Food and Agriculture Organization of the United Nations

Well-being dynamics in sub-Saharan Africa

A spatial perspective across territorial typologies

FAO Inclusive Agrifood Systems Working Papers No. 1

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Abstract

In sub-Saharan Africa (SSA), efforts to track poverty trends and spatially targeted interventions are constrained by a lack of recurrent and sufficiently granular data. In this paper, we address this lack of information by using a new dataset of spatially explicit welfare indicators (developed by Atlas AI) to examine the spatial distribution and temporal dynamics of welfare in the region. We also deepen our understanding of these dynamics by examining how variations in market proximity, biophysical and climatic characteristics have influenced welfare dynamics in the SSA region over the last two decades. We find that while continent-wide wealth and per capita expenditures have improved between 2003 and 2021, these trends have been highly concentrated in areas that are more urban, and within populations already at the top of the wealth distribution in 2003. Moreover, we find that there have been significant improvements in welfare for the parts of SSA with the lowest asset endowments at baseline, but limited or no progress in places that were in the middle or the bottom of the baseline expenditure distribution. The analysis shows that welfare progress has been particularly constrained in the tropical lowlands of SSA – where most of the rural population resides – and in desert and arid areas. Worryingly, these are also the agroecological zones that will likely expand as a result of climate change. Finally, rural populations living in areas where there is limited access to markets and biophysical conditions that constrain agricultural diversification potential have experienced virtually no improvement in welfare over the last 20 years.

Keywords: sub-Saharan Africa (SSA), dynamics of welfare inequality, poverty trends, Atlas AI indicators, market proximity, biophysical characteristic, climatic characteristic, climate change

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Abbreviations

AWI	asset wealth index
EOG	Earth Observation Group
FAO	Food and Agriculture Organization of the United Nations
DHS	Demographic and Health Surveys
DMSP	Defense Meteorological Program
GAEZ	Global Agro-Ecological Zones
GDP	gross domestic product
GHSL	Global Human Settlement Layer
GIS	geographic information system
GPS	Global Positioning System
GPW	Gridded Population of the World
GSD	ground spatial distance
IIASA	International Institute for Applied Systems Analysis
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
JAROS	Japan Resources Observation System Organization
JAXA	Japan Aerospace Exploration Agency
LGP	length of growing period
LSMS	Living Standards Measurement Study
PALSAR	Phased Array type L-band Synthetic Aperture Radar
PCA	principal component analysis
POP	population dataset
POV	population living below the extreme poverty line or extreme poverty levels
PPP	purchasing power parity
RCP	Representative Concentration Pathway
SD	standard deviation
SP	household per capita expenditures
SRTM	Shuttle Radar Topography Mission
SSA	sub-Saharan Africa
URCA	urban–rural catchment area
VIIRS	Visible Infrared Imaging Radiometer Suite

Introduction

The last 20 years have seen significant reductions in poverty in sub-Saharan Africa (SSA) as a whole. However, this progress has been highly uneven within and between the various countries of the region (World Bank, 2022). And while the data for monitoring poverty levels in SSA have improved in recent years, there remains a lack of spatial granularity in poverty estimates. This lack can often obscure important geographical disparities in poverty reduction, as generated by the various processes of economic development. Spatially explicit understandings of poverty and welfare dynamics are critical, given the importance of location in shaping household livelihood strategies – including agricultural potential and access to markets. While this is relevant for all regions of the world, it is particularly relevant for SSA, given its largely agrarian economies and the rapid growth of its urban agglomerations (Pesche, Losch and Imbernon, 2016).

The dynamic relationship between physical environment and welfare is widely recognized in the literature (Bigman and Fofack, 2000a; Dixon *et al.*, eds., 2019; Giller *et al.*, 2021; Nguyen and Dizon, 2017; Zhou and Liu, 2022). In particular, the literature on economic geography (Fujita, Krugman and Venables, 1999; Fujita and Thisse, 2002; Lall, Henderson and Venables, 2017; Puga, 1999) suggests that as economies grow, economic development tends to cluster in places that are more favourable for economic activity, for example because such places are endowed with greater natural resources, more suitable agroecological conditions and better market access. As these places experience income growth, they pull in new economic migrants, leading to rapid population growth and synergies created by the economies of agglomeration. The higher concentration of people and economic activities leads to economies of scale, which further sustain and reinforce growth cycles (Fujita and Thisse, 2002; Lall, Henderson and Venables, 2017; Nguyen and Dizon, 2017). At the same time, inequality is created between regions that are more and less endowed (Fujita and Thisse, 2002), with the latter facing difficulties in catching up. This suggests that geographical disparities between places are a fundamental element of the economic development process, and must be addressed through geographically targeted policy actions.

Welfare indicators that are aggregated at the national level mask existing spatial variabilities, giving a false sense of homogeneity within a country and within lower administrative levels (Henninger and Snel, 2002). In fact, poverty varies not only within countries, but also throughout other territorial typologies both within and across country borders. Unfortunately there is a lack of comparable survey data across both locations and time; this has limited analysis of the spatial trajectories of poverty and wealth accumulation (Liu, Liu and Zhou, 2017),[1] particularly for underrepresented and isolated communities (Janz *et al.*, 2023). Despite the significant progress that has been made by national statistical offices to enhance the quality of data collection and survey design, to date, multicountry analysis of African poverty has been hampered by differences in data collection tools, a lack of unified indices, issues in terms of

[1] Since 1995, only 18 of the 48 SSA countries listed in the World Bank's PovcalNet database had more than one household consumption survey to track poverty (Christiaensen *et al.*, 2012).

quality, and problems in the calculation of income and expenditure aggregates (Beegle *et al.*, 2016). Cross-country and continent-wide analysis has also been limited to measuring a single welfare indicator – i.e. usually consumption-based data gathered from individual country household surveys, adjusted by purchasing power parity (PPP) (Azzarri and Signorelli, 2020; Chen and Ravallion, 2010; Ferreira *et al.*, 2016; Jolliffe *et al.*, 2022), or deflators computed at irregular intervals of time (Christiaensen *et al.*, 2012).

In this study, we leverage a new dataset of high-resolution welfare indicators, as developed by the technology company, Atlas AI, to examine the spatial distribution and temporal dynamics of asset wealth, per capita expenditures, and poverty levels in SSA over the period from 2003 to 2021. We ask how welfare dynamics in predominantly agrarian societies are affected by the different geographical factors with which they are often associated – namely degrees of urbanization, global agroecological zones and dominant farming systems. These geographical factors, analysed as typologies, reflect a location's potential to access markets and populated areas, as well as its potential for diversification and growth in agricultural productivity. In providing some answers, we build on the work of past studies (Ratledge *et al.*, 2022; Yeh *et al.*, 2020; Bigman and Fofack, 2000b, 2000a; Giller *et al.*, 2021; Hengsdijk *et al.*, 2014), to analyse the spatial distribution and temporal dynamics of three specific and related welfare indicators – asset wealth, poverty, and per capita expenditures – across different territorial typologies in SSA, from 2003 to 2021. We also address gaps in several previous studies by examining welfare dynamics with a high level of spatial granularity over the last two decades.

Consistent with national World Bank estimates, we find general improvements in all three welfare indicators between 2003 and 2021.[2] However, our findings further demonstrate that most of the progress was concentrated in the more urban areas, and among populations that were already at the top of the wealth distribution in 2003. Moreover, rapid welfare improvements in urban areas and in places with populations at the top of the wealth distribution coincided with sharp increases in welfare inequality. Outside of these more economically dynamic areas, our findings show that welfare progress over the last two decades has been limited. This is particularly the case for places that were in the middle or bottom quintiles for expenditure distribution in 2003, the baseline year for the datasets. Many of these poor-performing areas are located in desert and arid climate zones, and in rural agroecological zones that are classified as tropical lowlands – where nearly three quarters of SSA's rural population live. Conversely, welfare progress has been significant in areas characterized by high-value, commercially oriented farming systems (e.g. fish-based and humid lowland tree-crop systems).

The analysis paints a worrying picture of the spatially uneven progress being made in improving welfare in SSA over the last 20 years, and makes a strong case for incorporating territorial approaches – along with better spatial targeting of poverty reduction actions – to address the unique needs and challenges of SSA's diverse geographies. Improving our understanding of the spatial features that influence poverty dynamics and distributions over time can help improve poverty mapping for better, more targeted poverty-reduction interventions in rural areas (FAO, 2021). Similarly, combining geographical targeting with common targeting approaches that are

[2] For more information, see the poverty headcount ratio at USD 2.15 a day (2017 PPP), as percentage of the population for SSA (World Bank Poverty and Inequality Platform): https://data.worldbank.org/indicator/SI.POV.DDAY?end=2019&locations=ZG&start=2003&view=chart

based on socioeconomic analysis can lead to more effective interventions that are better tailored to the geographical context and welfare of the population.[3]

The rest of this paper is organized as follows: The next section presents a literature review and conceptual framework of the different welfare indicators and spatial typologies considered in this study, as well as differences by territorial typology. The section on Methods and data describes the three welfare indicators generated by Atlas AI data, the different territorial typologies over which welfare dynamics are then explored, and the methods used. The final section presents the main Results, along with a discussion of key findings. The paper also includes an Annexes, which provides more detail on the data and some of the main findings.

[3] The literature already considers the advantages and disadvantages of geographical targeting on poverty alleviation programmes, and the ways in which geographic information systems may be suited to improve poverty mapping (Bigman and Fofack, 2000a). These should be complemented with different socioeconomic targeting mechanisms. For example, proxy means testing assigns a welfare score to the potential beneficiary based on project objectives and location welfare characteristics. Scores can also be constructed with multidimensional, index-based approaches (Alkire and Fang, 2019; Santos and Villatoro, 2018), or with the use of monetary, econometrics-based approaches. In practice, most interventions rely on more than one targeting mechanism.

Literature review and conceptual framework

This section provides an overview of the two analytical tools used in the study – welfare indicators and spatial typologies. It also identifies some of the most relevant literature with regard to the assessment of spatial relationships between them.

Welfare indicators

The study uses three indicators of well-being to enrich our understanding of welfare dynamics in SSA: asset wealth index, household per capita expenditures, and population living below the extreme poverty line. The use of multiple metrics has several analytical advantages. First, given that monetary and asset-based measures alone may not yield similar household rankings or identify the same populations consistently (Filmer and Scott, 2012), by using both welfare outcomes (i.e. expenditures per capita and their related poverty level) alongside a "stickier" measure of welfare (i.e. asset wealth), we can better triangulate the different aspects of welfare dynamics. In addition, asset wealth measures also have the advantage of avoiding some of the measurement problems associated with self-reported income and consumption, such as recall bias, seasonality, and time spent on data collection (Vyas and Kumaranayake, 2006). Indeed, they are easily measured with fewer questions as compared to consumption expenditures or income (Rutstein and Johnson, 2004). Asset wealth indices are also good indicators of a household's relative economic status, and tend to represent a more cumulative welfare condition than income or consumption. However, asset indices are less reliable for determining the temporal variability of household welfare, for which consumption or income-based variables perform better (Rutstein and Johnson, 2004). In this sense, expenditures (per capita, in our case) better reflect the variability of household welfare, while asset wealth indicates the state of household wealth accumulation at a particular point in time. The Atlas AI data also provide an additional advantage in terms of reliability: Other poverty prediction methods based on consumption usually ignore the untested assumption of over-time stability of consumption predictor variables (Christiaensen *et al.*, 2012). However, our data consider this assumption by using predictors that are sourced from both survey data and satellite imagery. Through machine-learning techniques, these predictors are able to model welfare estimators dynamically and over time. The process of training, validating and model-testing also allows for cross-validation and further improvement of welfare estimations.

Spatial typologies

We analyse welfare dynamics across three spatial typologies. The first typology explicitly disaggregates welfare estimates through the lens of a continuum of urban–rural catchment area categories across cities and towns. The contrast in welfare between urban and rural areas is more evident in SSA than in other regions (Pesche, Losch and Imbernon, 2016); hence the differences between areas that are more urban and those that are more rural deserve special attention. Moreover, previous studies have found that market access (i.e. in terms of proximity to more highly populated areas) and agglomeration economies (i.e. population density or the urban–rural spectrum) are crucial to explaining the persistence of spatial inequalities in the region (Nguyen and Dizon, 2017).

It is no surprise that the majority of the world's poor – 80 percent of those living in extreme poverty and 75 percent of those living in moderate poverty – live in areas that are administratively assigned as rural areas (Castaneda *et al.*, 2016). These estimates are often cited, but they mask a variety of territorial nuances between urban and rural contexts. Indeed, urban–rural is not a dichotomy but rather a continuum associated with variations in population densities, access to markets, services and institutions (Cattaneo, Nelson and McMenomy, 2021a; United Nations Department of Economic and Social Affairs, 2020). Despite their importance, development policies and programmes rarely account for these variations. In our study however, we acknowledge such distinctions, and use typologies along the urban–rural continuum to assess welfare dynamics in SSA.

The other two spatial typologies – agroecological zones and farming systems – were selected to explore the ways in which welfare dynamics are influenced by natural resource endowments and available agricultural production systems. Their selection for the spatial analysis of SSA is also linked to the importance of agriculture in the region: the sector employs around 52 percent of the workforce in SSA (ILO, 2021) and represents 17.2 percent of its gross domestic product (GDP) (World Bank and OECD, 2023). Previous studies have already highlighted the relevance of natural resource endowments for wealth and poverty dynamics (Azzarri and Signorelli, 2020), including the suitability of different places and farming systems for agricultural production (Dixon *et al.*, eds., 2019). In West Africa for example, the distribution of per capita expenditures and extreme poverty is found to vary across regions and agroecological areas, with lower levels of poverty in the more connected coastal areas (Bigman and Fofack, 2000b), and similarly less acute poverty in the rural coastal regions of Ghana for instance than in the savannah (Bigman and Fofack, 2000a). As Nguyen and Dizon (2017) point out, geography seems to have a strong relationship with agricultural productivity, even after accounting for differences in market access, agglomeration economies and the use of farm inputs. In short, while improvements in road infrastructure and population density are important, locations with less favourable geographical conditions can often remain less productive than others.

Agroecological zones and farming systems are distinct yet complementary spatial typologies that are highly relevant to rural welfare dynamics. While agroecological zones provide an indication of the agricultural potential of a place based on temperature, precipitation, and elevation, farming systems aggregate areas based on similar farming resources and patterns of production, and in many cases on similar agroecological and market access characteristics. Previous studies of farming systems have found that the potential for poverty reduction and agricultural growth is higher in areas where there is irrigation, and where cereal-root crops are produced. Conversely, the potential is lower in isolated farming systems such as forest-based systems, and in arid areas – where cash crops are less feasible and where road access is limited (Dixon *et al.*, eds., 2019). Indeed, several studies (Bigman and Fofack, 2000a, 2000b; Dixon *et al.*, 2019; Nguyen and Dizon, 2017) have noted that common characteristics of more economically dynamic farming systems include higher access to markets and services, and more diversified portfolios of agricultural activities.

As an important additional aspect, climate change is altering temperature and precipitation regimes around the world, thus shifting the spatial extent of different agroecological zones and farming systems (Rötter and Geijn, 1999; Thornton *et al.*, 2009; Kurukulasuriya and Mendelsohn, 2008). A critical concern is that climate change will increase the spatial extent of areas that are already struggling to provide a pathway out of poverty for the people living in them – such as deserts and tropical lowland areas – and thus impede poverty reduction efforts even further in SSA. In this regard, we also consider evidence on how agroecological zones are projected to grow or shrink as a result of climate change, and the relevant implications for well-being dynamics in SSA.

Methods and data

Our study is based on high-resolution welfare data provided by Atlas AI (Atlas AI, 2021), predefined geographical typologies based on urban–rural catchment areas (URCAs) (Cattaneo, Nelson and McMenomy, 2021a), Global Agro-Ecological Zones (GAEZ) (FAO and IIASA, 2023; Sebastian, 2009), and the classification of farming systems by selected seminal works (Dixon *et al.*, 2001; Garrity, Dixon and Boffa, 2012). These datasets are described in detail throughout the rest of this section.

The analysis presented in this paper is primarily descriptive, and seeks to assess how wealth accumulation, per capita expenditures and extreme poverty evolved over time and space in SSA. Since the spatial delineation for the geographical typologies (URCA, GAEZ and farming system categories) are only available for a single point in time, we started our descriptive analysis by transforming the images from pixel to shapefile format, to better identify the areas covered by each URCA, GAEZ or farming system category. We then extracted the Atlas AI welfare indicators for each year and for each geographical category, and calculated zonal statistics for the corresponding boundary (whether URCA, GAEZ or farming system category).

To account for the population living within a particular boundary, we weighted the values of the welfare indicators within the zone of interest (URCA, GAEZ or farming system category), by the size of the population within that zone.[4] Results should therefore be interpreted as weighted averages at the pixel level, adjusted by the population living in each geographical boundary (URCA, GAEZ or farming system category). For the bulk of the analysis, we exclude the urban areas category (as defined later in this section – see Urban–rural catchment areas), except when analysing welfare indicators through the URCA typology; this allows us to focus the analysis on welfare dynamics among rural populations.

Atlas AI data

The Atlas AI dataset consists of yearly indicators predicting (i) asset wealth index (AWI); (ii) household per capita expenditures (SP); and (iii) population living below the extreme poverty line or extreme poverty levels (POV). The data correspond to gridded images from the years 2003 to 2021, at a 1 km × 1 km ground spatial distance (GSD) resolution at the equator, comparable over time and space and available for all countries in the region, including those for which nationally representative household data are not available (Atlas AI, 2021; Jean *et al.*, 2016; Yeh *et al.*, 2020). (For a snapshot of the data in 2021, see Figure A1 in the Annexes.) The dataset helps to overcome some of the main drawbacks of using nationally representative household surveys to track poverty and welfare, including the large time gap between surveys (Yeh *et al.*, 2020), as well as the absence of poverty and asset wealth data at highly

[4] More specifically, the average welfare indicator as adjusted by population for a given zone is:

$$WI_j = \frac{\sum_{i=1}^{n} w_i * p_i}{\sum_{i=1}^{n} p_i}$$

with WI_j as the welfare indicator for the zone j in a given year, w_i as the welfare indicator in pixel i for that year in zone j, p_i as the population in pixel i for that year in zone j, summing over all pixels in the zone.

disaggregated levels. This allows for a better understanding of the geographical and temporal heterogeneity of wealth accumulation and poverty in ways that is not possible with survey-based approaches.

The predictions for the different welfare indicators were developed via machine learning, using multiple input data sources comprised of satellite imagery and large-scale, nationally representative surveys. The available reference data are generally divided into subsets for training, validation and model testing, to allow for cross-validation and model improvement using statistical best practices. The data have already been peer-reviewed (Yeh *et al.*, 2020) and used to assess the livelihood impact of the expansion of electricity access in Uganda (Ratledge *et al.*, 2022).

For the measure of AWI, Atlas AI combines survey-based asset and geographical information collected through Demographic and Health Surveys (DHS), as administered between 2003 and 2016 in more than 30 SSA countries.[5] A wealth index is constructed through a principal component analysis (PCA) of the asset variables,[6] by pooling together all available households and years (this guarantees consistency across time and space; for more information, see Yeh *et al.*, 2020). As a next step, a random forest model predicts village-aggregated values with satellite imagery from different sources,[7] and validates the inference product on set-aside data that the machine learning model has not seen. Several satellite-based sources of information are used to capture key features that predict wealth over time and space, such as roads, electrification, altitude, and population density. A deep machine learning model is then used to predict survey-based estimates from satellite imagery, producing asset wealth estimates in locations and times where survey data do not exist. Regarding the construction of the index, the average of the AWI computed in a given year for the entire population of Africa is equal to zero. To guarantee comparability across time, the AWI per pixel for preceding years is calibrated relative to the pixel values of the most recent calculation year (the mean-centring year or baseline). Hence, the normalized AWI is comparable within and across countries. In terms of interpretation, AWI values larger than zero correspond to asset wealth pixels that are higher than average, while AWI values smaller than zero correspond to asset wealth pixels that are lower than average.[8]

Despite the different steps taken to validate the images, model performance is limited in large

[5] The following variables are used to construct the wealth indicator: the number of rooms occupied in the household; whether or not it has electricity; the quality of its floors, water supply and toilet; and ownership of phone, radio, TV, car, and motorbike (Yeh *et al.*, 2020).
[6] Vyas and Kumaranayake (2006) describe the advantages and disadvantages of using the PCA method to construct a wealth index. Alternatives to PCA previously considered include correspondence analysis, multivariate regression and factor analysis.
[7] Landsat cover layers 6, 7, and 8 between 2003 and 2020 are used to determine land cover. The Shuttle Radar Topography Mission (SRTM) is used for elevation data for the year 2000, at a resolution of 1 arc second (approximately 30 m at the equator). Nighttime light data come from the Earth Observation Group (EOG), and are used to calculate luminosity from the 2004–2005 Defense Meteorological Program (DMSP) median composites, 2010 DMSP median composites, 2014 Visible Infrared Imaging Radiometer Suite (VIIRS) median composite, and the 2015–2020 VIIRS. Phased Array type L-band Synthetic Aperture Radar (PALSAR) from the Japan Aerospace Exploration Agency (JAXA) and the Japan Resources Observation System Organization (JAROS) uses the 25 m yearly mosaic to support cloud- and weather-free observations. The Global Human Settlement Layer (GHSL) population data uses 250 m population gridded data from the years 2000 and 2015, and 1 km settlement gridded data.
[8] Image manipulation and calculations were conducted in RStudio. The World Geodetic System 1984–WGS 84/Pseudo-Mercator, which is typically used for web mapping applications, was used as the projection system for the data. To merge it with the other geo-referenced datasets, the projection is modified to the WGS 84 system, such that it is consistent with the projection system of the other geo-referenced datasets used.

part by noise introduced from the training data (Yeh *et al.*, 2020). Additionally, the quality of predictions for areas with large amounts of missing data greatly depends on the density across time and space of surveyed households in neighbouring zones. Areas with missing data benefit from the predictions if they are surrounded by many surveyed households, as their predictions use a higher number of observations in the validation process. In contrast, predictions made with just a few households across time and space tend to be of lower quality, and make the validation process more difficult.

A similar process is used for the construction of SP and POV. The SP data refer to household per capita expenditures ("spending") of both durables and non-durable items per person, per day. The data are adjusted to 2011 PPP,[9] to account for differences in purchasing power among countries, as well as fluctuations in prices within countries over time (inflation) – thus guaranteeing comparability across countries and time. Household expenditures are captured through information collected by Living Standards Measurement Study (LSMS) surveys that were conducted from 2008 to 2014, and national poverty distributions come from PovcalNet (an interactive tool developed by the World Bank),[10] which provided information on 40 countries between 2003 to 2020. The pixel value expresses the average of the log-normally distributed spending of all households living inside that pixel. The POV is based on the SP data, and refers to the population living below the poverty line of USD 1.90 a day in 2011 PPP (i.e. extreme poverty). Although the poverty line is normally a consumption measure (income is less frequently used), poverty numbers are defined using the same threshold. Therefore, poverty is determined by the average daily household spending at the pixel level, and counts the population living below the poverty line in that pixel.

As in the case of the AWI, the SP and POV for preceding years are calibrated relative to the pixel values of the most recent calculation year (the baseline). As each raster cell in the Atlas AI dataset represents the average value for the population in that grid cell (1 km × 1 km), the average of the welfare indicator for a zone of interest (URCA, GAEZ or farming system category) must be weighted by the population that was living in the grid cell in that year. We then use the population dataset (POP) provided by Atlas AI.[11] POP measures the count (number) of people and their density (people per km^2) at the pixel level for Africa, for all the years considered in the study. This dataset enables us to adjust the welfare measures by the population living in the given country, region or geographical typology.

Urban–rural catchment areas

In this paper we use a geographical typology based on urban catchment areas (URCA) (Cattaneo, Nelson and McMenomy, 2021b, 2021a). URCA is a global spatial dataset for 2015, at a spatial resolution of 1 km × 1 km (around the equator), which identifies the catchment areas

[9] As a——— shortcoming however, PPP is adjusted at the national level rather than the subnational, giving a higher weight to urban prices. As a result, poverty numbers may be slightly biased between urban and rural areas. In other words, while PPP allows for comparison between countries, it does not capture the fact that the spatial variation in prices may be correlated with urban and rural categories.
[10] As of March 2022, PovcalNet was replaced by the Poverty and Inequality Platform; for more information, see: https://pip.worldbank.org/about
[11] The population estimates are aggregates from three trustworthy population sources: GHSL; Gridded Population of the World (GPW), Version 4; and WorldPop.

of urban centres and classifies the population around these cities based on the time needed to reach them. In total, 30 URCAs are identified, where each pixel represents the time needed to arrive at a settlement of a different size. We adapt these typologies by aggregating the 30 URCA categories available into the following four:

1. **Urban:** urban centres – either cities or towns of different sizes.
2. **Peri-urban:** areas that are accessible from any urban centre in under one hour.
3. **Peri-rural:** areas that are accessible from any urban centre in one to three hours.
4. **Hinterlands and dispersed cities:** areas that are accessible from any urban centre in over three hours, and that are not connected to any agglomeration of at least 5 000 inhabitants.

For a visual representation of the four categories, see Figure A2 in the Annexes.

Global Agro-Ecological Zones

The Global Agro-Ecological Zones (GAEZ) typology was jointly developed by the International Institute for Applied Systems Analysis (IIASA) and FAO over the past 40 years. The GAEZ typology clusters regions based on similar climatic and topographic conditions, reflecting their potential for crop cultivation. The information considered in these classifications includes historical data for the period from 1981 to 2010, on climate, soil, terrain, land features, population density, livestock density, protected areas and areas of high biodiversity value, as well as administrative boundaries. The data consolidate the following four land aspects (FAO and IIASA, 2023; Sebastian, 2009):

1. **Climate categories**: For Africa, these are classified into tropics, subtropics, and other zones (boreal, desert, etc.).
2. **Growing period**: Captures the time of the year when moisture and temperature are favourable for crop growth – in particular the length of growing period (LGP) in days – and classifies them as arid, semi-arid, subhumid, humid, etc.
3. **Thermal regime**: Captures the temperature of the growing period, average temperature, and number of days with temperature above certain thresholds, among others.
4. **Moisture regime**: Captures the potential evapotranspiration and precipitation characteristics of the area.

At the global level, the four land aspects produce a combination of 33 categories, 23 of which are found in SSA, with spatial resolution of 0.9 km by 0.9 km around the equator. The different GAEZ areas for Africa are plotted in Figure A3 of the Annexes. A detailed description of each GAEZ category is also provided in the Annexes (see Table A1), with average welfare indicators and population per pixel for 2021. From Table A1, we observe that 94.9 percent of the population live in only eight GAEZ categories (tropics, land with severe soil/terrain limitations, and desert and arid climates), which accounts for 94.8 percent of the total land area (in km^2) in SSA. Among the eight, tropical highland areas have a higher level of asset wealth and per capita expenditures than the other categories. Despite having the lowest AWI, poverty numbers are the lowest in the desert/arid climate category, due to the large expanses of area (in km^2) and low population densities often found in this category. The desert/arid climate category also has a very low level of land extension dedicated to cropland or tree cover; this reflects the types of production activities carried out, which are mostly related to livestock production. Poverty numbers are the highest in the humid terrains of tropical lowlands and highlands, which are also exposed to higher levels of annual rainfall (in mm). Previous studies also find higher levels of poverty in the warm and humid, tropical forests of the Democratic Republic of the Congo and in the warm, semi-arid and subhumid tropical areas near the southern Sahara (Azarri, 2014).

To analyse latent agricultural productivity, Table A2 of the Annexes provides data on potential yields (kg dry weight per hectare) by GAEZ categories for three main crops: maize, pearl millet and sorghum. Crop productivity is highly correlated with the availability of irrigated systems, which generally deliver higher yields than rainfed systems across the three crops. Focusing on the columns for potential yields for the period 1981 to 2010, we observe a high yield gap between irrigated and rainfed production of maize for all the GAEZ categories, which is more pronounced in tropical highland semi-arid and desert/arid climate areas. For pearl millet, the yield gap between irrigated and rainfed production is much smaller, with values very close in both types of systems for tropical lowland humid and tropical highland subhumid areas. Among the three crops, previous studies (Teixeira *et al.*, 2013) have already predicted negative impacts from high heat stress for maize production in SSA – namely in the Sahel and southeast areas of the continent. Climate change is thus expected to impact the potential yields of maize production presented in Table A2; this in turn is expected to put pressure on the GAEZ categories that are highly dependent on this crop, particularly when temperatures exceed 30 °C.

An additional source of stress relates to the projected impacts of climate change on the total area (in km^2) of the GAEZ categories (see Table A3).[12] Among the eight main categories studied, three are expected to increase in size by 2050 and by 2080 (desert/arid climate, land with severe soil/terrain limitations, and tropical lowlands in semi-arid and humid areas), to the detriment of the others, which are expected to shrink for the same periods. Overall, we observe better welfare performance in the already small tropical highland categories, which will reduce in area due to climate change. This is expected to put additional strain on future welfare dynamics.

Farming systems

A farming system describes a population of farm households having similar patterns with regard to resources, livelihoods, consumption, constraints and opportunities, and similar development strategies and interventions. Very often, they also share similar agroecological and market access conditions. Based on these criteria, 13 types of farming systems (out of a

[12] Projections are based on the Representative Concentration Pathway (RCP) 2.6 on greenhouse gas concentration (not emissions) trajectory, as adopted by the Intergovernmental Panel on Climate Change (IPCC).

total of 17 available categories) were classified for SSA; these consider agroecological zones, the provision of agricultural services, and the level of regular frequency or consistency of the agricultural activities within each system (Dixon *et al.*, eds., 2019; HarvestChoice, IFPRI and University of Minnesota, 2017; Koo *et al.*, 2016). (See also Figure A4 in the Annexes.) The data are drawn from an image that allows for spatial analyses and fine-grain visualization of farming systems and populations across SSA. This corresponds to over 350 000 grid cells at a spatial resolution of five arc minutes (10 km × 10 km around the equator), last generated in 2015. A detailed description of each farming system is provided in Table A4 of the Annexes, with average welfare indicators and population per pixel for 2021.

As seen in Table A4, SSA's highest populations live within the maize mixed and agropastoral farming systems, followed by root and tuber crop and highland perennial areas. In terms of average asset wealth for 2021, perennial mixed, fish-based, and humid lowland tree-crop areas show the highest levels, while forest-based systems show the lowest. For per capita expenditures in 2021, highland mixed and fish-based systems show the highest levels, while again, forest-based systems show the lowest. Finally, root and tuber crop, highland perennial and forest-based systems show the highest concentration of poor people per pixel. It therefore appears that poverty is particularly concentrated in less commercialized or less diversified systems (e.g. forest-based and root and tuber crop systems) that rely primarily on the production of maize, cassava and yams, and in arid and pastoral areas, where people depend mostly on livestock (cattle, sheep, goats and camels) along with a limited number of staple crops. As we move up to farming systems that are more integrated with markets, we observe slightly better welfare outcomes, a higher dependence on cash crops, and a more diverse portfolio of production activities. Humid lowland tree-crop systems concentrate on the production of coffee, oil palm and cocoa; perennial mixed systems on vines and fruits; and irrigated farming systems on rice, cotton, vegetables and some livestock. Fish-based systems, which have relatively higher welfare performance, rely not only on fishing activities but also on bananas, other cash crops and off-farm work. Maize mixed, agropastoral and cereal-root crop mixed systems combine livestock activities with the production of cash crops (tobacco and cotton) and staple crops (maize, sorghum and millet), and seem to perform slightly better than those in areas that are more isolated from markets, such as forest-based systems.

Results

This section presents the results of estimates for the welfare indicators across the different geographical typologies. The section begins by exploring the aggregate welfare dynamics in SSA, before delving into dynamics across the urban–rural continuum, agroecological zones and farming systems.

Overall trends: Asset wealth, expenditures and poverty dynamics in SSA

Figure 1 presents the evolution of welfare indicators over time for the entire SSA region,[13] both with and without urban areas (i.e. the first of the Urban–rural catchment areas, as defined in the section on Methods and data).[14] The most important observation is an overall – albeit limited – improvement in all three well-being indicators across the period analysed. Excluding urban areas does not change the overall trends across the period analysed. However, when urban areas are included, all three indicators have higher aggregate values. This suggests that the urbanization process is an important driver of asset wealth and increased expenditures.

As also illustrated in Figure 1 (see Panel A), asset wealth increased steadily between 2003 and 2021; there were peaks in 2004, 2015 and notably in 2017, and a sharp decline in 2019 that was followed by a rapid recovery until 2021. Given that the asset wealth data are trained using spatial features associated with asset accumulation (including for example access to electrification), the steady increase in the asset wealth index may be related to the supply of electricity in SSA, which significantly increased (by almost 5 percentage points) after 2016 (IEA *et al.*, 2022).[15] However, it is very likely that the sudden blips and peaks observed in asset wealth index (for instance, see the jump in 2017) may have been affected by data incomparability, changes in data classification, collation, and time lags that tipically come with the expansion of available large-scale data such as remote sensing data, street-level imagery, private technology data, and cheaper access to Global Positioning System or geographic information system (GPS/GIS) data capture use in survey data – in addition to advances in deep learning methods (Li *et al.*, 2022; Nowak *et al.*, 2020; Suel *et al.*, 2021). Data comparability issues have been observed, for instance, in nighttime light images before and after 2012, which use different units of measure and come from different sources (Li *et al.*, 2020).

[13] The Atlas AI data have only a few observations for North Africa – particularly in Algeria, Egypt, Libya, Morocco and Tunisia – due to large uninhabited areas in this region. For this reason, we decided to concentrate the analysis only on sub-Saharan countries, excluding small island countries. The final list of the sample is composed of: Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Côte d'Ivoire, Democratic Republic of the Congo, Djibouti, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Togo, Uganda, United Republic of Tanzania, Zambia and Zimbabwe.
[14] When interpreting the results, it should be noted that URCA information was obtained only for the year 2015; therefore, any pixels reflecting a certain feature in 2015 may not have had the same levels of urbanization in 2003.
[15] A similar trend is observed when using the variable of access to electricity (percentage of population); for more information, see: https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS?locations=ZG

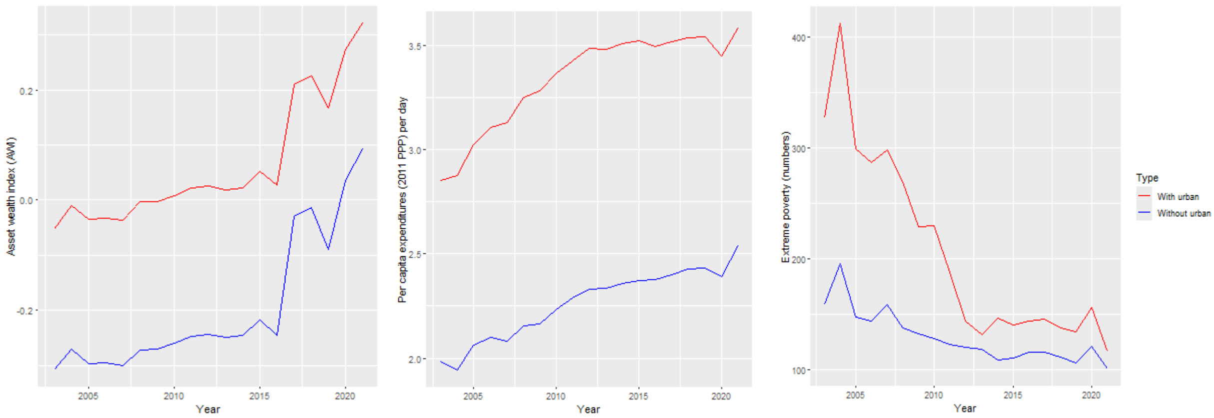
Similarly, the data show an increase in per capita expenditures over time (see Panel B). The trend is different from the AWI however, with per capita expenditures gradually increasing over time, and without the sharp increase observed for asset wealth in 2016. Also, a reduction in per capita expenditures is mostly observed in 2020 and not in 2019, suggesting that the effects of COVID-19 could have impacted household asset endowment and consumption differently.

Figure 1 also shows a steady but limited reduction in extreme poverty in rural areas (see Panel C). When urban areas are included however, the trend is not as smooth – there are sharp decreases – but to some extent, there are also increases in poverty (i.e. the number of poor per pixel); for example in the years 2004, 2007 (coinciding with spikes in commodity and fertilizer prices), and 2020 (coinciding with COVID-19). This speaks not only to the effect of urbanization on the reduction of poverty, but also suggests higher vulnerability to poverty in urban areas.

Figure A5 of the Annexes plots the extreme poverty measures (adjusted by population) of Figure 1 (see Panel C), along with the number of extreme poor (as percentage of population) from the World Bank Poverty and Inequality Platform (World Bank, 2023). The results from the Atlas AI data are consistent with the region's overall poverty headcount ratio (2011 PPP) (percentage of population) for the period from 2003 to 2019, as measured by the World Bank. In both, the Atlas AI data and the World Bank estimates show a steady decline in poverty, but with a slower pace in the last five years.

Figure 1. Welfare indicators (adjusted by population) across urban and rural areas, 2003–2021 (SSA)

A. Asset wealth index B. Per capita expenditures C. Extreme poverty



Notes: Panel A plots the region's yearly average asset wealth from 2003 to 2021. Panel B plots the yearly average of household per capita expenditures, per day, for each 1 km × 1 km pixel. Panel C plots the yearly average population living below the poverty line, for each 1 km × 1 km pixel. Calculations in blue exclude the urban URCA category, as defined in the section on Methods and data.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645

Figure 2 provides a visual representation of the spatial dimensions in asset accumulation in SSA.[16] The red pixels in Panel A and Panel B indicate where the asset wealth index was below

[16] The images of the AWI in Figure 2 are constructed as AWI × POP. As explained in the section on Methods and data, AWI (adjusted by population) cannot be calculated by simply dividing the images of AWI and population as AWI/POP. While using

zero in 2003 and in 2021 respectively, while the blue pixels indicate positive values for the same years. The expansion of blue pixels in 2021 indicates where progress in asset wealth was made, and highlights important spatial disparities. For example, there was improvement in coastal and inland areas of Western Africa (from Nigeria to Senegal) and Madagascar, and to a lesser extent in some parts of Cameroon, Chad, South Sudan, some parts of Eastern Africa (Ethiopia and east of Lake Victoria), parts of Zambia and Zimbabwe, and other parts of South Africa.

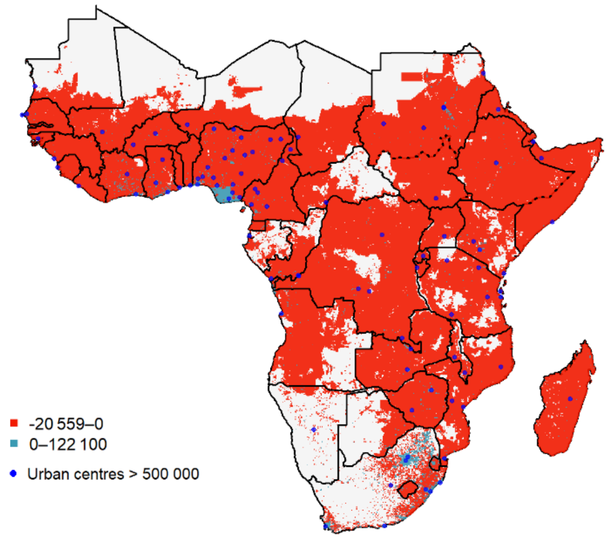
To better visualize the changes in asset wealth index over time, Panel C of Figure 2 categorizes pixels into four groups: (i) "++" for pixels that were positive in 2003 and in 2021 (in green); (ii) "+−" for pixels that were positive in 2003 but negative in 2021 (in cyan); (iii) "−+" for pixels that were negative in 2003 but positive in 2021 (in yellow); and (iv)"−−" for pixels that were negative in 2003 and remained negative in 2021 (in red). Based on these categories, Panel C shows that a relatively limited area of SSA maintained an above average AWI (in green), mostly around Port Harcourt in Nigeria and in northeastern areas from Pretoria in South Africa, towards Maputo in Mozambique. While most of SSA remained at below average levels of asset wealth in 2003 and 2021 (in red), virtually no areas in the region experienced a decline (in blue). Importantly, improvements are observed in many parts of SSA, which coincide with the blue areas already described for Panel B.

Figure A6 and Figure A7 of the Annexes show similar maps, portraying results for per capita expenditures and extreme poverty respectively. Since these variables are absolute values, we construct similar graphs as in Figure 2, classifying pixels as above or below the median (50th quantile) of total pixel values for the continent in 2003 and 2021, for both consumption and extreme poverty. In Figure A6, which depicts per capita expenditures, we observe significant spatial variation across the continent, as indicated by the different colours. Many areas that were above the median in 2003 remained above in 2021 (as indicated in green), while several areas showed no progress and remained stagnant (as indicated in red). In Figure A7, which illustrates poverty reduction, we see that progress appears to be concentrated only in some areas (in red), for example and most notably in some parts of Central Africa (Panel C). Conversely, large regions in the Democratic Republic of the Congo fared worse (in cyan), with an increase in the number of poor.

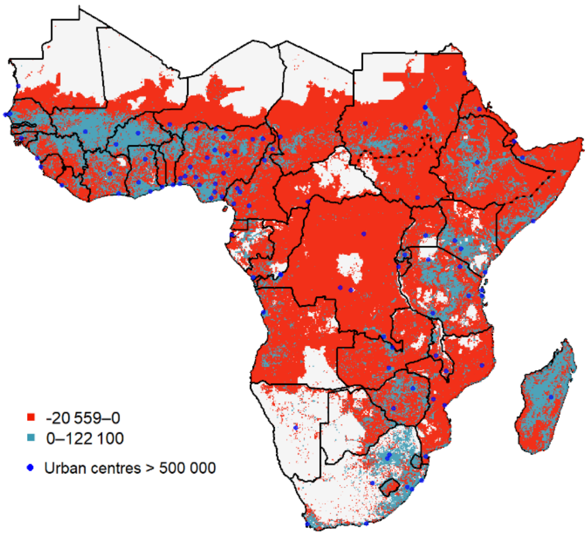
AWI × POP is not exactly equivalent to AWI (adjusted by population), it partially captures the adjustment by population, and preserves the characteristics of AWI on welfare accumulation.

Figure 2. Asset wealth spatial variation, 2003–2021 (SSA)

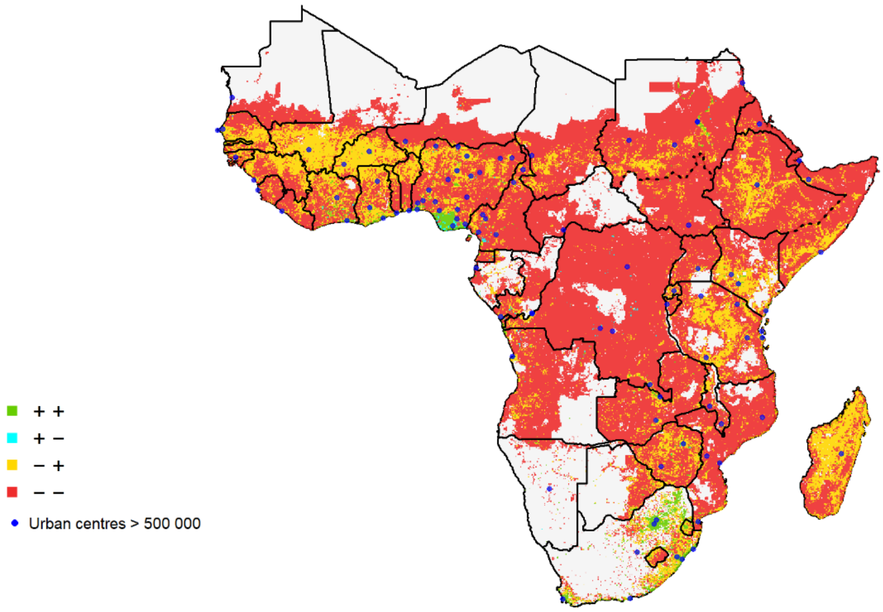
A. Asset wealth index 2003



B. Asset wealth index 2021



C. Evolution of asset wealth index (positive vs negative) between 2003 and 2021



Notes: Refer to the disclaimer on page ii for the names and boundaries used in this map. The final boundary between the Sudan and South Sudan has not yet been determined.
Calculations include the urban URCA category, as defined in the section on Methods and data. Panel A and B depict the image of AWI × POP in 2003 and 2021. While this is not exactly equivalent to AWI adjusted by population, it partially preserves the adjustment by population and the characteristics of AWI. We determine values above and below zero for 2003 and 2021. The categories are (i) + in 2003 and + in 2021 in green; (ii) + in 2003 and − in 2021 in cyan; (iii) − in 2003 and + in 2021 in yellow; and (iv) − in 2003 and − in 2021 in red.
Sources: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645, on **Esri.** 2017. Africa Cities. Updated on 9 December 2017. https://www.africageoportal.com/datasets/africa::africa-cities-1/about and on **United Nations Geospatial.** 2020. Map geodata UNmap25_shp. New York, USA, United Nations.

To understand the distributional dimensions of welfare dynamics in SSA, we track the average values of the three welfare indicators over time, for different quintiles of the expenditure distribution, where the quintiles are computed based on 2003 baseline values (see Figure 3).[17] For comparison, the figure also includes the average for all SSA (in red). Several important observations are evident from this analysis. First, there is a substantial gap in asset wealth and expenditures between the top quintile and the rest, indicating a high level of inequality between the top 20 percent and the rest of the population. Second, asset wealth seems to have improved at a faster rate than expenditures. To confirm this, Table 1 computes the slope of the indicators over time. It shows that asset wealth is increasing at faster rates for the richest quintiles in 2003 (as compared to the two lowest quintiles), but that this is not translating into growth at the same pace in per capita expenditures. Extreme poverty reduction, on the other hand, is concentrated in the top expenditure quintile – the only one showing a decrease. With respect to per capita expenditures, all the quintiles (except the richest) saw very limited increase, with slopes ranging around 0.13, as compared to an SSA average of 0.20.

Third, the evidence on poverty trends helps to unpack the uneven dynamics between expenditure quintiles.[18] What becomes evident in these trends (see Figure 3, Panel C) is that pixels in the highest asset quintile have a much higher relative number of people living in poverty per pixel. These are also the regions where poverty reduction has occurred in SSA, as it has been largely concentrated in more populous and urban areas (for example, see Table A5 in the Annexes). Conversely, the rest of the quintiles are spread across more rural areas, with lower population densities. Despite the improvements in asset accumulation and expenditures (see Table 1), these segments of expenditure distribution have seen marginal increases in poverty over time, due to a combination of population growth and limited economic dynamism in these areas. Additional information is provided in Figure A8 in the Annexes, where we ran a similar analysis – though only with the rural sample – to show similar trends (with the average of AWI and SP less spread across quintiles, due to the absence of urban areas).

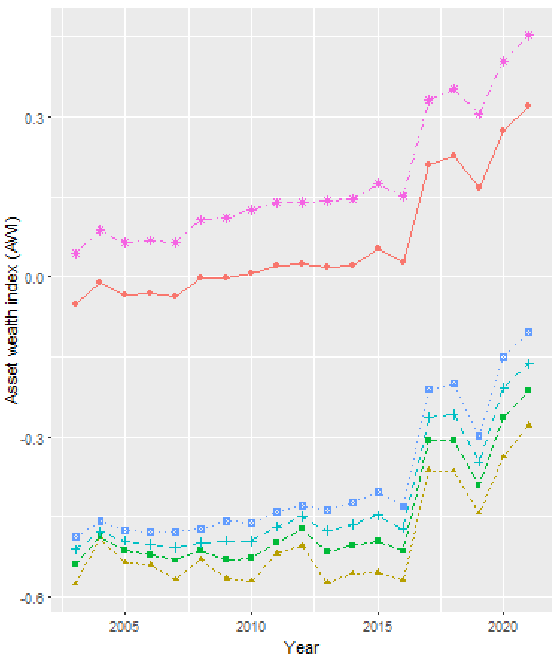
Finally, we ran a similar analysis, in this case using 2003 AWI quintiles to define the groups (see Figure A9 in the annexes). This analysis continues to show a large gap between the top quintile and the rest of the groups. Moreover, regions in the lower quintiles of the expenditure distribution experienced very limited improvements in expenditures over time – yielding a slight increase in extreme poverty – while important poverty reductions are observed in the fifth and first quintiles.

[17] As explained in the section on Methods and data, SP (adjusted by population) cannot be calculated by simply dividing the images of SP and population as SP/POP in 2003, and using the result to define the thresholds of the five quantiles. In fact, SP (adjusted by population) is only produced as a unique value for a specific geographical area. For this reason, we proceed by producing an image of SP × POP with 2003 as the baseline year, in order to define the thresholds of the five quantiles. As in Figure 2, this is not exactly equivalent to SP (adjusted by population), but it partially preserves the adjustment by population and the characteristics of SP on expenditures.

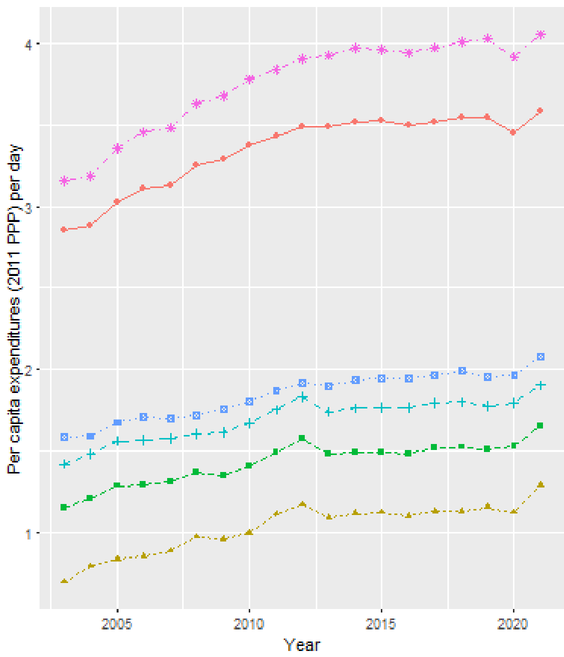
[18] A caveat in this regard is that the quintiles are based on the image of SP × POP in 2003, and do not completely account for the relative population within the pixel.

Figure 3. Welfare indicators (adjusted by population) across expenditure quintiles, 2003–2021 (SSA)

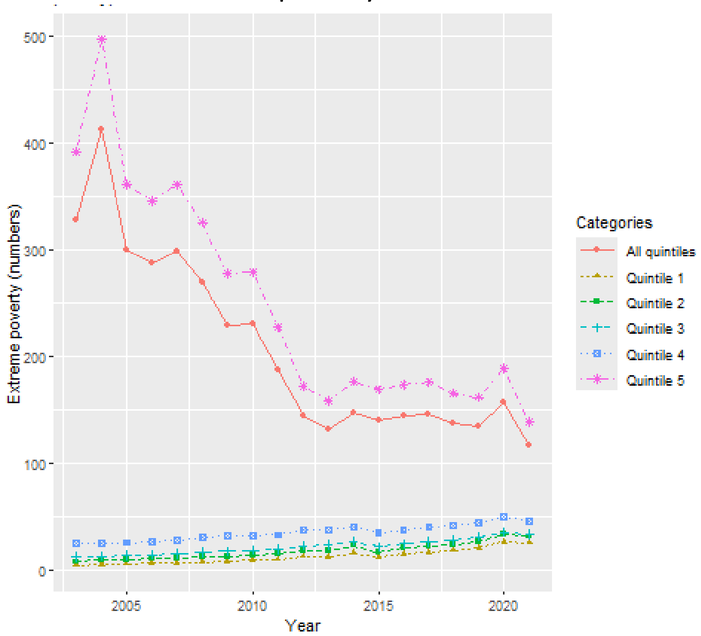
A. Asset wealth index



B. Per capita expenditures



C. Extreme poverty



Notes: Panel A plots the region's average asset wealth from 2003 to 2021. Panel B plots the average household per capita expenditures, per day, for each 1 km × 1 km pixel. Panel C plots the average population living below the poverty line, for each 1 km × 1 km pixel. Calculations include the urban URCA category, as defined in the section on Methods and data. Quintiles were defined by taking the image of SP × POP, with 2003 as the baseline year.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645

Table 1. Slope of different indicators (adjusted by population) across SP quintile, 2003–2021 (SSA)

	Asset wealth index	Per capita expenditures	Extreme poverty
Quintile 1	0.21	0.13	0.05
Quintile 2	0.27	0.11	0.06
Quintile 3	0.31	0.11	0.06
Quintile 4	0.35	0.13	0.06
Quintile 5	0.38	0.25	-0.80
All quintiles	0.34	0.20	-0.66

Notes: Calculations include the urban URCA category, as defined in the section on Methods and data. Quintiles defined taking the image of SP × POP in 2003 as baseline year. The slope is calculated for the values presented in Figure 3, as the linear fit of the yearly indicators aggregated for each quantile.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645

Welfare dynamics across urban–rural catchment areas

The analysis in the preceding section suggested potentially important differences in welfare dynamics between urban and rural areas in SSA. To explore these dynamics in more detail, this section examines differences in welfare indicators along the urban–rural continuum, as illustrated in Figure 4 and Table 2)

As shown in the figure, significant disparities exist between urban and rural areas. First, the further a place is located from an urban area, the worse it performs across all indicators. Second, as shown in the table, given that urban areas have large populations, they are also the areas where reductions in poverty have been most pronounced.[19] As also shown in the table, the extreme poor are more likely to live in urban rather than rural areas, with the number of urban poor being five times higher per pixel than in hinterlands and dispersed areas.

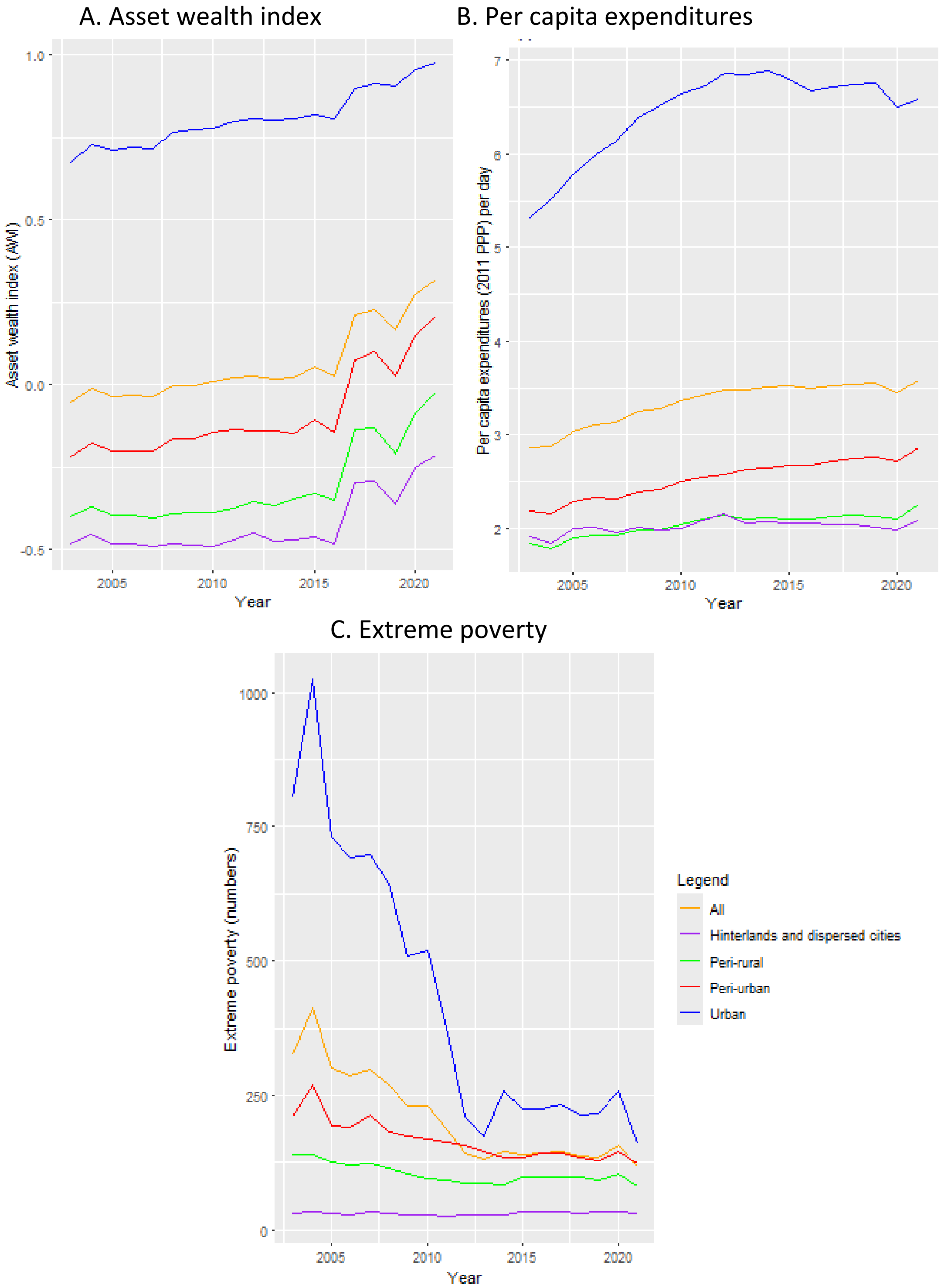
Third, the most remote rural regions – peri-rural, as well as hinterlands and dispersed – have experienced virtually no change in poverty or expenditure levels over time. Only peri-urban areas seem to have reached, on average per pixel, asset wealth and extreme poverty levels close to the SSA average (see Figure 4). This is consistent with previous studies, which show that as poverty reduction advances at national levels, poverty becomes concentrated in areas where the population is hardest to reach (Barrett *et al.*, 2006; Kraay and McKenzie, 2014; Nguyen and Dizon, 2017), such as remote rural areas (Janz *et al.*, 2023). The literature also points to the emergence of urban sprawls in peri-urban and suburban areas (Angel *et al.*, 2011; Keil, 2013; Mberu, Béguy and Ezeh, 2017; Todes, 2014). This also in turn relates to previous cross-country studies, which show that agglomeration in urban areas fosters more rapid economic growth, but also comes with higher income inequality (Christiaensen and Todo,

[19] In this regard, the existence of spatial variation on prices (for a typical consumption basket of goods) may lead to overstating poverty in hinterlands and dispersed cities, and understating it in urban areas.

2014).

Finally, Table 2 provides compelling evidence of the dynamic of rapid growth alongside high spatial inequality. While urban areas show substantially higher levels of asset wealth and per capita expenditures than the other groups (as shown in Panel A), they are also associated with the largest standard deviations for asset and expenditure variables (as shown in Panel B).

Figure 4. Welfare indicators (adjusted by population) across URCA categories, 2003–2021 (SSA)



Notes: Panel A plots the region's average asset wealth from 2003 to 2021. Panel B plots average household per capita expenditures, per day, for each 1 km × 1 km pixel. Panel C plots the average population living below the poverty line, for each

1 km × 1 km pixel. Calculations include the urban URCA category, as defined in the section on Methods and data. URCA categories (Cattaneo, Nelson and McMenomy, 2021b, 2021a) correspond to year 2015.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645

Table 2. Population and welfare indicators (adjusted by population) across aggregated URCA categories (SSA)

A. By category in 2021				
	Urban	**Peri-urban**	**Peri-rural**	**Hinterland and dispersed areas**
Population (sum)	304 710 006	582 172 130	267 954 604	66 121 914
Percentage population	25.0%	47.7%	21.9%	5.4%
Asset wealth index (AV)	0.97	0.21	-0.02	-0.22
Per capita expenditures (AV)	6.59	2.86	2.25	2.08
Extreme poverty (AV)	160	122	82	31
Km^2 (area)	64 607	4 381 304	8 580 403	11 099 537
B. Standard deviation (SD) over 2003–2021				
	Urban	**Peri-urban**	**Peri-rural**	**Hinterland and dispersed areas**
Asset wealth index	0.09	0.13	0.12	0.09
Per capita expenditures	0.47	0.21	0.12	0.07
Extreme poverty	264	37	18	2

Notes: AV = average. Calculations include the urban URCA category, as defined in the section on Methods and data.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645, on **Cattaneo, A., Nelson, A. & McMenomy, T.** 2021a. Global mapping of urban–rural catchment areas reveals unequal access to services. *Proceedings of the National Academy of Sciences of the United States of America*, 118(2): e2011990118. https://doi.org/10.1073/pnas.2011990118 and on **Cattaneo, A., Nelson, A. & McMenomy, T.** 2021b. Global Urban Rural Catchment Areas (URCA) Grid - 2021. In: *FAO Agro-informatics Data Catalog Portal*. [Cited 11 July 2023]. https://data.apps.fao.org/catalog/iso/9dc31512-a438-4b59-acfd-72830fbd6943

Welfare dynamics across Global Agro-Ecological Zones

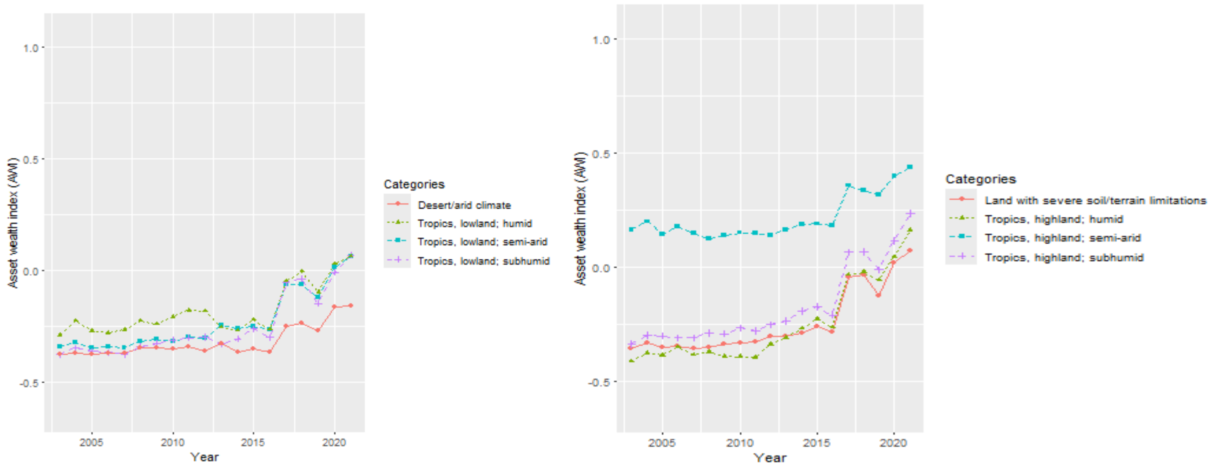
We now move to disaggregating the welfare indicators by GAEZ categories – albeit for rural populations only, as rural activities are more relevant than urban across GAEZ areas. Figure 5 plots the eight main GAEZ categories only, which account for around 95 percent of the population and total area (in km^2) of SSA. (The remaining GAEZ categories are presented in Figure A10 of the Annexes.)

Among the GAEZ categories represented in Figure 5, all of them appear to be closing the gap with the tropical highland semi-arid category (present in small pockets of Angola, Ethiopia, Kenya, Malawi, Namibia, South Africa, United Republic of Tanzania, Zambia and Zimbabwe). For assets and expenditures in general, tropical highlands appear to be performing better than tropical lowlands. Moreover, as shown in Panel C of Figure 5, tropical highlands have experienced rapid reductions in poverty compared to lowland regions – although they also have higher baseline poverty levels, due to their higher population densities. The stagnation in tropical lowland regions is worrisome, as they account for a very large proportion of the continent (58.9 percent of total area in km^2), and are home to most of SSA's rural population (72.5 percent).

Climate change is also putting increasing pressure on GAEZ areas in SSA. Although it is likely to increase the range of crops that can be grown in highland areas, climate change will make crop and livestock production more challenging in lowland areas, where temperatures are already high (Rötter and van de Geijn, 1999). Indeed, according to the Intergovernmental Panel on Climate Change (IPCC), rising temperatures in lower latitudes are expected to result in water stress, reduced nutrient quality in plants, and drops in livestock production – with particularly relevant impacts for rangeland and mixed systems that depend on crop residues as a dry-season feeding resource (IPCC, 2022; Thornton *et al.*, 2009). At the same time, tropical lowlands are projected to increase by 2050 and by 2080 as a result of the rising global temperatures, while tropical highlands are projected to shrink within the same periods, putting additional pressure on wealth dynamics (see also Table A3 in the Annexes). Although tropical highlands have achieved better results in recent decades, they are also mostly concentrated in small pockets of land in SSA (4.1 percent of the total area in km^2), which are projected to get even smaller. This will put additional pressure on the 13.3 percent of the population living in these areas.

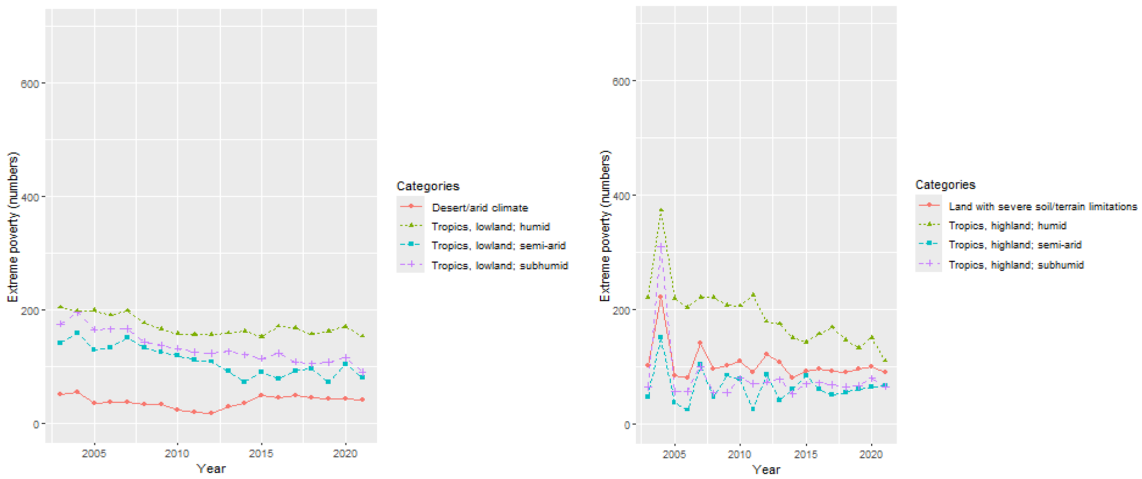
Figure 5. Welfare indicators (adjusted by population) across main Global Agro-Ecological Zones (SSA)

A. Asset wealth index



B. Per capita expenditures

C. Extreme poverty



Notes: Calculations exclude the urban URCA category, as defined in the section on Methods and data.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645 and on **FAO & IIASA.** 2023. Global Agro-Ecological Zones version 4 (GAEZ v4). In: *FAO*. [Cited 11 July 2023]. https://www.fao.org/gaez/en

Figure 5 shows that areas with arid terrain, desert areas, and very cool areas such as subtropical cool semi-arid and subtropical cool subhumid areas were worst off at the end of the period in terms of asset levels. Among these, the desert/arid climate zone is the most important, as it accounts for 27.7 percent of the total area (in km^2) and 4.5 percent of the rural population (see also Table A1 in the Annexes). As shown in Panel A of the figure, this zone presents the lowest level of asset wealth in recent years. Moreover, despite starting with much higher levels of expenditures and lower levels of poverty (as seen in Panel B and Panel C), expenditures for the desert/arid climate zone have stagnated over the last two decades. This stagnation is worrisome, given that the zone is projected to increase in size by 2080 due to climate change (as shown in the last column of Table A3, in the Annexes), further constraining the region's efforts to foster growth and poverty reduction. In particular, South Africa and parts of Botswana and Namibia are expected to become drier and to experience greater increases in temperature, due to the higher frequency of droughts and heatwaves foreseen towards the end of the 21st century (IPCC, 2022).

The figure also indicates that asset levels in subtropical zones are much higher compared to tropical zones, and have grown consistently during the 2003–2021 period (see also Figure A10 in the Annexes). However, as seen in Table A1 of the Annexes, subtropical zones account for only 1.6 percent of SSA's rural population, and the positive dynamics witnessed in these areas are unlikely to be replicable in tropical and arid zones.

Welfare dynamics across farming systems

We expect farming systems to shape potential for agricultural incomes in several ways. For example, different farm sizes are often associated with distinct farming systems (Hengsdijk *et al.*, 2014), which in turn influence the potential for agricultural incomes. Cereal-root crop mixed systems and irrigated farming systems are considered to have more potential for poverty reduction and agricultural growth (Dixon *et al.*, eds., 2019), while forest-based systems are considered to have comparatively limited potential due to physical isolation, lack of roads and high dependence on forest products. We also expect that farming systems in more arid areas –

and where pastoralists are located – will be poorer than those that rely more heavily on cash crops (such as cotton, coffee and cocoa) or perennial crops (Dixon *et al.*, eds., 2019).

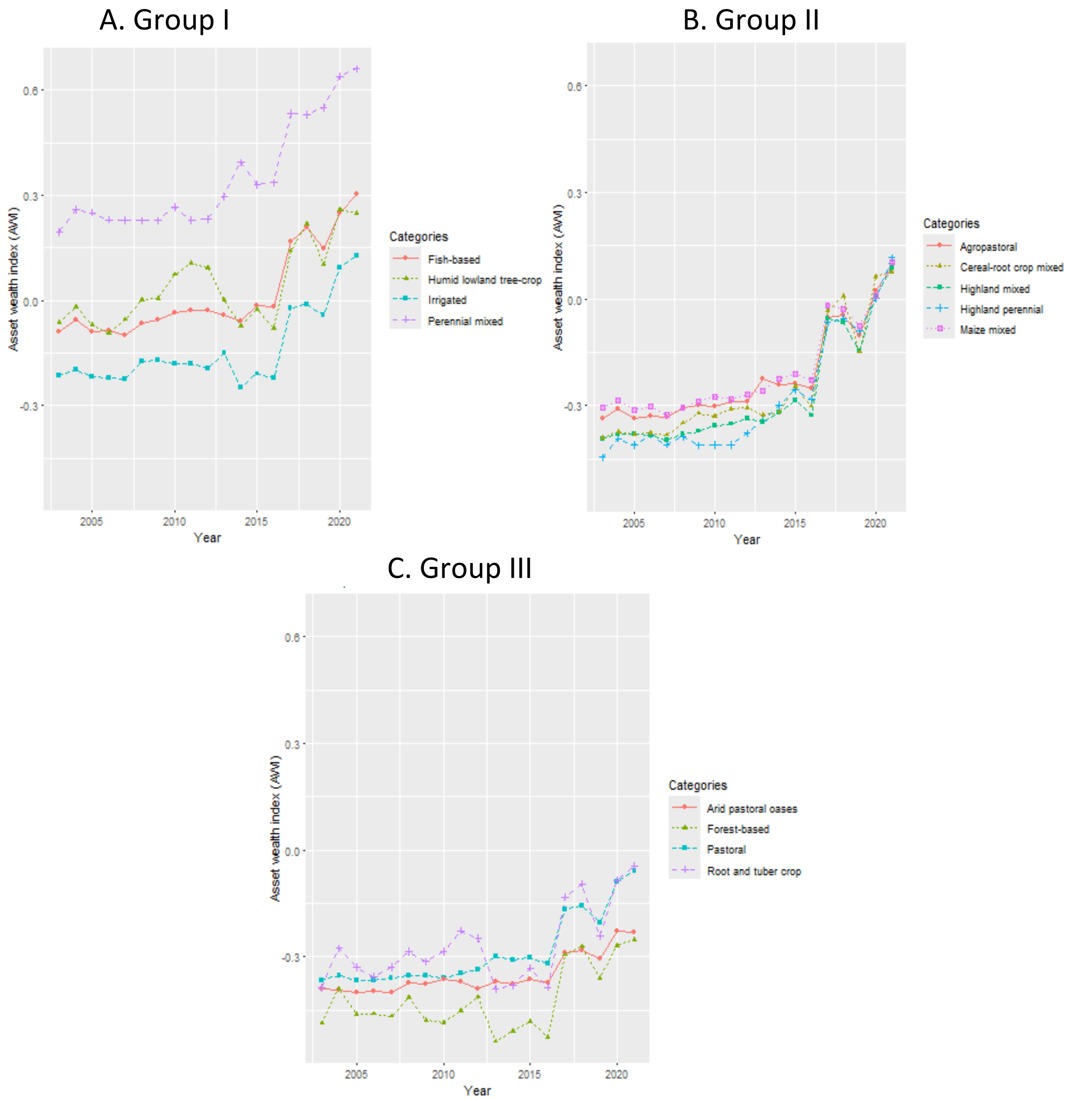
In exploring these differences, we can consider Figure 6, which portrays wealth accumulation from 2003 to 2021 across different farming system categories. (Figure A11 and Figure A12 in the Annexes describe well-being for per capita expenditures and poverty.)

We identify a first group in Figure 6, Group I (which includes perennial mixed, irrigated, humid lowland tree-crop and fish-based systems), with a higher average level of wealth accumulation and welfare performance. Among these, perennial mixed systems – followed by irrigated farming systems – appear to have higher levels of asset wealth and per capita expenditures, along with much lower levels of extreme poverty. Nevertheless, their dynamics seem to have stagnated for most of the period. Perennial mixed systems are primarily present in humid and subhumid agroecological zones; they involve the cultivation of vines, fruits and eucalyptus, and are present in South Africa, some parts of North Africa, and along the coastline (see Table A4 in the Annexes). Irrigated farming systems are present across SSA, and depend largely on the production of rice, wheat, cotton and livestock. The other two categories – humid lowland tree-crop systems (including coffee, cocoa, oil palm and some maize) and fish-based systems – present a high level of asset wealth and expenditures across the years, but remain affected by high levels of poverty. Overall, this first group of better-performing farming systems (perennial mixed, irrigated, humid lowland tree-crop and fish-based) accounts for only 17.2 percent of SSA's rural population, with limited potential for further expansion (see also Table A4 in the Annexes).

Group II reflects a second, middle category in terms of asset wealth, composed of areas with highland perennial, cereal-root crop mixed, agropastoral, highland mixed and maize mixed farming systems. Among these, highland perennial, cereal-root crop mixed and agropastoral systems have been performing reasonably well in terms of asset wealth and expenditures, which has in turn contributed to poverty reductions in recent years. With the other two categories however (highland mixed and maize mixed), although there has been an increase in per capita expenditures, this has not translated into large poverty reductions for the period. Importantly, this group of farming systems accounts for 61 percent of SSA's rural population.

It should be noted that climate change and expected increases in temperature threaten to undermine recent improvements in welfare across some of these farming systems. For example, the systems in this second group are highly dependent on cereal (particularly maize) and legumes, but rising temperatures pose a significant threat to the productivity of these crops (Bezner Kerr *et al.*, 2023). In particular, research shows that high levels of heat stress in the Sahel and in southeast Africa undermine current and future maize yields, with major implications for food security and poverty (Teixeira *et al.*, 2013).

Figure 6. Asset wealth index (adjusted by population) across farming systems (SSA, rural areas only)



Notes: Calculations exclude the urban URCA category, as defined in the section on Methods and data.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645 and on **FAO & IIASA.** 2023. Global Agro-Ecological Zones version 4 (GAEZ v4). In: *FAO*. [Cited 11 July 2023]. https://www.fao.org/gaez/en

Group III consists of farming systems with the lowest levels of asset wealth of all. They include forest-based systems, as present in the Democratic Republic of Congo and Congo; root and tuber crop systems, as located in the West Central areas of Africa; and pastoral and arid pastoral oases systems, which extend from Mauritania to the northern parts of Mali, Niger, Chad, Sudan, Eritrea, Ethiopia, Kenya and Uganda (close to the Sahara). Among these, forest-based and root and tuber crop systems show the worst performance across all farming systems (see Figure A11 and Figure A12 in the Annexes), with both having the lowest levels of asset wealth and per capita expenditures, and high levels of poverty. They are followed by pastoral and arid pastoral oases systems, which have lower levels of asset wealth, but slightly higher levels of per capita expenditures, and lower numbers for extreme poverty. However, both pastoral and arid pastoral oases systems appear to stagnate during the period of analysis. Moreover, all four of these farming systems have the lowest levels of market integration, and thus face acute challenges in terms of agricultural commercialization (Dixon *et al.*, eds., 2019). However, despite having low overall welfare indicators, these systems also have low yearly variability (SD) on asset wealth accumulation, which indicates generally lower levels of inequality (see also Table A4 in the Annexes). Taken together, these farming systems account for 20.5 percent of SSA's rural population. In the absence of climate adaptation, they are expected to face additional pressure from the increasing frequency of droughts and rising temperatures (Bezner Kerr *et al.*, 202).

Conclusion

Over the last 20 years, sub-Saharan Africa has witnessed notable improvements in poverty reduction, asset wealth accumulation, and expenditure growth at the regional level. However, large parts of the region have been excluded from these gains. This paper provides new evidence on the spatial dimensions of welfare dynamics in SSA, with a specific focus on how urban proximity, agroecological zones and predominant farming systems have influenced welfare trends between 2003 and 2021. It shows that positive welfare trends have been highly concentrated in more urbanized areas and among populations that were already at the top of the wealth distribution in 2003. Most rural areas of SSA have seen limited to no progress in reducing poverty, boosting expenditures, and accumulating assets. The analysis also shows that welfare progress has been particularly limited in the tropical lowlands of SSA, where most of the rural population resides, and in desert and arid areas. Worryingly, these are also the agroecological zones that will likely expand as a result of climate change. Finally, rural populations living in areas with farming systems that offer limited commercialization potential, or with biophysical conditions that limit potential for agricultural diversification have experienced virtually no improvement in welfare over the last 20 years.

The findings of this study demonstrate an urgent need for improvements in geographical targeting for agricultural development and poverty reduction policies and programmes in SSA. This is particularly the case given the impacts of climate change on the region, as such impacts will likely increase the spatial extent of farming systems and agroecological zones where progress on improving well-being has historically been the most limited. The analysis highlights the importance of strengthening linkages between urban and rural areas in order to enhance the welfare of rural people – including through improvements in transport and roads, and in agricultural market infrastructure. The results also indicate a need to invest in agricultural research and extension services that target the development and dissemination of productive, climate-adaptive practices and technologies, particularly for SSA's arid and tropical lowland areas. Not only have these areas experienced little to no progress in terms of welfare improvements, they are home to a large share of SSA's rural population – which will continue to grow as a result of climate change. At the same time, it should be noted that some agricultural activities may not offer a viable pathway out of poverty for many rural people in SSA, particularly those living in remote and marginal agroecological zones. In these contexts, supporting a viable exit from agriculture is critical. Among other actions, strategies to address this include long-term investments for increased human capital formation, and for extending financial and other relevant services in these areas.

Ultimately, identifying viable and effective strategies to reduce poverty and improve welfare in SSA requires a more explicit focus on the diverse spatial constraints and opportunities that exist in the region, and the ways in which such constraints and opportunities are likely to evolve in the future. The descriptive analysis presented in this paper contributes to a better understanding of the needs in the region, where they are most acute, and the spatial features that foster or hinder welfare dynamics. As the availability and quality of spatially explicit socioeconomic data continues to increase, our ability to better disentangle these dynamics will continue to improve. However, it is important to emphasize that these data should not be treated as a replacement for detailed household survey data and qualitative methods, but rather as an additional tool to improve our understanding of development challenges. Blending traditional survey-based approaches with novel spatial data is likely to be the most effective strategy for generating the evidence needed to identify and target location-specific interventions.

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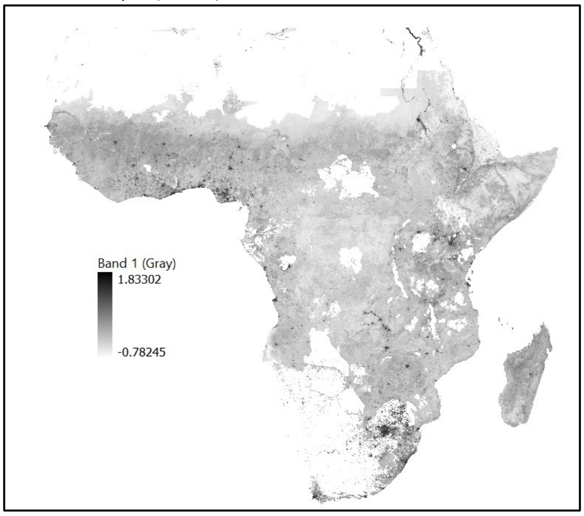
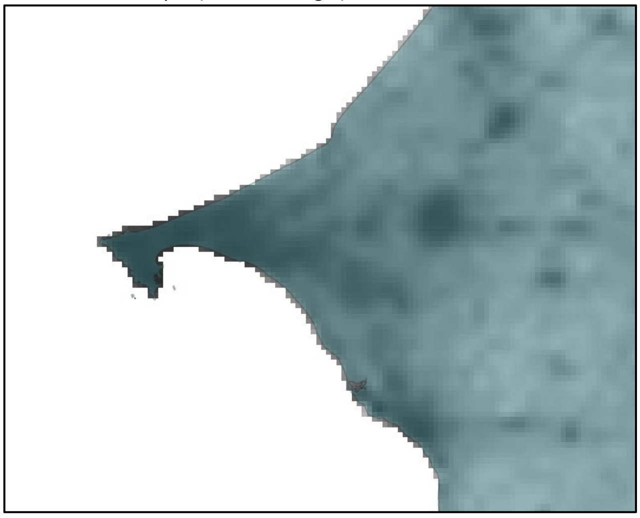
Annexes

Figure A1. Asset wealth index in 2021 (Africa)

A. Whole sample (Africa)

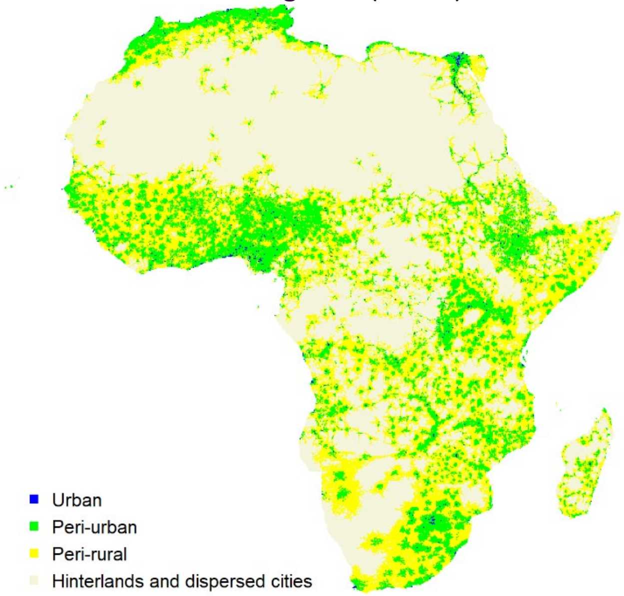


B. Subsample (Dakar, Senegal)



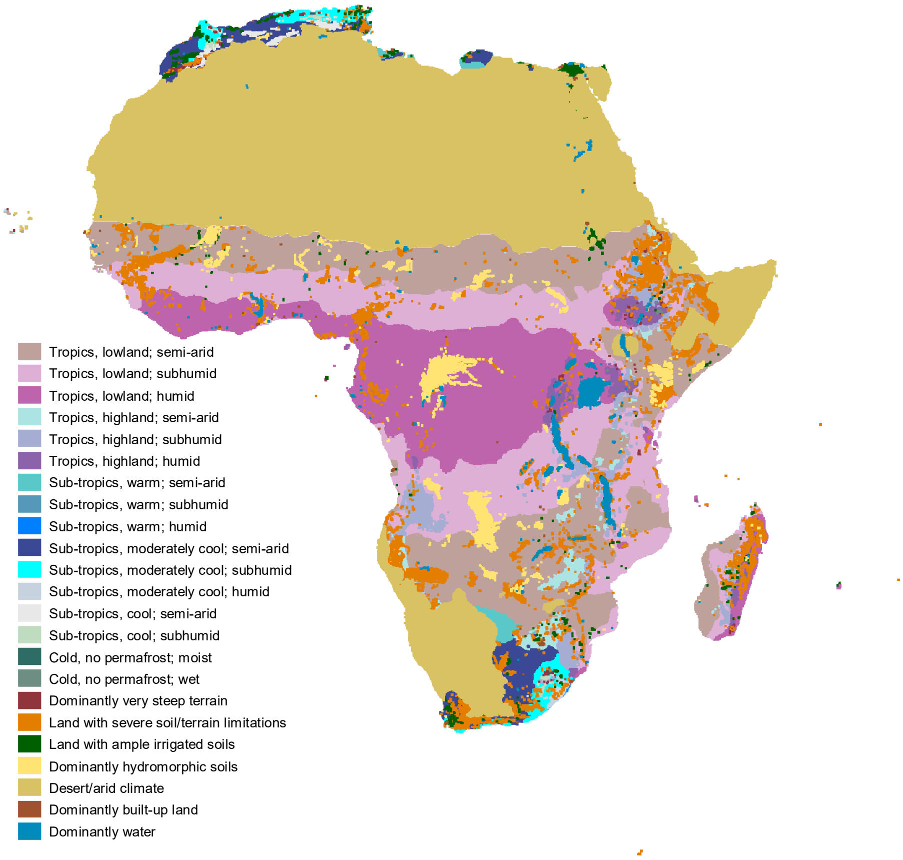
Note: Panel A plots AWI data for 2021 in Africa, while Panel B plots a subsample for the city of Dakar, Senegal in 2021. The blank areas in Panel A correspond to masked out values of AWI, mostly sparsely populated deserts, and large bodies of water.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021.
https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645

Figure A2. Urban–rural catchment area categories (Africa)



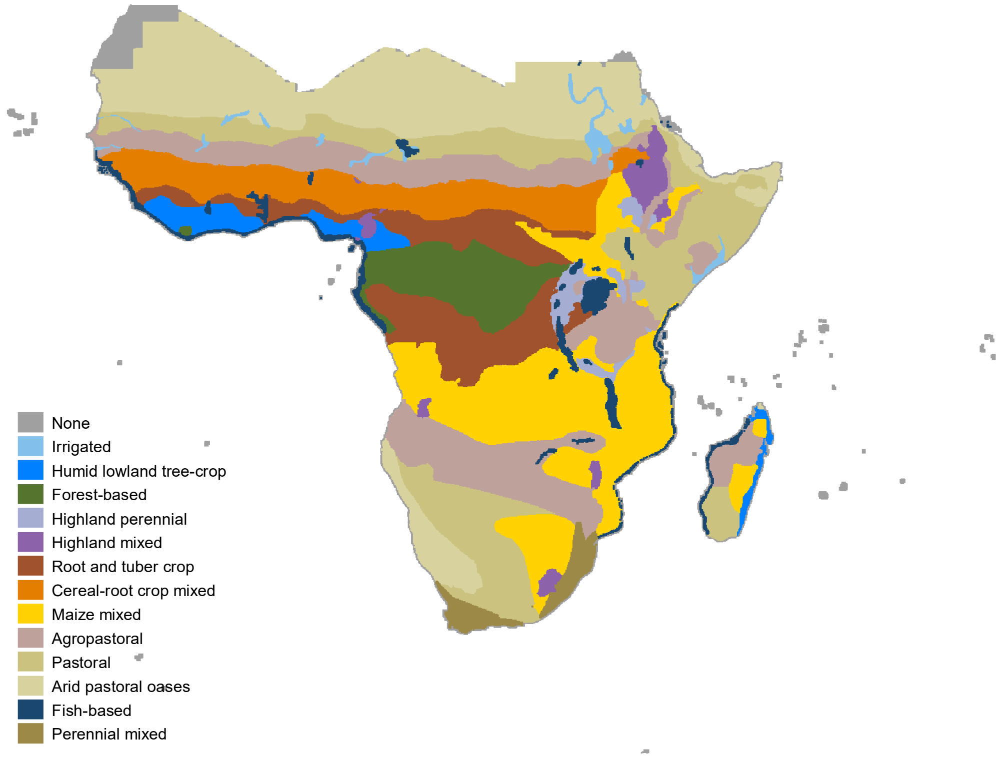
Note: The four aggregated URCA categories are as follows: (i) urban centres (shown in blue); (ii) peri-urban areas (in green); (iii) peri-rural areas (in yellow); and (iv) hinterlands and dispersed cities (in beige). URCA categories (Cattaneo, Nelson and McMenomy, 2021b, 2021a) correspond to year 2015.
Source: Authors' own elaboration based on **Cattaneo, A., Nelson, A. & McMenomy, T.** 2021. Global Urban Rural Catchment Areas (URCA). https://data.apps.fao.org/catalog/iso/9dc31512-a438-4b59-acfd-72830fbd6943

Figure A3. Global Agro-Ecological Zones (Africa)



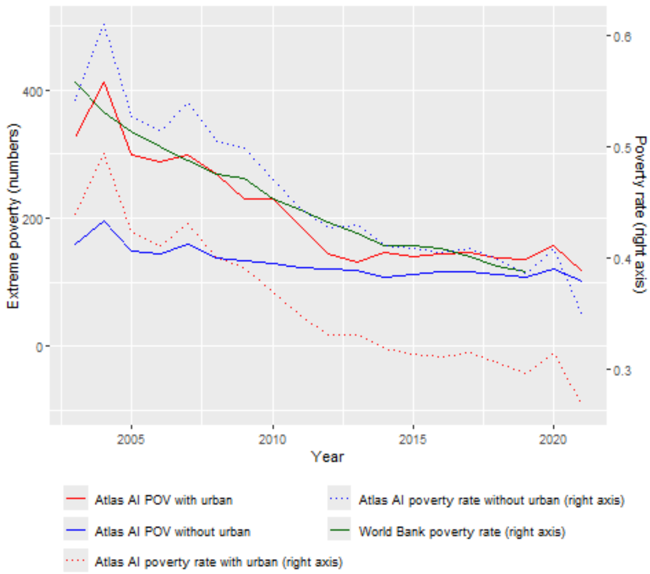
Sources: Authors' own elaboration based on **FAO & IIASA (International Institute for Applied Systems Analysis).** 2023. Global Agro-Ecological Zones version 4 (GAEZ v4). https://www.fao.org/gaez/en and on **Sebastian, K.** 2009. Agro-ecological Zones of Africa. https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HJYYTI

Figure A4. Farming systems (SSA)



Sources: Authors' own elaboration based on **Dixon, J., Garrity, D.P., Boffa, J.-M., Williams, T.O., Amede, T., Auricht, C., Lott, R. & Mburathi, G., eds.** 2019. Farming Systems and Food Security in Africa: Priorities for Science and Policy Under Global Change. Earthscan Food and Agriculture Series. Routledge, Oxon, UK. https://doi.org/10.4324/9781315658841, on **HarvestChoice, IFPRI (International Food Policy Research Institute) & University of Minnesota.** 2017. CELL5M: A Multidisciplinary Geospatial Database for Africa South of the Sahara.https://doi.org/10.7910/DVN/G4TBLF, and on **Koo, J., Cox, C.M., Bacou, M., Azzarri, C., Guo, Z., Wood-Sichra, U., Gong, Q. & You, L.** 2016. CELL5M: A geospatial database of agricultural indicators for Africa South of the Sahara. https://doi.org/10.12688/f1000research.9682.1

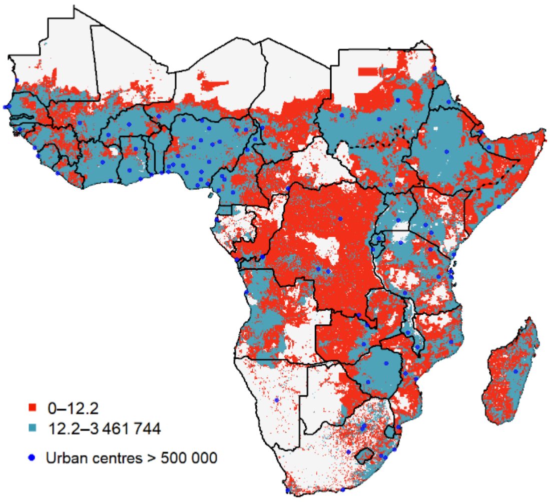
Figure A5. Extreme poverty (adjusted by population) and poverty rate, urban and rural areas (SSA)



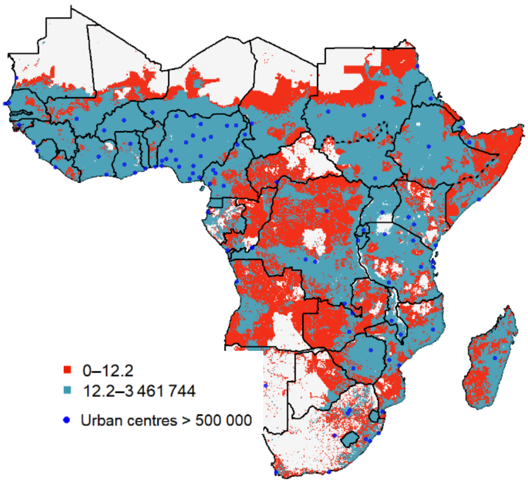
Notes: For Atlas AI data, the figure plots the yearly average population living below the poverty line, for each 1 km × 1 km pixel. Red indicates calculations that include the urban URCA category (as defined in the section on Methods and data), while blue indicates calculations that exclude it. From the right axis, green reflects the World Bank poverty measure, the poverty rate (percent) at USD 1.90 or poverty headcount ratio (2011 PPP) (percentage of population) for SSA. For Atlas AI data, poverty rate (percent) is calculated as the sum of the extreme poor in all SSA pixels, divided by the total population living there.
Sources: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645 and **World Bank.** 2023. Poverty and Inequality Platform. In: *Poverty and Inequality Platform*. [Cited 11 July 2023]. https://pip.worldbank.org

Figure A6. Per capita expenditures, spatial variation, 2003–2021 (SSA)

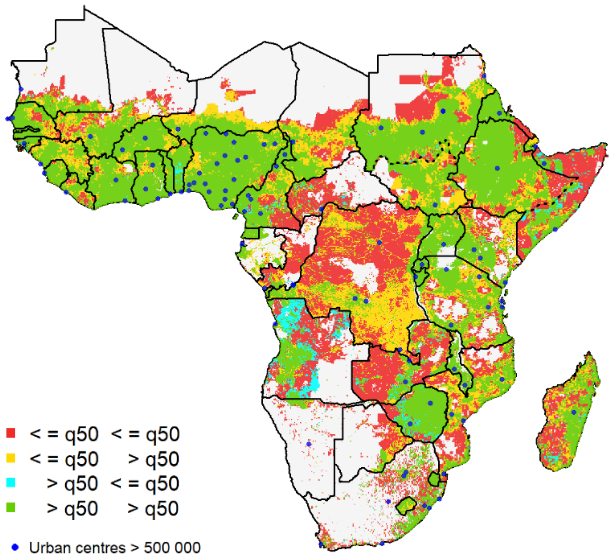
A. Per capita expenditures in 2003



B. Per capita expenditures in 2021



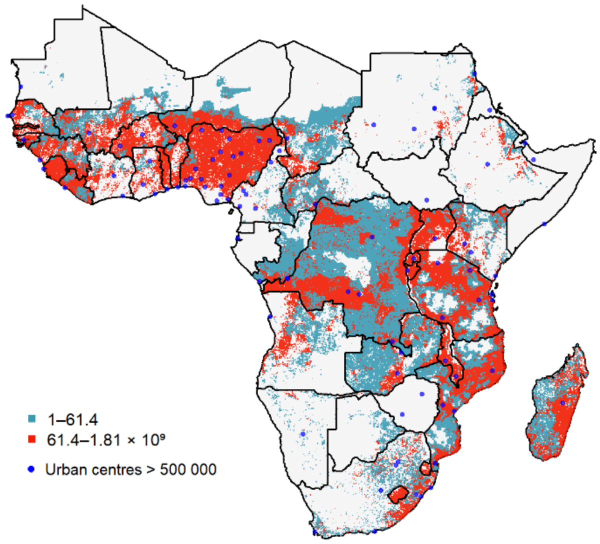
C. Per capita expenditures > q50 vs < = q50 in 2003 and 2021



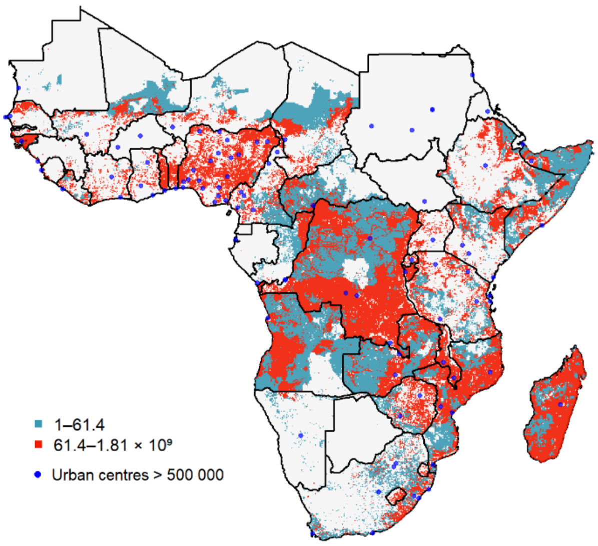
Notes: Refer to the disclaimer on page ii for the names and boundaries used in this map. Final boundary between the Sudan and South Sudan has not yet been determined.
Calculations include the urban URCA category, as defined in the section on Methods and data. Panel A and B depict the image of SP × POP in 2003 and 2021. While this is not exactly equivalent to SP adjusted by population, it partially preserves the adjustment by population and the characteristics of SP on expenditures. The 50th quantile or median (q50) is calculated for 2003, and used to determine values above and below it for 2003 and 2021. The categories are: (i) < = q50 in 2003 and < = q50 in 2021 in red; (ii) < = q50 in 2003 and > q50 in 2021 in yellow; (iii) > q50 in 2003 and < = q50 in 2021 in cyan; (iv) > q50 in 2003 and > q50 in 2021 in green.
Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645, on **Esri.** 2017. Africa Cities. Updated on 9 December 2017. https://www.africageoportal.com/datasets/africa::africa-cities-1/about and on **United Nations Geospatial.** 2020. Map geodata UNmap25_shp. New York, USA, United Nations.

Figure A7. Extreme poverty, spatial variation, 2003–2021 (SSA)

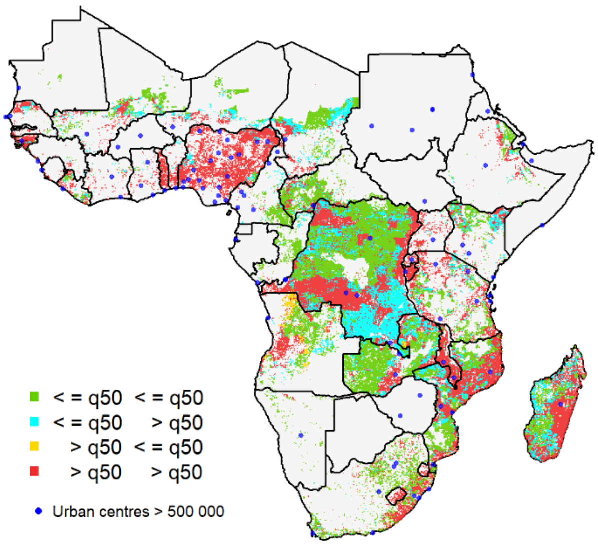
A. Extreme poverty in 2003



B. Extreme poverty in 2021



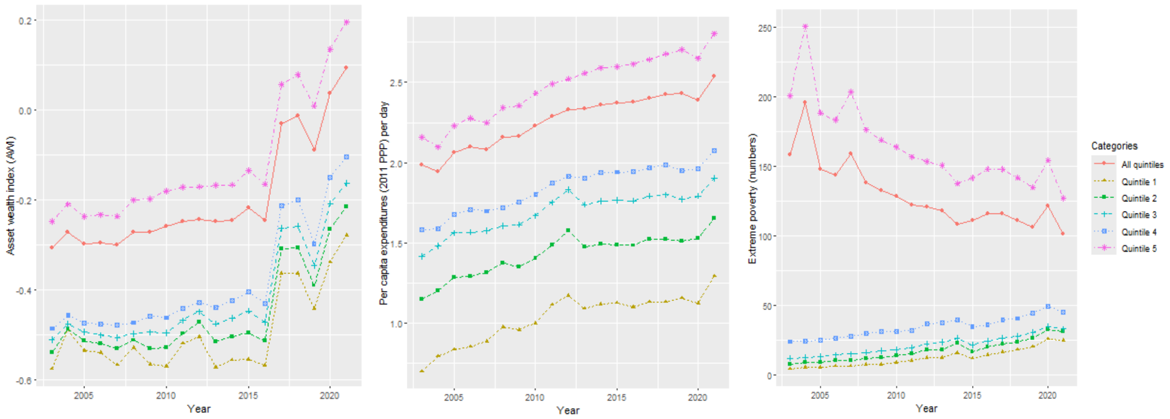
C. Extreme poverty > q50 vs < = q50 in 2003 and 2021



Notes: Refer to the disclaimer on page ii for the names and boundaries used in this map.Final boundary between the Sudan and South Sudan has not yet been determined.
Calculations include the urban URCA category, as defined in the section on Methods and data. Panel A and B depict the image of POV × POP in 2003 and 2021. While this is not exactly equivalent to POV adjusted by population, it partially preserves the adjustment by population and the characteristics of POV. The 50th quantile or median (q50) is calculated for 2003, and used to determine values above and below it for 2003 and 2021. The categories are: (i) < = q50 in 2003 and < = q50 in 2021 in green; (ii) < = q50 in 2003 and > q50 in 2021 in cyan; (iii) > q50 in 2003 and < = q50 in 2021 in yellow; and (iv) > q50 in 2003 and > q50 in 2021 in red.
Sources: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645, on **Esri.** 2017. Africa Cities. Updated on 9 December 2017. https://www.africageoportal.com/datasets/africa::africa-cities-1/about and on **United Nations Geospatial.** 2020. Map geodata UNmap25_shp. New York, USA, United Nations.

Figure A8.Welfare indicators (adjusted by population) across SP quintiles (SSA)

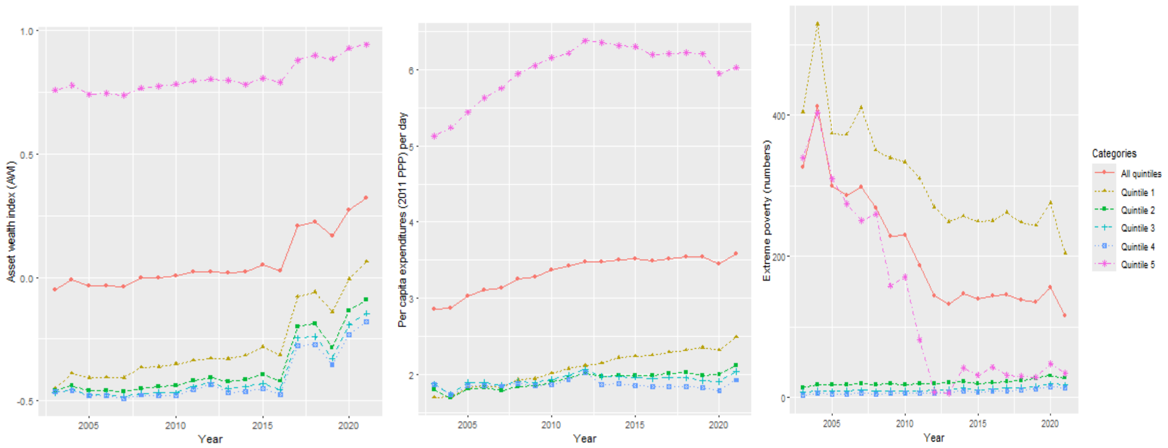
A. Asset wealth index B. Per capita expenditures C. Extreme poverty



Notes: Calculations exclude the urban URCA category, as defined in the section on Methods and data. Quintiles were defined by taking the image of SP × POP, with 2003 as the baseline year.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021.
https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645

Figure A9. Welfare indicators (adjusted by population) across AWI quintiles (SSA)

Asset wealth index B. Per capita expenditures C. Extreme poverty



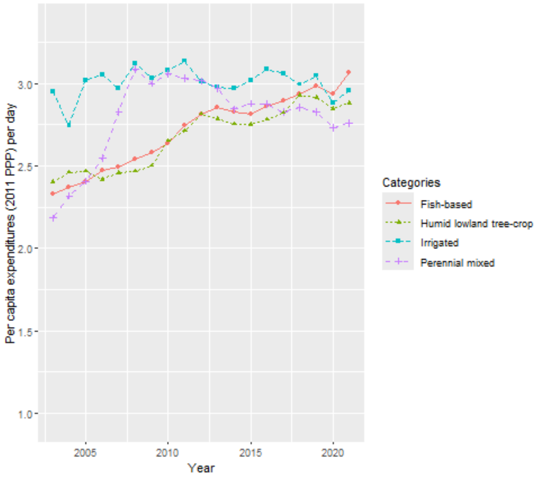
Notes: Calculations include the urban URCA category, as defined in the section on Methods and data. Quintiles were defined by taking the image of AWI × POP, with 2003 as the baseline year.
Source: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021.
https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645

Figure A10. Welfare indicators (adjusted by population) across other Global Agro-Ecological Zones (SSA)

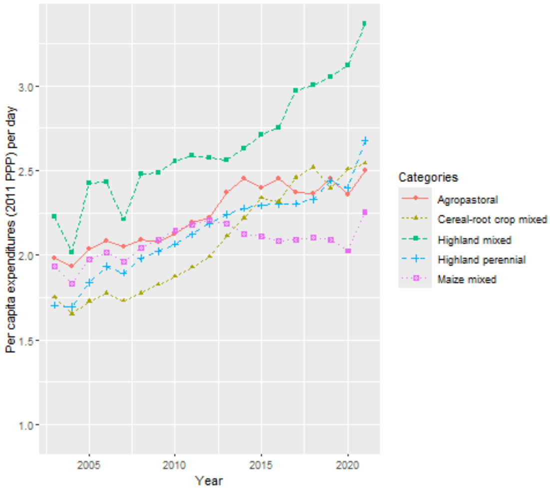
Notes: Calculations exclude the urban URCA category, as defined in the section on Methods and data.
Sources: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645, and **FAO & IIASA (International Institute for Applied Systems Analysis).** 2023. Global Agro-Ecological Zones version 4 (GAEZ v4). In: *FAO*. [Cited 11 July 2023]. https://www.fao.org/gaez/en

Figure A11. Per capita expenditures (adjusted by population) across farming systems (SSA)

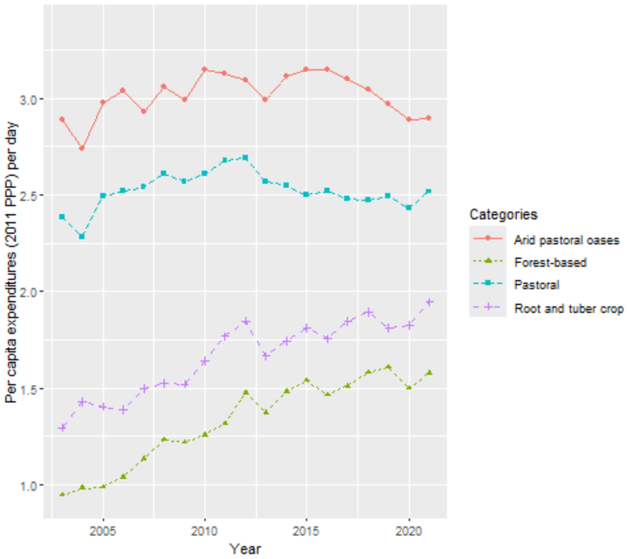
A Group I



B. Group II

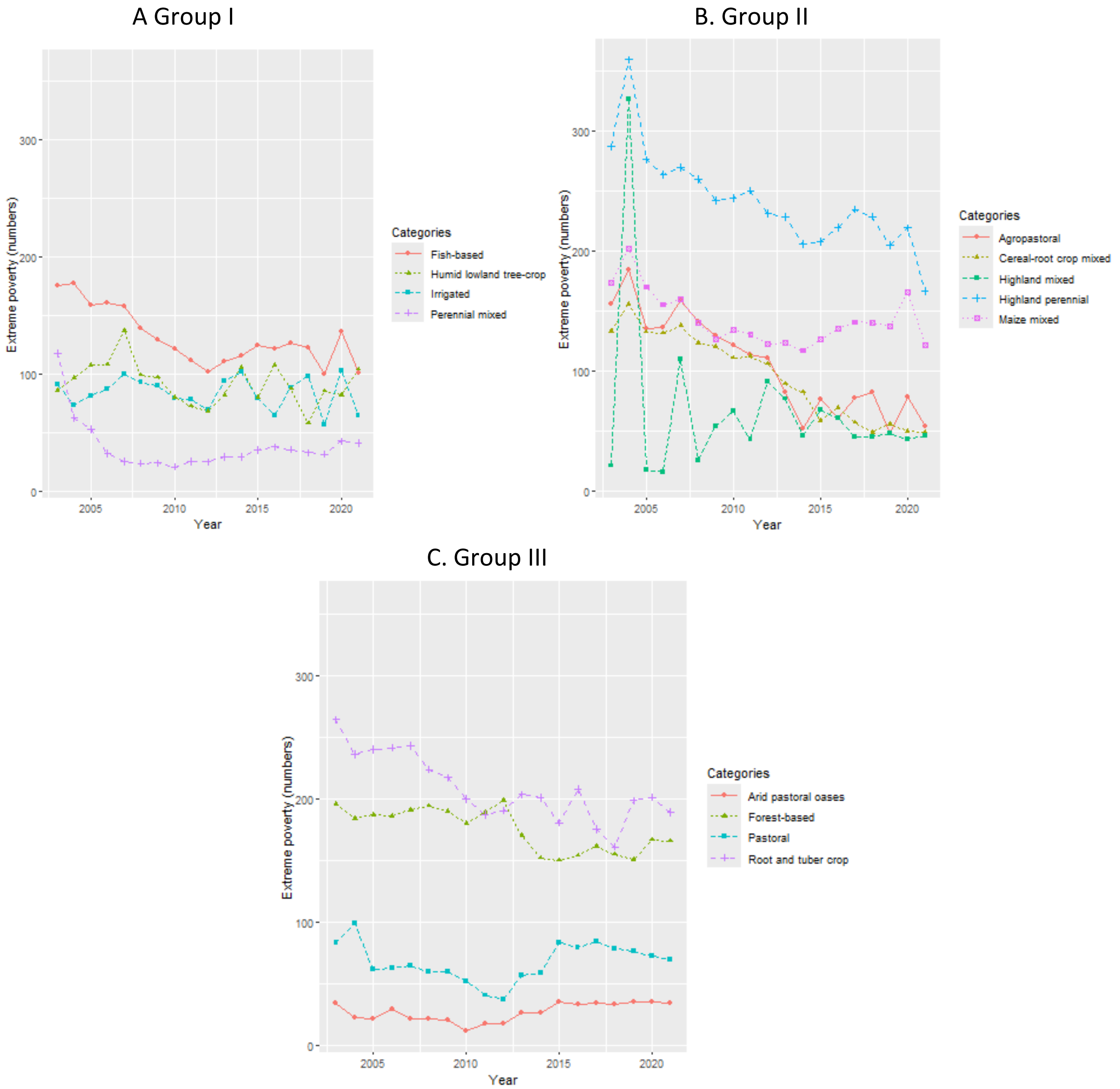


C. Group III



Notes: Calculations exclude the urban URCA category, as defined in the section on Methods and data.
Sources: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645, on **Dixon, J., Garrity, D.P., Boffa, J.-M., Williams, T.O., Amede, T., Auricht, C., Lott, R. & Mburathi, G.**, eds. 2019. *Farming Systems and Food Security in Africa: Priorities for Science and Policy Under Global Change*. Earthscan Food and Agriculture Series. Routledge, Oxon, UK. https://doi.org/10.4324/9781315658841, on **HarvestChoice, IFPRI (International Food Policy Research Institute) & University of Minnesota.** 2017. CELL5M: A Multidisciplinary Geospatial Database for Africa South of the Sahara. In: *Harvard Dataverse*. [Cited 11 July 2023]. https://doi.org/10.7910/DVN/G4TBLF and on **Koo, J., Cox, C.M., Bacou, M., Azzarri, C., Guo, Z., Wood-Sichra, U., Gong, Q. & You, L.** 2016. CELL5M: A geospatial database of agricultural indicators for Africa South of the Sahara. *F1000Research*, 5: 2490. https://doi.org/10.12688/f1000research.9682.1

Figure A12. Extreme poverty (adjusted by population) across farming systems (SSA)



Notes: Calculations exclude the urban URCA category, as defined in the section on Methods and data.
Sources: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645, on **Dixon, J., Garrity, D.P., Boffa, J.-M., Williams, T.O., Amede, T., Auricht, C., Lott, R. & Mburathi, G.**, eds. 2019. *Farming Systems and Food Security in Africa: Priorities for Science and Policy Under Global Change*. Earthscan Food and Agriculture Series. Routledge, Oxon, UK. https://doi.org/10.4324/9781315658841, on **HarvestChoice, IFPRI (International Food Policy Research Institute) & University of Minnesota.** 2017. CELL5M: A Multidisciplinary Geospatial Database for Africa South of the Sahara. In: *Harvard Dataverse*. [Cited 11 July 2023]. https://doi.org/10.7910/DVN/G4TBLF and on **Koo, J., Cox, C.M., Bacou, M., Azzarri, C., Guo, Z., Wood-Sichra, U., Gong, Q. & You, L.** 2016. CELL5M: A geospatial database of agricultural indicators for Africa South of the Sahara. *F1000Research*, 5: 2490. https://doi.org/10.12688/f1000research.9682.1

Table A1. Main GAEZ categories, characteristics and welfare indicators (adjusted by population) (SSA)

No.	GAEZ category name	Cropland	Grass and shrub	Tree cover	Other cover	Mean temperature (°C)	Annual rainfall (mm)	Area (km^2)	2021				SD 2003–2021		
									Asset wealth index	Per capita expenditures	Extreme poverty	Population	Asset wealth index	Per capita expenditures	Extreme poverty
1	Tropics, lowland; semi-arid	13.4	45.0	26.7	14.9	25.6	708	5 783 108	0.06	2.42	81	217 689 317	0.13	0.16	27
2	Tropics, lowland; subhumid	14.4	38.7	44.4	2.4	25.1	1286	4 609 567	0.07	2.28	91	200 520 870	0.14	0.19	28
3	Tropics, lowland; humid	10.5	15.9	71.7	1.9	25.6	2123	3 805 142	0.06	2.46	154	227 900 356	0.11	0.20	18
4	Tropics, highland; semi-arid	8.6	57.0	19.2	15.3	16.5	558	254 739	0.44	3.49	67	15 629 197	0.10	0.30	30
5	Tropics, highland; subhumid	15.8	46.6	32.9	4.7	17.2	1012	507 622	0.24	3.12	65	46 993 430	0.17	0.25	57
6	Tropics, highland; humid	18.8	28.4	49.2	3.6	17.3	1570	229 815	0.16	2.92	110	55 779 515	0.18	0.30	57
7	Subtropics, warm; semi-arid	19.2	32.4	16.4	32.0	23.3	601	79 184	0.37	5.3	12	309 097	0.14	0.42	17
8	Subtropics, warm; subhumid	26.9	24.9	39.8	8.4	22.6	1169	1 464	0.98	3.17	2	378 225	0.11	0.41	9
9	Subtropics, warm; humid	18.3	36.3	39.1	6.3	21.6	1656	1 376	0.9	2.89	7	347 354	0.11	0.36	24
10	Subtropics, moderately cool; semi-arid	16.0	42.0	11.0	31.0	17.4	379	318 616	0.74	3.16	56	4 376 777	0.12	0.29	33
11	Subtropics, moderately cool; subhumid	31.2	31.5	24.1	13.3	16.4	722	113 882	0.55	2.69	58	6 399 904	0.15	0.26	25
12	Subtropics, moderately cool; humid	23.0	27.5	44.8	4.6	17.2	1280	17 480	0.52	2.06	82	1 887 546	0.19	0.19	33
13	Subtropics, cool; semi-arid	9.9	58.2	13.7	18.2	11.4	360	291	-0.35	0.98	2	93	0.09	0.23	1
14	Subtropics, cool; subhumid	18.8	30.6	40.9	9.7	11.2	763	6 932	0.00	2.44	23	161 160	0.16	0.51	48
23	Cold, no permafrost; moist	3.1	20.1	71.4	5.4	-0.3	496	1 343	-0.07	2.93	6	104 428	0.12	0.28	56
24	Cold, no permafrost; wet	1.1	20.0	71.7	7.2	0.1	713	2 127	-0.1	2.69	46	146 462	0.13	0.26	11
25	Dominantly very steep terrain	3.0	32.6	43.5	20.8	6.7	1034	25 721	-0.04	2.76	78	1 963 804	0.13	0.22	36
26	Land with severe soil/terrain limitations	8.0	28.6	53.2	10.1	16.2	1368	976 078	0.07	2.66	90	41 680 003	0.14	0.18	32
27	Land with ample irrigated soils	62.2	17.3	8.3	12.1	19.2	868	65 550	0.4	3.22	63	10 232 707	0.14	0.18	11
28	Dominantly hydromorphic soils	12.7	35.3	40.7	11.3	9.8	887	408 206	-0.04	2.16	50	9 790 241	0.11	0.16	25
29	Desert/arid climate	1.1	14.2	1.4	83.3	21.7	127	6 685 673	-0.16	2.76	40	39 843 361	0.07	0.13	11
32	Dominantly built-up land	2.9	3.5	1.0	92.6	16.3	977	8 899	1.07	5.44	100	3 527 249	0.05	0.60	212
33	Dominantly water	0.3	1.9	1.0	96.8	6.0	584	205 840	0.05	2.31	199	6 088 769	0.11	0.14	69

Notes: SD = standard deviation. Calculations of welfare indicators and population exclude the urban URCA category, as defined in the section on Methods and data. Columns 10 to 13 correspond to the year 2021. The subtropics cool semi-arid category is only present in some small portions of North Africa, and in a few pixels in South Africa.

Sources: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645 and **Fischer, G., Nachtergaele, F.O., van Velthuizen, H.T., Chiozza, F., Franceschini, G., Henry, M., Muchoney, D. & Tramberend, S.** 2021. *Global Agro-Ecological Zones v4 – Model documentation*. Rome, FAO. https://doi.org/10.4060/cb4744en

Table A2. Potential yield (kg dry weight per hectare) across GAEZ categories (main crops) (SSA)

	Maize						Pearl millet					
	Irrigated			Rainfed			Irrigated			Rainfed		
No.	1961-1990	1971-2000	1981-2010	1961-1990	1971-2000	1981-2010	1961-1990	1971-2000	1981-2010	1961-1990	1971-2000	1981-2010
1	9516	9555	9593	6736	6701	6804	3429	3450	3490	2910	2905	2909
2	8397	8554	8571	7289	7493	7352	2256	2290	2289	2016	2062	2021
3	4772	5183	5250	4338	4788	4825	1508	1635	1681	1337	1490	1532
4	9060	8811	8633	4252	4101	3445	0	0	3916	0	0	3080
5	8714	8703	8693	6088	5968	5663	0	0	2760	0	0	2604
6	6885	7094	7163	6190	6244	6144	0	0	2778	0	0	1533
7	8029	7985	8827	2811	4038	5860	3225	3263	3210	1936	2204	1514
8	10784	10827	10906	10640	10632	10377	0	0	0	0	0	0
9	12464	12508	12595	12297	12009	11229	0	0	0	0	0	0
10	12755	12630	12746	5713	5251	5052	0	0	2835	0	0	1704
11	11914	11933	12035	9081	8967	8646	0	0	0	0	0	0
12	10549	10581	10690	9834	9740	9562	0	0	0	0	0	0
13	11251	11270	11426	4684	5027	4508	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0
25	8309	8340	8378	5551	5860	5741	3295	3143	3191	2772	2722	2588
26	7288	7357	7405	5495	5656	5583	2391	2394	2427	1991	1997	2025
27	9851	9928	10060	6698	6806	6761	2893	2878	2995	2405	2445	2422
28	10088	10123	10129	7440	7461	7640	3599	3616	3622	3058	3055	3042
29	9253	9261	9260	1450	1460	1370	3400	3417	3424	1296	1174	1174
32	7315	7322	7118	4843	4787	4615	2472	2499	2512	1927	1994	2084
33	7863	8236	8400	6729	7209	7248	2438	2453	2517	1964	1958	1998

	Sorghum					
	Irrigated			Rainfed		
AEZ	1961-1990	1971-2000	1981-2010	1961-1990	1971-2000	1981-2010
1	7412	7462	7517	5793	5751	5806
2	5939	6112	6151	5218	5418	5322
3	3471	3940	4083	3025	3422	3493
4	5210	4990	4789	3002	2691	2229
5	4737	4747	4728	3748	3719	3558
6	3436	3650	3708	3103	3298	3300
7	5377	5432	6956	3316	4048	3383
8	6734	6780	6821	6727	6781	6668
9	6194	6667	7041	6155	6637	6857
10	9313	9281	9284	5717	5471	5115
11	8104	8199	8314	6537	6604	6521
12	5605	5990	6268	5365	5746	5952
13	7897	7902	8887	5049	5236	5500
14	0	0	0	0	0	0
23	0	0	0	0	0	0
24	0	0	0	0	0	0
25	4404	4482	4526	3311	3522	3477
26	4722	4723	4888	3842	3861	3930
27	7149	7176	7374	5017	5005	4963
28	7898	7925	7914	6329	6257	6238
29	7211	7221	7219	1888	1802	1818
32	5630	5491	5329	3974	3949	3680
33	5776	5946	6066	4550	4934	5037

Notes: Crop tables correspond to input level classified as high for SSA, choosing EXC = 1 as protection/exclusion class indicator and LC = 8 for land cover class indicator. The variable of potential yield (kg dry weight per hectare) chosen was the one that considers the combinations of suitability classes VS + S + MS + mS land (where VS = very suitable land, S = suitable land, MS = moderately suitable land and mS = marginally suitable land). This is more indicative of the real situation with regard to potential yield in VS + S + MS + mS land, distribution of yields over the various suitability classes, and their extent. Tables provide yields for irrigated and rainfed areas, and for three time periods. For more information, see Chapter 7 of Fischer et al. (2021).
Sources: Authors' own elaboration based on FAO. 2023. Crop Summary Tables: Global Crop Profile and Crop Statistics. In: GAEZ Data Portal. [Cited 14 July 2023]. https://gaez.fao.org/pages/crop-summary

Table A3. Global Agro-Ecological Zone projections (area in km2) (Africa)

No.	GAEZ category name	Area (km^2) 2020	Area (km^2) 2050	Area (km^2) 2080
1	Tropics, lowland; semi-arid	5 929 611	6 147 987	6 202 759
2	Tropics, lowland; subhumid	5 251 469	5 209 270	5 104 919
3	Tropics, lowland; humid	3 682 768	3 641 662	3 688 563
4	Tropics, highland; semi-arid	105 772	74 997	90 302
5	Tropics, highland; subhumid	369 354	345 193	349 730
6	Tropics, highland; humid	231 058	204 383	210 013
7	Subtropics, warm; semi-arid	216 682	255 273	212 965
8	Subtropics, warm; subhumid	3 772	14 212	14 650
9	Subtropics, warm; humid	2 678		656
10	Subtropics, moderately cool; semi-arid	413 794	385 752	375 257
11	Subtropics, moderately cool; subhumid	231 222	206 952	209 138
12	Subtropics, moderately cool; humid	26 238	3 006	3 061
13	Subtropics, cool; semi-arid	16 727	12 572	12 463
14	Subtropics, cool; subhumid	6 341	3 389	4 592
15	Subtropics, cool; humid	437	164	164
23	Cold, no permafrost; moist	219	164	109
24	Cold, no permafrost; wet	1 804	1 804	1 804
25	Dominantly very steep terrain	37 990	37 772	38 154
26	Land with severe soil/terrain limitations	1 009 013	1 006 170	1 012 019
27	Land with ample irrigated soils	147 643	147 643	147 643
28	Dominantly hydromorphic soils	416 035	415 926	416 035
29	Desert/arid climate	11 560 983	11 547 318	11 566 614
32	Dominantly built-up land	12 026	12 026	12 026
33	Dominantly water	214 167	214 167	214 167
	Total	29 887 802	29 887 802	29 887 802

Notes: Data correspond to Africa as a whole. Projections in the table are consistent with the Representative Concentration Pathway (RCP) 2.6 on greenhouse gas concentration (not emissions) trajectory, as adopted by the IPCC. Although Category 15 appeared in the projections for this table, the welfare indicators analysed in the subsection of agroecological zones do not include that category. Category 15 is present in small areas of Lesotho and South Africa, but these areas were not captured by the raster images of the welfare indicators.
Sources: Authors' own elaboration based on based on projections provided by **FAO's Geo-Spatial Unit** in the Land and Water Division (NSL). 2024. *Global Agro-Ecological Zone projections*. Frome, FAO.

Table A4. Main farming system characteristics and welfare indicators (adjusted by population) (SSA)

No.	Farming system name	Principal livelihoods	Location	Access to services	Area (km^2)	2021				SD 2003–2021		
						Asset wealth index	Per capita expenditures	Extreme poverty	Population	Asset wealth index	Per capita expenditures	Extreme poverty
1	**Irrigated**	Rice, cotton, vegetables, rainfed crops, cattle, poultry	Across Africa	Medium-high	363 281	0.13	2.96	65	30 413 391	0.11	0.09	14
2	**Humid lowland tree-crop**	Cocoa, coffee, oil palm, rubber, yams, maize, off-farm work	Central West	High	629 684	0.25	2.88	104	66 184 460	0.11	0.19	18
3	**Forest-based**	Cassava, maize, beans, cocoyams	Central	Low	1 346 659	-0.25	1.58	166	19 611 800	0.09	0.22	17
5	**Highland perennial**	Bananas, plantains, ensete, coffee, cassava, sweet potatoes, beans, cereals, livestock, poultry, off-farm work	East	High	418 464	0.12	2.68	167	90 586 681	0.17	0.26	41
6	**Highland mixed**	Wheat barley, tef, peas, lentils, broadbeans, rape, potatoes, sheep, goats, livestock, poultry, off-farm work	Across Africa	Low-medium	472 742	0.09	3.36	46	53 006 447	0.15	0.34	68
7	**Root and tuber crop**	Yams, cassava, legumes, off-farm work	West Central	Low-medium	2 233 840	-0.05	1.94	190	93 373 884	0.11	0.2	27
8	**Cereal-root crop mixed**	Maize, sorghum, millet, cassava, yams, legumes, cattle	West Central	Medium-high	2 044 253	0.08	2.54	49	86 614 575	0.16	0.32	36
9	**Maize mixed**	Maize, tobacco, cotton, cattle, goats, poultry, off-farm work	East Central South	Medium	3 936 134	0.10	2.26	122	161 184 059	0.13	0.1	22
11	**Agropastoral**	Sorghum, pearl millet, pulses. sesame, cattle, sheep, goats, poultry, off-farm work	Across Africa	Low-medium	3 634 993	0.09	2.50	53	151 260 063	0.13	0.19	41
12	**Pastoral**	Cattle, camels, sheep, goats, remittances	South East West	Low	3 640 223	-0.06	2.52	70	58 252 449	0.1	0.1	16
13	**Arid pastoral oases**	Irrigated maize, vegetables, date palms, cattle, off-farm work	Across Africa	Very low	4 588 176	-0.23	2.90	34	11 348 648	0.06	0.11	8
14	**Fish-based**	Marine fish, coconuts, cashews, bananas, yams, fruit, goats, poultry, off-farm work	Across Africa	Medium-high	439 294	0.30	3.07	101	41 941 613	0.13	0.23	24
16	**Perennial mixed**	Vines, fruit, eucalyptus	Coast hinterlands South North	High	301 293	0.66	2.76	41	14 882 394	0.15	0.26	22

Notes: Extreme poverty refers to numbers of people in poverty (not depth of poverty), and is a relative assessment for this region (*Dixon et al.*, 2001). Calculations of welfare indicators and population exclude the urban URCA category, as defined in the section on Methods and data.

Sources: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645, on **Dixon, J., Garrity, D.P., Boffa, J.-M., Williams, T.O., Amede, T., Auricht, C., Lott, R. & Mburathi, G.**, eds. 2019. *Farming Systems and Food Security in Africa: Priorities for Science and Policy Under Global Change*. Earthscan Food and Agriculture Series. Routledge, Oxon, UK. https://doi.org/10.4324/9781315658841, on **HarvestChoice, IFPRI (International Food Policy Research Institute) & University of Minnesota.** 2017. CELL5M: A Multidisciplinary Geospatial Database for Africa South of the Sahara. In: *Harvard Dataverse*. [Cited 11 July 2023]. https://doi.org/10.7910/DVN/G4TBLF and on **Koo, J., Cox, C.M., Bacou, M., Azzarri, C., Guo, Z., Wood-Sichra, U., Gong, Q. & You, L.** 2016. CELL5M: A geospatial database of agricultural indicators for Africa South of the Sahara. *F1000Research*, 5: 2490. https://doi.org/10.12688/f1000research.9682.1

Table A5. Number of URCA pixels per quintile (percentage distribution across URCA categories) (SSA)

	Urban	Peri-urban	Peri-rural	Hinterland and dispersed areas
Quintile 1	0.0%	5.5%	16.5%	37.0%
Quintile 2	0.0%	9.0%	21.1%	27.5%
Quintile 3	0.0%	14.7%	24.3%	18.6%
Quintile 4	0.1%	24.8%	22.8%	12.5%
Quintile 5	99.9%	46.1%	15.4%	4.4%

Notes: Calculations include the urban URCA category, as defined in the section on Methods and data. Quintiles were defined by taking the image of SP × POP, with 2003 as the baseline year.
Sources: Authors' own elaboration based on **Atlas AI.** 2021. Spending, v.2021; Asset Wealth Index, v.2021. https://data.apps.fao.org/catalog/iso/689763ee-e60c-449e-bd9a-be70c7615645, on **Cattaneo, A., Nelson, A. & McMenomy, T.** 2021a. Global mapping of urban–rural catchment areas reveals unequal access to services. *Proceedings of the National Academy of Sciences of the United States of America*, 118(2): e2011990118. https://doi.org/10.1073/pnas.2011990118 and on **Cattaneo, A., Nelson, A. & McMenomy, T.** 2021b. Global Urban Rural Catchment Areas (URCA) Grid - 2021. In: *FAO Agro-informatics Data Catalog Portal*. [Cited 11 July 2023]. https://data.apps.fao.org/catalog/iso/9dc31512-a438-4b59-acfd-72830fbd6943

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