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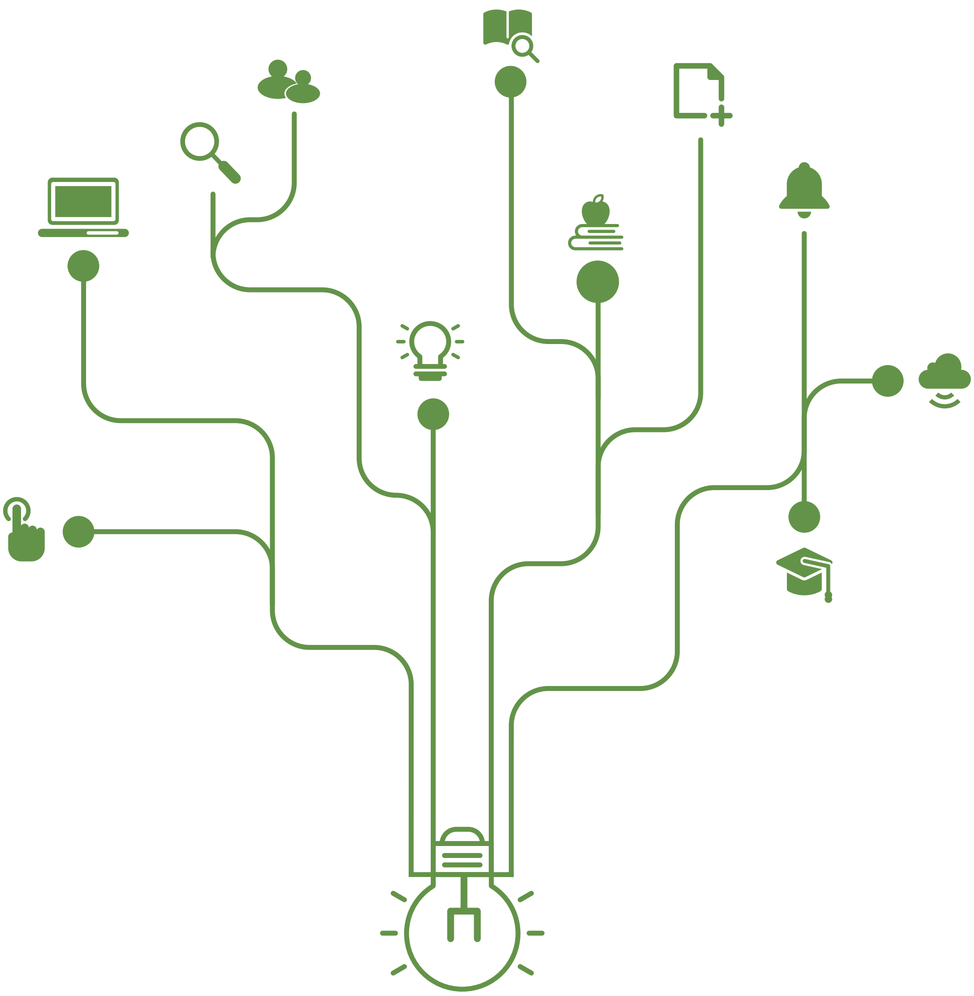
Huijoo Shon (Seoul National University)
HeeRae Lee (Seoul National University)
Booyuel Kim (Seoul National University)



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Spatial pattern of aid allocation at the regional level: Evidence from 38 sub-Saharan African countries

Authors
Huijoo Shon
Graduate student
Graduate School of Environmental Studies, Seoul National University
hjshon009@snu.ac.kr

HeeRae Lee
Graduate student
Graduate School of Environmental Studies, Seoul National University
hrlee9611@gmail.com

Booyuel Kim
Assistant Professor
Graduate School of Environmental Studies, Institute for Sustainable Development (ISD), Seoul National University
booyuel@snu.ac.kr

Summary

This study aims to analyze the geographical patterns of aid in the 21st century for 38 countries in sub-Sahara Africa and to identify the spatial exclusion of aid at the regional level. We calculated the spatial exclusion level (SEL) of aid by comparing the multidimensional poverty index (MPI) and aid spend, considering different sectors; health, education, and water & sanitation. Geocoded data from International Aid Transparency Initiative (IATI) was utilized and the number of projects is roughly 250,000. We found that the regions with higher MPI received less aid, leading to high spatial exclusion levels (SEL). Then, we identified that regions with similar SELs tend to cluster. Also, aid concentrated in regions that have urban properties or high accessibility. This spatial inequality of aid has intensified over time. The findings emphasize the need to target the appropriate sector of aid in consideration of spatial exclusion and regional geography.

Introduction

This paper analyzes the aid allocated to sub-Saharan Africa (SSA) in the 21st century based on the geography of poverty. We emphasize the importance of spatial inclusion of aid by identifying regions that are not receiving the sectoral aid needed relatively in comparison to less poor regions. The background behind criticizing aid inequality in SSA is that spatial patterns of sectoral aid allocation have not received enough empirical attention in previous literature.

Following the Millennium Declaration in 2000, the United Nations (UN) adopted the Millennium Development Goals (MDGs) and in 2015, the Sustainable Development Goals (SDGs). The international society has supported developing countries with aid for combating poverty over the past 20 years ((UN 2000, UN-DESA 2016)). The distribution of net ODA from 2000 to 2019 was $ 6,984 billion in the whole world (1,078 billion in Africa), while net ODA continues to increase in all parts of the world, including Africa ((OECD 2021)). In addition, as an attempt to reduce the socioeconomic inequality between countries, regions, and specific population groups, UN introduced the promise 'Leave no one behind (LNOB)' as a universal value of the 2030 agenda as well as SDG 10 'reduced inequalities' ((UN 2013, UNSDG 2019)). For inclusive growth, international organizations have focused on impoverished areas, communities, and poor people excluded from policies and services ((Collier, Dollar, and Bank 2002, OECD 2018, WB-CGD 2008)).

Aid from main multilateral donors in the 21st century aimed to reduce poverty in many parts of the world ((UN 2019, WB 2016, AfDB 2016)). However, many prior studies criticized the spatial inequality of aid and empirically found that aid allocations show a tendency of non-poor targeting. These studies have pointed out that aid allocation is related to socioeconomic or geographical characteristics of regions ((Dipendra 2020, Briggs 2017, 2018b, Öhler and Nunnenkamp 2014, Jablonski 2014, Desai and Greenhill 2017, Masaki 2018)). Despite these efforts for providing new knowledge on aid allocation at the regional level, spatial inclusion and regional geography related to aid have not received enough attention. Also, the analysis of these studies was limited to single-country, short periods, or only a few donors.

The question that we attempt to answer is "Was aid allocated to multidimensionally poor regions in the 21st century?". More specifically, "Which regions experience spatial exclusion of sectoral aid considering poverty levels? What are the specific physical or human geographical properties of these regions?" Thus, this research aims to analyze spatial patterns of Multidimensional Poverty Index (MPI) and aid allocation in 38 SSA countries and investigate the issue of aid exclusion at the regional level (sub-national level) by aid sector using geocoded data of aid. This paper emphasizes the importance of spatial inclusion of aid by identifying regions that experience aid concentration or exclusion and examining the geographical patterns of aid allocation at multiple scales. The concept of inclusive aid allocation we define in this study is that poor regions need to receive more aid and that the regional demands need to be acknowledged by aid sector.

To evaluate the spatial exclusion issue of aid allocation, the first stage of analysis provides the Spatial Exclusion Level (SEL) value by comparing MPI and aid spend adjusted by the poor population. This section will show whether regions have received much aid or were unable to benefit from it. Moreover, the variance of spatial exclusion level, Spatial Exclusion Level Disparity (SELD), is utilized for aid sector analysis. The following section introduces a multi-scale analysis of spatial and temporal patterns of aid allocation. At this stage, we examine which geographical characteristics of each region are related to its spatial aid patterns.

This study presents the following results. First, regions with higher poverty levels received less aid in most countries, and regions with similar SELs tended to cluster. Furthermore, the spatial exclusion intensity of aid allocation varied by aid sector. Significantly, the water & sanitation sector shows a large SEL disparity. Second, aid concentrated in urban areas and some rural areas with highly dense populations and good accessibility. This bias of aid allocation has become more intense than in the past. Moreover, aid tends to persist in the same place regardless of the poverty level, and that trend is more evident in the health sector. In conclusion, the spatial exclusion patterns of aid have been present for 20 years. There existed the different (or contrasting) geographical characteristics of spatially excluded regions and concentrated regions. Thus, we conclude that understanding the relationship between aid allocation and geographical characteristics is crucial for the spatial inclusion of aid at the regional level.

We contribute to previous literature that criticized the chronic non-poor targeting pattern of aid by presenting regional SEL and investigating the geographical properties of spatially excluded or concentrated regions. These findings suggest a need to enhance spatial inclusiveness and accuracy in targeting regional poverty. To our knowledge, this is the first research that tackles spatial pattern of aid covering 38 SSA countries and 20 years, utilizing approximately 250,000 projects from International Aid Transparency Initiative (IATI) at the regional unit (administrative area of the subnational 1st level). Thus, this study emphasizes the importance of transparent aid data construction through the contribution of various stakeholders for understanding aid patterns and developing new strategies of aid allocation.

Background

Geography of poverty and spatial inclusion of aid

The geography of poverty emphasizes the need for multidimensional poverty measuring and alleviating strategies, including accurate targeting at the regional or micro-scale ((Zhou and Liu 2019); (Bigman and Fofack 2000)). The reason for the regional level approach is because poverty shows a close relation to geographical characteristics (location, climate, landscape, economy, political system, and history) ((Bird, McKay, and Shinyekwa 2010, Arndt et al. 2016, Sachs 2005, Diamond 2013, Barbier 2010, Bird, Higgins, and Harris 2010)). Similarly, SDGs also deal with spatial inequality and geographical characteristics ((UN 2013, UNSDG 2019, UN 2019)). Moreover, the effects are geographically limited, although spillover effects of aid projects vary depending on aid sectors, recipients, regions, or aid spend ((Dipendra 2020, Briggs 2018b, Marty et al. 2017)). These facts suggest the importance of sectoral aid targeting that acknowledges the multidimensionality of poverty at the regional level. Therefore, we have designed our methods to evaluate spatial patterns of aid allocation using the ‘spatial inclusion’ concept.

The foremost goal of inclusive growth is the equality of opportunity and shared prosperity ((Ianchovichina and Lundstrom 2009, WB 2014, de Mello and Dutz 2012)). The need for inclusive growth is because when growth is not inclusive, this can be a barrier in accomplishing sustainability ((Ali and Son 2007, Jones 2013)). Although the issues of inclusion and exclusion have been discussed in various aspects, [1] as for the geographical dimension, spatial inclusion has become the keyword ((Dietz 2018, WB 2015)). Spatial inequality problems have increased as socially excluded people cluster in certain areas not covered by policies and public services ((WB 2015, UN-Habitat 2015, Cameron 2005, Bird, McKay, and Shinyekwa 2010)). Furthermore, spatial poverty cannot be easily tackled and tends to last for long periods due to the interaction between residential regions and local people ((Zhou and Liu 2019); (Liu and Xu 2016); (Cazzuffi et al. 2020)). Although spatial analysis is essential for inclusive growth, the geographical scale covered in prior studies focused on urban or periphery urban areas ((Wang 2008); (Espino 2015)).

We have expanded the geographical scale and go beyond the urban area discussion to address regional inequality and spatial exclusion of aid for the following two reasons. First,

1) Discussions regarding exclusion and inclusion revolve around the following aspects: social exclusion and participation ((Arnstein 1969, Berghman 1995, Silver 1994, Room 1995)); social relation((Gerometta, Haussermann, and Longo 2005)); economic inclusiveness and policies((Arezki et al. 2012, Collier, Dollar, and Bank 2002)); inclusive cities ((Schreiber and Carius 2016, Wang 2008)).

spatial inclusion covers the accessibility of policies and infrastructure and spatially concentrated poverty ((CPRC 2004); (WB 2015)). By expanding the analysis scale to rural areas in developing countries, we can discuss the insolation issue of rural areas and regional poor-targeting in context of spatial inclusion. Several precedent studies have pointed out the importance of aid or policy intervention support to deprived regions ((Dipendra 2020, Zhou and Liu 2019)).

Second, studies on exclusion have explained the social process that induces exclusion and relational issues within regions and population groups ((Cameron 2006); (Gerometta, Haussermann, and Longo 2005); (Room 1995)). This point of view helps us understand the dynamics of aid allocation because spatial inequality of aid (the phenomenon of when regions receive too much or little aid concerning their poverty rate) could be a relational issue between regions. Simultaneously, this inequality is a problem of the political-economic process that reinforces aid exclusion or concentration to specific regions.

Many preceding studies have discussed the factors that strengthen or sustain the geographical disparity of poverty utilizing the relationality concept ((Elwood, Lawson, and Sheppard 2016)). A study on Uganda suggested that the cause of persistent poverty in northern regions of Uganda was due to the political and economic marginalization in comparison to Southern regions ((Hickey 2009)). Therefore, to understand the inequality problem, it is essential to compare the geography of regions that have been rejected or received relatively enough attention through policy intervention. Also, it is needed to address the concentration of decision-making power and resources ((UN-CDP 2018)) rather than only focusing on those 'left behind'. Thus, there is a need to locate aid excluded or concentrated regions by comparing the poverty levels and aid spending and to analyze the physical and human geographical characteristics of both regions.

The scope of this study was set as sub-Saharan Africa (SSA), which needs the most attention regarding the spatial exclusion problem because poverty rates remain high, the inequality of income, education, health, and infrastructure continue to increase ((Sahn and Stifel 2003, Kanbur and Venables 2005, Adams 2018, Beatriz et al. 2018, Achten and Lessmann 2020, Kim 2008, De Magalhães and Santaeulàlia-Llopis 2018)). Therefore, tackling aid is essential for emphasizing inclusive growth to reduce inequality and achieve sustainable development in Africa ((Asongu 2016, Asongu and Odhiambo 2019)). Furthermore, regional and local aid targeting for the poor is especially important in SSA, because poor people experience spatial segregation and remoteness within countries ((Briggs 2018b)), and internal migration is less active than in other continents ((de Brauw, Mueller, and Lee 2014)).

Aid allocation and geography at regional level

Understanding the characteristics of spatial patterns of aid at the regional level is crucial for developing future aid allocation strategies to accomplish spatial inclusion of aid. However, due to the limited availability of data, not enough progress was made in regional-level research on aid allocation compared to national-level. With the introduction of geocoded aid data by AidData ((Strandow et al. 2011)) and D-portal of IATI Registry ((IATI 2021b, a)), more studies have been conducted on aid allocation at the regional level ((Dipendra 2020, Desai and Greenhill 2017, Briggs 2018b)).

First, prior research criticized non-poor targeting aid allocation in many countries around the world ((Öhler and Nunnenkamp 2014, Öhler et al. 2019)) and many African countries ((Anaxagorou, Efthyvoulou, and Sarantides 2020, Briggs 2018b, Dreher et al. 2021)). Similar findings were discovered in national-level studies conducted in India ((Nunnenkamp, Öhler, and Sosa Andrés 2017)), Malawi ((Marty et al. 2017, Nunnenkamp, Sotirova, and Thiele 2016)), Kenya ((Briggs 2014, Jablonski 2014)), Nigeria ((Kotsadam et al. 2018)), Nepal ((Dipendra 2020)), and China ((Zhang 2004)). Especially, many prior studies found that World Bank and AfDB allocated aid to regions with more population, wealth, and infrastructure compared to others ((Öhler and Nunnenkamp 2014, Öhler et al. 2019, Briggs 2018b)).

Recently, more empirical studies addressed the regional characteristics that influence aid allocation in the political-economic perspective. Regional characteristics such as local conflicts in Africa ((Öhler and Nunnenkamp 2014)) and electoral incentives in Kenya ((Jablonski 2014)) were identified as factors that affected the aid allocation of multilateral donors. Studies also investigated the effects of political factors such as electoral motives (political support) ((Anaxagorou, Efthyvoulou, and Sarantides 2020)), birth regions of political leaders ((Dreher et al. 2019, 2021)) on Chinese aid allocation.

On the other hand, some studies suggest that the relationship between regional characteristics and aid may differ depending on the donor. For instance, World Bank aid is influenced by regional conflicts, unlike AfDB aid projects ((Öhler and Nunnenkamp 2014)). Moreover, Chinese aid allocation is manipulated considering political leaders while World Bank aid is not ((Dreher et al. 2019)). Furthermore, a case study of Nepal found that allocation patterns differed by implementing organization types ((Dipendra 2020)). However, considering the strong evidence of bias of aid (ethnic composition, population, economic level, infrastructure level, health level etc.) that was consistent in most studies, regional characteristics are still important in understanding aid patterns.

The number of regional-level studies has recently increased, whereas country-level studies on aid allocation have developed for a long time. Many studies at the country level pointed out that aid was influenced by humanitarian purposes as well as the political and economic interests of donors ((Alesina and Dollar 2000, Deaton 2015, Nunnenkamp and Thiele 2006, Collier and Dollar 2002, Berthélemy 2006)). Many researchers have also structuralized various factors that influence aid into aid models ((McGillivray 2003, McKinley and Little 1979)) or aid markets ((Sumner and Mallett 2013, Barder 2009)). Thus, now there is a need to understand the aid allocation mechanism at the regional level by accumulating knowledge through various means.

Precedent regional studies have shed light on the discussion of poverty targeting at the subnational level and have especially tackled the issue of non-poverty aid targeting. However, there are three main limitations to these studies. First, past literature was not able to analyze the unequal spatial and temporal patterns of aid by incorporating and visualizing large data samples that cover long periods. Secondly, previous studies were not able to connect aid sectors and poverty dimensions to develop accurate aid strategies important for spatial inclusion of aid. The majority of research does not classify aid sectors and has not discussed where to allocate what type of aid. Lastly, these studies were not able to entirely cover the substantial amount of aid projects conducted after the introduction of MDGs. This indicates the difficulty in obtaining aid data. Most studies have utilized geocoded data of AidData[2] ((Briggs 2018a, b, Anaxagorou, Efthyvoulou, and Sarantides 2020, Dreher et al. 2021, Öhler and Nunnenkamp 2014, Nunnenkamp, Öhler, and Sosa Andrés 2017, Custer et al. 2017, Iacoella et al. 2021)). Several studies conducted their analysis on different aid data such as national statistics ((Dipendra 2020)), Aid Information Management System data (AIMS) ((Briggs 2018a)), and the IATI dataset ((Desai and Greenhill 2017)).

Contributions to literature

This study contributes to the existing literature in these three aspects. First, we incorporated the spatial inclusion theory to calculate Spatial Exclusion Level (SEL) to better understand poor-targeting issues. We provide SEL by comparing aid and poverty levels of each region relative to other regions within the country. Furthermore, we address the aid exclusion issue in the context of poverty geography by mapping the regional SEL to capture the regional differences or similarities (clustering). Then we examine geographical characteristics of regions that experience the concentration or exclusion of aid. In this way, we analyzed the relationship between SEL and geography beyond the relationship between aid and poverty.

Second, this study has specified a poor targeting method that compares poverty dimensions and aid sectors at the regional level. For this, we have reviewed literature related to poverty measurements ((Santos and Villatoro 2018, Alkire and Foster 2011, Alkire et al.

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2) AidData is a widely used platform that provides stable aid data constructed by the College of William and Mary, Development Gateway, Brigham Young University, and University of Texas Austin.

2015, Bárcena-Martín, Pérez-Moreno, and Rodríguez-Díaz 2020, Robles Aguilar and Sumner 2020)) and utilized the MPI for investigating the poverty rate and the number of the poor by each dimension at the regional level. Considering that the SDGs and inclusive growth emphasize encompassing different dimensions of poverty beyond the distribution of income or assets ((de Mello and Dutz 2012)), discussing sectoral aid and regional poor targeting is essential. Thus, we examined the heterogeneity of spatial patterns by aid sector in all stages of our study.

Lastly, this study has expanded the time and space scope by utilizing aid data over 20 years in 38 SSA countries for analysis, using geocoded data provided by D-portal from IATI. As a result, by analyzing the spatio-temporal patterns of aid allocation using time units of 5 and 10-years, we discovered the problem of intensifying spatial inequality of aid over time. Also, we present geographical interpretations on aid patterns at multiple levels (subnational region, county, macro-region, continent).

Aid dataset from D-portal constructed by IATI covers a large number of aid projects reported by various organizations. However, this platform is open for donors and recipients to report aid projects, lowering the stability of the data. Thus, we have conducted strict data cleaning, and to confirm the validity of this data, we compared it to ODA statistics provided by OECD. As a result, this study was conducted on a large aid sample (250,000 projects) of 38 countries over 20 years.

Data and Methods

Data and Scope

This study utilized aid and poverty data constructed at multiple geographical scales to conduct a multi-scale analysis by combining aid allocation and regional characteristics. Regional-level (sub-national level) is the main spatial unit for calculating SEL (Spatial Exclusion Level) of aid using poverty level and aid spending.

The aid data used in the study include location coordinates provided by D-portal from IATI ((IATI 2021b, a)).[3] All aid projects that began from 2001 were analyzed. The dataset included many variables, but data cleaning was conducted for key variables such as the project period, spending, location coordinates, aid sector, and project status to enhance the

3) We have compared the geocoded data of two organizations (AidData and IATI). However, considering that our study discusses the patterns of aid since the beginning of MDGs, we have used the IATI dataset which could cover the 20-year period. Furthermore, to enhance the credibility of the data set, we have cleaned problematic observations (repetitive data, location error, project period errors).

data quality. For the same projects at different locations, spending was equally divided by the number of locations. This data preparation process followed the methods of prior studies ((Briggs 2017, 2018b, Nunnenkamp and Thiele 2006)). Thus, aid programs with the same title were counted as different projects if location coordinates were different.

We used the Multidimensional Poverty Index (MPI) provided by OPHI (Oxford Poverty & Human Development Initiative) for poverty measurements of regions. [4)] MPI is calculated in three dimensions: health, education, and quality of life ((Alkire and Foster 2011, Alkire et al. 2011)). The health dimension consists of two indicators (nutrition and child mortality), education consists of two indicators (academic level and enrollment), and quality of life consists of six indicators (cooking fuel, sanitation, drinking water, electricity, housing, and assets). Most countries that provide national MPIs also provide regional MPIs (subnational MPIs). We use the administrative zone used by OPHI as the spatial unit for SEL calculation and regional analysis.

For SEL calculation, MPI dimensions and aid sectors were matched. This process made it possible to analyze aid in three sectors: health, education, and water & sanitation. We selected three sectors from matching the ten indicators of MPI and the 44 sectors of aid provided.[5)]

As for polygon data of the regional level, we used shapefiles provided by the DHS program's Spatial Data Repository ((USAID 2021)). However, for countries that did not provide DHS shapefiles or had different regional divisions compared to regional MPI divisions of OHPI, the Global Administrative Areas (v.3.6) data provided by the Database of Global Administrative Areas (GADM) was used ((GADM 2018)).[6)]

GHS (Global Human Settlement) Functional Urban Area of 2015 provided by Joint Research Centre (JRC) of European Commission ((Schiavina et al. 2019a)) was used as urban area (polygon) data. Functional Urban Area (FUA) are the areas where at least 15% of the population commute to the main urban center ((Schiavina et al. 2019b)). The resolution (projection) of this spatial data is 1km and World Mollweide was used as the coordinate system.

The spatial scope for analysis was selected considering the possibility of obtaining data

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4) MPI calculations utilize USAID's Demographic and Health Surveys (DHS) and UNICEF's Multiple Indicator Cluster Survey (MICS). MPI is presented more than once every year since 2013 and measured by using the most recent DHS or MICS survey.

5) The health dimension of MPI corresponds with four categories (General Health, Basic Health, Non-communicable diseases (NCDs), Population Policies/Programmes & Reproductive Health) of the aid data, while the education dimension of MPI is linked with the four groups (Education, Level Unspecified, Basic Education, Secondary Education) of aid data. The quality-of-life dimension of MPI does not fully correspond to aid data. Thus, two indicators of MPI's quality of life (Drinking water and sanitation) were linked to aid data's water and sanitation category.

6) Three countries that do not provide DHS data (Central African Republic, Guinea-Bissau, Sudan) and Mauritania had different administrative units from MPI’s regional divisions defined by OPHI. Furthermore, country borders of two data sources (DHS and GADM shapefiles) overlap in some cases. Considering the aid projects allocated in this overlapping area, we reformed polygon shapes according to actual country borders.

and the SSA country list provided by the OPHI and Africa Union (AU).[7] SSA countries mentioned throughout the paper are 38 countries that were selected. The dataset of these countries was cleaned and a total of 251,963 aid projects with a spend of $ 282,938 million were analyzed.[8]

Statistical methods

To analyze the spatial exclusion problem of aid at the regional level, we calculate the spatial exclusion level of region j, country i (SEL_{ij}). A region's SEL_{ij} is obtained by subtracting the standardized value of the poor population-adjusted aid from the standardized value of the regional MPI value. The equation for SEL and standardized values by each country is the following.

$$SEL_{ij} = stdzn(MPI_{ij}) - stdzn(poor\ population\ adj.\ AID_{ij})$$

Where $Z_{score_{ij}} \equiv (x_{ij} - \mu_i)/\sigma_i$.[9]

The equation above was based on the spatial inclusion concept that more poor regions should receive more poor population-adjusted aid spend. Since the poverty rate and aid spend have been standardized and compared to those of other regions in the country, it is possible to identify whether a region has received more aid or not enough considering its poverty status. If aid has successfully targeted poverty, the variance of SEL should diverges closer to 0. If $stdzn(MPI_{ij})$ is high and $stdzn(poor\ population\ adj.\ AID_{ij})$ is low, the SEL value will be high. Regions with a positive SEL value are spatially excluded regions while regions with negative SEL values are spatially concentrated regions.

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7) The spatial scope for analysis was selected considering the possibility of obtaining data and the SSA country list provided by the OPHI and Africa Union (AU). OPHI provides national MPIs for 42 countries categorized as SSA according to UN standards. Still, regional MPI for three countries (Seychelles, South Africa, and South Sudan) were not available and were excluded from the study. Two countries (Botswana and Togo) where DHS and GADM do not provide the same administrative district data as the administrative division of OPHI's regional MPI were also excluded from the study. We have included Sudan, so that this study includes all the countries that are classified as SSA country in AU or UN standards and where all data can be obtained. 'The SSA countries' mentioned throughout the paper are these 38 countries selected for the analysis.

8) To confirm the credibility of IATI aid spending data, we have compared it to ODA spend information provided by OECD. The distribution of net ODA of OECD countries to about 50 countries in Africa between the years 2000 and 2019 was $1,094,246 million. 38 countries from about 50 African countries were analyzed in this study and approximately 29.7% of aid projects provided by IATI include location coordinates. Consequently, authors determined that the IATI data could be used for analysis, because 33% of OECD ODA spending is $364,748 million (33% of 38 countries is $218,849 million) and total aid spend in our study was $282,938 million. Moreover, the percentage of aid projects that include location coordinates vary by country (mean 36.6%, standard deviation 13.35%), but considering that the correlation between the number of aid projects before and after data cleaning is high (spearman test results: rho=0.89, p-value<0.001), a country comparison was deemed possible.

9) As a normalization method, there is the Min-Max Normalization (Min-Max scaling) that matches the scale between 0-1. However, it has the disadvantage that outliers can heavily influence the values. Regional MPI and poor population-adjusted aid size, used for SEL calculations, are influenced by the region's socioeconomic characteristics (area, population, and aid size). There exist regions that show extreme differences in socioeconomic characteristics. Therefore, in this study setting, the standardization method that normalizes observations to have an average of 0, deviation 1, makes it possible to measure how far values have deviated from the mean.

The MPI of region j, country i (MPI_{ij}) is the mean value of regional MPI of 20 years (2001 ~2020).[10] Although MPI surveys of each country were conducted at different periods, we have attempted to maximize the availability of data and conduct country comparisons (Table 1. in Appendix).[11]

As for $poor\ population\ adj.\ AID_{ij}$, AID_{ij} was divided by and the time span is identical to MPI data (2001 ~ 2020). $poor\ population_{ij}$ is the regional average of the number of the poor data provided with the MPI data of OPHI. We used the poor population of regions instead of the entire population to calculate aid spend per capita, essential for accurate poor targeting.

The reason SEL_{ij} value was calculated in a country is because the total amount of aid received by country shows big differences due to historical, political, and geographical issues. Thus, after each of the values was standardized within a country, it was possible to compare SEL between 490 regions of 38 countries. Suppose the SEL value for region 'a' in Country A and region 'b' in Country B are high and similar. In this case, these two regions have similarly experienced exclusion from aid within their own country.

Further on, this study has attempted to analyze the geographical patterns of all aid and three aid sectors. To obtain the SEL of sector *k* (SEL_{ijk}), we first calculate the MPI of aid sector *k* using 6 indicators from the10 indicators surveyed in MPI. k represents the aid sectors health, education, and water & sanitation. Therefore, *MPI* and *pop_adj.AID* were calculated by region and sector.

$$SEL_{ijk} = stdzn(MPI_{ijk}) - stdzn(poor\ \ population\ \ adj.\ \ AID_{ijk})$$

To obtain MPI_{ijk} there is a need to understand how the MPI value is derived. can be decomposed into the weight of indicator l (w_l) multiplied by the censored headcount ratio (CH_l). *CH* represents the proportion of people who are multidimensionally poor and deprived in each of the indicators. (Further specifications of MPI calculation are explained in (Alkire et al. 2011, Alkire et al. 2015, Alkire and Santos 2014))

$$MPI = w_1 CH_1 + w_2 CH_2 + \ldots + w_{10} CH_{10}$$

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10) The MPI values of each country are available for the year the country provided the survey data (DHS or MICS). However, some countries have conducted the survey multiple times ((Alkire, Roche, and Vaz 2017)). To maximize the use of data, we have calculated the mean values of MPI for each country if the number and name of regions was identical.

11) We have observed the change of regional MPI for countries that provided more than two survey results for validity testing. The regional ranking or poverty level for yearly MPI did not show much change. Thus, validity for using the average of the MPI over 20 years was confirmed.

From the equation above the contribution of sector k for MPI is the sum of multiplying CH_l and w_l of two indicators l, which then is MPI_k (poverty index of sector k). To obtain MPI_k, w_l needed for MPI calculation was utilized.[12)]

$$MPI_{health} = \frac{1}{6} * CH_{Xld\ Mortality} + \frac{1}{6} * CH_{Ntrition}$$

$$MPI_{education} = \frac{1}{6} * CH_{Years\ of\ Schooling} + \frac{1}{6} * CH_{Xld\ School\ ※endance}$$

$$MPI_{water\ \&\ sanitation} = \frac{1}{18} * CH_{Improved\ Sanitation} + \frac{1}{18} * CH_{Safe\ Drinking\ Water}$$

Like the calculation of $poor\ population\ adj.\ AID_{ij}$, the poor population by indicator was used to obtain $poor\ population\ adj.\ AID_{ijk}$. However, sector consists of 2 indicators with different numbers of poor people. Thus, the average number of the poor was used. $Nmber\ of\ poor\ by\ sector$ was calculated with the equation below.

num.of poor in the health sector= (num. of poor on Child Mortality + num. of poor on Nutrition)/2

num.of poor in the education sector= (num. of poor on Years of Schooling + num. of poor on Child School Attendance)/2

num.of poor in the water & sanitation sector= (num. of poor on Improved Sanitation + num. of Drinking Water)/2

Furthermore, the Spatial Exclusion Level Disparity (SELD) by country and sector is the SEL variance value. By analyzing the variance of SELs, it is possible to investigate which country or aid sector is experiencing severe inequality of SEL.[13)]

$$SELD_i = \frac{\sum_{j=1}^{N_i} \left(SEL_{ij} - \overline{SEL_i}\right)^2}{N_i}$$

12) It is possible to compute the contribution of sector on regional MPI by incorporating the method (contribution of indicator on national MPI) ((Alkire et al. 2011)). However, comparison between regions is not possible with this rate value. Using , an absolute value made it possible to compare the poverty levels between regions by aid sector.

13) MPI and aid spend were standardized and subtracted to obtain SEL. Then, the country's average SEL becomes 0. Thus, the appropriate method for comparing SEL is variance because it helps identify the level of spatial inequality.

Results

Descriptive statistics

This paper analyzed 251,963 aid projects that sent $283 billion to 38 SSA countries in the 21st century. By aid sector, $36 billion was spent on health, $26 billion on education, and $20 billion on water & sanitation. Once total aid spend is divided by the yearly mean value of the population for 20 years (926 million), the amount of aid received by one person for 20 years is approximately $283 for total aid, $38 on health, $27 on education, and $22 for water & sanitation.

If the amount of aid is divided by the number of poor people rather than the total population, aid spend provided to a poor person for the past 20 years was $513 for total aid, $166 health aid, $97 education aid, and $49 on water & sanitation. However, according to earlier studies, we cannot be certain that the poor were the only people who receive aid ((Marty et al. 2017, Dipendra 2020, Briggs 2018b, Anaxagorou, Efthyvoulou, and Sarantides 2020, Öhler et al. 2019)). Thus, the aid divided by the total population can better predict of the reality (amount of aid per capita over 20 years).

We used aid spending, MPI, and the number of poor population data of 490 regions in SSA to obtain SEL values. The average aid spends at the regional level in the 21st century was $577 million for total aid, $73 million for health aid, $51 million for education, and $41 million for water & sanitation aid.

The average MPI is 0.34, and the variance is 0.03. The poverty level by country does not show a big change over time. The average poor population is approximately 1,125,000 and Std. Dev. is 2,328,000 (The average of total population, and Std. Dev. are 1,891,000 and 3,004,000). Surveys for MPI and poor population have been conducted different times for each country, one time at the least and four times at the most (<Appendix> Table 2). We utilized the number of poor populations in place of the total regional population when calculating SEL to critically examine whether aid in SSA targeted the poor (considering that there can be more poor people in rural areas).

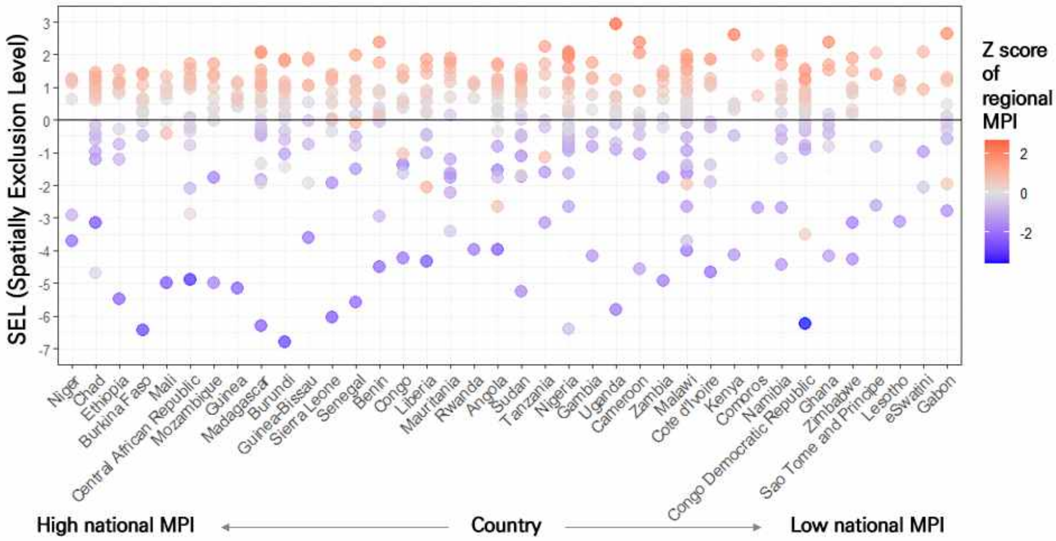

Figure 1. SEL and MPI of 490 regions in SSA

Notes. In the X-axis, countries with a higher MPI are listed from the left and countries with lower poverty levels to the right. The Y-axis shows the SEL (Spatial Exclusion Level) for total aid and includes all 490 regions (-7 ~ 3). The point colors represent the standardized values of regional MPI () calculated by country (high : red, low : blue, close to 0: grey). Thus, if the point color is darker (closer to dark blue or red), this depicts that the region's poverty level diverges further away from the average.

The points that have positive SEL values are the spatially excluded regions. In contrast, the points that have negative SEL values are the spatially concentrated regions. The reason why the y-axis of the graph is longer in the negative direction from zero is because the level of aid concentration in the relatively less poor area (with low) is higher than level of aid exclusion in the relatively poor areas (with high).

Spatial exclusion of aid

Spatial exclusion level (SEL)

By analyzing the SEL value of 490 regions, we found that relatively poor regions within a country experienced spatial exclusion of aid. This pattern was consistently observed in each country and by aid sector. In <Figure 1> regions with high standardized MPI scores (red points) rank higher in SELs, indicating that relatively poor regions within a country receive less aid leading to spatial exclusion of aid. In contrast, regions that rank low in standardized MPI scores have lower SELs, which means less poor regions tend to receive more poor population-adjusted aid. Through this figure, we can observe that poverty rates and aid spend do not correspond, which then results in spatial exclusion of aid.

More specifically, the regions that show low SEL (regions close to blue by country) are mostly the country's capital cities or metropolitan areas. MPI is very low in these regions, but aid tends to concentrate. Exceptionally, there are poor regions with high MPI that have received more aid relative to other poor regions. These regions are red points below zero

SEL depicted in <Figure 1>.

SEL heterogeneity by aid sector can be observed in (Figure 6 in <Appendix>). The number of spatially excluded regions is 306 regions for total aid, 300 regions for the health sector, 285 regions for education, and 313 regions for the water & sanitation sector. Through these figures, it is possible to conclude that spatial exclusion is more severe in the water & sanitation sector. More specifically, 21,22 and 13 regions in the order of health, education, and water & sanitation have a SEL value higher than 2. Although the number of spatially excluded regions is the lowest in the education sector, there are regions with extremely high SEL values. This result emphasizes the need for special attention towards regions that are experiencing serious level of exclusion in the education sector. However, the heterogeneity of each aid sector is high, and this shown by the results that the SEL of 140 regions from 490 regions changes signs (-, +) by aid sector. Thus, poverty targeting by aid sector according to poverty dimensions is of great importance.

SEL Disparity (SELD)

Spatial Exclusion Level Disparity (SELD) is the variance of regional SEL that can explain the national level's spatial inequality issue. When there are more regions with big differences between standardized MPI and aid (regions with high absolute SEL values), the intensity of spatial inequality (the SELD value) is higher. The SELD average of total aid by country is 3.13 with a standard deviation of 0.49. These results show that there exists a difference in the level of SELD by country and aid sector. SELD values were exceptionally high in Rwanda (3.97), Comoros (3.89), Guinea (3.86), and low in Gabon (2.23), Chad (2.27), Liberia (2.32). Country SELD average in order by sector was health (2.90), education (2.73), and water & sanitation (3.26). Such results show that national SELD is higher in water & sanitation than in other sectors.

Countries with high SELD in total aid (e.g. Rwanda, Comoros, and Guinea) also showed high SELD in each aid sectors as well. However, this correlation is not consistent in all countries. For instance, SELD of total aid and water & sanitation sector in Sao Tome Principe and Lesotho was greater than 3 while lower than 1 in the health and education sector. These results are observed because of the disparity between sectoral SEL, highlighting the need for poverty targeting by sector.

We have calculated the SELD of all 490 regions without country control for a robustness check of SELD results. SELD was 3.00 for total aid, 2.84 for the health sector, 2.71 for the education sector, and 3.14 for the water & sanitation sector. The ranking values were consistent with the sector SELD average including the country control. Figure 6 in

<Appendix> shows that education SELD is lower compared to other sectors. These results imply that special attention is needed in the order of water & sanitation, health, and education when analyzing the spatial inequality and exclusion issue at the national scale.

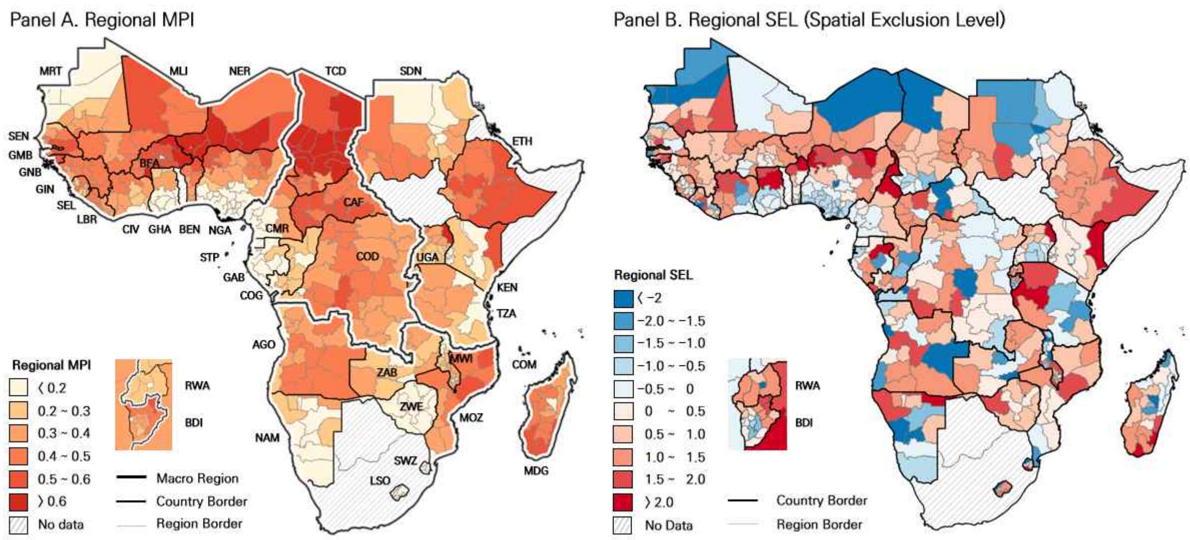

Figure 2. Regional MPI and SEL (Spatial Exclusion Level)

Notes. Panel A depicts the regional Multidimensional Poverty Index (MPI) at the continent scale because the regional MPI is not standardized. It shows the mean value of regional MPI of 20 years (2001 ~2020) which was used for calculating regional SEL in the paper.
Panel B presents the regional Spatial Exclusion Level (SEL) calculated with standardized regional MPI and poor population-adjusted aid spend at the national scale. The more a region's color is closer to red, the more the region has experienced exclusion from receiving aid. Macro regions were classified according to AU standards, except Mauritania (categorized as West Africa in UN standards & North Africa in AU standards).

Spatial patterns of SEL

<Figure 2> shows the relation between geographical characteristics (poverty level and accessibility) and the spatial distribution of regions that experienced aid concentration or exclusion. The pattern of aid concentrating to urban areas and aid exclusion in rural areas is consistent in most countries (Panel B, <Figure 2>). Above all, regions with similar SELs (spatially excluded or concentrated region) tended to cluster at multiple scales(country and macro region).

This generalization is significant when comparing MPI and SEL spatial distribution at the macro region or country scale. In the Western area, SEL values are low in regions near the Atlantic coastal area. On the other hand, the values are high in inland border areas close to landlocked countries (Mali, Burkina Faso, and Niger). This pattern is related to the geographical characteristic that poverty rates tend to rise in regions further away from coastal areas. Furthermore, in Eastern Africa, regions that suffer from chronic poverty and low accessibility (Eastern deserts of Ethiopia and Kenya, Northern Uganda, Southern Tanzania, Northern Burundi, and Eastern Rwanda) experienced aid exclusion. This pattern was consistent in Madagascar where most regions received insufficient aid, except the central area and northern coastal areas that are relatively less poor. In the Southern region, many spatially excluded regions were in Northern Mozambique, Eastern Zambia, and rural areas of Malawi, where poverty rates are high and population density is low. Lastly, areas that showed high MPI in Central region (border area of DR Congo and Angola) were spatially excluded regions.

Despite the difference in the number of regions, land area of regions (Administrative districts) and landform between countries, spatial patterns of SEL were consistent at the continental scale. Especially, socioeconomic characteristics of regions with high population density (high level of urbanization and infrastructure) is related to aid concentration in these areas. On the other hand, alienated areas with low population density were excluded from receiving aid. This result suggests that there is a correlation between the distance to highly populated areas and aid allocation. Furthermore, some regions share similar geographic characteristics (dense population or alienation) with regions in other neighboring countries. Thus, aid concentration and exclusion problems are transboundary.

Exceptionally, some regions are far from densely populated areas or have high poverty levels which result in low SEL values. There is a need for further studies that understand the economic, political, historical, and cultural characteristics that have formed such patterns.

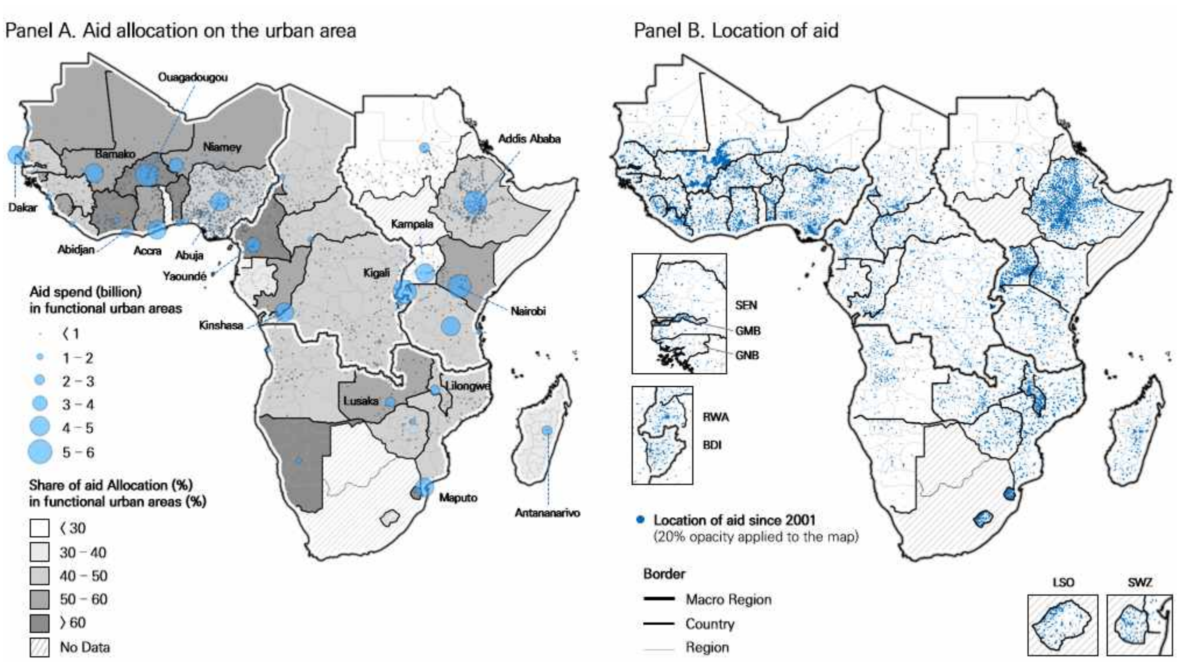

Figure 3. Distribution of aid allocation at micro level

Notes. Panel A depicts the share of aid allocated to functional urban areas (FUA) where 15% of the population commutes to the main urban center. The circles depict aid spend within the FUA at the microscopic level (1km resolution) and the smallest circles are the FUA that received aid less than $1 billion. The choropleth map at the national level shows the share of aid spend to the FUAs of each country. The number of legends was adjusted according to the number of observations by category. Panel B depicts the location of all aid projects that were analyzed in this study. Countries that have small land area (GMB, GNB, RWA, BDI, LSO, and SWZ) are enlarged in the map. The opacity of the point color is 20%, making the color of places that have received much aid darker.

Spatial patterns of aid

As a result of an exploratory analysis on spatial patterns of 251,963 projects at different spatial units, aid tends to concentrate in regions with specific geographical characteristics such as the level of urbanization, accessibility, and whether the region received aid in the past. Such results could be related to the differences in geographical characteristics between regions which have low or high SEL values.

Aid concentration at micro level

First, 32.97% of total aid projects and 47.81% of total aid spend was allocated to areas defined as functional urban areas ((Schiavina et al. 2019b)) based on 2015 standards. A significant amount of aid was allocated to the urban areas, considering that the land area of functional urban areas (in which at least 15% of the population commutes to the main urban center) takes up only 0.39% of all 38 countries' land area. The urban areas that have received large amounts of aid among the 1409 cities analyzed in this study are the capital cities or megacities of each country. Panel A in <Figure 3> depicts the disparity of aid spend between these major cities and other cities. Major urban areas like Addis Ababa, Ouagadougou, Nairobi, Kigali received more than $ 5,000 million, and the following 30 major cities received $ 1000 million. 34 major cities have received $ 105,623 million of aid. These major cities take up 0.25% area of the 38 countries, and the amount of aid spent on these cities is 37.33% ($ 282,938 million).

Furthermore, the level of concentration in urban areas showed a difference by aid sector and country. Aid spend was high in the order of the health sector (57.27%), water & sanitation (52.47%), and education (36.00%). Health and water & sanitation aid went to highly populated urban areas. Aid distribution was also different by country. Based on total aid spend, Burkina Faso (74.02%) ranked highest, Rwanda (73.01%), Eswatini (71.51%), Namibia (63.74%), Cameroon (63.74%) followed. In 18 countries, 50% of aid spend was allocated to urban areas (<Figure 3> Panel A). When taking the aid sector and country into consideration at same time, urban areas in Burkina Faso, Sierra Leon, Ethiopia received much health aid. Education aid allocated to urban areas of Rwanda, Cameroon, and Sierra Leon. As for the water & sanitation sector, Eswatini, Namibia, and Cote d'Ivoire allocated much aid to their cities.

Second, among the rural regions that cover most of the land area in SSA, areas that are relatively dense in population and are easily accessible tend to receive more aid (<Figure 3> Panel B). Highlands in Ethiopia, the rift valley area, and the main corridor near Lake Victoria connecting Kenya-Uganda-Rwanda-Burundi receive more aid in the Eastern region. In the Western region, aid has concentrated in coastal areas from Nigeria to Senegal, the borders between Northern Nigeria - Niger, and Burkina Faso - Mali. Including the Central and Southern regions, aid concentrated in rural areas with relatively more residents and have better access to main roads.

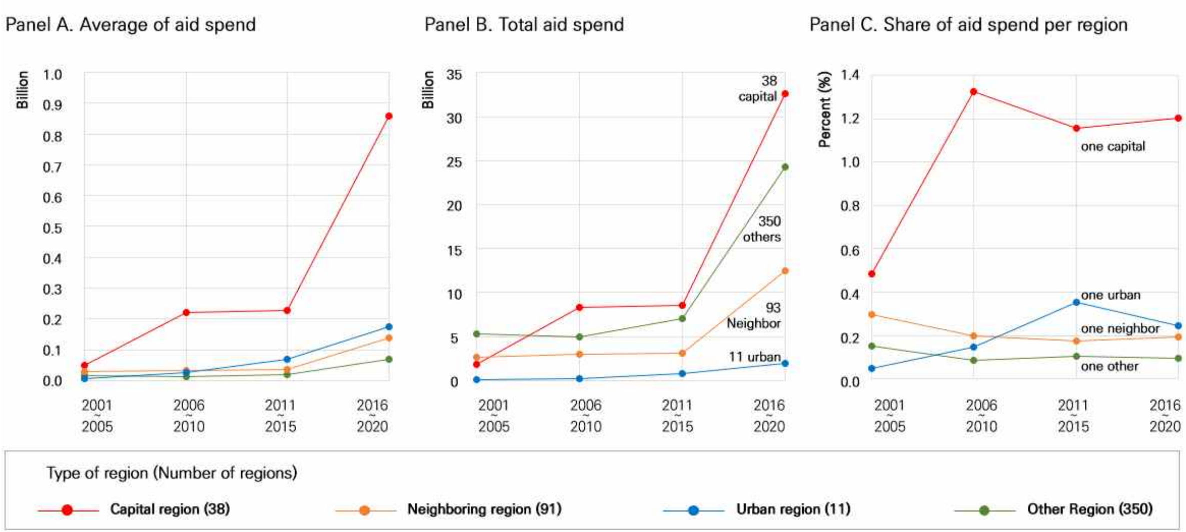

Figure 4. Change of regional aid spend by region type (5-year unit)

Notes. The graph above depicts aid spend average (Panel A), total (Panel B), and the aid share of a region by type (Panel C) calculated in 5-year units. The types of regions were classified as Capital region (regions that include the capital), Neighboring region (regions that neighbor the capital), Urban regions (regions that include other major cities), and Other (mostly rural regions).

Panel A shows the average of aid spend after the 490 regions were classified into the four types of regions. Panel B shows the total aid spend by region type. Panel C shows the share of aid spend per region by type which was calculated with the following equation: .

Therefore, is 100%.

We only included the projects that their starting dates and expiring dates were in the range of each 5-year period. This was done because it is difficult to obtain the exact aid spend of each project per year. For instance, the projects classified into the 2001~2005 period have begun and ended in that period. Thus, projects that were conducted between 2004~2006 were excluded for this part of our analysis. As a result, the number of aid projects included in this part of analysis was 139,209 projects (55.2% of total), and the total aid spend of these projects was $117billion (41.5% of total).

Temporal patterns of aid

The spatio-temporal patterns of aid show that over time aid tends to concentrate in capital regions, regions that neighbor capital cities, and urban regions. For this part of analysis, aid since 2001 was divided into 5-year units and 490 regions were classified into the four region types. The results showed that aid concentration in 'capital regions' were most intense among the four types. In all region types the regional average of aid spend showed an increase, but the value of 'capital regions' sharply increased during the period of 2016~2020 (<Figure 4> Panel A). Panel B in <Figure 4> shows that the overall aid spend in 'other regions' (mostly rural regions) increased, but Panel C shows that the aid spend share of one 'other region' declined. Especially, when we look at the share of aid spend per region, the share of one 'capital region' was around 1% for the past 15 years, while the share of one 'other region' was about 0.1%. These spatio-temporal patterns not only support the previous results of spatial pattern analysis (aid concentrating tendency to rural areas that have high accessibility and to urban areas), but also imply that the spatial inequality problem of aid allocation has intensified over time.

For a more detailed analysis of the temporal patterns and aid sectors, we increased the number of analysis samples by categorizing aid projects into a 10-year unit (84.6% of total aid projects and 71.5% of aid spend). The results showed that aid tends to allocate in regions that have already received aid, especially in the health sector. The Pearson correlation coefficients were 0.55 for total aid, 0.61 for the health sector, 0.35 for education, and 0.39 for the water & sanitation sector (all results are significant at p-values < 0.001).

By analyzing the spatial and temporal patterns of aid allocation, we confirmed that aid concentrated in urban and rural areas with high population or good accessibility and that this concentration has been more intense than the past. Furthermore, aid tends to persist in same places regardless of poverty level, and that trend is more evident in the health sector. In this section of analysis, we identify the unequal distribution of aid and discover the differences of geographical characteristics between spatially excluded regions and the others (spatially concentrated regions).

Discussion

Spatial exclusion problem of aid & Geography

This study found that the relationship between SEL and regional geography was evident in most SSA countries, regardless of each country's poverty level. That relationship becomes clear in terms of geographic characteristic differences between the aid concentrated regions and others (excluded regions). In other words, the tendency of aid concentrating to specific regions with distinct characteristics implies that the geography of regions broadly is related to spatial patterns of aid allocation. These findings are important for understand the spatial exclusion problems of aid.

We examined urban properties, administrative or political status within a country, accessibility, and previous project experience as specific geographical characteristics. We find that aid concentrated to urban areas, capital cities, regions adjacent to the capital or with well-established infrastructures, and regions with previous aid experience. Considering that the regions mentioned above are most likely not rural or remote areas, the tendency of aid concentrating to regions with urban properties is evident. This is consistent with results of prior studies that suggest the tendency of aid concentrating to high densely populated regions and capital cities ((Öhler et al. 2019)), regions with better accessibility ((Briggs 2018b)) and high political status ((Dipendra 2020)). Many resources show urban bias in the African context ((Majumdar, Mani, and Mukand 2004)) and aid allocation also shows the same patterns ((Masaki 2018)). In this perspective, the paper emphasizes the spatial inclusiveness of aid considering regional geography.

However, there is a need to take a cautious approach about spatial inclusion of aid. The challenge of inclusive growth is that inclusion and exclusion could coexist ((Jackson 1999, Stewart 2000, Cameron 2006)). The inclusion of a specific group or region could lead to the exclusion of another. Therefore, spatial inclusion of aid needs the proper balance between regions and between aid sectors. This can be possible by diagnosing multidimensional poverty and preparing long-term aid strategies at the regional level. It is in line with the importance to conduct a diagnosis to meet the demands of aid sectors (Sachs, 2005).

Multiple scale approach for spatial inclusion

One of the important findings of this study is that spatial exclusion of aid is occurring at multiple scales. This study analyzed the spatial pattern of aid by dividing it in different geographical scales. First, at the macro-region scale, spatial patterns (exclusion or concentration) of aid are transboundary. This pattern is related to the fact that physical & human geographical characteristics (poverty levels, urbanicity, etc.) have spatial correlation and show the interaction between neighboring regions beyond country borders.

Second, at the country scale, spatially excluded regions cluster. Regions with similar SEL values tend to show a cluster within a country, which implies that these areas need more attention considering the spatial poverty trap.

Third, at the regional scale, aid concentrates in areas with urbanicity or good infrastructure. In particular, the two maps in <Figure 3> confirmed the concentration of aid to main corridors with better infrastructure and smaller regions with urbanicity regardless of any country.

Many aid critics have criticized the lack of attention towards local conditions, proper aid implementation, absence of feedback systems and homegrown institutions, and one-way approaches (centrally planned or top-down approaches) ((Acemoglu and Robinson 2012, Deaton 2015, Easterly 2006, Easterly and Williamson 2011, Williamson 2009)). Moreover, due to the limitation of the geographical influence range of aid, the aid allocation strategy for spatial inclusiveness should be made by considering the geographical context as much as possible.

Poor targeting by aid sector and poverty dimension

Lastly, this study assumes that sectoral aid targeting is the key to accomplishing the foremost purpose of aid. As a result of analyzing heterogeneity by aid sector, the spatial exclusion problem was severe in the water & sanitation sector. However, the education sector also needs attention because the disparity is the largest and the SEL of some regions was extremely high. The health sector faces a lower possibility of spatial exclusion and disparity compared to other sectors. Yet, such results are relative and spatial inclusion needs attention in all aid sectors. Moreover, aid spend share of functional urban areas and aid persistence in same regions was the largest in the health sector. These results show that the allocation of health aid in each country shows low disparity at the regional level, but much aid was distributed to urban areas at the continental scale for a long time. Based on these findings, the importance of sectoral aid targeting at the regional or more micro levels was confirmed.

Conclusion

The international society has emphasized the need to overcome all forms of disparity and inequality through SDG 10, 'reduced inequalities' ((UN 2019)) and the universal value 'No one left behind ((UN 2013, UNSDG 2019)). Aid has been the prevalent method implemented for combating poverty and inequality among many countries in SSA. However, critics challenged the effectiveness and adequacy of aid allocation for a long time by discussing whether aid has successfully targeted the poor region. For this reason, we suggest the need to analyze spatial patterns of aid in the perspective of poverty geography and spatial inclusion. We also conducted this study to emphasize the importance of poverty targeting by sector at the regional level to accomplish the SDGs.

This paper empirically analyzed the geographical patterns of aid in SSA. We calculated the SEL (spatial exclusion level) of 490 regions in 38 SSA countries using geocoded aid data of IATI and MPI data of OPHI over 20 years. Moreover, a multi-scale exploratory spatial data analysis (ESDA) on aid allocation was performed and a temporal analysis was added to identify the change of aid distribution over time.

This study provides the evidence for intensifying spatial exclusion of aid since 2001 and the need for spatial inclusion of aid in the future. First, aid in the 21st century showed the tendency to concentrate in regions where poverty rates were relatively lower than others. In other words, many poor regions have experienced a deficiency of aid. We pointed out this phenomenon as spatial exclusion of aid because it is a problem regarding the disparity of attention (and interventions) between spatially excluded regions and the others (aid concentrated regions).

Second, the problem about spatial exclusion of aid was related to geography at multiple scales. Regions with similar SELs tended to cluster, which means similar geographic characteristics results in similar SELs. As a result of spatial analysis on aid distribution, aid concentrated in urban and rural areas with highly dense population and good accessibility. Temporal patterns over the past 20 years show that this tendency of concentration has become more intense than the past. Additionally, aid tends to persist in same places regardless of the poverty level.

Lastly, one of main findings is that heterogeneity is evident by aid sector. Thus, an accurate diagnosis of poverty at a micro-scale should be done by identifying the exact dimension of poverty rather than simply estimating the income level. Following this diagnosis, aid project allocation could be in line with the demands for a specific aid sector. According to the results of this study, (1) the regional unequal aid distribution issue needs to be tackled for the water & sanitation sector, (2) regions that show high SEL values in the education sector require attention (3) and for the health sector, the issue of excessive aid concentration to urban areas must be discussed in the future.

The originality of the paper is that we analyzed aid allocation based on the spatial inclusion concept. Moreover, the paper is unique in its research scope and data by covering about 250,000 aid projects for 20 years in 38 countries. Moreover, the methodology contributes to literatures by connecting aid sectors and poverty dimensions and comparing those values at the regional level. On top of that, the paper includes geographical interpretations by analyzing clustering (similarity) and heterogeneity of geographical characteristics at multiple scales.

However, future studies using causal inference are needed to analyze factors that impact aid allocation at micro levels ((Briggs 2018b, Desai and Greenhill 2017)). Further on, studies that discuss aid at multiple scales will be able to enhance the spatial inclusiveness of aid allocation. The further incorporation of geospatial data to analyze the progress of aid will enable many scholars and the international world to take a step closer to accomplishing the

SDGs.

Appendix

Table 1. Descriptive statistics I (Basic information by country and Aid data of ITAI)

Country info.				Aid data (project count)			Aid spend Per poor (unit: $ 1,000)			
Country	ISO	Macro region	Num. region	Geocoded data (%)	Aid data provided	Aid data used	All sector	Health	Edu.	Water
Angola	AGO	S	18	37	4,898	3,339	145	84	42	30
Benin	BEN	W	12	34	7,283	4,440	452	173	55	97
Burkina Faso	BFA	W	13	34	7,148	5,117	515	151	68	80
Burundi	BDI	C	18	40	7,286	5,124	396	219	70	52
Cameroon	CMR	C	12	39	9,302	6,916	312	194	112	75
Central African Rep.	CAF	C	17	60	8,077	5,785	804	165	145	36
Chad	TCD	C	21	55	7,937	5,415	334	137	30	31
Comoros	COM	E	3	67	3,021	1,646	530	427	414	220
Congo, Rep.	COG	C	26	39	22,431	3,044	350	277	1,069	126
Congo, Democratic Rep.	COD	C	12	56	4,322	15,198	207	155	139	21
Côte d'Ivoire	CIV	W	11	41	7,887	5,421	289	232	137	40
eSwatini	SWZ	S	4	31	3,018	1,932	597	1,258	779	347
Ethiopia	ETH	E	11	26	35,985	30,316	325	106	65	25
Gabon	GAB	C	10	49	3,603	1,394	1,036	998	1,796	186
Gambia	GMB	W	8	42	2,824	1,855	530	230	213	57
Ghana	GHA	W	10	23	11,624	7,495	437	301	360	129
Guinea	GIN	W	8	39	9,006	5,802	263	134	78	21
Guinea-Bissau	GNB	W	9	59	4,106	2,145	523	257	71	66
Kenya	KEN	E	8	16	14,021	8,538	309	212	212	106
Lesotho	LSO	S	4	31	3,674	2,605	568	1,012	1,013	625
Liberia	LBR	W	15	21	5,572	3,670	722	350	169	58
Madagascar	MDG	E	22	49	9,423	5,935	250	112	55	16
Malawi	MWI	S	28	26	10,718	7,278	385	416	215	96
Mali	MLI	W	9	32	22,411	19,246	560	187	76	80
Mauritania	MRT	W	13	47	4,979	2,949	559	205	175	104
Mozambique	MOZ	S	11	20	13,238	9,825	437	271	148	67
Namibia	NAM	S	13	28	3,916	1,685	994	255	3,063	127
Niger	NER	W	8	40	9,790	6,167	456	144	49	38
Nigeria	NGA	W	37	31	24,857	17,172	147	137	35	36
Rwanda	RWA	E	5	27	7,040	4,503	641	180	429	90
Sao Tome and Principe	STP	C	4	62	2,032	841	1,337	1,348	1,593	794
Senegal	SEN	W	14	34	9,267	5,645	670	137	160	190
Sierra Leone	SLE	W	14	31	8,487	4,050	551	385	107	48
Sudan	SDN	E	18	41	15,039	8,980	140	149	19	11
Tanzania	TZA	E	9	18	9,484	7,079	303	197	212	58
Uganda	UGA	E	15	23	18,664	13,283	413	167	150	75
Zambia	ZMB	S	10	19	8,808	6,212	304	289	94	133
Zimbabwe	ZWE	S	10	22	6,285	3,916	306	688	398	72
Sum	-	-	490	-	367,463	251,963	-	-	-	-

Notes. Macro-region was used for mapping according to AU (African Union) and UN standards of region division (E: Eastern, W: Western, S: Southern, C: Central). 'Num. of region' means the number of regions by country and the number of total regions is 490 which was the total sample at regional (subnational) scale in our study.
Geocoded data (%) is the share of data including geocode among all aid data provided by International Aid Transparency Initiative (IATI). All geocoded aid data is 'aid data provided' and after data cleaning the aid data used in this study is 'aid data used'. 'Aid spend per poor' is the value obtained by dividing the poor population by aid spend.

Table 2. Descriptive statistics II (MPI data of OPHI)

ISO	Year $_{t-3}$		Year $_{t-2}$		Year $_{t-1}$		Year $_{t}$		num. of years	MPI			
	mpi	poor pop	mpi	poor pop	mpi	poor pop	mpi	poor pop		All	Health	Edu.	Water & Sani.
AGO							15-16	18	1	0.28	0.06	0.09	0.05
BEN	06	10	11-12	13	14	16	17-18	18	4	0.36	0.07	0.13	0.05
BFA							10	18	1	0.52	0.10	0.21	0.07
BDI							16-17	18	1	0.40	0.09	0.11	0.05
CMR			04	09	11	13	14	18	3	0.26	0.07	0.07	0.04
CAF							10	18	1	0.46	0.13	0.12	0.07
TCD							14-15	18	1	0.53	0.11	0.18	0.08
COM							12	18	1	0.18	0.04	0.06	0.03
COG					11-12	17	14-15	18	1	0.15	0.04	0.02	0.03
COD							17-18	18	2	0.33	0.08	0.07	0.06
CIV							16	18	1	0.24	0.05	0.10	0.04
SWZ							14	18	1	0.08	0.02	0.01	0.01
ETH					11	13	16	18	2	0.53	0.13	0.14	0.08
GAB							12	18	1	0.07	0.02	0.01	0.01
GMB			05-06	10	13	17	18	18	3	0.27	0.08	0.09	0.03
GHA			08	09	11	11	14	18	3	0.14	0.03	0.04	0.02
GIN	05	09	12	13	16	17	18	18	4	0.42	0.10	0.15	0.05
GNB							14	18	1	0.37	0.08	0.13	0.05
KEN					08-09	11	14	18	2	0.20	0.06	0.03	0.04
LSO							18	18	1	0.08	0.02	0.02	0.01
LBR							13	18	1	0.32	0.06	0.09	0.05
MDG					08-09	17	18	18	2	0.42	0.07	0.14	0.07
MWI							15-16	18	1	0.24	0.05	0.06	0.03
MLI					06	10	18	18	2	0.47	0.11	0.17	0.06
MRT					07	10	15	18	2	0.31	0.06	0.10	0.05
MOZ					09	09	11	18	2	0.46	0.08	0.13	0.06
NAM					06-07	10	13	18	2	0.18	0.05	0.03	0.03
NER					06	09	12	18	2	0.62	0.13	0.22	0.08
NGA	11	10	13	13	16-17	17	18	18	4	0.27	0.08	0.08	0.04
RWA					10	11	14-15	18	2	0.30	0.07	0.07	0.04
STP					08-09	12	14	18	2	0.12	0.03	0.04	0.02
SEN					10-11	10	17	18	2	0.36	0.12	0.13	0.03
SLE			10	10	13	16	17	18	3	0.37	0.08	0.10	0.06
SDN							14	18	1	0.28	0.06	0.08	0.05
TZA							15-16	18	1	0.27	0.06	0.06	0.05
UGA							16	18	1	0.27	0.06	0.06	0.05
ZMB					13-14	17	18	18	2	0.25	0.06	0.06	0.04
ZWE	10-11	10	14	12	15	17	19	18	4	0.14	0.04	0.02	0.03

Notes. The MPI values of each country are available for the year the country provided the survey data (DHS or MICS). However, some countries have conducted the survey multiple times. To maximize the use of data, we have calculated the mean values of MPI for each country if the number and name of regions was identical. ‘Year t’ is the most recent year of MPI data used in this study. 'Year t-1' is the year in which OPHI provides MPI data before ‘year t.’ 'year t-2' is the year in which OPHI provides MPI data before ‘year t-1.’

In OPHI dataset, the year of the survey used for MPI calculation is different from the year of the statistic used for calculating poor population. The first value (left column) of each year is the year of conducting the survey used to calculate the MPI. the second value (right column) of each year is the year we obtained the number of poor necessary for calculating the MPI as well. We obtained regional MPI and poor population data of all available years from 2001 to 2020. Then, all the values were averaged by each country and region for analyzing.

Table 3. Descriptive statistics III (data of aid projects and population)

	All sectors	Health	Education	Water & sanitation
N	251,963	52,787	21,739	17,299
Aid Spend (billion $)	283	36	25	20
population adj. aid Spend ($)	305	38	27	22
Poor population adj. aid Spend ($)	513	166	97	49
Poor population (average of 20 years) (thousand)	551,278	216,555	258,427	421,098
Population (average of 20 years) (thousand)	926,796	-	-	-

Notes. For the same aid program at different locations, aid spending was equally divided by the number of locations. After this calculation the number of total samples in this study was 251,963. All sectors cover Health, Education, Water & sanitation and others. Population adjusted aid spend is . Poor population adjusted aid spend is . We calculated average of poor population by aid sector for 20 years using OPHI data which provides poor population by poverty dimension. For example, the number of poor population in the health sector is the population experiencing deprivation in the two indicators used to measure the health dimension of MPI.

Table 4. Descriptive statistics IV (data of 490 regions)

		Mean	Std. Dev.	Min	Max
Aid spend	**All**	577	1,216	1	10,495
	Health	73	203	0	2,407
	Education	51	152	0	1,715
	Water & Sani.	42	91	0	894
MPI	**All**	0.34	0.17	0.01	0.71
	Health	0.08	0.04	0.01	0.17
	Education	0.10	0.07	0.00	0.29
	Water & Sani.	0.05	0.02	0.00	0.11
Poor population	**All**	1,125	2,329	2	35,268
	Health	442	1,024	1	15,276
	Education	528	1,211	1	19,139
	Water & Sani.	859	1,940	1	30,008
Population	**Pop.**	1,891	3,004	8	39,599

Notes. All variables above except for population are used for calculating the SEL of 490 regions (is ‘.’ Summary statistics of (regional) population are for reference.

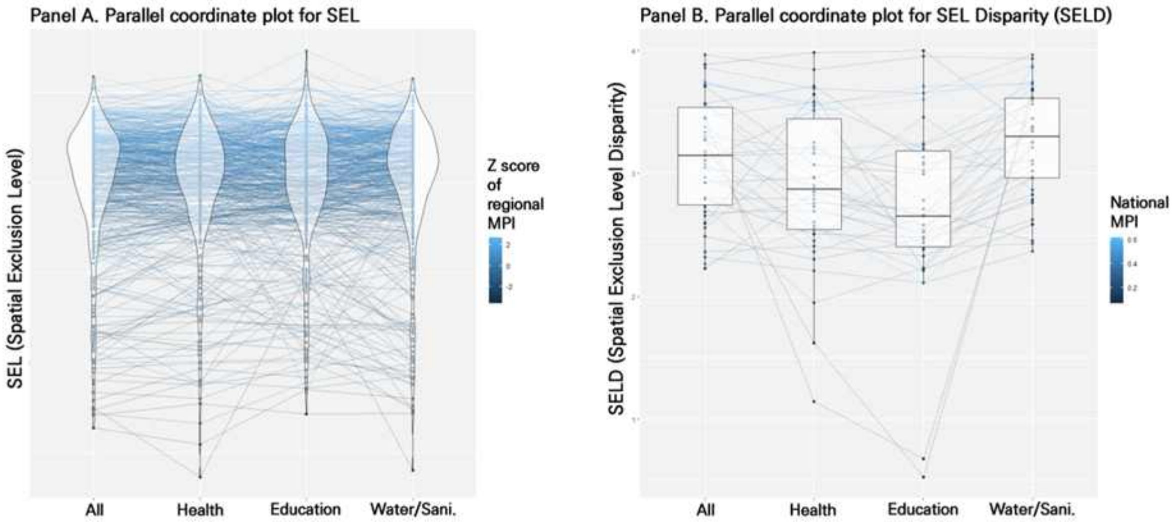

Figure 5. Heterogeneity of SELs in 490 regions and SELDs in 38 countries by aid sector

Notes. Panel A. The x-axis shows the total aid and the three sectors of aid while the y-axis shows the SEL value of each category. Through this figure we can observe that the SEL values of total aid and by sector is similar but not identical. The violin plot which shows the weights of SEL values shows that heterogeneity exists even where similar SEL values cluster.

Panel B. The SELD values of 38 countries by total aid and three aid sectors are shown through a box plot and parallel coordinate plot. The SEL variance within a country (or in other words the spatial inequality of aid allocation) shows differences between aid sectors. The aid sector heterogeneity depicted in Panel A and Panel B highlight the need for sectoral and regional poor targeting.

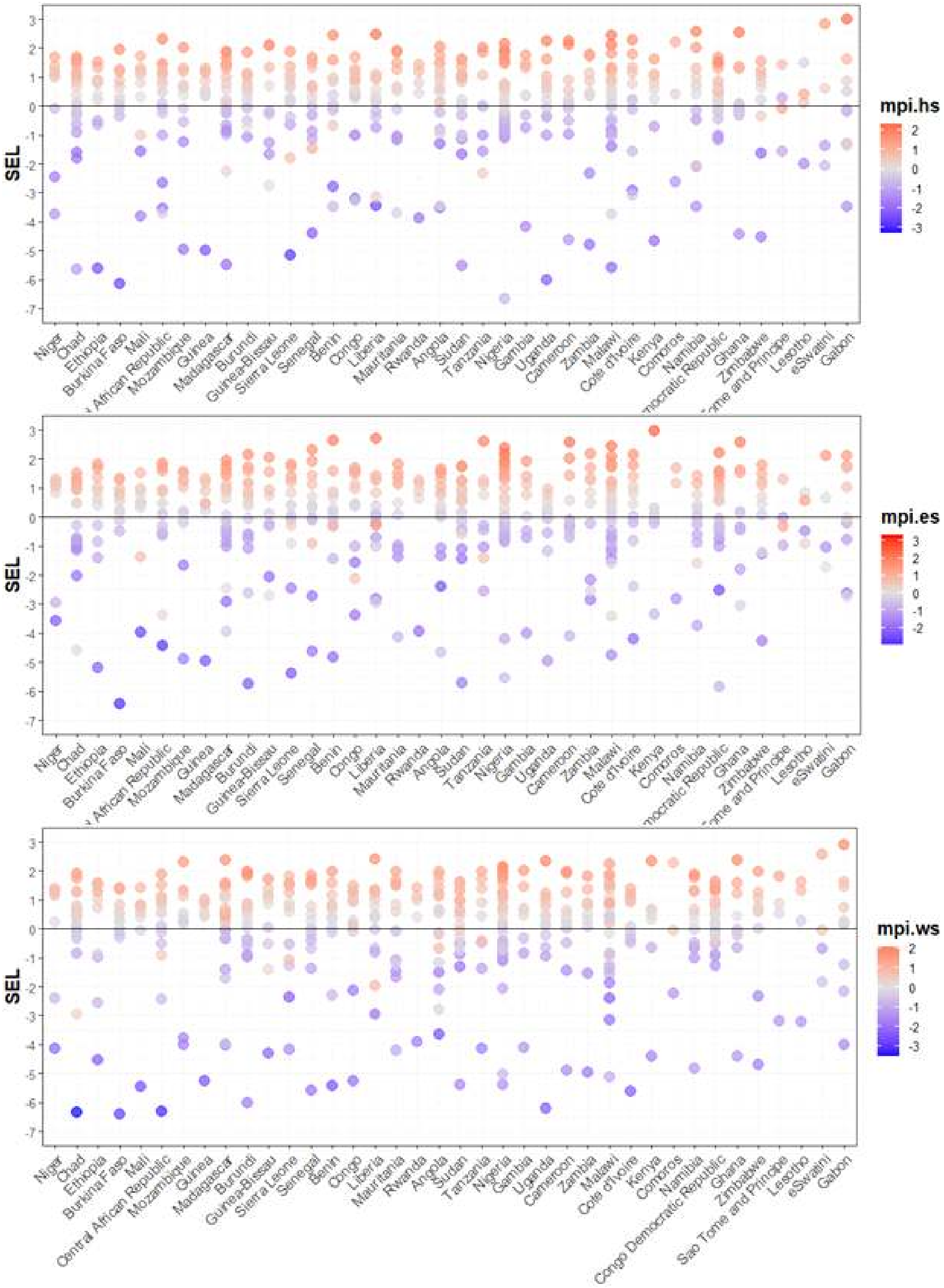

Figure 6. SEL by aid sector

Notes. From above, Health, Education, and Water & Sanitation sector.

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