



Briefing note

Aid allocation within countries

Does it go to areas left behind?

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Key findings

- Donors need to be working with governments more effectively to ensure a better distribution of resources in line with need across these countries. Aid is not as well correlated with need as it should be at sub-national levels.
- Significant data gaps remain when considering the sub-national distribution of aid. Of the 21 countries scoped for this project, only five had sufficiently granular data on aid for us to attempt this exercise.

1. Introduction

Much attention has been paid to aid allocation across countries, including whether aid should target poor people or poor countries. There has been less focus on where aid is spent when it reaches recipient countries, at sub-national levels. This is becoming an increasingly important issue in the context of the ‘leave no-one behind’ agenda. This focuses not on country aggregates but on the needs of individuals and groups, which can vary widely within countries. In Kenya, a middle-income country, more than 80% of middle- and upper-income households in Nairobi have access to basic maternal and child healthcare,¹ but this figure is just 25% for rural and poorly educated households in remote regions (ODI, 2016). Understanding not only which countries receive aid, but how it is distributed when it gets there is therefore crucial.

This short note presents new analysis on the relationship between aid allocation and sub-national estimates of poverty in four countries: Afghanistan, Bangladesh, Honduras and Nigeria. We also consider health aid and health access in two of these (Honduras and Nigeria). These countries have been selected because all of them will present their National Voluntary Reviews on progress towards the Sustainable Development Goals at the July 2017 High-Level Political Forum. They all also have good, accessible datasets on aid, disaggregated to the sub-national level.

2. Methodology

Data on aid was obtained from AidData’s sub-national, geospatial research datasets (AidData 2016a-d) and geocoded data published under the International Aid Transparency Initiative (IATI).² AidData, in partnership with Development Gateway, collected these datasets from countries’ Aid Information Management Systems (AIMS), where available, and geo-referenced them. This involved collecting and triangulating location information from donor documents and project appraisals and evaluations to identify precise project coordinates. Projects which are allocated to and spent by the government directly – for example, budget support operations – or those targeting central government operations or policy were excluded.³ The data for Afghanistan, Bangladesh and Honduras is from 2014, and for Nigeria is from 2013 – the most recent year available in each case.⁴

To assess distribution of poverty across countries, two datasets were used. The first was night-time lights (NTL) per capita (DOD/USAF/AFWA 2017, Center for International Earth Science Information Network 2016.) Research has demonstrated that NTL can be a reliable proxy for local economic development, especially in countries where baseline luminosity is low and survey data is harder to collect. A World Bank study found a strong positive relationship between changes in NTL and changes in GDP in a sample of 46 sub-Saharan African countries (Bundervoet et al, 2015); one could reasonably expect that this relationship would also hold at the sub-national level. Therefore, while NTL is not a perfect measure of poverty, it is a useful indicator for this study because of the availability of data at varying spatial scales, which is not the case for most poverty statistics.

The second dataset was the Oxford Poverty and Human Development Initiative’s Multidimensional Poverty Index (MPI), (Alkire and Robles, 2016), which assesses poverty across various dimensions including health, education, child mortality and school attendance. This data is only available for countries at the regional level, which undermines its utility for a more granular analysis. To check the robustness of our analysis, we correlated the two datasets in the two countries in which it was possible to do so (Nigeria and Honduras) and found, as expected, an inverse correlation: regions with higher levels of NTL per capita tend to have fewer poor people.

For the health-specific analysis, the same data on aid were used, with only health-related projects included in the dataset. Health access was measured by the Composite Coverage Index (CCI) of maternal and child health services, derived from the most recent Demographic and Health Survey or Multiple Income Cluster Survey (WHO 2015). Health analysis was only conducted for Honduras and Nigeria as there was insufficient data to do so for the other two countries.

If aid was allocated sub-nationally in line with the ‘leave no-one behind’ principle, we would expect:

- Aid to be negatively correlated with NTL, as we expect greater levels of NTL to indicate greater levels of economic activity
- Aid to be positively correlated with Multidimensional Poverty, as set out in the MPI
- Aid to be positively correlated with health need, as determined by the CCI

1. As measured by the Composite Coverage Index or reproductive, maternal, newborn and child health (RMNCH) service delivery

2. For Bangladesh, a representative sample of nine donors that AidData had previously geocoded using IATI was used. AIMS were used for the other three countries

3. For the Afghanistan AIMS, flows that were implemented by the Government of Afghanistan were included. We included projects with a precision code of 1,2,3,4, and 6 in the AidData database. A precision code of 6 indicates that projects are distributed in multiple locations without precise coordinates, which we assume are distributed evenly across the country. This accounts for 5% or less of aid in Afghanistan, Honduras and Bangladesh, but 31% in Nigeria. Precision codes 1-4 indicate a more precise location can be identified.

4. For Afghanistan, Bangladesh and Nigeria, geocoded aid accounted for 95% or more of total aid in the relevant year, excluding aid allocated to and spent by the government directly. In Honduras, only 65% of aid in 2014 was geocoded, which is a limitation to the findings.

Causality may also run in the other direction: areas with more aid may see higher NTL or lower poverty as a consequence of aid. This would be most evident in the case of rural electrification projects and NTL. For the purposes of this study, however, we use a similar approach to that used in multi-country studies (see, for example, Greenhill et al. 2015), and assume that aid should be correlated with current levels of need.

In each country, we conducted regressions with and without population as an independent variable. This is because both aid and NTL are likely to be positively correlated with population. This influences the results in Honduras in particular (as described below).

3. Main findings

3.1 In Nigeria and Honduras, aid appears to be well correlated with need

Total aid to Nigeria by region in 2013 was positively correlated with poverty (as measured by the MPI) and negatively correlated with NTL. Taken together, these results suggest that areas with high levels of poverty, or lower levels of economic activity tend to also receive higher levels of aid. This result held whether or not we controlled for population. The distribution of aid in Figures 1 and 2 below suggests that aid is concentrated in the northern districts. The correlation between health aid and the proportion of the population without access to healthcare (as measured by the CCI) is also positive and statistically significant, suggesting that health aid is being directed to areas with the lowest levels of health coverage, as shown in Figures 3 and 4. However, these figures also show that not every region with low levels of access to healthcare receives high amounts of aid.

Figure 1. Aid per capita in Nigeria, by region (2013)

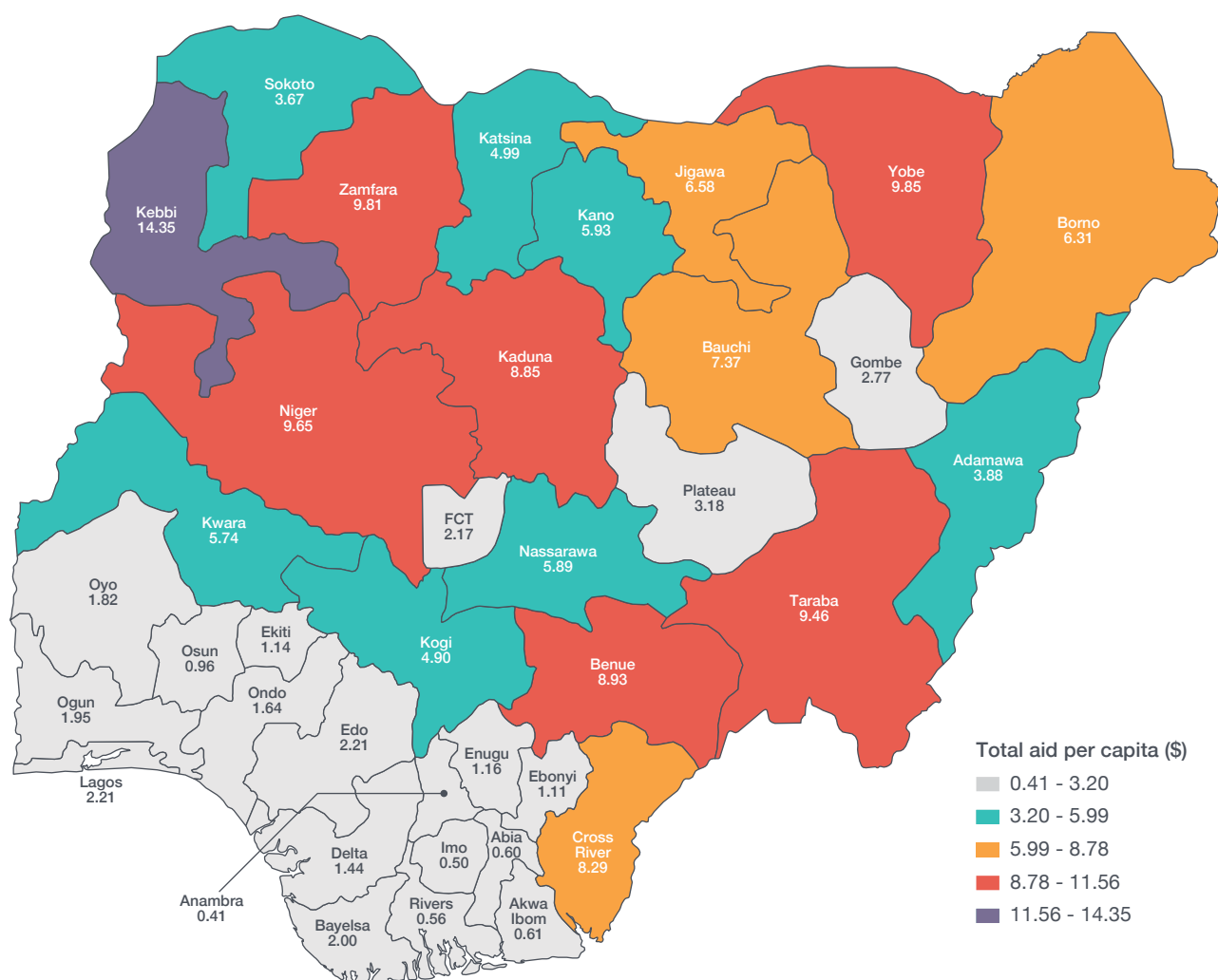


Figure 2. Luminosity in Nigeria by region (2013)

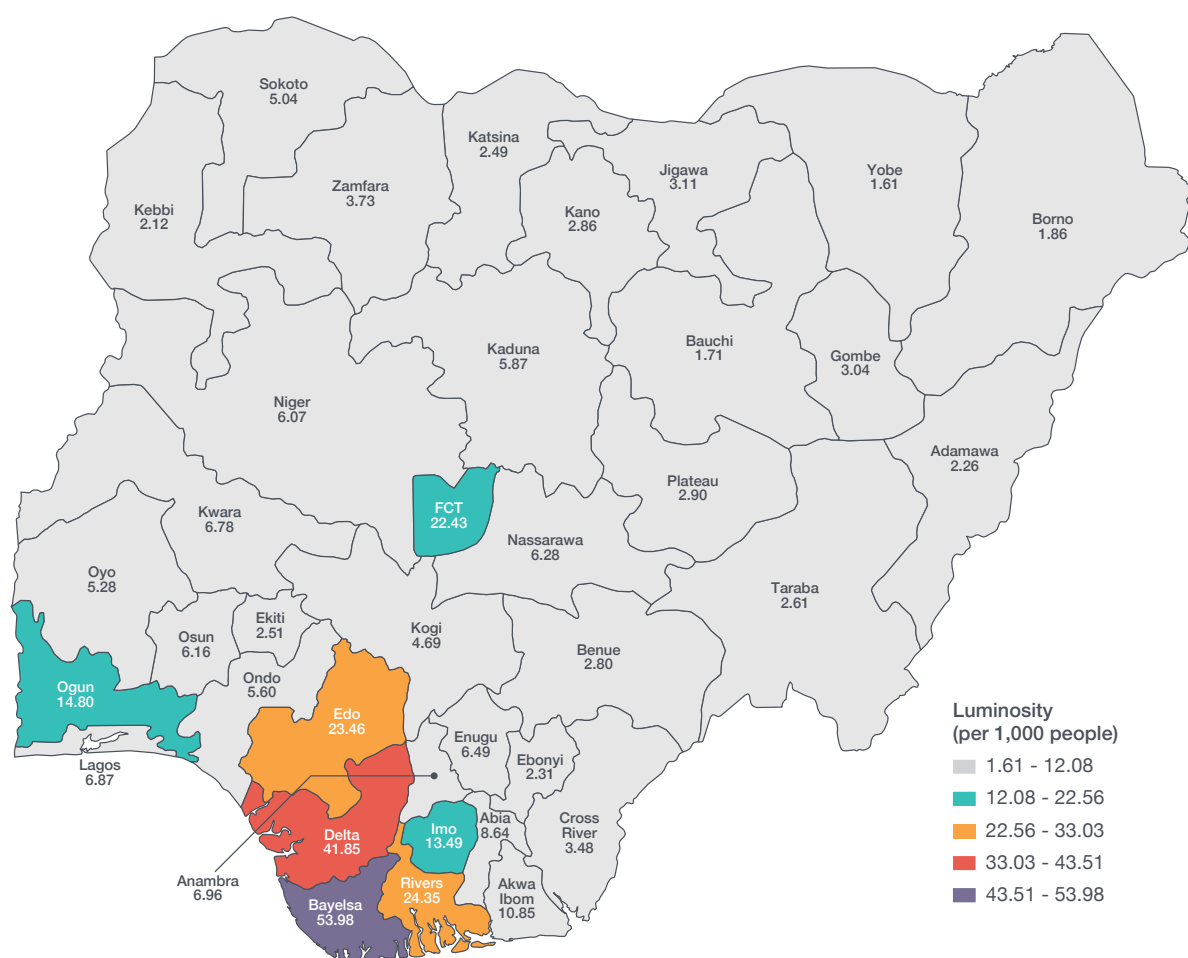


Figure 3. Health aid per capita in Nigeria (2013)

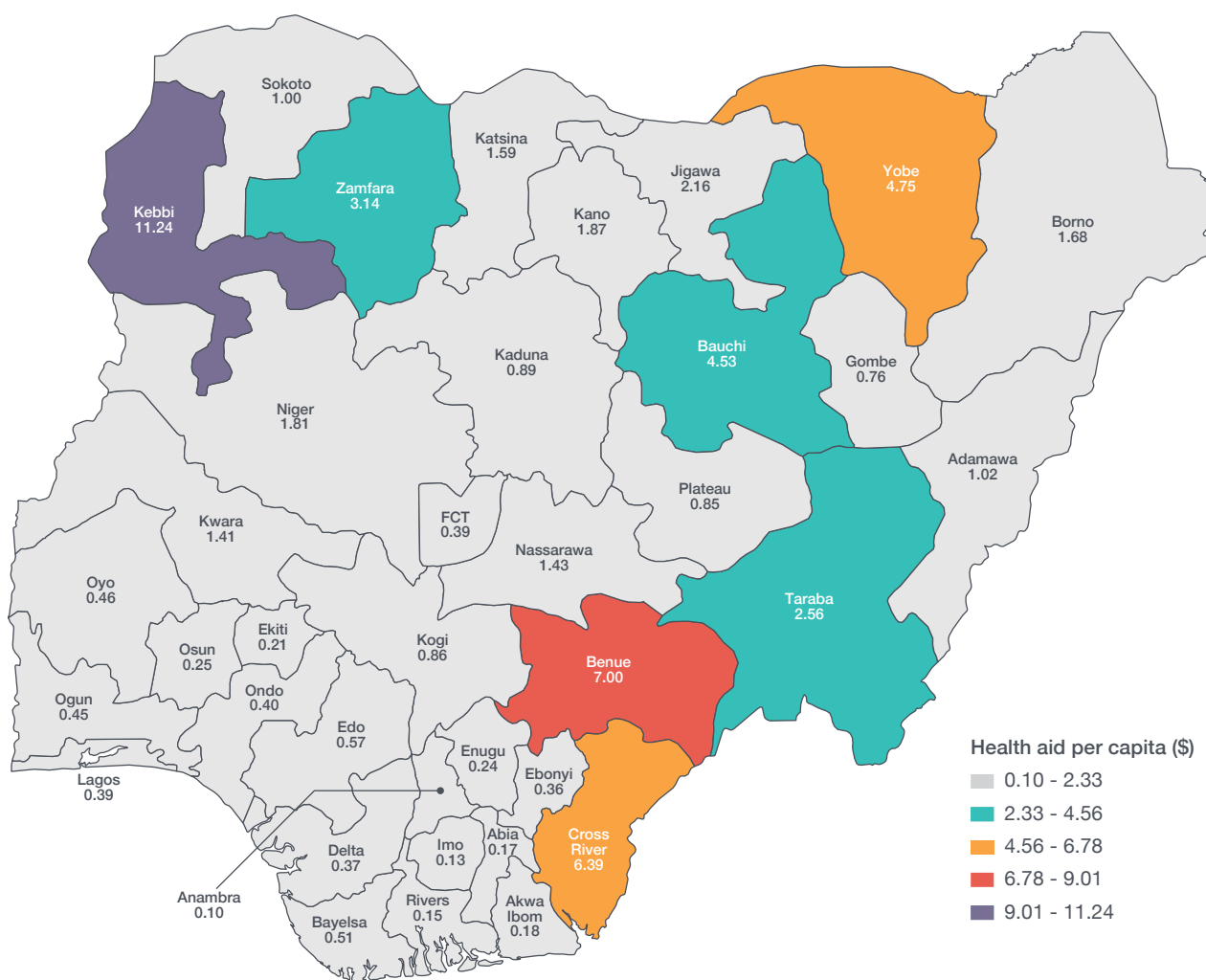
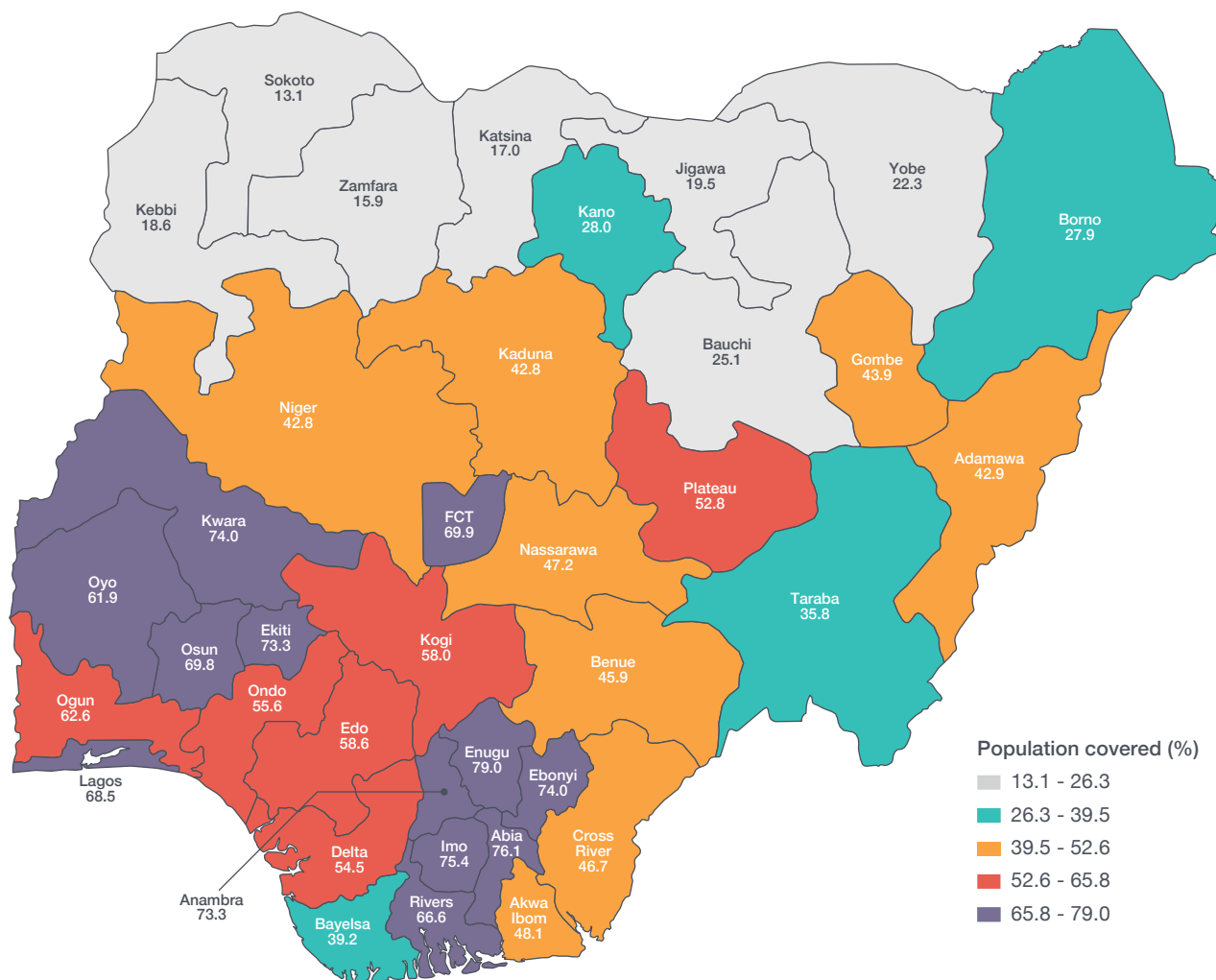


Figure 4. Composite Coverage Index in Nigeria by region (2013)



In Honduras, total aid per region appeared to be positively correlated with NTL, but once we controlled for population the relationship became negative, suggesting that the positive correlation was due to both aid and NTL being correlated with population. This negative relationship is more in line with what we would expect if aid was allocated according to the ‘leave no-one behind’ principle. We also found a statistically significant negative relationship between aid per capita and NTL per capita. This also suggests that aid is well correlated with need.

Unlike Nigeria, however, no relationship between aid and MPI was found, even controlling for population.

Health aid also appears to be positively correlated with health needs in Honduras, with a statistically significant relationship between aid and the proportion of the population without access to healthcare. This relationship also held once we controlled for population. It should, however, be noted that geocoded aid only covers 65% of the total amount of relevant aid in Honduras – a potential caveat to the finding.

Figure 5. Total aid per capita in Honduras by region (2014)

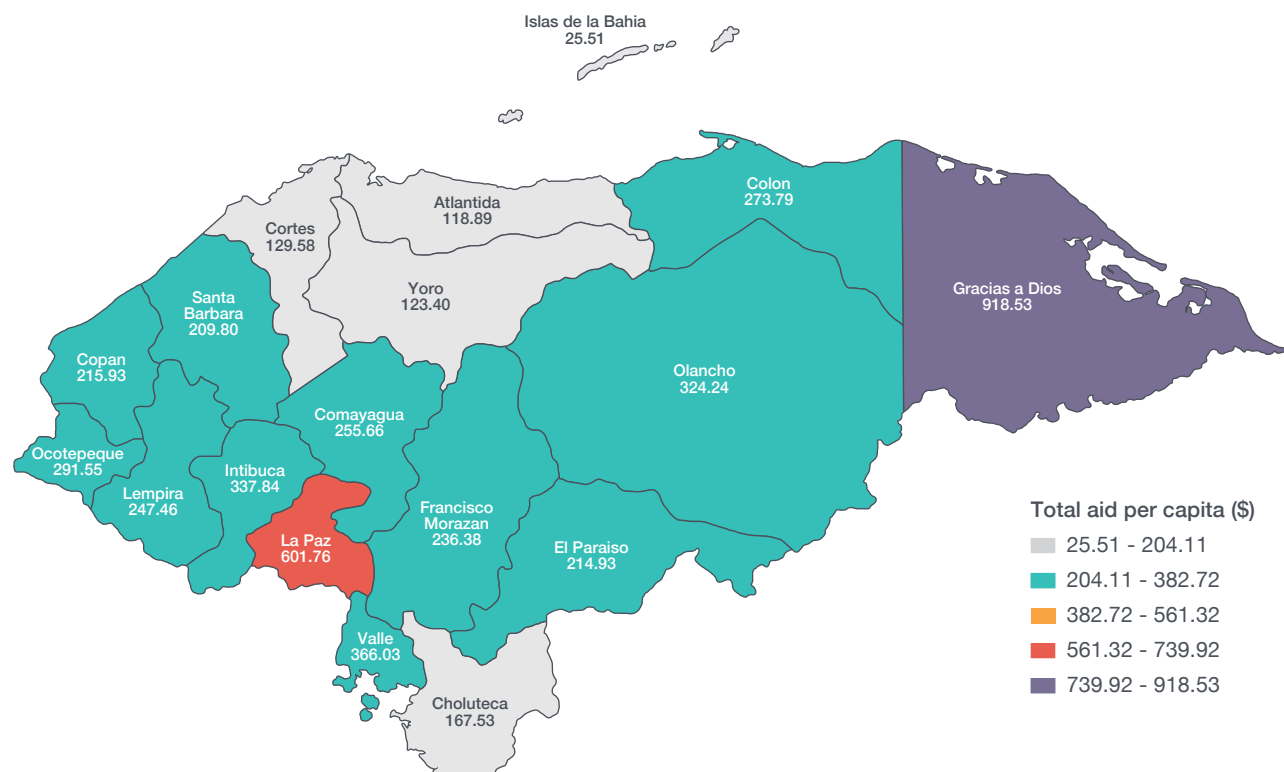
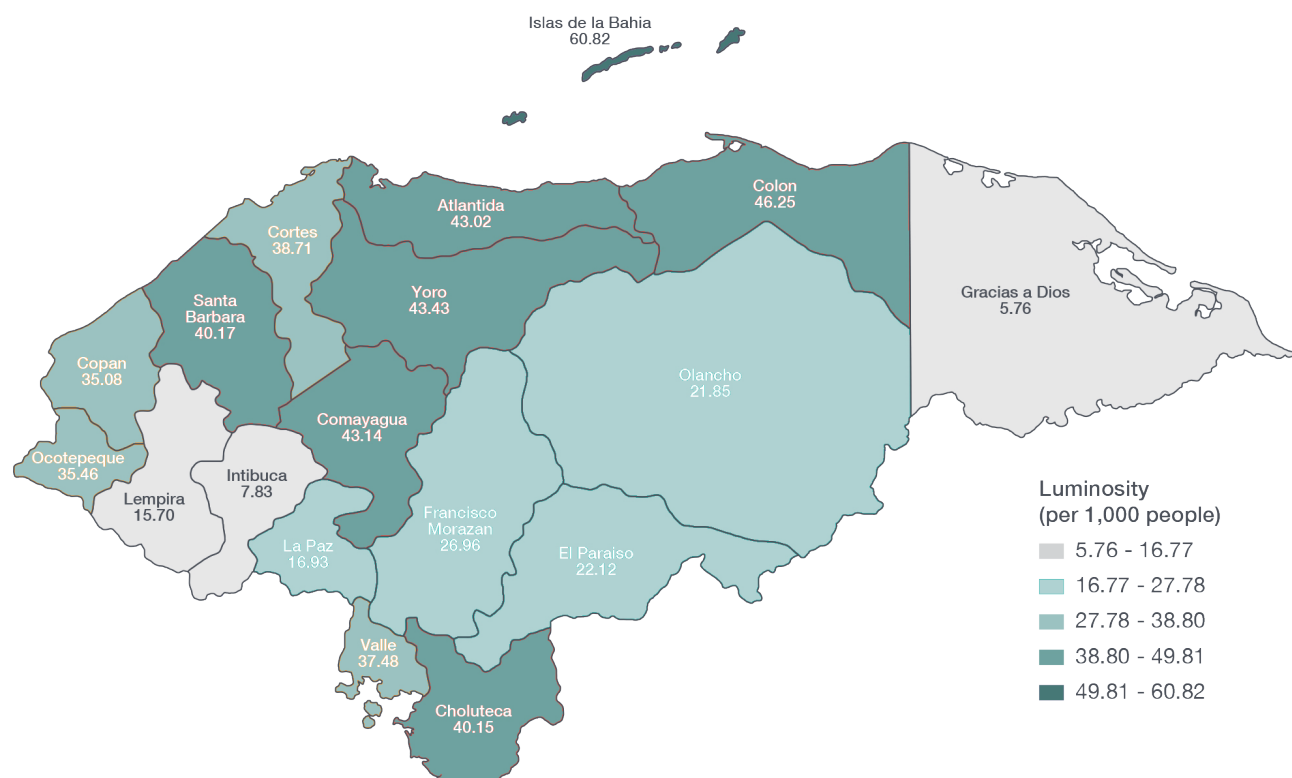


Figure 6. Luminosity in Honduras by region (2013)



3.2 In Afghanistan and Bangladesh, aid appears to be spent in the regions with lowest need

In Afghanistan and Bangladesh, aid is positively correlated with NTL, whether or not we control for population. However, we did not find any relationship

between aid per capita and NTL per capita. Similarly, no relationship was found between aid and MPI, irrespective of whether we controlled for population. This suggests that aid is not well correlated with need, as regions with higher levels of NTL appear to get more aid.



Marma women return home from the village market in the ethnically unique and geographically isolated Chittagong Hill Tracts.
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Figure 7. Total aid per capita in Afghanistan by district (2014)

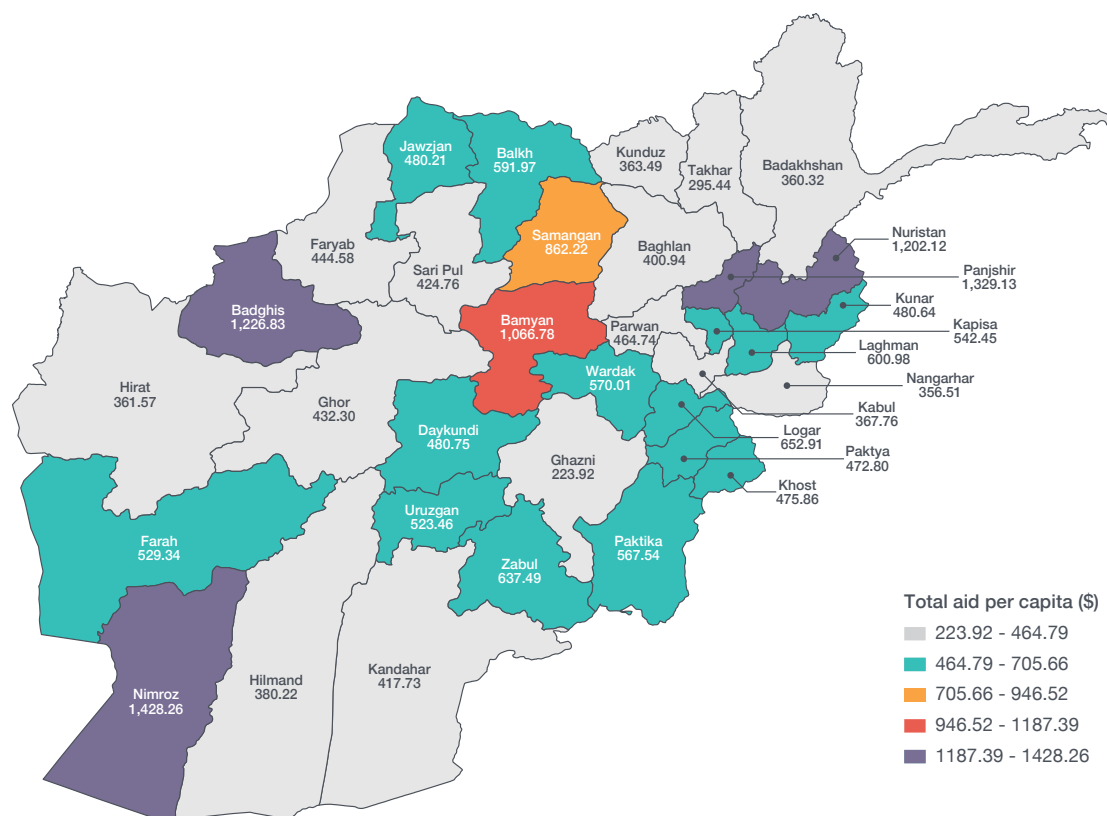


Figure 8. Luminosity in Afghanistan by district (2014)

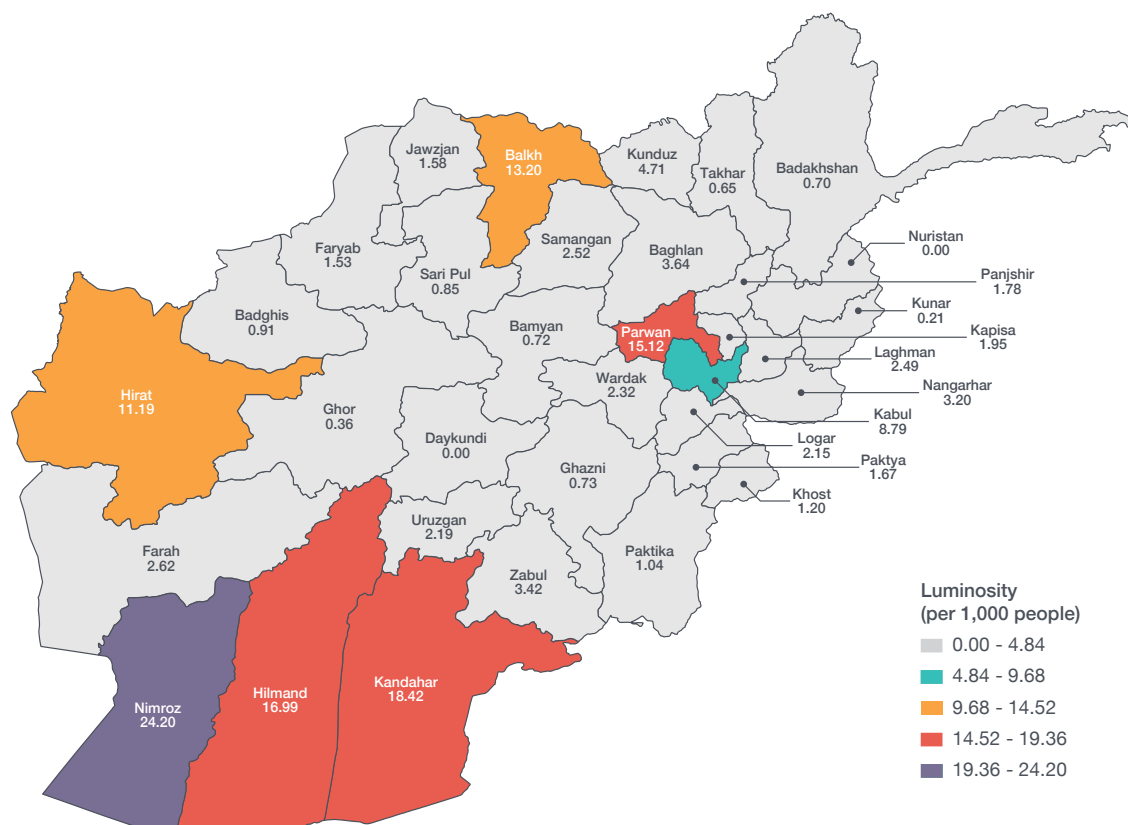


Figure 9. Total aid per capita in Bangladesh by region (2014)

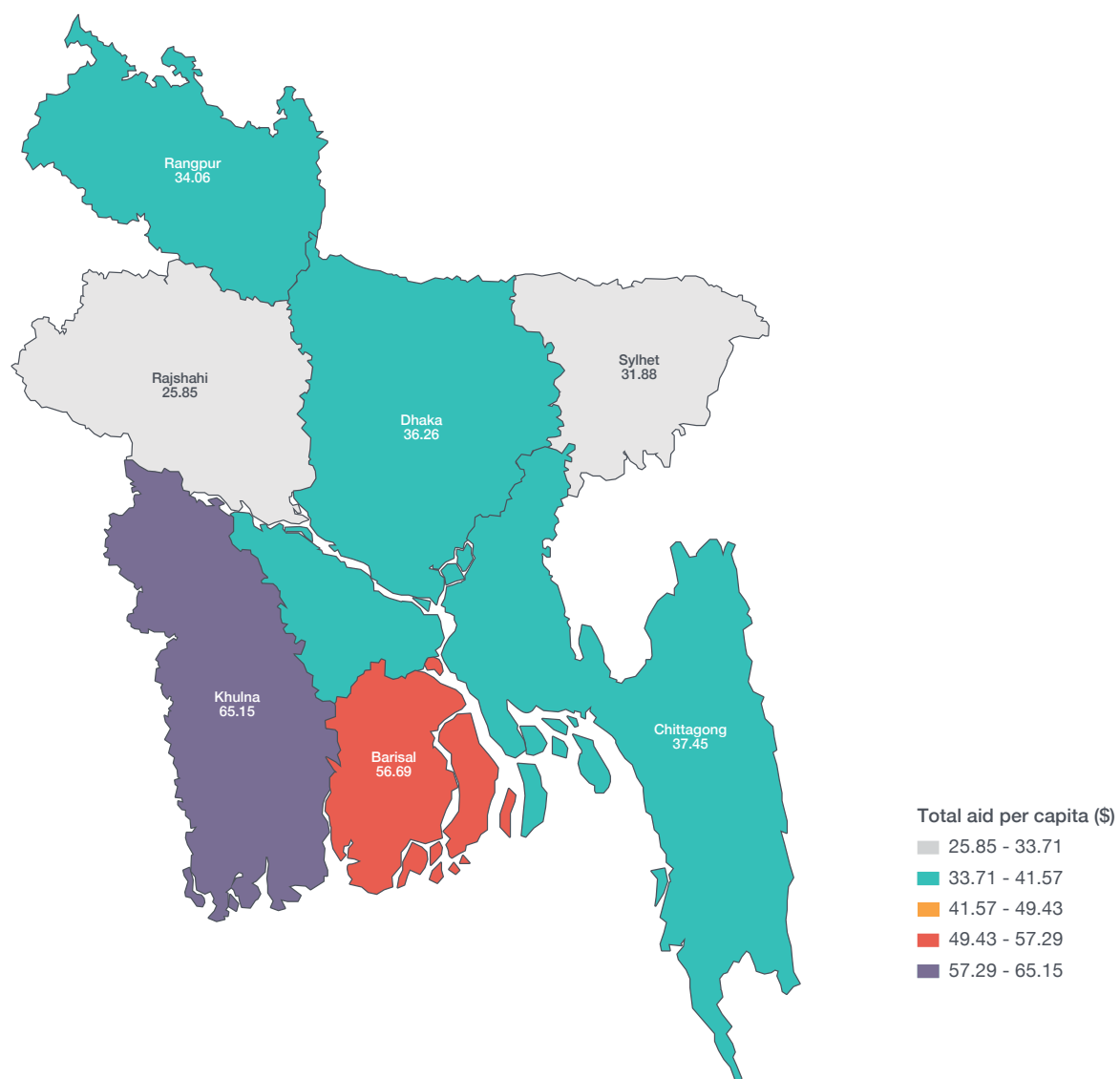
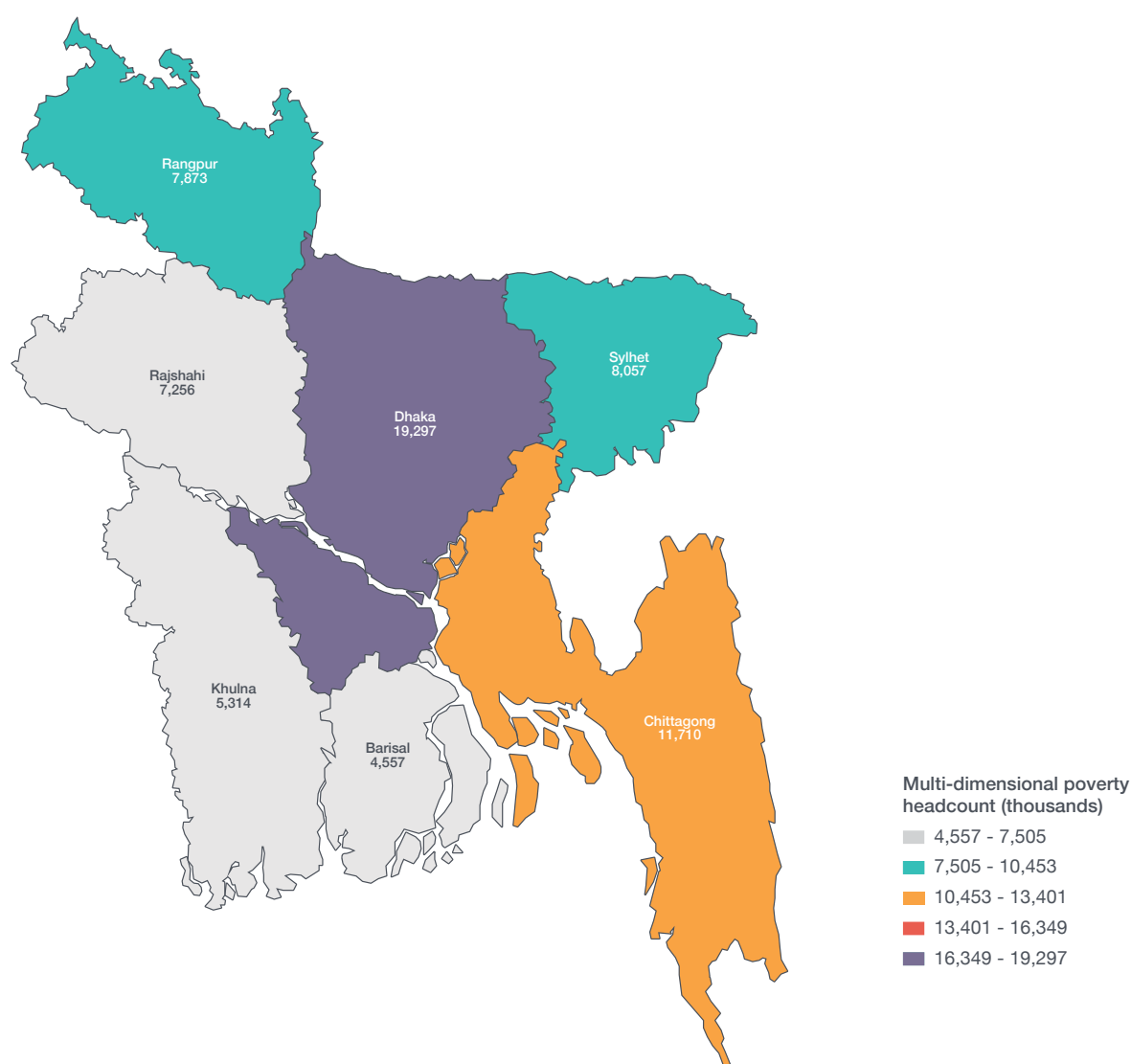


Figure 10. Multidimensional poverty in Bangladesh by region (2012)



Conclusion

The analysis presented is purely quantitative and involves no detailed field research. Further case study research might indicate whether there are good reasons for the distribution of aid across each country. We have had to use night-time lights as a proxy for poverty and economic activity, as other data are not sufficiently disaggregated, so it is possible that better data would show a more encouraging picture in Afghanistan and Bangladesh. In Honduras, only a proportion of aid is geocoded, meaning that we may not be seeing the full picture. Further research should also consider including a larger number of countries to check whether these patterns are replicated elsewhere.

Notwithstanding these caveats, two broad conclusions can be drawn from this analysis:

1. Donors need to be working with governments more effectively to ensure a better distribution of resources in line with need across these countries.

Aid is not as well correlated with need as it should be at sub-national levels. In only two out of the four countries examined did we find a negative, statistically significant correlation between aid and NTL. In the other two countries, we found a statistically significant correlation in the ‘wrong’ direction (i.e. a positive correlation).

2. There remain significant data gaps when considering the sub-national distribution of aid. Of the 21 countries scoped for this project, only 5 had sufficiently granular data on aid for us to attempt this exercise. This makes it difficult to understand whether these patterns are replicated elsewhere. Given the prominence of the ‘leave no-one behind’ agenda, donors and governments should work together to accelerate their efforts to make information about aid publicly available at a more granular level.

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