Introduction to the Sustainable Development Goals Trends and Tables

The Millennium Development Goals (MDGs) provided a comprehensive framework for monitoring socioeconomic progress as they set forth specific, time-bound, and quantified targets for addressing extreme poverty in its many dimensions, while also promoting gender equality, education, and environmental sustainability. When the MDGs concluded in 2015, significant gains had been made in most parts of the world, particularly in Asia and the Pacific as documented in *Key Indicators 2015*. While there is much cause for celebration, there remains an unfinished agenda due to uneven progress across the goals and across countries, and the uneven opportunities for people to share the benefits of development and progress.

In September 2015, leaders of 193 member states of the United Nations (UN) convened at the UN General Assembly in New York to launch the Sustainable Development Goals (SDGs). Also known as the Global Goals, they present a universal plan of action to build on the progress achieved through the MDGs by addressing social, economic, and environmental aspects of sustainable development. Like the MDGs, the SDGs set forth quantifiable targets to be achieved by 2030 (with a 2015 baseline) for ending poverty, protecting the planet, and ensuring that all people enjoy peace and prosperity. The global indicator framework of the SDGs was approved during the 47th Session of the UN Statistical Commission in March 2016. Although it is still subject to further refinements and improvements as a wider array of analytical tools and innovative data sources emerge, we have a clearer picture of just how much data the world needs to help meet the Global Goals.

The approved global indicator framework of the SDGs consists of 17 goals, 169 targets, and 230 indicators. The current set of indicators is grouped into three tiers. Indicators classified in Tier 1 have a clear, established methodology and data are regularly collected by many countries. Tier 2 indicators, although they have an established methodology, are not regularly collected by many countries. Tier 3 indicators do not have an established estimation methodology and standards. Of the 230 indicators, approximately 40% have an established methodology and are regularly collected. This means that there is a huge task confronting national statistical systems to produce and compile such data. Given that the data requirements for monitoring progress and ensuring accountability toward realizing the 17 SDGs are numerous and can be a challenge for the statistical systems of both developing and developed countries, it is imperative to explore how we can capitalize on new data sources for compiling the SDG indicators.

Part I of *Key Indicators 2016* examines the status of economies of Asia and the Pacific on the SDG agenda using empirical data for selected indicators from the global indicator framework. The second section provides a brief description on how big data can be used to address some of the data gaps associated with SDG monitoring.

Section 1. Sustainable Development Goal Indicators in Asia and the Pacific

Integrating the economic, social, and environmental dimensions of sustainable development to so as to enable everyone to fully participate in the growth processes is one of the tasks enshrined in the SDGs. The SDGs set out a plan of action to create a better future for the people and its planet by promoting prosperity, peace, and partnership (Figure 1.1).

Figure 1.1: Five Ps of the Sustainable Development Goals

Source: Adapted from http://www.un.org/sustainabledevelopment/sustainable-development-goals/.

To ensure that all countries will keep track of the achievement of the SDGs, monitoring of these indicators is imperative. Monitoring should be based on a wide variety of indicators at a more regular frequency so that programs can be developed and fine-tuned to facilitate each country's achievement of the goals. The UN Inter-agency and Expert Group on SDG Indicators (IAEG-SDGs) has been working on an indicator system for the measurement of the SDGs and a core set of 230 indicators has already been developed. Accounting for national circumstances in individual countries, this will be complemented by indicators at the national and subnational levels as committed by member states. Some thematic indicators are also being developed.

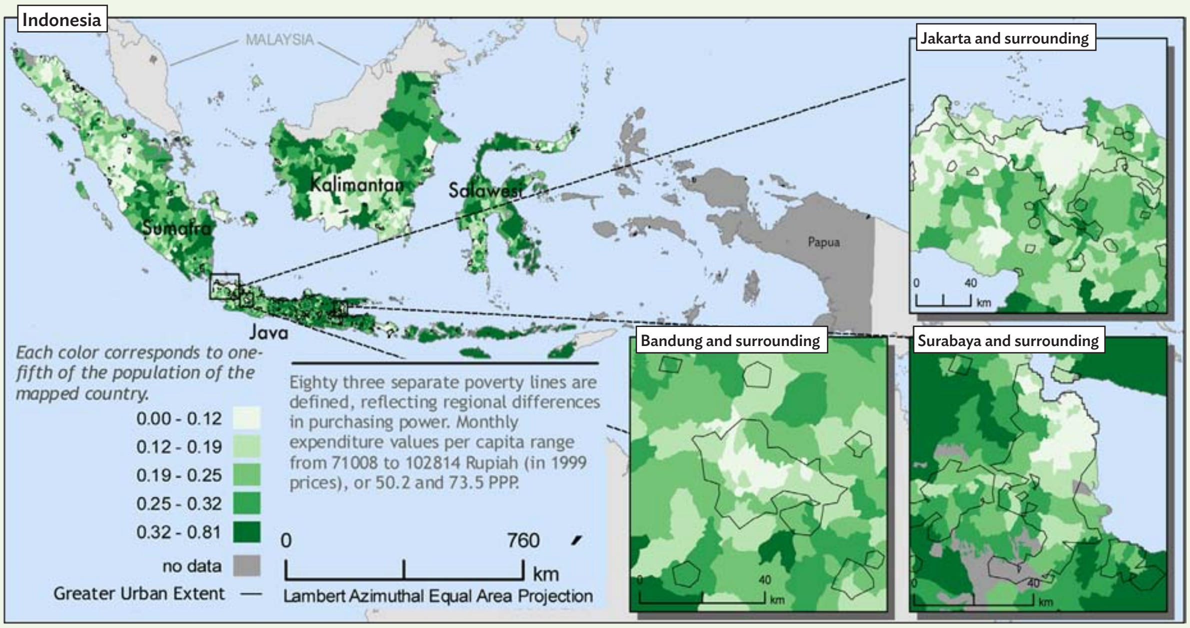
The indicator system associated with the SDGs should necessarily be linked to the policy cycle that starts with policy formulation, followed by policy legitimation, policy implementation, policy evaluation, policy change, and back to the formulation of new policies (Hak, Janouskova, and Moldan 2016). In the policy evaluation stage, the role of indicators is very crucial to ensure that certain strategies are adequately aligned toward achievement of the goals.

Along the principle of "leave no one behind", data disaggregation is also an important facet of indicators that will be developed specifically for the vulnerable segments of society. Box 1.1 provides a brief description of the analytical techniques that can be used for disaggregating the SDG indicators.

Box 1.1: Analytical Techniques for Disaggregating the Indicators of the Sustainable Development Goals

The lack of disaggregated data is one of the main issues raised regarding the monitoring framework of the Millennium Development Goals (MDGs). Although the data collected for MDG monitoring allowed tracking of how countries fared in terms of different social and economic indicators relative to other countries, they did not reveal how inequalities within each country changed over the years. This provided limited empirical evidence on which segments of a country's population made significant progress or lagged behind in terms of the MDGs. From a policy perspective, this is problematic because there are limited data to guide the design of intervention programs meant to appropriately target the disadvantaged. In response to this concern, the 2030 Agenda for Sustainable Development has espoused the "leave no one behind" principle, which requires appropriate Sustainable Development Goal (SDG) indicators to be estimated for different subpopulation groups based on income class, gender, ethnicity, and geographic location, and other relevant dimensions.

Sample Poverty Map: Poverty Headcount Index in Indonesia, 2000



Sources: Center for International Earth Science Information Network (CIESIN), Columbia University. 2005. Poverty Head Index – Indonesia, Administrative Level 3: Subdistrict [Map]. Poverty Mapping Project: Small Area Estimates of Poverty and Inequality. Palisades, NY; NASA Socioeconomic Data and Applications Center (SEDAC). Small Area Estimates of Poverty and Inequality, v1 (1991–2002). http://dx.doi.org/10.7927/H49P2ZKM

Several strategies can be adopted to provide disaggregated SDG data and each technique entails varying levels of analytical rigor and data requirements. In the case of indicators estimated based on survey data, disaggregation requires that each subpopulation group for which estimates need to be provided is adequately represented in the survey. However, many of the national statistics offices from developing countries do not have adequate financial resources to employ sample sizes that are large enough to provide reliable estimates for different subpopulation groups. On the other hand, there are several small area estimation (SAE) techniques that "borrow strength" from other data sources that have wider coverage to be able to increase the effective sample size of surveys artificially. For example, the classic method proposed by Fay and Herriot (1979) uses optimal weighting strategies to combine survey and model-based estimates to improve the precision of their proposed estimator. Over time, more sophisticated SAE techniques have been developed. The methodology proposed by Elbers, Lanjouw, and Lanjouw (2003) is a good example of a more advanced SAE technique that is widely used in poverty mapping exercises. In general, the methodology entails regressing a certain income measure (e.g., household expenditure or income) on various correlates using survey data. The methodology requires that these correlates are available in both survey and census data. Out-of-sample prediction is then used to impute the chosen income measure by applying the estimated regression coefficients into the census data. Using the information on income imputed for each unit of the census, poverty measures can then be estimated for any desired level of disaggregation, although most of the initiatives have focused on disaggregating poverty numbers based on geographic location. Nevertheless, similar SAE techniques that are grounded on the same methodology may be employed to disaggregate other SDG indicators, provided that its data requirements are met.

continued.

Box 1.1: *(continued)*

Availability of Small Area Poverty Estimates in Asia and the Pacific

Country	Level of Disaggregation
Armenia	district
Azerbaijan	rayon (district)
Bangladesh	upazila (subdistrict)
Bhutan	subdistrict
Cambodia	commune
Fiji	tikina (district)
India	district
Indonesia	village
Nepal	district
Mongolia	soum (district)
Pakistan	district
Papua New Guinea	local-level government area
Philippines	city, municipality
Thailand	subdistrict
Viet Nam	district

Note: A number of studies on district-level poverty estimates for some of India's states were conducted in recent years.
The table above is not a comprehensive list of small area poverty estimates that are publicly available in Asia and the Pacific.
Sources: ADB compilation from international development organizations, national statistical agencies, and various sources.

However, there are several situations when it is more ideal to explore alternative methodologies to conventional SAE techniques for disaggregating the SDG indicators, e.g., reference period of the survey is far from that of the census (or other administrative records) or no conventional data collection tools exist. In such cases, big data and other new forms of data can be potentially tapped into to provide disaggregated estimates. For example, data on nighttime lights derived from satellite images can be used to provide geographically disaggregated measures of economic output. In an ongoing study undertaken by Glaeser et al. (2015), sophisticated computer algorithms are being used to process Google Street View images of houses to predict household income in New York City. A similar methodology could be explored to map wealth and poverty in other corners of the world where conventional poverty mapping tools are not available. On the other hand, a recent study by Marchetti, Guisti, and Pratesi (2016) makes use of Twitter-based emotion data (computed in the iHappy index) as a means of predicting the share of food consumption in a household's expenditure in Italy at the provincial level.

As seen above, there are several studies that have already shown that satellite images, data from everyday gadgets, social sites, and other high-throughput tools are high-density data that can be good predictors of various population traits. Since these types of data are usually high-density and available at very granular level, they can be considered promising data sources for SAE that can supplement the conventional data collected by national statistical agencies.

Sources:
C. Elbers, J. Lanjouw, and P. Lanjouw. 2003. Micro-level Estimation of Poverty and Inequality. *Econometrica* 71(1): 355–364.
R. Fay and R. Herriot. 1979. Estimates of Income for Small Places: An Application of James–Stein Procedures to Census Data. *Journal of American Statistical Association* 74 (1979): 269–277.
E. Glaeser, S. D. Kominers, M. Luca, and N. Naik. 2015. Big Data and Big Cities: The Promises and Limitations of Improved Measures for Urban Life. *NBER Working Paper 21778*. Cambridge MA: National Bureau of Economic Research (NBER).
S. Marchetti, C. Guisti, and M. Pratesi. 2016. The Use of Twitter Data to Improve Small Area Estimates of Households' Share of Food Consumption Expenditure in Italy. *AStA Wirtschafts- und Sozialstatistisches Archiv* 10(2): 79–93.

This section provides a summary of the selected SDG indicators that are widely available in ADB member countries. The data compiled here are mainly from the UN Department of Economic and Social Affairs, Statistics Division's SDG Indicators Global Database, i.e., the official SDG data repository, and data from international organizations and economy sources.

The SDG Indicators Global Database compiles data that are either directly produced by different international agencies based on their respective areas of expertise and mandates (e.g., proportion of population living below international poverty line estimated by The World Bank), data that are estimated from sample surveys which are financed and carried out by international agencies (e.g., health indicators that are estimated using data from the Multiple Indicator Cluster Surveys (MICS) and Demographic and Health Surveys (DHS)), unadjusted data that are compiled by international agencies based on what is directly produced by national statistical offices and other country sources, or data adjusted by international agencies based on what is directly produced by national statistical offices and other country sources. International agencies introduce statistical adjustments to facilitate data comparability across countries, impute estimates for years wherein data are not available, harmonize data when they are compiled from multiple national sources (e.g., surveys, administrative, and other sources) or address data quality issues. For detailed description of how international agencies compile their SDG-related data, readers may refer to the metadata available on the SDG Indicators Global Database's website.

Given the reasons cited above, the data compiled by national statistical agencies do not always match with the data compiled by international agencies. Hence, some of the data presented in this publication may differ from those available within countries.

The indicators are accompanied by a short analysis and supporting information presented in figures, boxes, and tables that are summarized according to the five themes: People, Planet, Prosperity, Peace, and Partnership. Most of the statistics presented in the tables and charts are usually presented for two data points between 2000 and 2015. In the succeeding discussion, these are occasionally referred to as the initial year (usually a year between 1998 and 2007 that is closest to 2000) and latest year (usually any year closest to 2015) depending on available data. There are also exceptions to this approach because the years for which data are available vary widely across countries. The 2015 figures shall serve as the baseline from which progress with respect to the SDGs can be assessed. However, there are instances when the latest estimates are even prior to 2010, indicating lack of timely data for monitoring the SDGs. The data for initial years allow us to gauge how countries have performed over the past 15 years and could be indicative of their future performance.

At the end of each section, issues in monitoring the goals and data gaps are briefly discussed to provide information to countries and other development partners on the amount of resources needed by statistical systems to produce and analyze the SDG indicators.