**Chapter 4.**

**Monitoring the interlinked goals – data and measurement considerations**

# **Introduction**

This report monitors the progress of the World Bank’s new vision, aimed at guiding policy actions to create a world free of poverty on a livable planet. Table 1 presents the set of vision indicators chosen to track this progress, encompassing three key dimensions: poverty, prosperity, and a livable planet. The livable planet indicators cover aspects such as climate risks and mitigation, healthy ecosystems, and essential life necessities.[[1]](#footnote-2)

This chapter summarizes key points regarding the data and measurement of these indicators in aspects relevant to what this report covered. It highlights areas for action to improve data availability and measurement for better monitoring of this expanded vision. It begins by discussing the main data sources used for the indicators and some challenges and ongoing work. Additionally, it addresses key measurement challenges and potential short-term improvements to the indicators.

**Table 1: World Bank’s vision indicators**

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| **Chapter** | **Vision indicators** |
| 1. Poverty | Percentage of global population living in poverty (at $2.15/day and $6.85/day) |
| 2. Prosperity | Global average income shortfall from a prosperity standard of $25/day |
|  | Number of countries with high inequality |
| 3. Livable Planet | Global greenhouse gas emissions (gigatons of CO2 equivalent) |
|  | Percentage of people at high risk from climate-related hazards globally |
|  | Millions of hectares of key ecosystems globally |
|  | Percentage of people facing food and nutrition insecurity globally |
|  | Percentage of people with access to basic drinking water, sanitation services, or hygiene globally |

Source: World Bank (World Bank, 2024a)

# **Data sources, some challenges and ongoing work**

Data underpins the development process. Without it, understanding the living conditions of people is impossible. Policymakers aiming to alleviate poverty, build resilience, and promote sustainable well-being need accurate data to make informed decisions. Better data is also key to understand and manage the trade-offs associated with climate policies.

The value of data to facilitate development and ensure no one is left behind, as encapsulated in the Sustainable Development Goals (SDGs), can be enhanced if data is reliable, timely, and can be disaggregated by key demographic characteristics. Data does not only help governments in service delivery, preparing for and responding to emergencies, and prioritizing marginalized, underserved population subgroups, but it provides the populace with the information they need to hold governments accountable, and make better political decisions, for example during elections (Jolliffe et al., 2023; World Bank, 2021, 2015).

## Improvements in survey data coverage have been significant but still lag where data is needed the most

Household survey data, in particular household budget surveys continue to be at the core of the monitoring of the World Bank vision. This data is needed to track poverty, multi-dimensional poverty, shared prosperity, high inequality, and it is the basis for the quantification of the share of people at risk of extreme weather events. These data are also foundational to modelling and projections on the potential impacts of climate change on welfare and for understanding trade-offs related to climate policies.

Overall, there has been substantial progress in the availability of household budget survey data containing information on income and/or consumption. The previous versions of this Report, *Poverty and Shared Prosperity Reports* (PSPRs), typically had a three-year lag in reporting baseline (observed based on surveys) global poverty and shared prosperity estimates. This report has only a 2-year lag in reporting baseline global estimates. Despite the COVID-19 pandemic, there has been sufficient survey data coverage for the world and all regions for this report to present baseline poverty data and shared prosperity data until 2022, except the Middle East and North Africa, a conflicted-affected countries (see box 2, chapter 1).

Globally, between 1998 and 2022, the average number of available survey data sets per country increased from 2.1 to 9.9, almost a five-fold increase. Upper-middle- and high-income countries drove this progress. However, more survey data has also become available in lower income regions, with improvements in data quality, frequency, and processing time. For example, the World Bank in collaboration with the West African Economic and Monetary Union (WAEMU) Commission has produced two rounds of comparable and high-quality survey data sets for member countries in 2018/19 and 2021/2022 (Castaneda et al., 2024, 2022). There have been also gains in collecting new data for highly populated countries, such as Nigeria.[[2]](#footnote-3)

Despite progress, fewer than half of the countries around the world had a survey in 2020 or later (see Figure 2). Regions with many small countries and island states lag behind. For example, East Asia and Pacific includes many Pacific islands that are not very populous and have infrequent surveys. This also applies to high-income countries, although survey data is also unavailable for some large high-income countries, such as Japan, resulting in population-weighted coverage rates in high-income countries that are less than upper-middle-income countries. With less than half of countries with survey data, FCS and low-income countries in particular continue to lag behind (Figure 1). These countries have consistently had the least survey data covering them since 1998, and the pace of progress is slow compared to richer countries.

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| **Figure 1: Cumulative number of surveys per country** | **Figure 2: Share of countries with data in 2020 or later** |
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Source: Poverty and Inequality Platform (PIP)

Note: The classification of countries by fragile, conflict-affected, and violent (FCV), International Development Association (IDA), and income status is based on the latest available data for year 2022.

### More is needed in terms of prioritizing funding for traditional surveys in low-income settings.

Collecting good data is costly and the public-nature of development data implies that that it is usually undersupplied (Chin, 2021).[[3]](#footnote-4) Traditional collection of surveys can be prohibitively high in settings where budgets are constrained. For example, it would cost about $1billion (in 2014 prices) to field surveys in 78 IDA countries once every three years in the period 2016-2030 (Kilic et al., 2017). The World Bank has lent $2 billion to 40 countries, mostly in Sub-Saharan Africa, since the introduction of the Data for Policy Initiative in 2020 (Dabalen et al., 2020). Yet, with constraint budgets it is hard to prioritize data vis a vis other development needs.

### Beyond costs, data challenges also lie in the ability to access the data.

Many countries, both high and lower income, do not share microdata for various reasons. This is for example why MENA does not have good data coverage for monitoring poverty (e.g. the last household survey in Egypt was collected in 2022 and it is still not publicly available). This is not an issue exclusive to household surveys. For example, the International Energy Agency (IEA) has valuable energy data behind paywalls, limiting its use for climate research. More effective data governance is key in creating an environment where data can be produced, used, re-used, and shared safely, while ensuring that the benefits of data are shared equitably (World Bank, 2021).

The Atkinson Commission Report on Global Poverty recommends greater financial investments in data and data systems, as well as international coordination and accountability for data (World Bank, 2017). Within the wide range of competing policy interests, building capacity in national statistical systems should be prioritized more than ever before.

## One critical area of focus going forward is further data integration, where linking various big data sources can enrich survey data

Enhancing the interoperability and integration of household surveys with censuses, geospatial data, administrative records, and non-traditional sources such as earth observation and call detail records, can increase the cost-effectiveness and relevance of survey data production. This approach can achieve higher levels of accuracy and granularity in both spatial and temporal resolution, which is only possible through data integration. One successful application is the linkage of survey data and census data with geospatial data for poverty mapping (Corral et al., 2023, 2022).[[4]](#footnote-5)

Georeferencing is key for integration of data with spatial features. Georeferenced survey data can validate and calibrate machine learning models that combine this data with publicly available satellite imagery and processed geospatial data to derive precise estimates of poverty, asset wealth, and agricultural outcomes at high spatial resolution. This integration allows for more detailed and accurate analyses, which are crucial for policymaking and resource allocation. Georeferencing is key for measuring vulnerability to climate hazards where hazard information needs to be linked with household surveys to identify populations at risk. We discuss this in more detail in the next subsection.

Another element related to data integration is the inclusion of common variables across core surveys, which enhances the ability to bridge information between different surveys effectively. For example, one of the challenges of the current multidimensional poverty measure (MPM) is precisely the difficulty in combining poverty data with non-monetary dimensions of well-being that are collected in other surveys, such as nutrition data. The livable planet indicator on the percentage of people with access to basic drinking water, sanitation services, or hygiene globally, is not comparable with the indicator of water and sanitation in the MPM due to differences in ways these variables are defined across surveys. By standardizing certain key variables, such as demographic information (e.g., age, gender, income), geographic location, and basic health indicators, it becomes easier to link and compare data from various surveys. This harmonization allows for more comprehensive analyses and facilitates the combination of datasets to generate richer, more detailed insights.

Furthermore, including common variables facilitates the use of advanced analytical techniques, such as machine learning and AI, to identify patterns and correlations across larger, more diverse datasets. This can lead to more accurate predictive models and better-informed decision-making.

## Modernizing household surveys is also increasingly important for enhancing projections of welfare using AI.

Currently, the estimation of global poverty relies on traditional sources of data (i.e., surveys), complemented with machine-learning models to validate poverty predictions (Mahler et al., 2022). Despite progress in the availability of surveys, these traditional methods produce measures of household welfare too infrequently to meet the needs of many policymakers. Official measures of poverty are derived from household surveys, even in ideal settings are only conducted every few years.

More research is needed to accurately predict changes in welfare over time using big data sources such as geospatial data or call detail records. So far, the evidence suggests that predicting changes over time is challenging, especially on a global scale (cite typology though not yet published?). For instance, Marty and Duhaut (2024) compare different models and data sources to predict poverty, finding models explain only between 4-6 percent of variation in asset-wealth over time (26 percent being the maximum in one country). Predicting non-monetary welfare indicators such as food security over time has so far been found to be more feasible than predicting monetary or asset-based welfare indicators (see for example, Andree et al. (2020) or Tang et al. (2022)). Mahler et al. (2022) find that on the country-level, using data from national accounts to nowcast poverty outperforms more complex models using a variety of geospatial variables. More research is needed in how the accuracy of machine learning models in estimating changes in monetary poverty and other welfare metrics using big data sources can be enhanced.

Yet, to support these more advanced analytics, household surveys need to be "AI-ready". This would require investments in comprehensive metadata documentation and the adoption of standardized, interoperable data practices. Detailed descriptions for all variables, along with clear documentation of data collection methodologies, are essential for ensuring AI algorithms understand the context and nature of the data. Provenance information, including data sources and processing history, helps maintain reliability and allows for replicable studies. Standardized data formats and metadata, as well as APIs for seamless data access, enhance interoperability with various AI tools and platforms. Using ontologies and taxonomies to classify and relate data elements further aids AI systems in interpreting and analyzing the data.

## Estimating GHG emissions

It is not possible to measure global GHG emissions directly, but there are methods to estimate them, and various sources provide data for this indicator. The measurement status of greenhouse gas (GHG) emissions involves various approaches and data sources (see for example National Academies of Sciences, Engineering, and Medicine (2022)).[[5]](#footnote-6) The primary sources of GHG emissions data include national inventories, satellite observations, and sector-specific measurements. National inventories, compiled by countries and reported to international bodies such as the United Nations Framework Convention on Climate Change (UNFCCC), provide detailed emissions data by sector. Satellite observations enhance these inventories by offering independent, high-resolution data, particularly useful for detecting emissions from remote areas and verifying self-reported data. Sector-specific measurements focus on key emission sources such as energy production, transportation, and agriculture.

Despite advancements in technology and data integration, challenges remain in achieving comprehensive, real-time global coverage of emissions, standardizing measurement methodologies, and ensuring data accuracy and transparency. Ongoing efforts aim to address these challenges and improve the precision and reliability of GHG emissions data.

The estimated accuracy of emissions from fossil fuel combustion and industrial processes are deemed high, as quantities of fossil fuels and other emissive materials produced (such as cement and steel) are well known (Crippa et al., 2023). Yet, anthropogenic emissions from the land use, land use change and forestry (LULUCF) subsectors are more challenging to quantify because of the complexity of terrestrial ecosystem and the difficulties of disentangling natural from anthropogenic fluxes. Measuring emissions from LULUCF is particularly challenging and there are often discrepancies between measurement approaches (Friedlingstein et al., 2020; Grassi et al., 2023). Differences arise from the definition of land-use (change), for instance whether absorbed carbon from managed forests is counted into national emissions. Comparable LULUCF data is furthermore not available prior to 2000, making historic comparisons difficult, and LULUCF emissions for 2021 and 2022 are extrapolated in the data used for this report.

The World Bank’s new indicator of global GHG emissions is based on the Joint Research Center’s Emissions Database for Global Atmospheric Research (EDGAR), augmented by preliminary estimates for the land use, land use change and forestry (LULUCF) using a hybrid-inventory approach that were developed for the Research Center’s annual report, GHG Emissions of all World Countries, 2023 (Crippa et al., 2023). For more highly disaggregated, country-level non-LULUCF emissions, a more granular EDGAR dataset (EDGAR v8.0) is used, which includes national estimates of annual emissions disaggregated by 37 subsectors and 28 GHGs (CO2, CH4, N2O, and 25 different F-gases) from 1970 to 2022.[[6]](#footnote-7) These data, when aggregated to the global level, are nearly identical to the EDGAR Report data. To account for the discrepancy in global values of EDGAR and the aggregation of national LULUCF data from Grassi et al. (2023) a small residual factor by sector and gas is included.

While GHG emissions started to accelerate during the 19th century when industrialization began, this report depicts more recent trends in emissions, as disaggregated data, for instance by type of greenhouse gas or economic sector (including LULUCF), is only available since 1990, and for all sectors by country since 2000. As mentioned above, greenhouse gas emissions remain in the atmosphere for centuries. While we focus on emissions trends from 1990 onwards in this report due to data availability and quality, there are estimates for historical emissions (see e.g. Jones *et al.* (2023)). It is important to consider that the stock of emissions in the atmosphere is what matters for warming and reducing emissions going forward is of essence to limit future impacts of climate change (Eyring et al., 2021; IPCC, 2023).

## Data used for climate hazards and ongoing work

The livable planet indicator on the *percentage of people at high risk from climate-related hazards globally* is defined as the number of people globally who are both exposed to a set of key climate-related hazards (floods, droughts, cyclones, and heatwaves) and are also highly vulnerable (i.e., have a propensity to be adversely affected or unable to cope with the impacts), as a share of global population. Specifically, people are counted as at high risk from climate-related hazards if they are exposed to at least one hazard and are identified as highly vulnerable on at least one dimension of vulnerability. Next, we summarize key data sources related to hazards and ongoing work to improve the data estimates. More information can be found in Doan et al (2023).

***Droughts:***

The indicator uses Historic Agricultural Drought Frequency data from the FAO, depicting the annual frequency of severe drought events from 1984 to 2022. These events are defined using the Agricultural Stress Index (ASI), based on remote sensing vegetation (NDVI) and land surface temperature (BT4) data, combined with historical agricultural cropping cycles. Severe drought is identified when a Vegetation Health Index (VHI) falls below 35 percent over a growing season. The ASI value represents the percentage of affected crop or grassland pixels within each administrative unit. Annual frequencies are converted into approximate return periods, with any location recording at least one severe drought from 1984 to 2022 considered exposed to a 39-year return period event. The dataset, restricted to rural areas, maps regions where more than 30 or 50 percent of cropland or grassland was affected in any growing season, with return periods ranging from 5 to 39 years based on historical frequency. An area of ongoing work is to generate probabilistic estimates of drought using this data, to derive 100-year return periods which are used for the other hazards.

***Floods:***

The indicator utilizes modelled pluvial and fluvial flood maps from the 2019 Fathom Global 2.0 flood hazard dataset. Fluvial floods result from rivers overflowing due to intense precipitation or snowmelt, while pluvial floods occur from heavy rainfall leading to saturated soil or overwhelmed drainage systems. The Fathom dataset provides maximum inundation depths for these floods at a resolution of approximately 90 meters, covering return periods from 5 to 1,000 years. It is important to note that the data assumes no flood defenses, which might overestimate exposure in some regions, particularly those with effective flood protection.

For coastal flooding, a separate dataset by Deltares (2021) is used, which models flooding caused by tides and storm surges at the same resolution and using the same digital elevation model as Fathom 2.0. The coastal flood data depicts maximum depths for return periods from 0 to 250 years. The Fathom flood maps for 231 countries were merged to create global fluvial and pluvial maps for each return period, which were then combined with the global coastal flood maps to produce a comprehensive global flood hazard map. This map, covering return periods from 5 to 100 years, shows the maximum inundation depth of any flood type. An update to Fathom 3.0 is planned for the coming year.

***Heatwaves:***

The indicator uses modelled 5-day heatwave maps from the World Bank Climate Change Knowledge Portal (CCKP). This probabilistic dataset shows the maximum 5-day average of the daily maximum Environmental Stress Index (ESI) at a resolution of approximately 30 km for return periods between 5 and 100 years. The ESI approximates the Wet Bulb Globe Temperature (WBGT) using temperature, relative humidity, and solar radiation, adjusted for systematic underestimation from solar radiation. Derived from hourly ERA5 climate reanalysis data, the maximum 5-day average was calculated for each year from 1950-2022, detrended, and fit to generalized extreme value distributions to estimate return levels for a 5-day heatwave event. Ongoing work aims to develop a more spatially detailed measure of heat, to increase measurement accuracy and align with other indicators.

***Cyclones:***

The indicator uses global modelled tropical cyclone maps from Bloemendaal, Haigh, de Moel et al. (2020). The tropical cyclone dataset is created using the Synthetic Tropical cyclOne geneRation Model (STORM), which resamples 38 years of historical cyclone track data from the International Best Track Archive for Climate Stewardship (IBTrACS). This extends the dataset to represent 10,000 years of cyclone activity, covering all tropical cyclone basins except the South Atlantic due to insufficient historical data. The results were validated against historical observations and previous studies. The STORM dataset shows the maximum 10-minute average sustained wind speed at a resolution of approximately 11 km for return periods from 10 to 10,000 years. While it does not include storm surge and heavy precipitation, these factors are considered in modelled flood maps and included in the multi-hazard analysis.

# **Vision indicators measurement – caveats and areas for improvement**

The World Bank’s new vision encompasses a broader scope, focusing on inequality and environmental sustainability in addition to poverty. This expanded vision requires enhanced measurement efforts across various dimensions.

The rest of this chapter shifts the focus from data to measurement across four areas. The first area deals with measuring inequality, discussing challenges such as differences between consumption and income data, the underreporting of top incomes in household surveys, and discrepancies between household surveys and national accounts data. The second area concerns non-monetary measures and delves into the measurement of food insecurity given the complexity of the concept and measurement challenges of the selected indicator. The third area focuses on capturing vulnerability and climate risks more accurately. The final area reflects on the challenges to forecast the impacts of global warming on poverty given the discussions presented in chapter 3.

While these selected measurement areas are prioritized, other measurement topics remain important. For instance, within-household inequality, though not discussed here, is crucial. In addition, we do not discuss in detail measurement challenges related to WASH or healthy ecosystems. On WASH, the indicator is clear, and the main challenge is advancing on having better coverage of the hygiene dimension. On health ecosystems, at the time this report was being completed, the indicator was not yet finalized. Therefore, this indicator will be discussed in future editions of the report as well as other upcoming flagship reports on Planet indicators.

## With the added focus on inequality and the prosperity gap, there is a need to better measure the entire distribution of income or consumption.

#### Welfare aggregates: Consumption and income-based measures

The World Bank’s methods applied for assessing material well-being have been designed over the years primarily to measure poverty. With the added focus on inequality and the prosperity gap, the Bank’s methods need to evolve and expand from the bottom of the distribution to the entire distribution (Haddad et al., 2024; Kraay et al., 2023).

The temporal smoothing behavior of consumption, particularly for the poorest households, tends to make it the preferred aggregate for measuring poverty. This is especially the case in developing economies, which typically depend more on agriculture and have a larger informal sector – both factors making income surveys potentially biased. In advanced countries, however, it is much easier to capture incomes of individuals and hence, income surveys are conducted and reported.[[7]](#footnote-8) Most of the countries in Latin America and Caribbean and all high-income countries report income surveys while most other countries report consumption survey. Out of 169 countries, the latest survey for 104 was based on consumption.

Despite these differences, both aggregates are used indistinctively in the measurement of the World Bank goals to maximize the number of countries monitored. Although this creates issues of comparability in the measurement of poverty, it allows the coverage of the global goals to be expanded. The distinction becomes more problematic, however, in the analysis of prosperity and inequality where larger parts of the distribution matter. A clear issue is that countries in Latin America and the Caribbean typically use income data, while in Sub-Saharan Africa consumption data is more readily available. The two regions stand out with high levels of inequality, but the differences in their underlying welfare measures makes it difficult to compare their levels of inequality.

Earlier studies indicate that while levels of inequality may differ, the change in inequality and country rankings are relatively consistent regardless of whether income or consumption measures are used. World Bank (2016), compares both income- and consumption-based Gini indexes across several countries in Eastern Europe and Central Asia for the same years. Figure 1b plots the income Gini (left axis) against the consumption Gini (right axis) for all the countries where such a comparison is possible for 2013. It is evident that consumption-based Gini indexes are considerably lower than income-based Gini indexes. However, the rankings remain relatively similar. Figure 1b also examines whether inequality trends differ when using consumption instead of income. The analysis in Figure 4 of chapter 2 also points to the same results. Yet, significant more work is needed in collecting both income and consumption data and assessing the implications of using one of the other for monitoring global shared prosperity and inequality.

**Figure 1. Inequality levels and trends using income and consumption**

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Source: Poverty and Shared Prosperity Report 2016. Taking on Inequality. World Bank.

#### Capturing top incomes for measuring inequality

The World Bank indicator on high inequality is derived from household surveys, which often underrepresent the wealthiest individuals due to issues like underreporting and non-response (Atkinson and Piketty, 2007; Haddad et al., 2024). The smaller sample size of the very rich exacerbates this problem. Additionally, surveys typically fail to adequately capture entrepreneurial and capital income (Burkhauser et al., 2015; Flachaire et al., 2023; Piketty et al., 2019; Yonzan et al., 2022). As a result, inequality measured using survey data is generally lower than when using data that includes the wealthy, such as administrative tax records (Piketty and Saez, 2006; Saez and Zucman, 2016).

While tax data is not specifically designed to measure inequality, it better captures the incomes of the wealthy. This leads to higher inequality estimates compared to those derived from surveys alone. Efforts to "correct" the top end of survey data have been made at the country level (Burkhauser et al., 2015; Flachaire et al., 2023; Jenkins, 2017; Piketty et al., 2019). However, outside high-income countries, tax data is limited and often provides an incomplete picture due to the lack of comprehensive personal income taxes (van der Weide et al., 2018).

Moreover, the best method to combine survey data with administrative records remains unclear. The approach taken to merge these data sources can significantly affect inequality estimates (Alvaredo et al., 2023; Auten and Splinter, 2024; Flachaire et al., 2023).

Hence, a comprehensive adjustment to all countries around the world for underreporting at the top is still not feasible. The World Inequality Database (WID) systematically adjusts survey data for missing top incomes, using a range of sources including tax data where available but also national accounts (Blanchet and Chancel, 2016; World Inequality Lab, 2024). As expected, the adjusted Gini index (taken from WID is greater than the survey-based Gini (using the World Bank data), as indicated by the upward sloping lines in Figure 2a. This shows that an adjustment for underreporting at the top would have direct implications for measuring the number of countries with high inequality. However, it is important to bear in mind that the threshold value for high inequality would also have to be adjusted if adjusted Gini indices are used. The threshold of 40 was set at approximately the top 3rd of countries, using survey-based Gini indices.

Figure 2a also shows that some countries show lower levels of inequality with the WID adjustment, which requires further investigation. The WID acknowledges that the data are not of the same quality in all countries (World Inequality Lab, 2024). Even in well-established cases, debates continue on what has driven changes across time – is it the changes in incomes at the top or the changes in income reporting in the tax data (for the debate in the US case, see Brookings 2024).

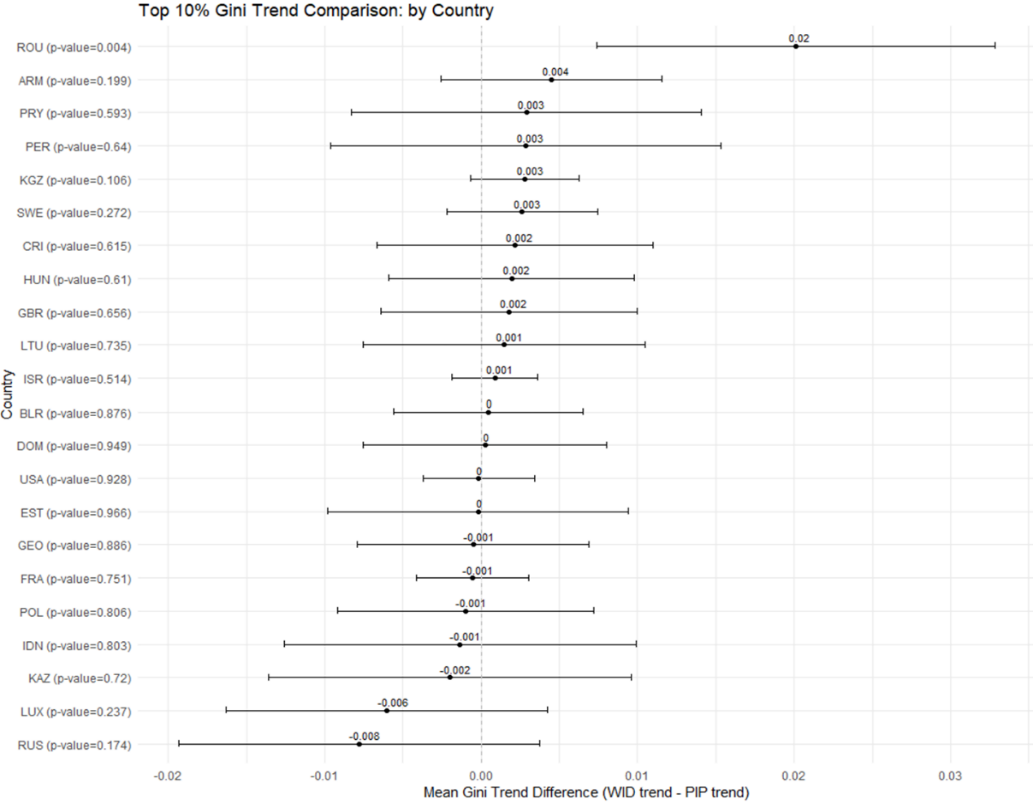
**Figure 2: Differences in levels of Gini largely driven by the underestimation of top incomes in survey data**

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| 1. Comparison of Gini | 1. Comparison of top income shares |
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Note: Compares the top income of survey and top income in data adjusted using tax records. See also Atkinson and Piketty (2001) for rich countries.

Regardless of the level differences, it is reassuring to know that the changes across time for income surveys and income tax data remain fairly close. Figure 2b compares the trend in the top 10 percent income share from the two sources. The two series track reasonably well. Figure 3 reports the differences in the Gini changes over time for select countries with enough data to conduct the test. Besides Romania, where the trend in the Gini index of the WID is 2 percentage points higher on average than the trend in the same from PIP, the differences in trends in all other countries are not significantly different from zero. In other words, the levels might be different, but the changes are comparable both incorporating top incomes and not.

**Figure 3: Comparison of country trends in the Gini index between WID and PIP**



#### Inconsistencies between Household Surveys and National Accounts

It is not just at the top of distributions that household surveys may fail to capture income and consumption. Household surveys routinely omit certain spending, such as spending on durable goods or housing, and at times do not capture all relevant food consumption due to limitations in the questionnaires or because of poor data quality (Foster and Daylan 2024). Partly for these reasons, large gaps have been observed between mean income and consumption from household surveys and national accounts (Deaton 2005, Ravallion 2003, Prydz et al 2022).

Some researchers have responded to this misalignment between surveys and national accounts by arguing that mean income or consumption in household surveys should be scaled up to match mean national income or household expenditure as measured in national accounts (Sala-i-Martin and Pinkovskiy 2014). More sophisticated methods such as the WID approach (Figure 3) also distributes national accounts aggregates to create a distribution of income or consumption (Piketty et al. 2018).

This rescaling can be problematic, and more research is needed on this area. National accounts are not immune to measurement error themselves (Ravallion 2003). National accounts data have been found to change dramatically when the base year is changed (Economist 2014), to be overestimated by autocrats (Martinez 2022), underestimated to get more foreign assistance (Kerner, Jerven, and Beatty 2017), and to have ample room for improvement in developing countries (Angrist et al. 2021). Furthermore, the literature that scales up to national accounts typically ignores the issue of how to adjust the poverty lines, which have been set with a survey-based distribution in mind. In addition, national accounts and household surveys do not measure identical concepts. For example, some spending from consumption aggregates is deliberately excluded because it is deemed to be less relevant for households’ welfare (Mancini and Vecchi 2022).

For these reasons, the Atkinson Commission on Global Poverty argued that a more nuanced approach to deal with measurement concerns in household survey data is to adjust for these concerns rather than to introduce new concerns with national accounts data (World Bank, 2017)

## Non-monetary welfare: Improving the measurement of the livable planet indicator of food insecurity

Important dimensions of welfare are not captured by monetary measures. The World Bank’s multi-dimensional poverty measure (MPM) fills this gap by aggregating poverty in both monetary and non-monetary terms. As noted in the 2018 PSPR, the MPM could be expanded with additional dimensions (such as health and security), but this importantly depends on the availability of these data (World Bank, 2018). The data concerns will not be the focus here since they have been discussed in the 2018 PSPR (World Bank, 2018).

The inclusion of the planet indicators (see table 1) brings more explicit recognition of these non-monetary dimensions. One of the key additions to the World Bank’s new vision is the inclusion of food and nutrition security. Furthermore, the new Global Scorecard proposes to measure food and nutrition security using the Food Insecurity Experience Scale (FIES), and further highlights another critical food security outcome- share of children under five that are stunted- as another key indicator to be tracked by the World Bank. Here, we briefly describe the complexity of the concept of food and nutrition security, how the approach proposed in the Global Scorecard might align with best measurement practices, and ongoing efforts to improve global measurement.

The most commonly used definition of food security was agreed upon by stakeholders at the 1996 World Food Summit, with the original formulation stating that food security is “a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life.” In practice, food security is described through four dimensions- (a) food availability or the existence of enough food for people to eat, (b) food access or the ability of individuals to financially afford and physically access food that is available to eat, (c) food utilization or the ability of individuals to properly absorb the micro- and macro-nutrients in the foods that they eat, and (d) stability or individuals being food secure in all dimensions at all times (e.g., Barrett 2010).

Each of the dimensions of food security are hierarchical in the order listed above, where adequacy in a food security dimension requires adequacy in the previous dimension. For example, adequate food availability is necessary, but not sufficient, for adequate food access. And the chain continues all the way through food stability. Furthermore, each dimension of food security is itself multidimensional. For example, food access includes both the consumption of an adequate number of calories and a sufficient quality of food consumed (e.g., Barrett 2010).

As described above, the food security outcomes tracked in the Global Scorecard- the FIES and the share under five that are stunted- correspond to measures of food access and food utilization, respectively. Although important indicators, it is very difficult to properly measure and describe changes in food and nutrition security with two indicators given the four separate dimensions of food and nutrition security and the multidimensionality of each dimension. But beyond the multidimensionality, the food access dimensions are particularly difficult to measure precisely, and there is a significant amount of measurement error in any single measure, such that it becomes difficult for a single food access measure to accurately capture the concept.

There are two separate sources of measurement error introduced in the measurement of food access. First, it is difficult to precisely measure the calorie and nutritional content of all food consumption. Although there are several ways to estimate these figures, the methods that produce the most precise estimates involve individual-level surveys that are complex, expensive, difficult to analyze, and nearly impossible to perform on a large scale (e.g., Gibson 2005; Fiedler et al. 2013; etc.).[[8]](#footnote-9) In the absence of these difficult-to-collect and expensive data, researchers often turn to household consumption and expenditure surveys (HCES's) to measure the quantity and quality of foods consumed (e.g., Wiesmann et al. 2009; etc.).

However, estimates from HCES's are subject to a substantial amount of measurement error. For example, there is a wide range of macro- and micro-nutrients contained in nearly all individual food items captured in a typical HCES and it is difficult to assign the caloric and nutritional content of each food item consumed (e.g., USDA 2019). It is also difficult to identify the nutritional content of many processed foods and food consumed outside of the household that are becoming important increasingly to modern diets (e.g., Deaton and Subramanian 1996). These issues compound other traditional sources of measurement error that affect the measurement of expenditure in HCES's, such as recall biases, impacts of different questionnaire formats, and a wide variety of other concerns (e.g., Beegle et al. 2012; etc.). The variance on estimates of the quantity and quality of food consumption are therefore large and are potentially increasing over time as households consume more processed foods and meals outside of the household (e.g., Tandon and Landes 2011; Tandon and Landes 2014).

In addition to the difficulty of measuring the nutritional content of food consumption, the second source of measurement error in measuring food access is driven by the fact that many of the dietary needs of individuals are unobservable and based on individual choices and activities (e.g., Institute of Medicine of the National Academies 2006). Although many studies make assumptions regarding caloric needs of individuals based on their age, sex, and assumed activity level (e.g., FAO 2023; etc.), such uncertainties further add to the extensive measurement error in food access metrics.

Given these difficulties and the need to obtain estimates of food access in real time and in data-poor environments, practitioners and researchers have increasingly relied on metrics that are relatively easy to implement while also approximating the degree of food access in its many dimensions (e.g., Swindale and Billinsky 2006; WFP 2009; Maxwell and Caldwell 2008; etc.). Two common approaches include (1) measuring dietary diversity and the frequency with which individuals and households consume certain food groups, such as the Food Consumption Score and the Household Dietary Diversity Score (e.g., Swindale and Billinsky 2006; WFP 2009); and (2) measuring food coping strategies often associated with consuming too little or consuming a poor quality diet, such as the Coping Strategies Index and the Reduced Coping Strategies Index (e.g., Maxwell and Caldwell 2008).

However, others have argued that additional psychological aspects related to food access should be captured in standard metrics (e.g., Webb et al. 2006; etc.). An additional set of experiential measures of food access, such as the Food Insecurity Experience Scale, the Latin America and Caribbean Food Security Scale, and the Household Food Insecurity Access Scale, extend food access measurement to these dimensions by asking about food coping strategies and anxiety over insufficient food access (e.g, Maxwell et al. 2014). However, there are significant additional challenges to incorporating anxiety regarding poor food access and other subjective measures. In particular, answers to subjective welfare questions depend on respondent-specific scales that: (1) may not be comparable across individuals or stable over time; (2) are potentially subject to frame-of-reference effects; and (3) suffer from measurement errors, over and above those affecting traditional welfare metrics (e.g., Ravallion 2013; Benjamin et al. 2023; Tandon 2024; etc.).

Given these difficulties, there is a growing literature illustrating that many of the food access metrics described above do not overlap when collected from the same household (e.g., Maxwell et al. 2014; Broussard and Tandon 2016; etc.). Because of these factors, it is often recommended that food access is captured using more than a single measure and that improvement in food access should be validated across each broad category of food access metrics, using at least one dietary diversity-based indicator and at least one coping-strategy-based indicator (e.g., Vaitla et al. 2017; IPC 2023; etc.).

Recent research further illustrated the difficulty in interpreting estimates of food access that use the FIES alone. Using evidence from 10 West African countries, Lain et al. (2024) illustrate that there is a similar prevalence of food insecurity according to the FIES amongst segments of the population that are likely undernourished and segments that are likely not undernourished in four out of 10 countries. Furthermore, the authors found that there is a relatively large prevalence of food insecurity according to the FIES in the segments of the population that is least likely to be undernourished in five out of the 10 countries. Although the work cannot identify exactly why these differences exist between the FIES and other food access metrics in several countries, one possibility highlighted is the difficulty interpreting subjective questions on food access that are a significant component of the measure.

Although best practices suggest utilizing multiple food access metrics at the household level to validate changes in food access, the FIES is the only household-level indicator that is currently available globally. The only other indicator available is the Prevalence of Undernourishment (PoU), which is calculated from a combination of national accounts data, food balance sheets, and household surveys (e.g., FAO 2023). Thus, it is important to interpret changes in the FIES cautiously, to interpret those changes along with changes in the PoU, and to corroborate changes using closely aligned measures, including extreme poverty (e.g., Lain et al. 2024).[[9]](#footnote-10)

Even at the country level, these challenges of utilizing multiple food access metrics remain. In a recent stock-taking exercise of the statical system across regions, it was found that there were significant gaps in the types of information available with which to measure progress towards improving food access using official statistics (e.g., Maxwell et al. 2024). For example, in East Asia and the Pacific region, out of 16 countries covered by World Bank global poverty databases,[[10]](#footnote-11) only one country collected more than a single food access metric in the most recent household survey from which monetary poverty was estimated. Furthermore, of these countries, eight collected only the FIES, and six collected no food security information at all (e.g., Maxwell et al. 2024). Given difficulties in following best practices even within individual countries regarding the measurement of changes in food access, the same caveats that apply at the global level also apply to the vast majority of individual countries.

However, there are efforts under way to improve global and country monitoring of food access. In particular, Maxwell et al. (2024) more fully illustrates the insufficiency of food access measurement at both the global and country level. The work further identifies how existing information contained in the detailed food consumption modules in the extensive collection of household consumption surveys from across the world can be used. In particular, the work illustrates for a set of West African countries that existing data can be used to construct measures of calorie consumption, undernourishment, and diet quality across the world, and that in a set of West African countries these indicators all align well with more standard and existing food access metrics. And lastly, the work further offers guidance on how best to improve food access measurement in national statistical systems going forward, including multiple food access metrics in each survey, utilizing more of the consumption data to refine existing food security statistics, and ways that might reduce some of the noise in trying to infer the calorie content of consumption quantified using non-standard units.

## Measuring climate risks for people and its components

The new vision also tracks the percentage of people at risk of extreme weather events. Measuring the risk from climate-related hazards is a complex task. Each of the three components of the indicator–hazards, exposure, and vulnerability–is composed of multiple dimensions, making the indicator a highly complex measure. The combination of all three adds to the complexity. In the following, we discuss some of the key limitations and future areas of improvement.

#### Measuring hazards and exposure

The definition of hazards requires a selection of hazards which are likely to impact the welfare of people from a broader set of all possible hazards (Doan et al., 2023). The indicator considers four climate-related hazard events–floods, droughts, heatwaves and cyclones–which have significant impacts on livelihoods (IPCC, 2023).[[11]](#footnote-12) Geopyhsical hazards and environmental factors, such as earthquakes or air pollution, as well as climate trends such as sea-level rises, are not considered. It also omits some climate-related hazards such as wildfires, which rising temperatures make more devastating (IPCC, 2023).[[12]](#footnote-13)

The measure only considers the localized impact of the hazards. However, hazards also have indirect effects and spillovers, such as changes in prices or demand spurred by shocks in other regions (Cevik and Gwon, 2024; Hallegatte et al., 2016). Capturing transmission and indirect channels requires vast data including localized input-output data. Exposure through location can also be endogenous to hazards as these drive mobility (World Bank, 2023).[[13]](#footnote-14) Accounting for indirect effects is not feasible at this stage for a global indicator because of data requirements and the fact that these vary across settings (Cevik and Gwon, 2024; Somanathan et al., 2021). The measure thus represents a lower bound estimate of the population at risk from climate hazards.

Second, for each hazard, an intensity level that corresponds to an extreme event and the probability that such an event occurs needs to be selected to define the population exposed. The choice of intensity thresholds is based on literature to define what constitutes a severe event with potential to cause significant welfare impacts to the exposed population (Doan et al., 2023). A limitation may be that there is a trade-off between global and context-specific numbers, as the impact of intensity levels can vary between contexts. The probability of occurrence for events is given by its return period, which reflects the likelihood that a hazard occurs at or above a specific intensity in a year. For all hazards except for drought, a return period of 100 years is used, that reflects a larger than 50 percent chance of experiencing an event during a person’s lifetime.[[14]](#footnote-15) For droughts, data only goes back 39 years and there is ongoing work to generate probabilistic scenarios.

To derive populations that are exposed to hazards, Doan *et al.* (2023) overlay and resample urbanization data (GHSL) with gridded population data (GHS-POP). Hazard intensities and probabilities are then matched with these cells to define the share of urban and rural population exposed to the different hazard types. A key constraint is the different spatial resolution of indicators. Hazard data is resampled to match the population grids, so that each cell is exclusively classified as rural or urban and exposed or not exposed.[[15]](#footnote-16) Resampling of different spatial resolutions can introduce measurement error. For instance, floods are measured with a resolution close to 90 meters, whereas the spatial resolution for cyclones is about 11 kilometers, and 30 kilometers for heatwaves. Work is underway to have a more fine-grained spatial resolution for heatwaves, which however tend to be less localized than floods, for example.

#### Measuring vulnerability and risk to climate hazards

Similar considerations apply to measuring vulnerability. Vulnerability captures deprivations of households along seven dimensions (see the appendix of chapter 3 for more details).[[16]](#footnote-17) There is a range of additional factors that could matter for households’ coping and adaptive capacity which are currently not included in the vulnerability index, such as the type of assets that households hold, insurance, such as health or home insurance, or gender.[[17]](#footnote-18) In some cases, these variables are not available or comparable for a large enough global sample, and in other cases variables are not deemed to add sufficient additional information on vulnerability. A globally comparable indicator also implies that it may not be relevant to the same extent in all countries. For example, in terms of thresholds, a household is considered vulnerable if no adult has primary education. Outside of low-income countries, this threshold may not be relevant. Furthermore, some vulnerability dimensions may be more specific to certain hazards than for others. Electricity access makes the usage of fans more likely which reduces the impacts of heatwaves (Carleton et al., 2022), but floods or storms may destroy electricity infrastructure. These interconnections between hazards and vulnerability remain an area for future work.

In contrast to the availability of global gridded data on hazards, data on vulnerability mostly comes from household surveys and is (i) much more spatially aggregated for several of the dimensions, and (ii) not available in surveys for all countries. As data on vulnerability is typically only representative or available at subnational administrative regions, assumptions need to be made on the distribution of characteristics along exposed and non-exposed grids within the region. For the risk indicator, it is assumed that populations in exposed and non-exposed areas do not differ along vulnerability characteristics. While this might be a strong assumption, Doan *et al.* (2023) test assigning different vulnerability characteristics to exposed and non-exposed areas, and find that this would lead to less than a one percentage point difference in results in most areas.

A person is considered vulnerable if they belong to a household deprived in any of the dimensions. If all vulnerability indicators were collected in one survey in all countries, one could directly infer whether a person is vulnerable along at least one dimension. While most data is available in the Global Monitoring Database (GMD), data on social protection, financial inclusion, and some of the non-income dimensions missing in GMD for a particular country are based on other surveys, censuses or administrative datasets.[[18]](#footnote-19) Data from other sources are fused into the data from the GMD by randomly assigning households as vulnerable or non-vulnerable based on the rate of vulnerability observed in the strata that the household belongs to (strata are based on information on rural/urban, welfare quintile and subnational level if available).[[19]](#footnote-20),[[20]](#footnote-21) The share of vulnerable people (at least one dimension) are then calculated for the region for which the data is representative. These steps are repeated 100 times to account for household heterogeneity within each subgroup, and the final number is the average share of vulnerable households among these repetitions. This approach preserves the share of those that are vulnerable across datasets, however, inevitably the imputation approach introduces some inaccuracy. The population at high risk from extreme hazards is then calculated by multiplying the share of vulnerable with the population exposed.[[21]](#footnote-22) Another important area for future research is whether being at risk already changes populations behavior and welfare, even without the materialization of shocks.

The final measure of risk currently does not differentiate between populations that are more or less frequently affected by hazard events above respective thresholds, or by varying levels of intensity above the threshold. Furthermore, the cumulative effects of low-intensity but high-frequency events can also be sizeable for people’s welfare (Hallegatte et al., 2020). The impacts of some hazards are immediate, such as flooding or cyclones, whereas others are slower (e.g., heatwaves), and costs between different types of hazards are likely to differ. The indicator thus reflects the extensive rather than intensive margin of impacts. Furthermore, probability distributions of hazards will likely change in the future due to climate change, and what the most meaningful hazards are for human welfare today are not necessarily the same that will be most impactful in the future. Doan *et al.* (2023) provide analyses of choosing different return periods of hazards. Reflecting how climate change will affect return periods, and how this will determine exposure rates of populations, is an area of ongoing research.

A further caveat is that survey data is not available for every year across all countries, which also affects this indicator like the monetary and non-monetary poverty indicators. In addition, within one country, data sources can be from different years, which could introduce measurement error in the imputation process. For some countries the last available survey is too old for it to be included in the indicator. For income and consumption there are well-founded methods of extrapolating and interpolating across years, but not for the other indicators. Therefore, countries for which surveys are too old are excluded from the vulnerability indicator.

The first-best option to improve the measurement of vulnerability are better and more frequent household surveys. Including all indicators in a comparable manner in household surveys across countries would reduce biases from the imputation process. Consultations on such harmonization are underway. More frequent surveys would allow to have a more accurate and up-to-date picture of vulnerability.

## Projecting emissions, warming, and their impact on poverty forecasts- some reflections

There is broad consensus that global warming (caused by anthropogenic emissions) will have negative consequences for economic growth and poverty reduction in the future. However, there is considerable uncertainty around the exact effect sizes. These depend on a variety of factors and assumptions (Tol, 2024). In this report, rather than presenting a wide range of possible impacts on poverty in the future, we limit the analysis to a description of directional impacts. Rising temperatures and climate hazards are already impacting large populations today (Dang et al., 2023; Hallegatte and Walsh, 2021). There is ongoing work at the World Bank estimating how much historic and current national greenhouse gas emissions contribute to poverty globally, by incorporating the externality of global temperature increases through national emissions.

The measurement challenges facing poverty, prosperity and planetary indicators are amplified when used to project future outcomes. These challenges can broadly be grouped into two categories. First, is the uncertainty of modeling what will happen to future poverty and planetary indicators when considered in isolation. If countries’ incomes grow in accordance with the most optimistic scenarios in the Shared Socioeconomic Pathways, then global extreme poverty, and even poverty at higher lines, will be eliminated within decades.[[22]](#footnote-23) These projections have been criticized for being misaligned from historical experiences (Welch, 2024). This is most relevant for low-income countries, where projected growth rates in the next decades exceed experienced growth rates by several orders of magnitude. If historical growth performances will continue in the coming decades, then extreme poverty is unlikely to fall drastically in the coming decades (see Chapter 1). Global emissions may likewise evolve on very different paths depending on the continued use of fossil fuels and the adoption of mitigation policies.

**Figure 4: Projections in GDP per capita vary significantly between SSP scenarios**

Source: World Bank calculations based on SSP projection data, accessed through the IIASA SSP Scenario Explorer 3.0.1.  
Note: Each line represents the GDP per capita projection from one of the five SSP scenarios from either the IIASA model (Crespo Cuaresma, 2017) or by the OECD model (Dellink et al., 2017).

The second category of uncertainty emerges when analyzing the interdependence between poverty, prosperity, and planetary indicators. Studies on the future economic damages of global warming vary drastically in their conclusions. Burke et al. (2015) find that global GDP could be reduced by 20-30 percent by the end of the century, while Nordhaus (1992) suggests a reduction of 2-3 percent in a no abatement scenario. Newell et al. (2021) run 800 plausible models linking temperature to GDP and find that global GDP losses in the best performing models range from 84% to 359% gains. To these uncertainties should be added the uncertainties regarding the within-country distributional impact of temperature changes, as well as the many other impacts of climate change related to extreme weather events, such as tipping points and sea-level rise. Modelling human behavior and adaptation, as well as changes in policies is near to impossible, but will have a crucial impact on planetary outcomes and on how these planetary factors translate in poverty and prosperity.

When these two uncertainties are compounded – the uncertainties related to what will happen to poverty and emissions in the future, and uncertainty in modelling the interaction between them -- the range of possible future outcomes is massive. According to one paper that addressed parts of these uncertainties, the impacts of climate change on extreme poverty in 2070 could be anywhere between 4 million to 306 million (Moyer et al. 2023). A direct result of this uncertainty is a large variance in the social cost of carbon, which is a frequent input to loss and damage calculations and cost-benefit analysis of current mitigation policies. It is vital that work continues to reduce the range of these uncertainties.

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1. World Bank Scorecard <https://documents1.worldbank.org/curated/en/099121223173511026/pdf/BOSIB1ab32eaff0051a2191da7db5542842.pdf> [↑](#footnote-ref-2)
2. This ensures that recent data cover at least half of the population globally and in low- and lower-middle-income countries, which is the coverage threshold required for reporting the global poverty aggregate (World Bank, 2024b). [↑](#footnote-ref-3)
3. The potential benefits of data are almost limitless; there are direct benefits to individuals and indirect benefits or spillovers to the society. Data can be used, re-used, shared and re-shared for several purposes, both intended and unintended (World Bank, 2021). However, like all public goods, because they are non-rivalry and non-excludable in consumption, private producers are unable to charge commensurate prices to cover the huge cost of production and reflect the marginal benefits accruing to all consumers. Without the intervention of governments, data will thus remain scarce. [↑](#footnote-ref-4)
4. <https://unstats.un.org/unsd/statcom/53rd-session/documents/BG-3a-Position-Household-Survey-for-Next-Decade-E.pdf> [↑](#footnote-ref-5)
5. See also <https://edgar.jrc.ec.europa.eu/methodology> [↑](#footnote-ref-6)
6. EDGAR v8.0's GHG estimates for combustion and industrial processes are based on the application of IPCC GHG accounting methodology across all countries. EDGAR uses data from the IEA, Energy Institute, UNFCCC, FAO, and other reputable sources to derive GHG emissions at subnational and sub-sectoral level based on activity and emission factors. [↑](#footnote-ref-7)
7. Conceptually, income is a measure of the potential purchasing power of all goods and services while consumption is a direct measure of the goods and services that the individual or household has actually obtained. Richer individuals and households tend to save more compared to poorer households. This means that on average the inequality of consumption (realized outcomes) is usually lower than that of income for the same set of households. In addition, while consumption tends have less fluctuations over time, income, is generally more volatile in the sense that it may be influenced greatly by seasonal factors or by interruptions in employment, particularly in the agricultural and informal sectors. Households can also declare zero and even negative income on a survey but exhibit a consumption level that is strictly positive drawing from savings. Sudden losses of employment can reduce income dramatically, but changes in consumption depend on the availability of factors such as safety nets and within- and between-household transfers, and on whether shocks are transitory or permanent (Jappelli and Pistaferri, 2010). Other issues such as consumption of home-produced foods also tends to be difficult to capture in surveys leading to comparatively zero or negative income. [↑](#footnote-ref-8)
8. For example, one method is observed-weighted food record data. See Gibson (2005) for details. [↑](#footnote-ref-9)
9. Under plausible and empirically supported assumptions, undernourishment is concentrated amongst the extreme poor. And thus, the degree of overlap between the FIES and extreme poverty is informative on whether those that are moderately or severely food insecure are those that are most likely to be undernourished. [↑](#footnote-ref-10)
10. These figures omit countries in which the most recent household survey was fielded before the FIES was developed in 2014. [↑](#footnote-ref-11)
11. Please see “WBG SCORECARD FY24-FY30 METHODOLOGY NOTE” for further details on data sources and measurement for the included hazards and vulnerability indicators. [↑](#footnote-ref-12)
12. Wildfires are also direct consequences of human activity such as arson or negligence, and global data availability limits accuracy of predictions, for instance because effects can be felt in different locations than fires themselves (think of smoke and air pollution) (Qiu et al., 2024). [↑](#footnote-ref-13)
13. The effect of climate shocks on migration is complex, where household responses depend on levels of assets and risks of staying, and where rapid-onset shocks (such as floods) have stronger effects than slow-onset changes (Kaczan and Orgill-Meyer, 2020). [↑](#footnote-ref-14)
14. A return period refers to the average time it takes for an event at a specific intensity level to occur, or put differently the probability of an event occurring every year. A 100 year return period means that on average a specific event occurs once every 100 years. Naturally, this means that it can occur more often than once in 100 years. With an average global life expectancy of around 70 years, the probability of experiencing an extreme weather event with a 100-year return period is about 50%. [↑](#footnote-ref-15)
15. Note that the urban and rural distinction is relevant for drought hazards and transport as a physical propensity to experience to severe loss (vulnerability). Both are only measured for rural areas. [↑](#footnote-ref-16)
16. The dimensions are income, education, social protection, financial inclusion, water, energy and transport. [↑](#footnote-ref-17)
17. Natural disasters disproportionally affect women, in terms of income, employment and life expectancy (Erman et al., 2021). Power dynamics and traditional gender-roles influence how women are affected by natural disasters, and are able to cope in the aftermath (Lankes et al., 2024). Extreme weather events have been shown to increase domestic violence against women (Abiona and Koppensteiner, 2018; Sekhri and Storeygard, 2014). Access to and control of assets are important determinants in the vulnerability to climate change, according to which women are highly disadvantaged within households. Women still shoulder the majority of domestic work, which becomes even more pronounced after disasters, hindering their ability to pursue or resume employment (Eastin, 2018; Erman et al., 2021). Not being able to engage in income-generating activities further reduces long-run opportunities and exacerbates vulnerabilities. Eastin (2018) shows that climate shocks and natural disasters are associated with declines in women's economic and social rights, and that this decline is more pronounced in poorer and more agricultural societies., [↑](#footnote-ref-18)
18. Other data sources include the World Bank ASPIRE (social protection), World Bank FINDEX (financial inclusion), World Bank Global Electrification Database (energy), the WHO-UNICEF Joint Monitoring Program (water) and the UN Sustainable Development Center indicator (transport). [↑](#footnote-ref-19)
19. For countries which have some missing data but near universal values for certain variables (such as electricity, water or social protection access), the near universal value is assumed for the whole population. [↑](#footnote-ref-20)
20. The definition of variables can vary across surveys. For example, surveys in the GMD typically include a variable on ‘improved water access’. The relevant variable for the SDGs and for the Scorecard indicator however is access to ‘basic drinking water, sanitation services, or hygiene’, which could make comparisons between indicators difficult. Please see “WBG SCORECARD FY24-FY30 METHODOLOGY NOTE” for further details. [↑](#footnote-ref-21)
21. Note that to aggregate grid-level exposure to subnational regions, the population count in grid cells that are partially covered by administrative units is weighted by the fraction of the grid cell covered by the statistical region. [↑](#footnote-ref-22)
22. The Shared Socioeconomic Pathways (SSPs) are a set of five scenarios developed by the climate research community, which depict different pathways of how global society, demographics, and economics might change over the next century and how these changes could impact greenhouse gas emissions and global warming (Riahi et al., 2017). [↑](#footnote-ref-23)