDS Alternative Minimum. See "National Human Development Report; Georgia 2001-2002" United Nations Development Programme. Tbilisi, Georgia.
[12] Other criteria can also apply like indication of past success in community engagement, the presence of the community within a conflict zone, participation of women, etc.

donor agency may strive to work with the worst off relative to other members of the chosen community, these may not be the worst off in Georgian society in general.
In summary, programs may not reach the poorest segments of the Georgian population due to the inability of the poor to reach minimum levels of eligibility. The message is that understanding the different types of poor people gives knowledge about their capacities and their likelihood of involvement in a project. A combination of poverty maps, census data and poverty profiles might need to be used to further define project target areas and potential beneficiaries.

5.3 Depth of poverty, poverty rate or the concentration of poor people?

There are several indicators of poverty that can be of importance in deciding the geographical location of a project. One that is most often looked at is the poverty rate or the percentage of poor people over the total population. Poverty maps for the winter of 2001 show that the regions of Adjara, Samtskhe-Javakheti, Mtskheta-Mtianeti and Shida Kartli had most of their districts with high poverty rates.

However, it can be the case that a given district, let us call it "A", presents a high poverty rate but a low poverty gap indicating that while the majority of its population is poor, they are close to the poverty line. Another district, for example "B", could show a lower poverty rate but a higher poverty gap. This would indicate that while district "A" has a greater percentage of the population below the poverty line, the poor in district "B" are on average worse off than those in district "A". The project designer would need to evaluate whether it is more important to work in districts that have a greater poverty rate or a greater poverty gap.

Furthermore, the project designer could be more interested in securing replication of lessons learned from other poor people. In this case, the concentration and the total number of poor people begin to play an important role. The maps presented in this report show that the districts with the highest poverty rates are not those in which the greatest numbers of poor people live. Specifically, poverty is concentrated in the towns of Kutaisi, Batumi and Rustavi, the Tbilisi districts of Isani-Samgori, Gldani-Nadzaladebi, and Vake-Saburtalo, and the districts of Gori and Zugdidi. All together, these locations account for 32.5% of all poor people in Georgia. These districts and towns are not the ones with the highest poverty rates but because a lot of people live in them they contain a high number of poor people.

The geographical concentration of poor people plays a major role in the replication and catalytic effects of a project. These two effects might want to be well thought out as part of the project design process. Targeting the very poor will demand higher levels of project investment per unit of participant, as the very poor often have (relative to less poor families) less, not only capital assets, but also knowledge on how to benefit from projects. As long as projects need to concentrate resources per beneficiary, it is important that replication and catalytic effects are maximized.

An example of efforts to combine good targeting with catalytic effects is a CARE project in west Georgia. The agency works with partners in each community who are required to represent the interests of the poorest and most vulnerable. Once the target districts have been identified, the choice of where to work at the local level is influenced by the so-called "contagion" and "clustering" effects. The contagion effect reflects the number of sites in which one needs to work in order to catalyze change in a given geographical area. If the contagion effect is estimated to be 1-7, then one individual is expected to pass knowledge to about seven others within a given geographical range[13]. In this example, it would mean that for a given area, one could target 15% of all communities and still achieve an effect on the remaining ones. In turn, the "clustering effect" reflects the impact from the concentration of communities in a given area. The higher the concentration of communities, the easier it is for experiences to be shared. Thus the contagion effect works better in the presence of a high clustering effect. Together, contagion and clustering effects can greatly maximize the impact per unit of project outlay.

[13] For example, within a ten kilometer range, if this is estimated as the average distance that an individual travels outside her community.

5.4 Will there be a need for local targeting?

Poverty maps can be used as "intermediate" tools between national and local level targeting. Even if the project's priority is reaching the poor and a district has been identified, accurate targeting can require the application of local targeting methods.
For purposes of illustration, we refer to the work of the World Food Programme (WFP) and Save the Children (STC) in food emergency relief in Javakheti during the draught of 2000. The targeting applied by WFP/STC involved several steps. The first task was to do a baseline survey that identified 500,000 people as potential beneficiaries. Second, there was an identification of the most "food insecure" families among the original 500,000 potential beneficiaries. This "most insecure" group included those with no access to land, people who had obtained 25% or less of the regular yield the previous year, single headed households, families with more than four children less than 16 years of age, single or lone pensioners and other characteristics commonly associated with high poverty risk.

The third step was to ask the local *Sakrebulos* for a list of potential recipients who could meet the characteristics identified with food insecurity. WFP/STC checked the accuracy of these lists by means of surveys[14]. In several instances, the surveys showed that the lists provided by the *Sakrebulos* contained high numbers of ineligible families. In all these cases, the *Sakrebulos* were requested to correct the lists. The attention given to accurate targeting resulted in lists that were corrected and food distributed mostly to targeted recipients[15].

Two aspects of this experience provide lessons to other interventions. The first is that correct targeting demanded increased administrative and monitoring costs and that the agencies involved had the resources to invest and the technical capacity to design targeting and monitoring programs. The second is that the objective of the program was clear in its direct targeting of the most food insecure families. The combination of resources to invest in targeting, technical capacity to conduct targeting and a clear objective were understood as crucial aspects of the program.

[14] These surveys covered a representative sample of the original lists.
[15] WFP/STC allowed the recipient to distribute food among his/her extended family or neighbors as he/she saw fit. This decision respected local traditions about food sharing among community members. In other words, the project allowed the recipient, not the *Sakrebulos*, to decide on whether and how food would be shared.

6. FUTURE STEPS

This project has developed maps for poverty rates, poverty gaps, and concentration of poverty. It has also put into GIS format census variables that can be combined with welfare indicators to improve targeting of projects. However, this is a first step in a process aimed at generating robust data for targeting purposes. The findings and outputs of this project would be greatly strengthened by undertaking the following tasks:

6.1 Confirm findings using the new sampling design of the SDS household surveys

After the implementation of the Census of 2002, the SDS modified the sampling design of its household surveys. In brief, the sampling units of the household survey are now the same as in the census unit. This change will allow for a greater accuracy in the production of poverty maps[16]. It would be of importance to generate poverty maps for several quarters so as to confirm the findings of this project. For example, in the winter of 2001, Racha and Svaneti, which are mountainous and isolated regions, failed to show districts significantly poorer than the national average. The development of poverty maps for several quarters of data would allow us to explore whether this finding is only a feature of winter 2001 or whether it remains consistent over time.

6.2 Explore temporal patterns for the distribution of poverty: maps for summer periods

The findings of this project are strictly valid for the winter of 2001 and probably also valid for the winter season in general. This is because the geographical distribution of poverty takes time to change and therefore the picture today can remain valid for several years. In addition, there have not been substantial changes in regional development in Georgia for at least the last five years. The benefits of economic growth have accrued to a minor group of the population that is concentrated mainly in Tbilisi and a handful of other towns. Therefore, the pattern of poverty observed in the winter of 2001 can remain valid for several winters to come.

However, there is a substantial change in poverty rates from winter to summer that has been reflected in household surveys conducted by both the SDS and UNDP. It is likely that the geographical distribution of poverty will change depending on the season. In general, the construction of several poverty maps for different quarters would allow us to explore temporal patterns in the geographical distribution of poverty. These patterns can be of importance for multi-year projects because the geographical priority for a project could therefore change over time, particularly, from winter to summer.

[16] The method to generate poverty maps can be understood as a way of linking the information from the census and the household survey. Using the census units in the sampling design of the household surveys allows a better identification of so-called "location effects". See Annex A for a summary description of the method.

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8. ANNEX A: METHODOLOGY

The basic idea behind the methodology is as follows: first a regression model of log of family consumption was estimated using the survey data and employing a set of explanatory variables that are common to the survey and the census. Next, parameter estimates from that regression were used to predict log of family consumption for every household in the census. Finally, a set of poverty indicators (e.g. headcount, poverty gap, etc) was constructed for districts using these predictions.

The method can be divided into three stages[17]. The first is associated with defining and selecting the set of comparable variables common to the survey and the census. The second stage involves defining regression models using the survey data while the third stage involves the estimation of family consumption for every family in the census.

First stage

The first stage involved the selection of those variables that were comparable between the survey and the census. The main objective is to ensure that survey variables can reasonably be understood as containing the same information as the corresponding census variables. This task demands determining whether the questions in the survey and the census are similarly asked, whether answer options are reasonably similar, and whether the variables from the survey and census are statistically similarly distributed over households in the population census and in the household sample survey. This evaluation was repeated for each of the nine regions in which the survey data is representative of the population. Below we show selected variables that were found to be comparable and were used in the regression models:

- Number of rooms
- Presence of central gas system
- Presence of individual gas system
- Number of pensioners
- Number of children (0-6)
- Number of children (7-15)
- Presence of a head of household with higher education
- Presence of a head of household with vocational education
- Age of head of household
- Number of breadwinners
- Share of working age men (16-64)
- Presence of individual hot water system
- Log of household size
- Square root of log of household size
- Share of pensioners in family
- Ethnic origin
- Share of breadwinners
- Share of all children (0-15)
- Living space
- Connection to sewerage system
- Marital status
- Presence of a widow in a house with individual gas system
- Presence of head of household with higher education and presence of individual gas system
- Presence of a self-employed person or a person who has worked for a wage in the previous three months
- Total area of the house of apartment
- Presence of an individual gas system and ethnic Georgian origin

[17] For a full description of the method, see Elbers *et al,* 2002.

- Average number of families with water supply in the district
- Average number of families with individual gas system in the district

Second stage

The second stage estimation involved modeling log of family consumption at the lowest geographic level for which the survey is representative. In Georgia, this is at the regional level. The second stage begins with an association model of log of family consumption for a household *k* where the explanatory variables are a set of observable characteristics[18]:

(1) $$\ln y_k = E[\ln y_k | \mathbf{x}_k] + \varepsilon_k$$

These observable characteristics were variables present in both the survey and the census. Using a linear approximation to the conditional expectation, we model the household's logarithmic consumption as

(2) $$\ln y_k = \mathbf{x}'_k \boldsymbol{\beta} + \varepsilon_k$$

In our particular dataset, the vector of disturbances, $\boldsymbol{\varepsilon}$, was distributed normally. The model in (2) was estimated by Ordinary Least Squares using the household survey data. The fitness of the models for each region was as follows:

Region	R^2
Kakheti	0.390
Tbilisi	0.456
Shida-Kartli	0.437
Kvemo-Kartli	0.412
Samtskhe-Javakheti	0.549
Adjara	0.508
Guria	0.469
Samegrelo	0.377
Imereti	0.471

Third stage

In the third stage analysis, we combine the estimated second stage parameters with the observable characteristics of each household in the census to generate predicted log of family expenditures and simulated disturbances. We conducted a series of simulations, where for each simulation *r* we draw a set of first stage parameters from their corresponding distributions estimated in the second stage. Thus we draw a set of beta coefficients, $\tilde{\boldsymbol{\beta}}^r$, from the multivariate normal distributions described by the second stage point estimates and their associated variance-covariance matrices. Then, for each household we simulated the disturbance term $\tilde{\varepsilon}_k^r$, from data using bootstrap method. We then simulated a value of expenditure for each household, $\hat{y}_k^r$, based on both predicted log family expenditure, $\mathbf{x}'_k \tilde{\boldsymbol{\beta}}^r$, and the disturbance terms:

(3) $$\hat{y}_k^r = \exp\left(\mathbf{x}'_k \tilde{\boldsymbol{\beta}}^r + \tilde{\varepsilon}_k^r\right).$$

Finally, the full set of simulated log family expenditures, $\hat{y}_k^r$, are used to calculate estimates of the welfare measures for each spatial subgroup.

This procedure was repeated 1,000 times drawing a new $\tilde{\boldsymbol{\beta}}^r$ and disturbance terms for each simulation. For each subgroup, we take the mean and standard deviation of each welfare measure over all 1,000 simulations. For any given location, these means constitute our point estimates of the welfare measure, while the standard deviations are the standard errors of these estimates.

[18] Because the census and the survey do not use the same cluster, we deviated from the original method outlined in Elbers *et al*, 2002.