Food and Agriculture Organization of the United Nations

Wellbeing dynamics in sub-Saharan Africa (SSA): a spatial perspective across territorial typologies

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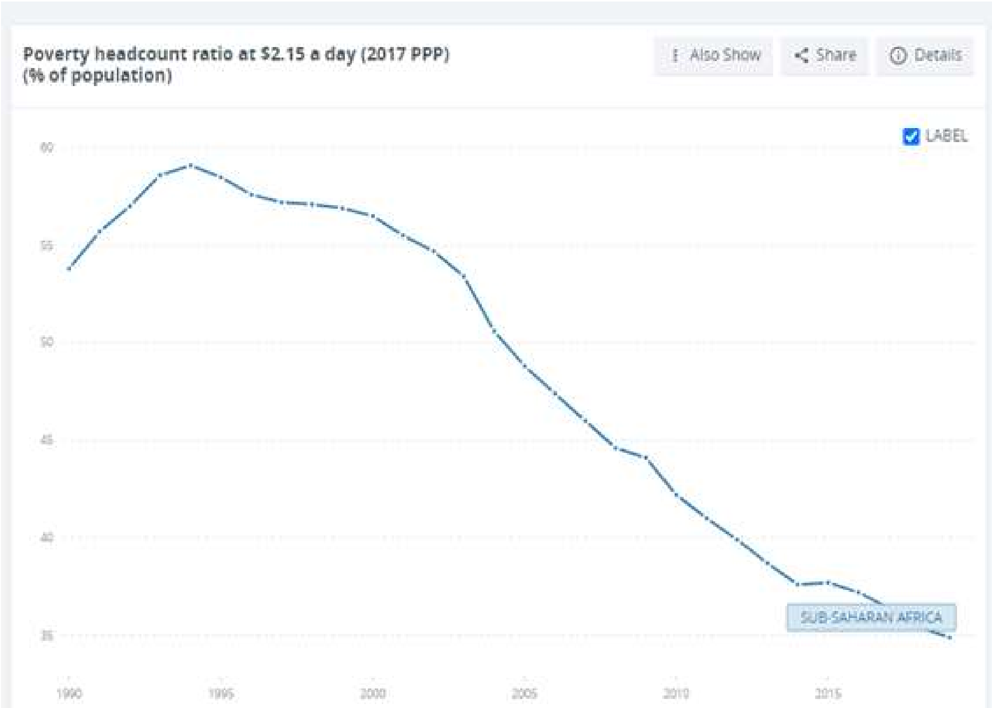
AFD Geo4Impact 2025

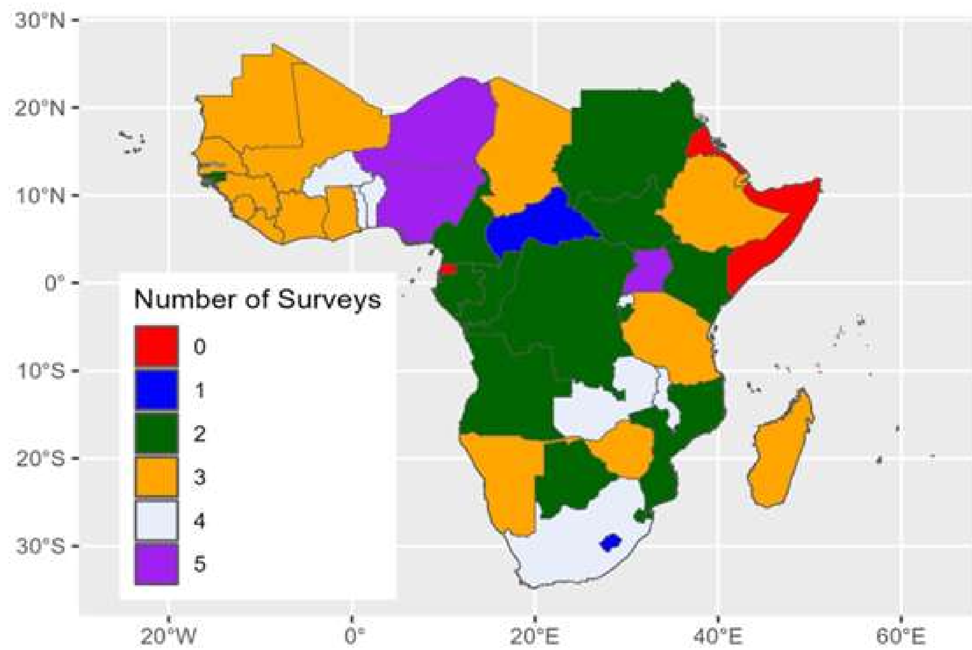
27 May 2025

Poverty in SSA: Positive Trends, but Limited Data



World Bank headcount poverty estimates for Sub-Saharan Africa

Number of national surveys conducted per country 2003-2021



Motivation

Challenges to Tracking and Analysing Poverty Dynamics in Sub-Saharan Africa

- Reliance on infrequent survey data collection (Yeh et al., 2020)
- Lack of comparable survey data across time and space (Liu, Liu and Zhou, 2017).
- Data not representative at lower administrative levels (Henninger and Snel, 2002)

Why this matters

- Despite substantial reductions in estimated head-count poverty, the number of people living in poverty remains stubbornly high
  - Persistent poverty and economic stagnation likely has distinct spatial features (market access, infrastructures, agricultural suitability, etc…)
- Substantial temporal dynamics in poverty and wealth
  - Economic shocks, extreme weather, conflict, public investments, etc..
- A better understanding of the spatial features and temporal dynamics of wealth and poverty will improve targeting of poverty-reduction interventions (FAO, 2021).

Contribution

- **We examine the spatial distribution and temporal dynamics of welfare in SSA**
  - **ATLAS-AI**: Highly spatially disaggregated dataset tracking poverty and welfare in SSA covering the period 2003 to 2021
  - **3 territorial typologies**:
    - Urban-rural continuum or Urban-Rural Catchment Areas (URCA)
    - Global Agro-ecological zones (GAEZ)
    - Farming System (FS)

- **The 3 typologies are related with the unequal distribution of welfare progress in SSA, and reflect potentials in terms of access to markets, population density and agricultural potential.**

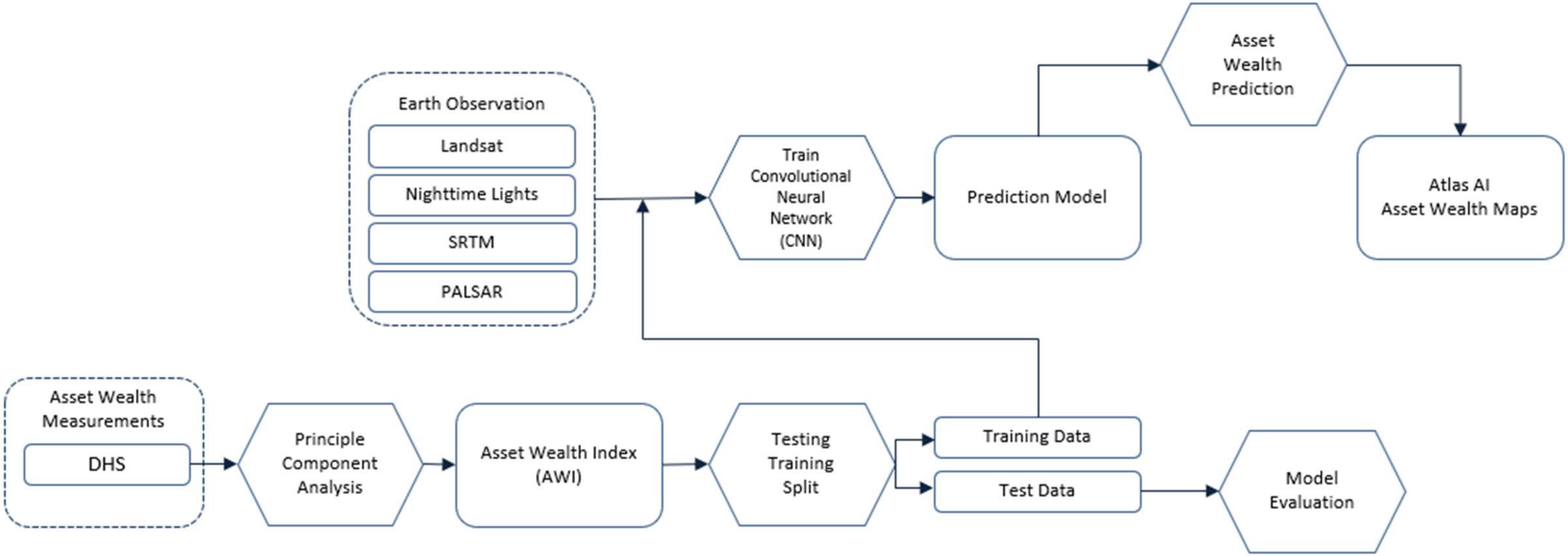
The ATLAS-AI data

Set of **yearly satellite images of asset wealth index (AWI), per capita expenditure (SP) and poverty (POV) from 2003 to 2021** at 1kmX1km resolution for 43 SSA

METHODS:

1. Combine asset wealth indicators (SP, POV) from the household **Demographic Health Surveys (DHS),** using a PCA for all HH and years available.
2. Modeling with **deep learning** and training public **Landsat surface reflectance, nighttime light** images, etc. to capture feature images that predict wealth (SP, POV) over time and space. Model is used to **predict asset wealth (SP, POV) in locations and time where survey data do not exist**.
3. Produces **normalized** comparable variables within and across countries
4. Data already validated (Yeh et al., 2020; Ratledge et al., 2022)

The ATLAS-AI data (AWI): in more detail



Landsat 6, 7 and 8 surface reflectance imagery to determine land cover.
Shuttle Radar Topography Mission (SRTM) digital elevation data in 2000 at a resolution of 1 arc-second (30m).
Nighttime Lights luminosity from 2004-2005 DMSP median composites, 2010 DMSP median composites, 2014 VIIRS median composite, and 2015-2020 VIIRS.
Phased Array type L-band Synthetic Aperture Radar (PALSAR): yearly 25 meters for cloud and weather-free observations.
DHS surveys 2003-2016 for 30 countries.
Global Human Settlement Layer (GHSL) Population Data: 250-meter population grid data 2000-2015, 1 km settlement grid data.

The ATLAS-AI variables

Asset Wealth Index (AWI): index of average asset wealth per pixel. Yearly AWI average for Africa equal to zero.

- AWI>0 wealthier than average

Spending (SP): household per capita expenditures ("spending") of durables-non durables, adjusted to **2011 PPP dollars (International dollars) per person-day.**

- 2011 USD Purchasing Power Parity as unit of estimation; accounts for changes over time in prices within countries (inflation) and differences in purchasing power between countries. **Time and regions comparability**

Poverty (POV): population living below the extreme poverty line (determined by mean daily household spending (SP) per pixel)

- Pixel value as the mean of the log-normally distributed spending values of all households in that pixel.
- **Extreme poverty line of $1.90/day (extreme poverty) only for SSA**

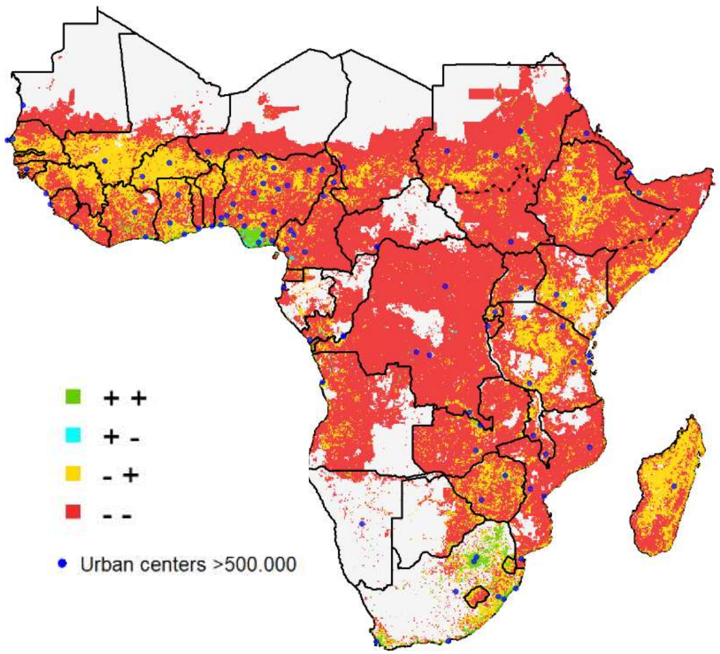
Population (POP): count of people (number) living in the pixel.

AWI-SP-POV adjusted by population living in country-region-GAEZ (j) in a year as:

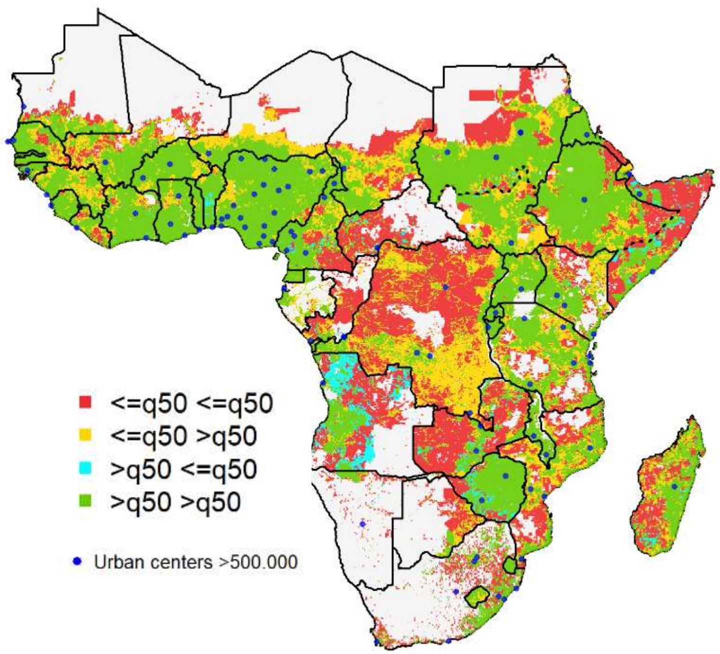
$$WI_j = \frac{\sum_{i=1}^{n} w_i * p_i}{\sum_{i=1}^{n} p_i}$$

The ATLAS-AI variables (evolution from 2003 to 2021)

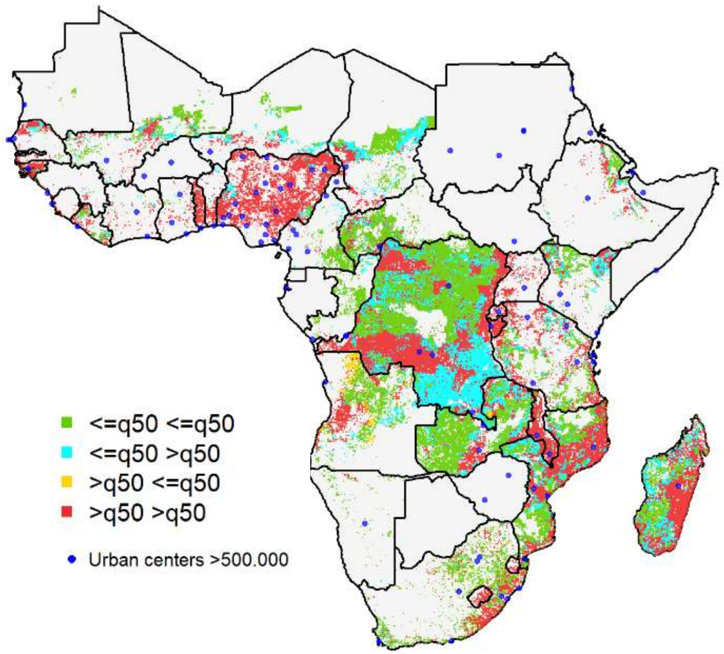
Asset Wealth (AWI) (+/-)



Per capita expenditures (SP) >q50 vs <=q50



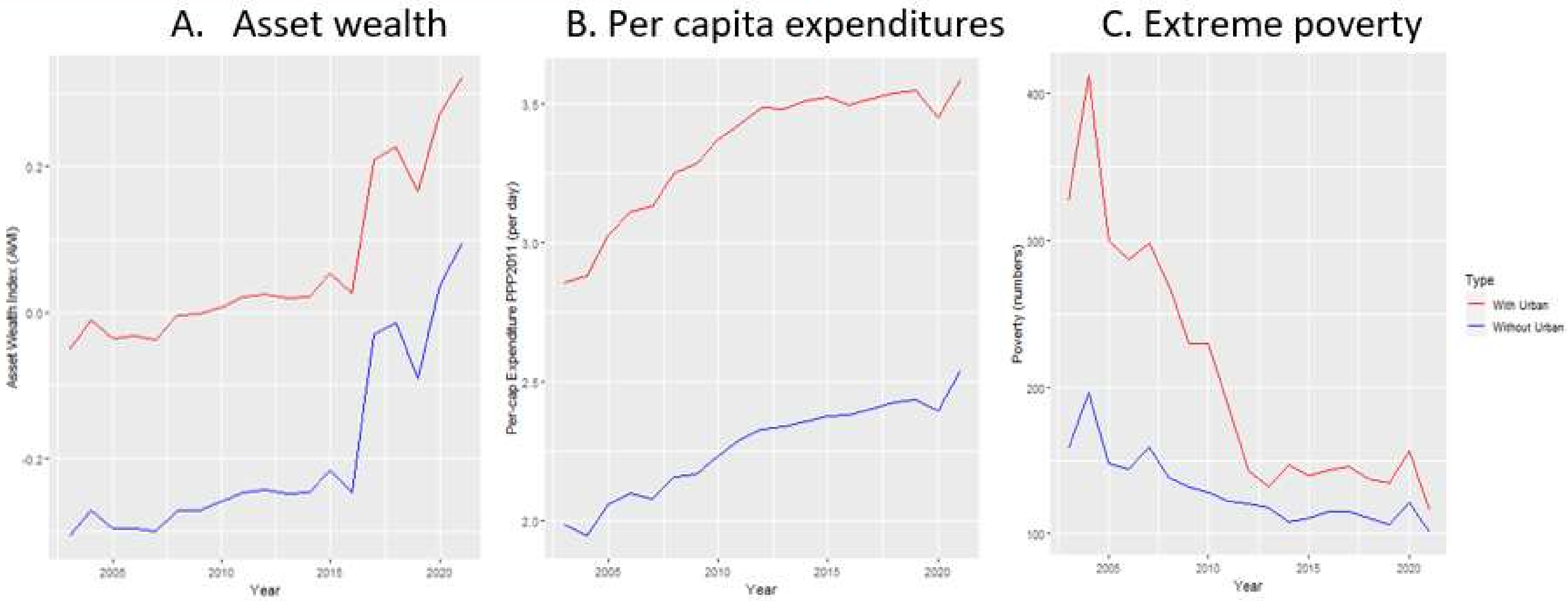
Extreme Poverty (POV) >q50 vs <=q50



Using welfare variable X POP in each year

Main findings

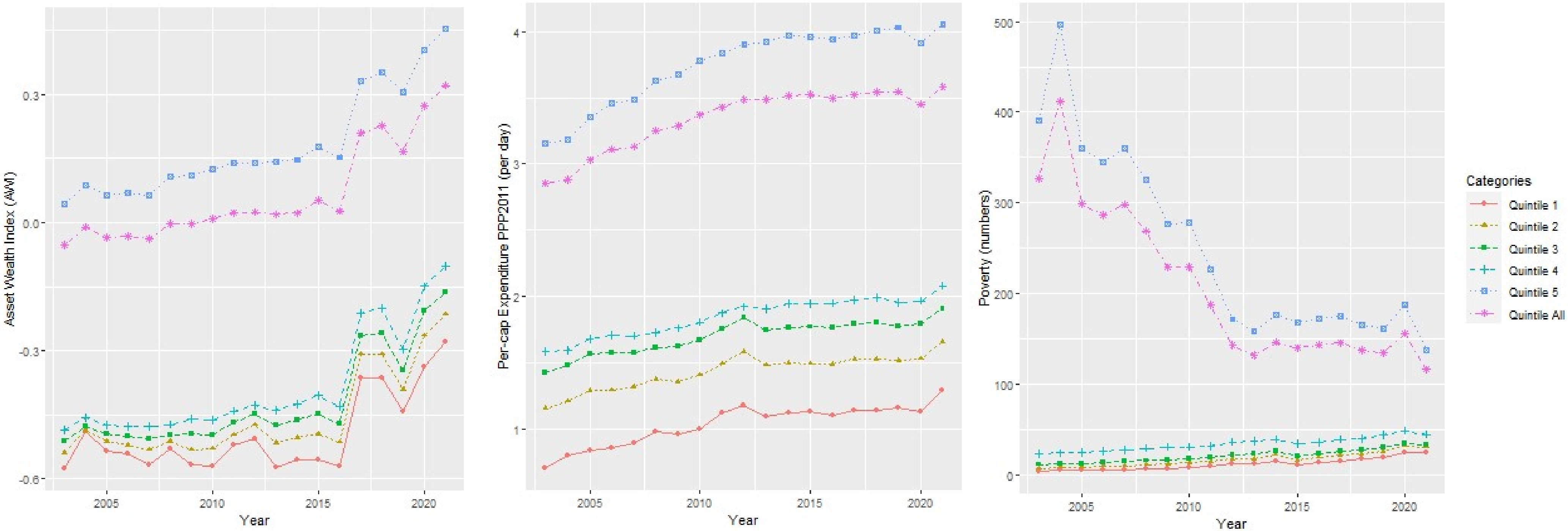
Welfare and poverty trends in SSA (average adjusted by POP): 2003-2021



i) **Welfare improvement in SSA**
ii) **Welfare gaps**
iii) **Significant POV reductions but POV numbers still high in urban areas (more POP)**

Growth and Stagnation: Quintile Analysis (exp)

A. Asset wealth | B. Per capita expenditure | C. Extreme Poverty

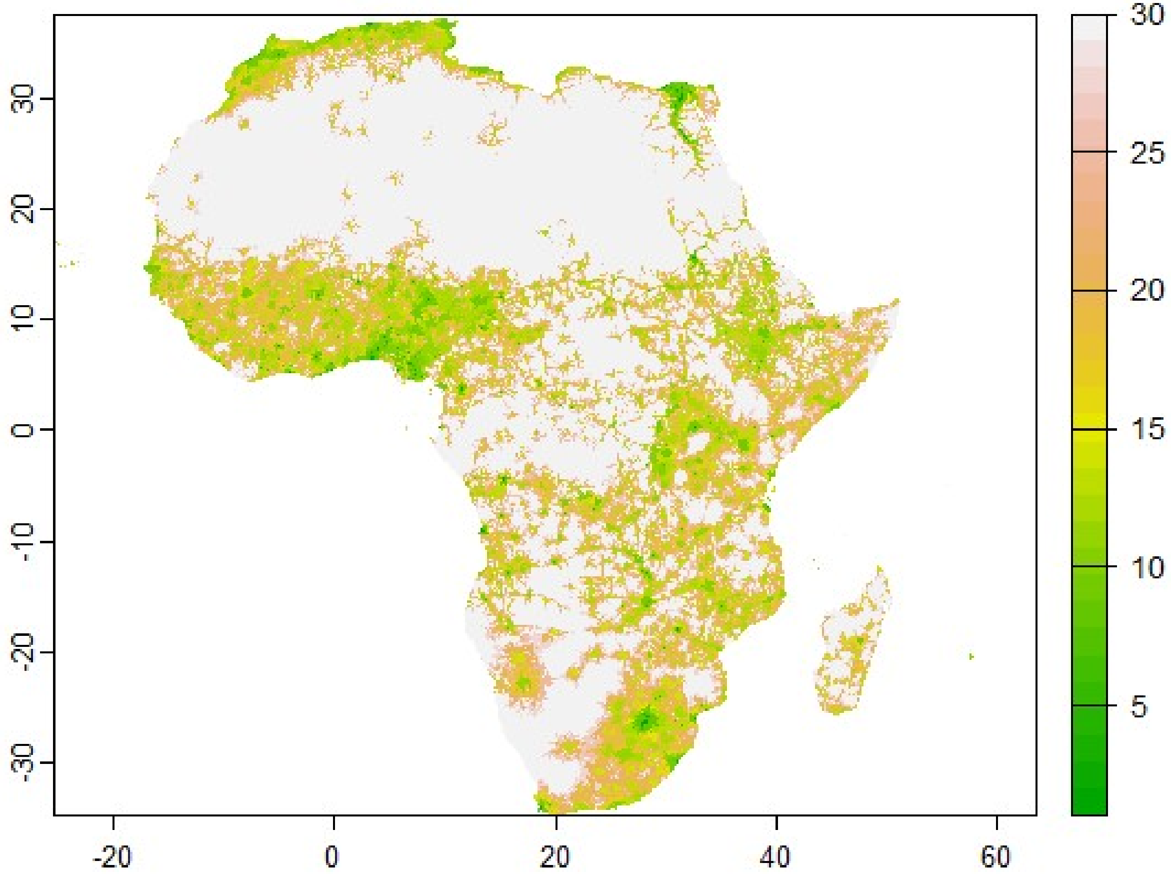


QUINTILE (using SP*POP in 2003):

i) Welfare improvement **concentrated in Q5** (mostly **urban**)
ii) Important POV reductions in Q5 but numbers still high
iii) Other quintiles (highly rural, lower population density) largely stagnated (but smaller POV numbers)
iv) Same patterns hold excluding urban areas.

	Asset Wealth	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
Quintile All	0.34	0.20	-0.66

Merging by Urban-Rural Catchment Areas (URCA)



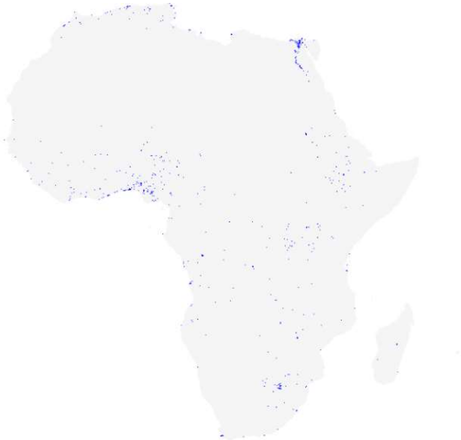
A global spatial dataset for 2015, spatial resolution of 1kmX1km

30 **URCAs**, where each pixel represents the time needed to arrive to an agglomeration of a different size.

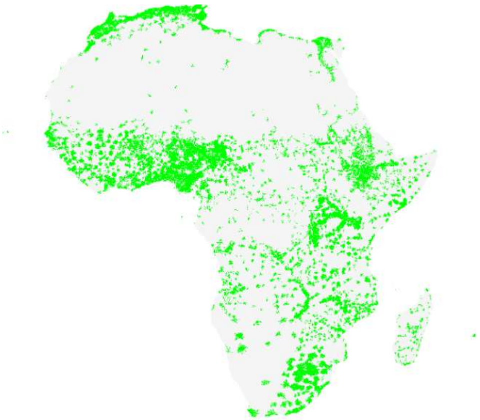
Source: based on Cattaneo et al. (2021)

Merging by Urban-Rural Catchment Areas (URCA)

A. Urban

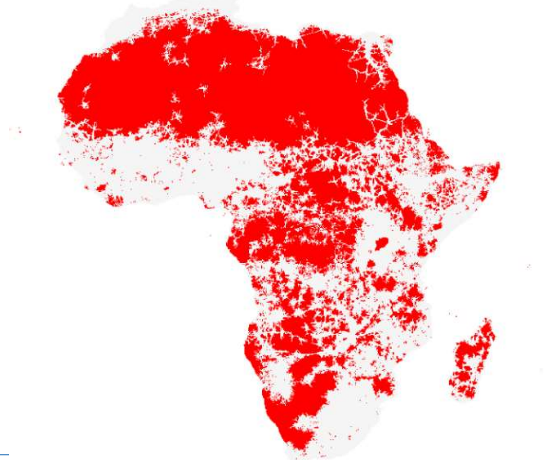


B. Peri-urban



C. Peri-rural

D. Hinterland and dispersed towns



Source: based on Cattaneo et al. (2021)

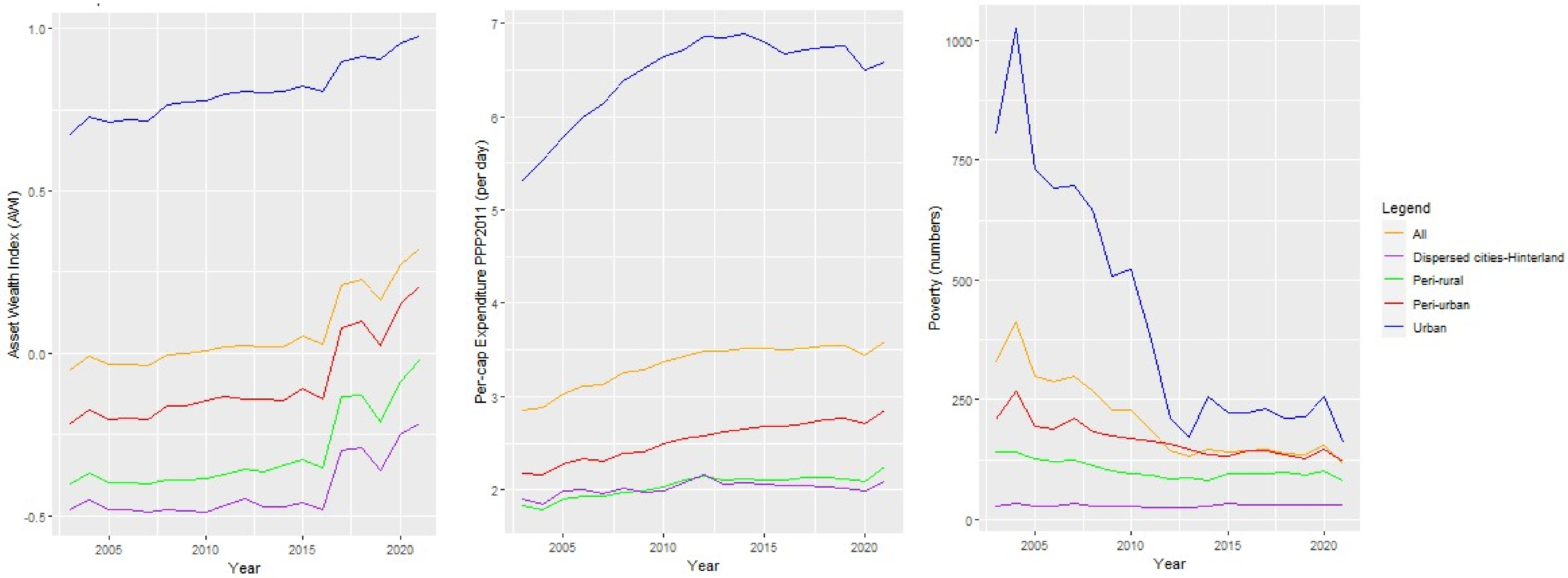
30 **URCAs** simplified in 4 categories:

A. **Urban** (urban centers of different sizes, **URCA 1-7**)
B. **Peri-urban** (the time to reach urban centers being less than 1 hour, **URCA 8-14**)
C. **Peri-rural** (the time to reach urban centers being between 1-3 hours, **URCA 15-28**)
D. **Hinterland and dispersed towns** (**URCA 29-30**)

	Urban	Peri-urban	Peri-rural	Hinterland-dispersed
Population SSA 2021	304 710 006	582 172 130	267 954 604	66 121 914
Percentage population	25.0%	47.7%	21.9%	5.4%
Km2 (area)	64 607	4 381 304	8 580 403	11 099 537

AWI-POV-SP across URCA in SSA

A. Asset wealth B. Per capita expenditures C. Extreme Poverty

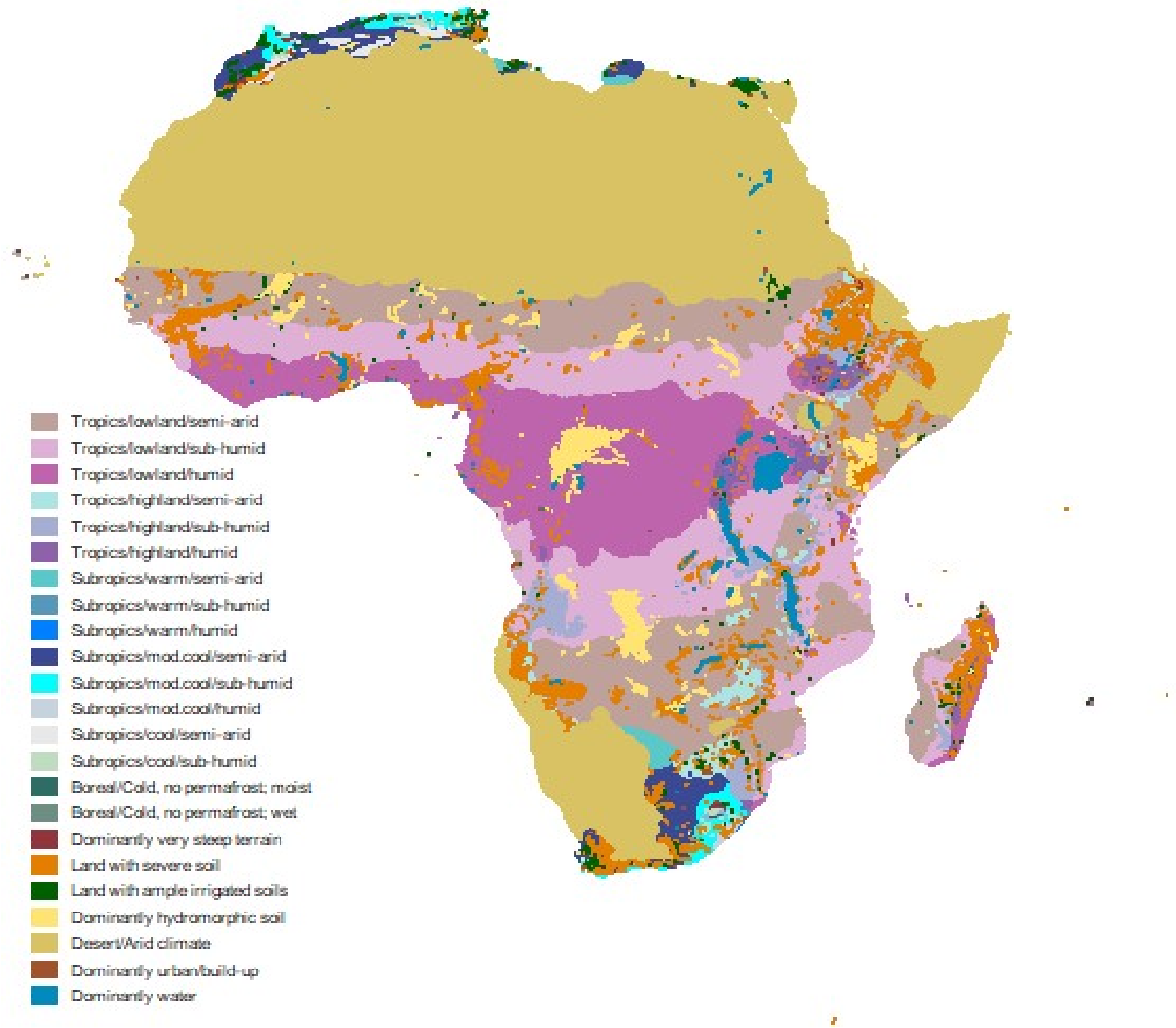


i) Higher AWI-SP but also **higher poverty in urban areas (more people).**

ii) Also progress in peri-urban areas, with AWI and POV getting closer to the SSA average

iii) The further from the urban centres, the lower the welfare progress (the more rural areas struggling)

Merging by Global Agro-ecological Zones (GAEZ)



GAEZ: A global spatial dataset using data 1981-2010, spatial resolution 0.9 km by 0.9 km

33 categories capturing 4 land aspects:

- Climate categories
- Thermal regime
- Moisture regimes
- Growing period

Broad categories of soil/terrain qualities, areas with irrigated soils and land with severely limiting bio-physical constraints (very cold, very dry (desert), very steep terrain, very poor soil/terrain conditions). **Reflects potential for crop cultivation.**

Only 23 categories for SSA

Source: based on the Global Agro-ecological Zones (GAEZ) project FAO-IIASA (2023) and Sebastian (2009).

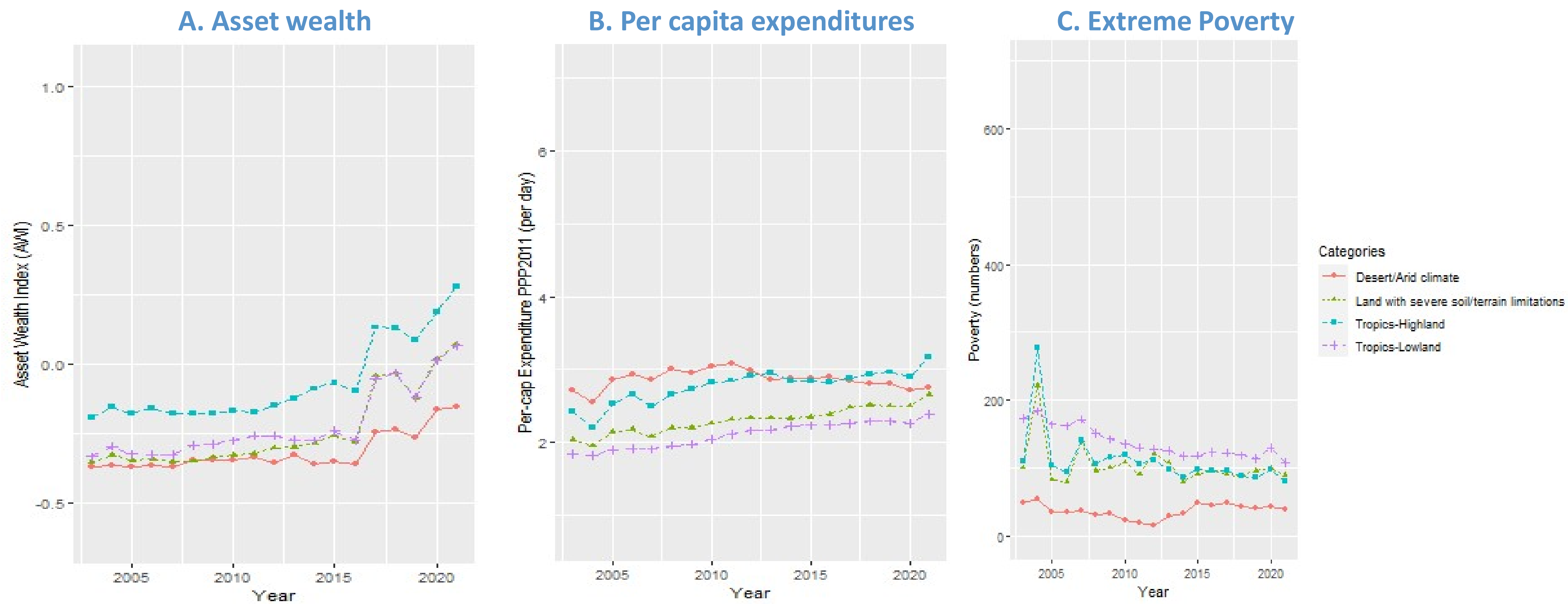
MAIN GAEZ CHARACTERISTICS

CAT	GAEZ	Cropland (%)	Grass + Shrub (%)	Tree cover (%)	Other cover (%)	Mean Temperature (°C)	Annual Rainfall (mm)	POP (%)	Area (km2) (%)
1	Tropics, lowland; semi-arid	13.4	45.0	26.7	14.9	**25.6**	708	**24.4**	**24.0**
2	Tropics, lowland; sub-humid	14.4	38.7	44.4	2.4	**25.1**	1286	**22.5**	**19.1**
3	Tropics, lowland; humid	10.5	15.9	71.7	1.9	**25.6**	2123	**25.6**	**15.8**
4	Tropics, highland; semi-arid	8.6	57.0	19.2	15.3	16.5	558	1.8	1.1
5	Tropics, highland; sub-humid	15.8	46.6	32.9	4.7	17.2	1012	5.3	2.1
6	Tropics, highland; humid	18.8	28.4	49.2	3.6	17.3	1570	6.3	1.0
26	Land with severe soil/terrain limitations	8.0	28.6	53.2	10.1	16.2	1368	4.7	4.0
29	Desert/arid climate	1.1	14.2	1.4	83.3	**21.7**	127	4.5	**27.7**

Source: based on the Global Agro-ecological Zones (GAEZ) project FAO-IIASA (2023) and GAEZ documentation

- We exclude urban areas and focus on only 8 GAEZ that account for 95% of SSA population and 95% area (km2)
- Tropical-highlands cover small area (km2), milder climate but getting smaller according to the projections from NSLD-NSL FAO division.
- Tropics-lowlands and desert/arid climate cover large areas, higher temperature, large POP and getting bigger.

Welfare indicators across main GAEZ (exclude urban)

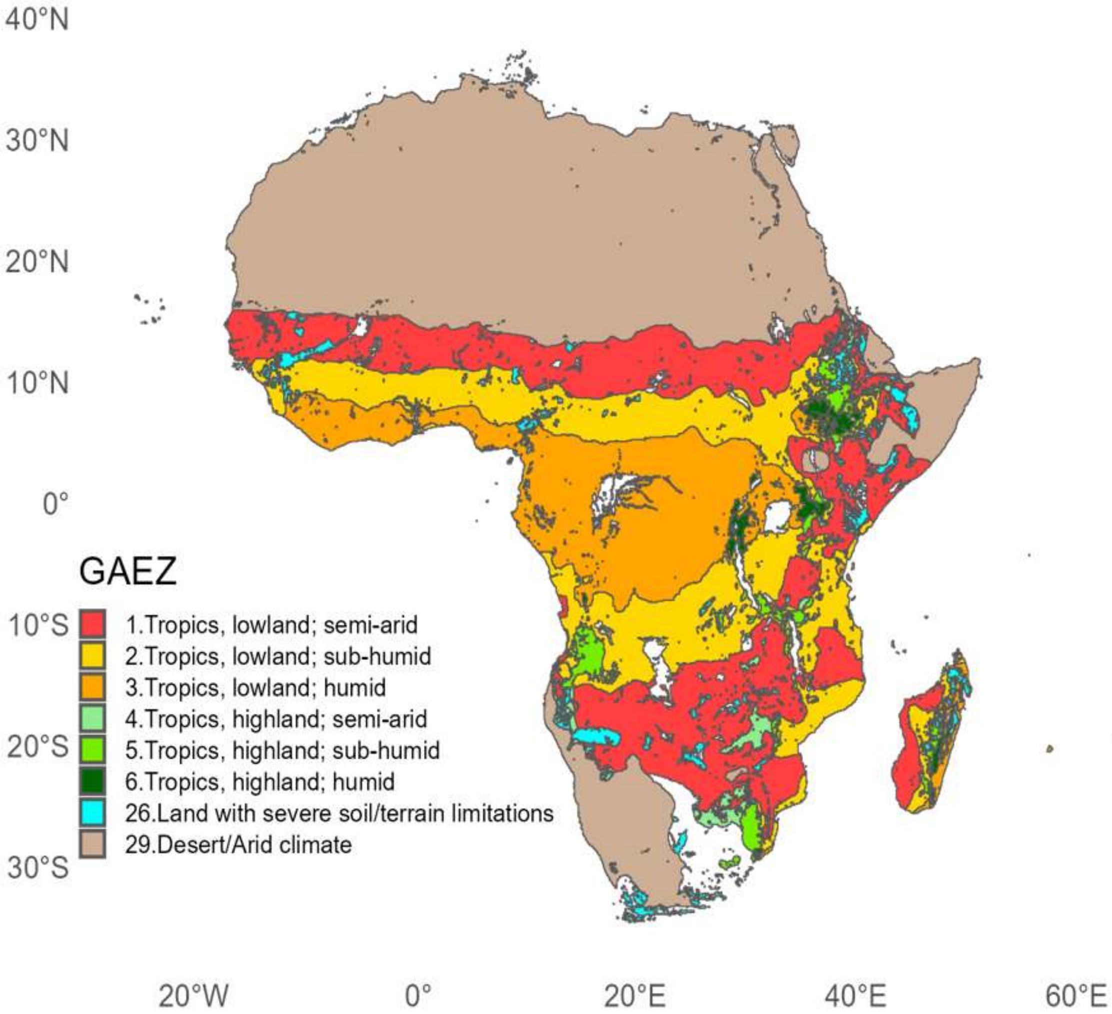


i. **Tropical highlands: better than tropical lowlands** (tropical highland humid exception but achieved a reduction in POV). Opportunities in crop suitability, **exposed to lower temperatures but concentrated in small areas and shrinking.**

ii. **Tropical lowlands struggling and desert and arid** (the lowest AWI, lower SP and lower POV) **stagnated**.

iii. Both **exposed to higher temperature, projected to suffer from climate change, bigger areas, getting bigger.**

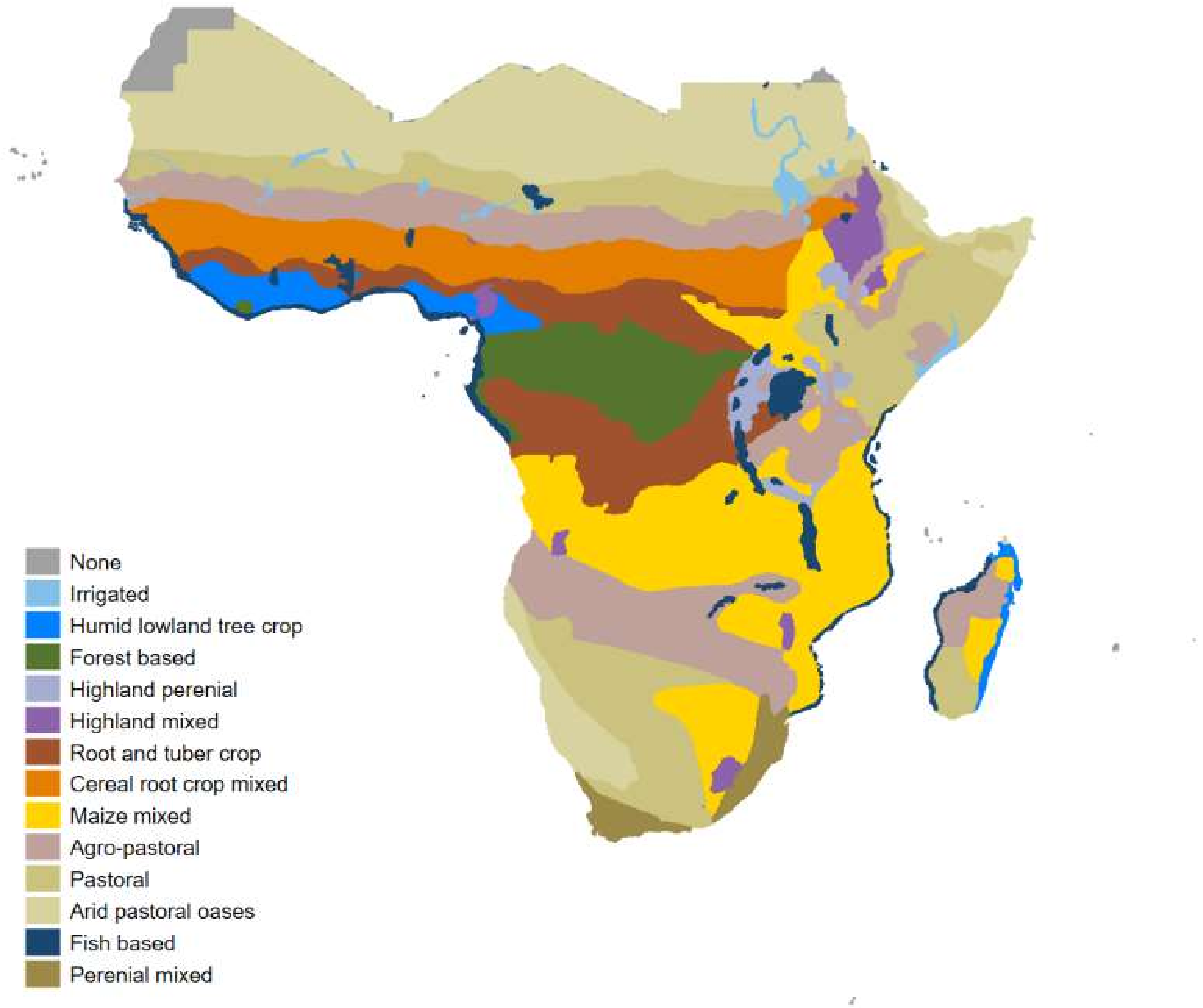
Merging by Global Agro-ecological Zones (GAEZ)



GAEZ areas under stress of climate change and underperforming in terms of wellbeing dynamics

Source: based on the Global Agro-ecological Zones (GAEZ) project FAO-IIASA (2023) and Sebastian (2009).

Merging by Farm system (FS)

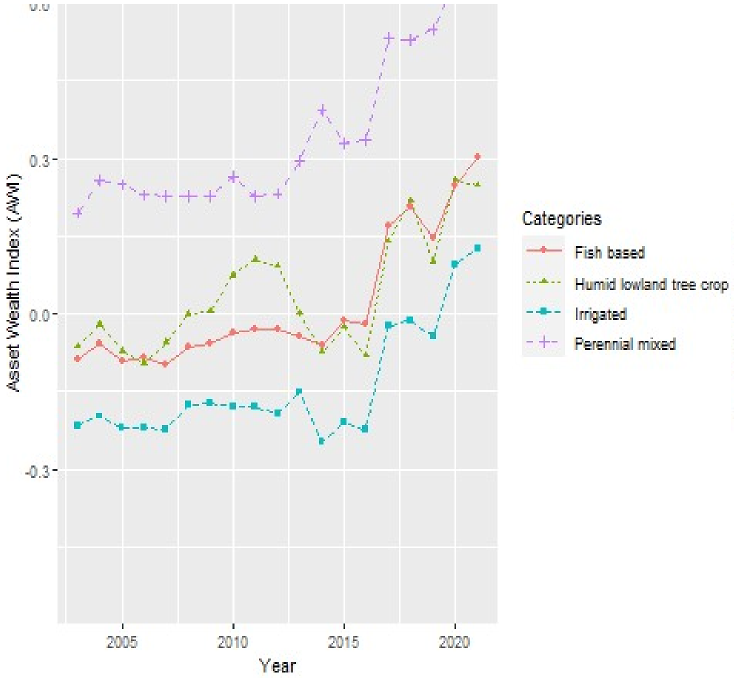


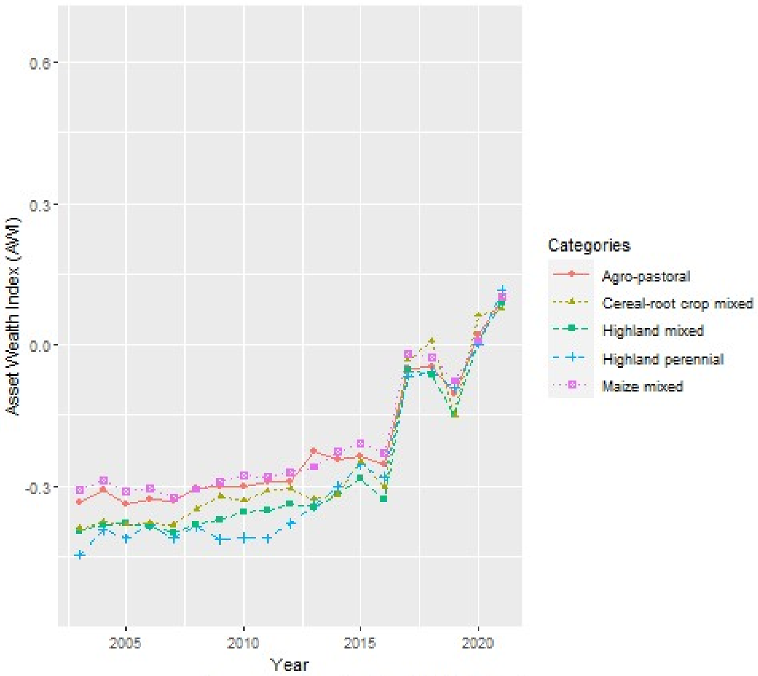
Source: based on Garrity et al. (2012) and Dixon et al. (2019)

Farm system (FS):
Spatial dataset for 2015, with resolution of 10kmX10km

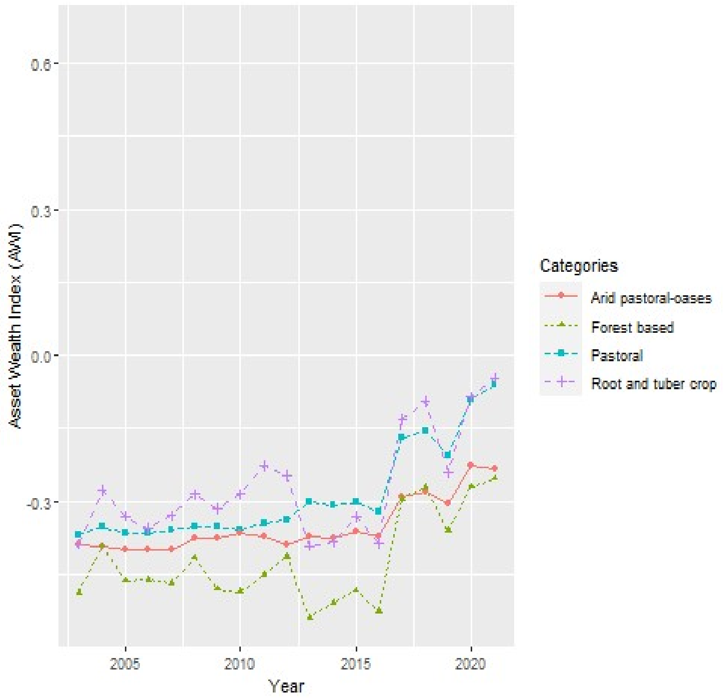
- A population of farm households with similar patterns of resources, livelihoods, consumption, constraints and opportunities, that have similar bundles of development strategies and interventions. Often, sharing similar AEZ and market conditions. **13 FS categories in SSA**

Asset wealth across Farming Systems (excluding urban)

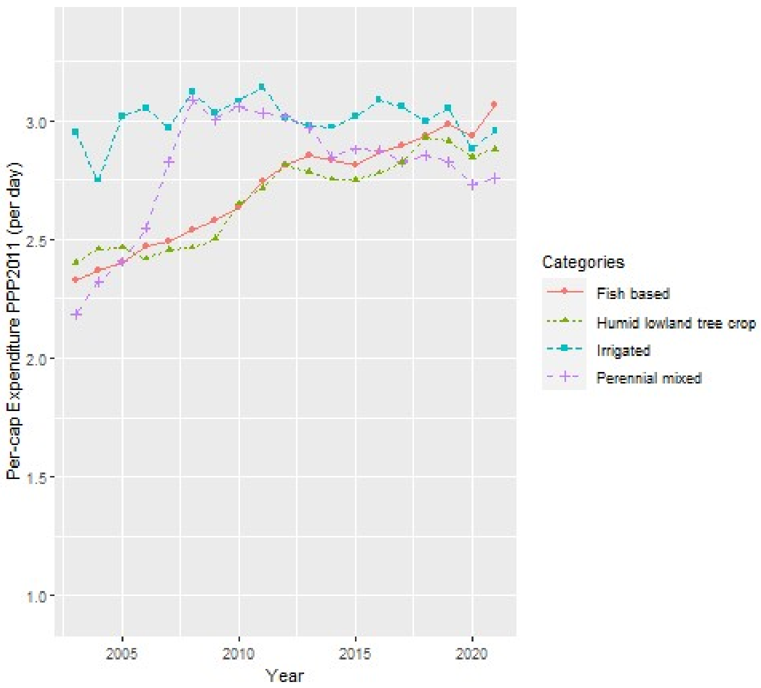


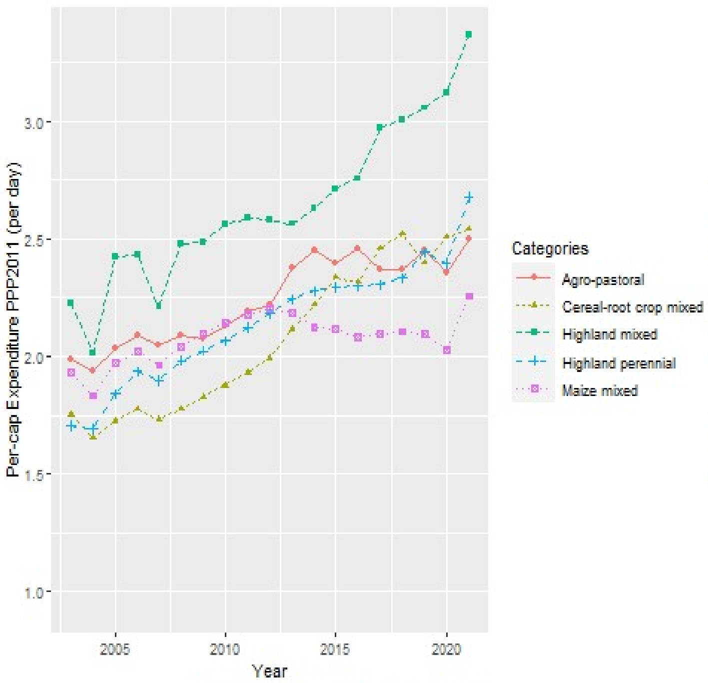


Source: calculations based on ATLAS AI dataset

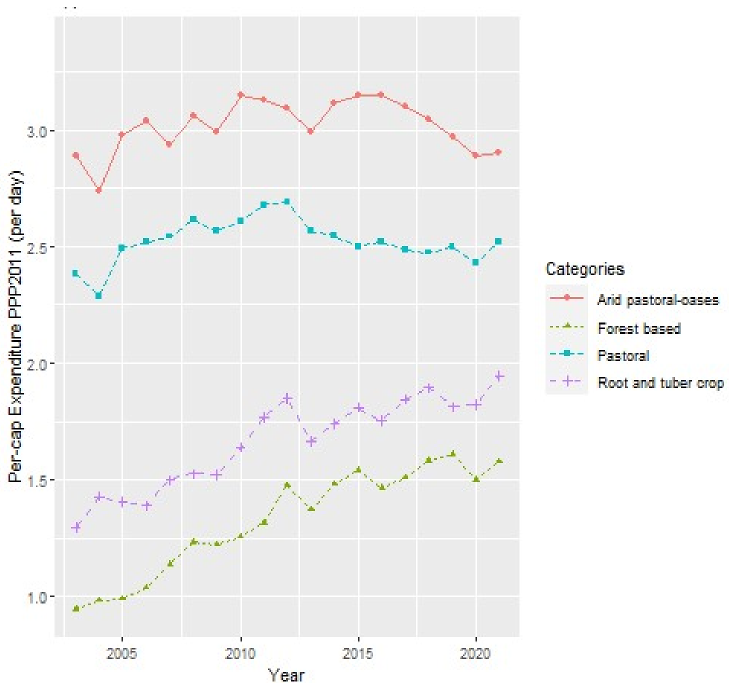


Per capita expenditures across Farming Systems (excluding urban)

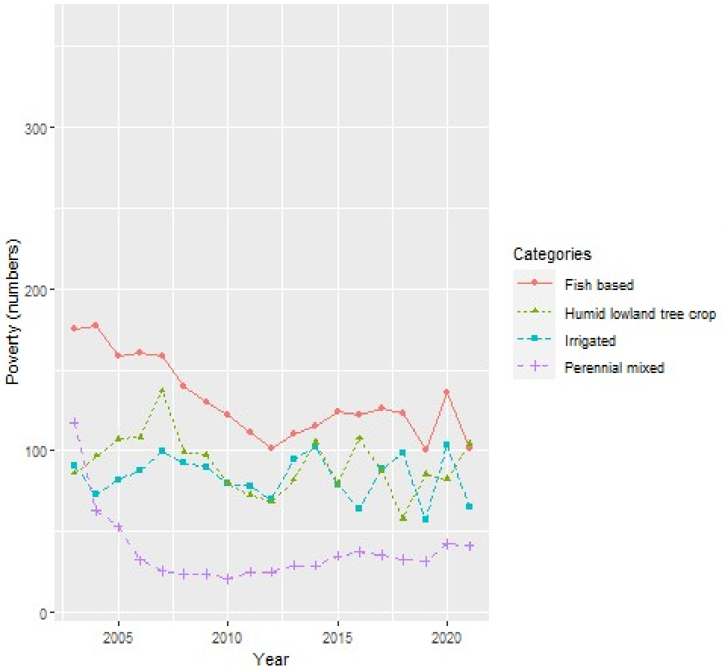


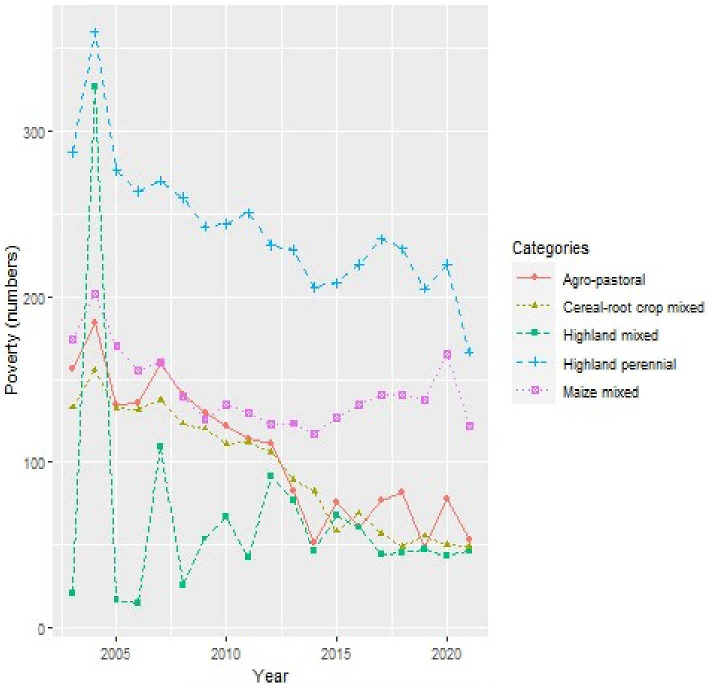


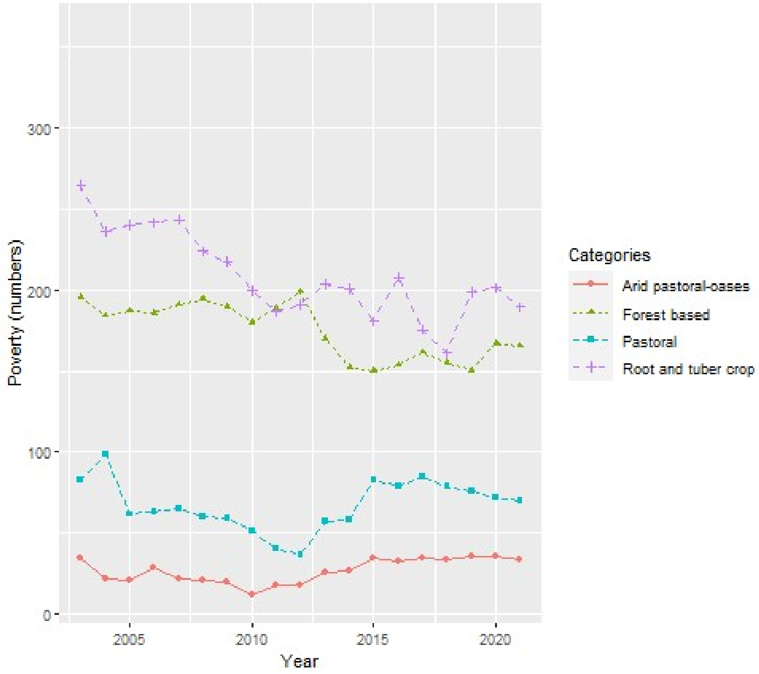
Source: calculations based on ATLAS AI dataset



Extreme poverty across Farming Systems (excluding urban)



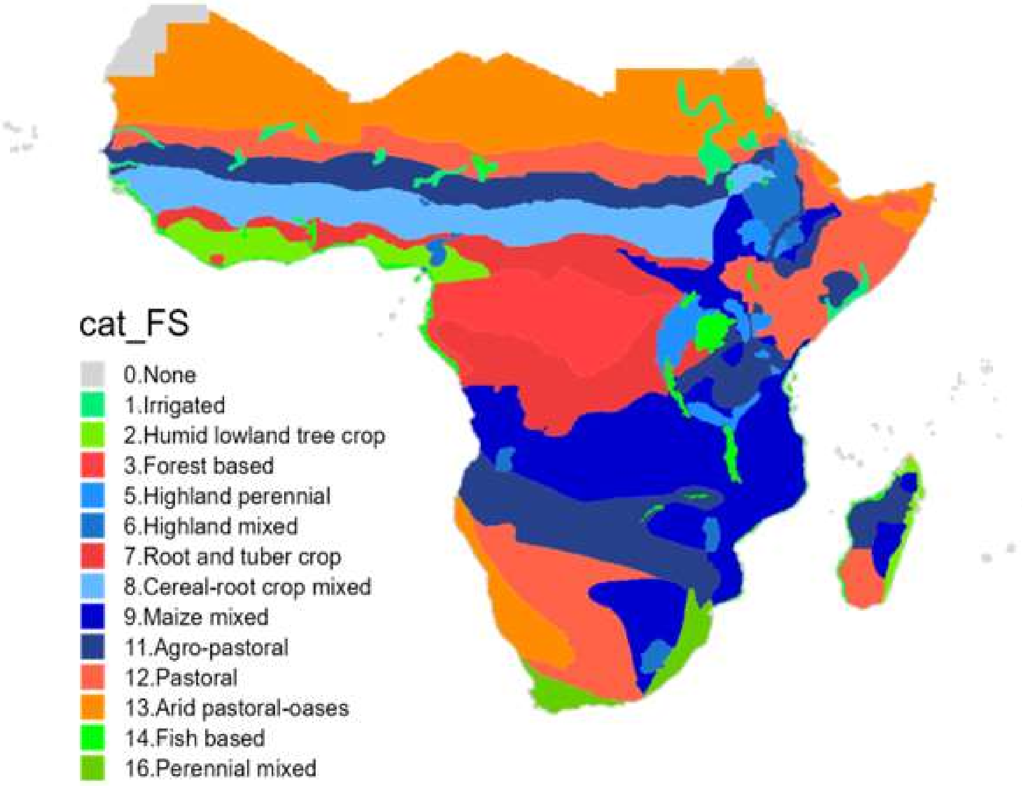




Source: calculations based on ATLAS AI dataset

i. **1 group: high to medium access to markets, higher AWI and more diversified portfolio**
    i. High welfare levels but stagnated (perennial mixed and irrigated)
    ii. Others at lower welfare levels (humid lowland tree crop and fish based) but reducing POV
ii. **2 group with modest performance, medium to low access to markets, medium AWI. High threat from CC and highly dependent on staple crops (maize particularly).**
iii. **3 group: low access to markets, low AWI and limited diversification. High threat from CC, highly dependent on maize, root-tuber crops and livestock in arid-pastoral.**
    i. Bad performance (forest based and root and tuber crop)
    ii. Stagnated or worse (pastoral and arid pastoral-oases with slightly higher SP and lower POV)

Merging by Farm system (FS)



CAT	FS-name	Principal Livelihoods	Access to services	POP (%)	Area (km2) (%)
1	**Irrigated**	**Rice, cotton, vegetables, rainfed crops, cattle, poultry**	**Medium-high**	**3.4**	**1.5**
2	**Humid lowland tree crop**	**Cocoa, coffee, oil palm, rubber, yams, maize, off-farm work**	**High**	**7.4**	**2.6**
14	**Fish based**	**Marine fish, coconuts, cashew, banana, yams, fruit, goats, poultry, off-farm work**	**Medium-high**	**4.7**	**1.8**
16	**Perennial mixed**	**Vines, fruit, eucalyptus**	**High**	**1.7**	**1.2**
5	Highland perennial	Banana, plantain, enset, coffee, cassava, sweet potato, beans, cereals, livestock, poultry, off-farm work	High	10.2	1.7
6	Highland mixed	Wheat barley, tef, peas, lentils, broadbeans, rape, potatoes, sheep, goats, livestock, poultry, off-farm work	Low-medium	6.0	1.9
8	Cereal-root crop mixed	Maize, sorghum, millet, cassava, yams, legumes, cattle	Medium-high	9.7	8.4
9	Maize mixed	Maize, tobacco, cotton, cattle, goats, poultry, off-farm work	Medium	18.1	16.1
11	Agro-pastoral	Sorghum, pearl millet, pulses. sesame, cattle, sheep, goats, poultry, off-farm work	Low-medium	17.0	14.9
3	**Forest based**	**Cassava, maize, beans, cocoyams**	**Low**	**2.2**	**5.5**
7	**Root and tuber crop**	**Yams, cassava, legumes, off-farm work**	**Low-medium**	**10.5**	**9.1**
12	**Pastoral**	**Cattle, camels, sheep, goats, remittances**	**Low**	**6.5**	**14.9**
13	**Arid pastoral-oases**	**Irrigated maize, vegetables, date palms, cattle, off-farm work**	**Very low**	**1.3**	**18.8**

17.2% POP

20.5% POP

Source: based on Dixon et al. (2019), HarvestChoice-IFPRI and University of Minnesota (2017) and Koo et al., (2016).

Summary of main findings

QUANTILES

- Most of welfare progress in urban areas of the wealthier quintiles, while other **rural quintiles largely stagnated**
- Progress reflects increased public expenditure (governments and donors), which may have not being enough to move population out of poverty.

URCA

- Significant **welfare progress in urban areas,** with important poverty reductions (in Q5)
- **The further from the urban centres, the lower the welfare progress (rural areas struggling)**

GAEZ

- **Tropical highlands performing better.** Exposed to lower temperatures, concentrated in small areas that are shrinking.
- **Tropical lowlands struggling and desert and arid stagnated.** Exposed to higher temperature and climate change, in bigger areas, getting bigger

Farming Systems

- **Welfare progress correlated with medium access to markets, AWI and more diversified portfolio (scalable?)**
- Those underperforming projected to suffer from climate change, highly dependent on maize.

Conclusions

- Spatially-explicit welfare data holds significant potential on understanding poverty dynamics and enhance policy interventions (spatially targeted).
- But as a complement not as a replacement to face-to-face methods
  - Contextual factors, micro-level processes, and local power dynamics matter

PAPER HIGHLIGHTS:

- Overall improvement: welfare (per capita expenditures) has risen continent-wide.
- Uneven progress: gains are concentrated in urban areas and among already wealthier populations.
- Neglected regions: tropical lowlands, desert and arid areas—home to the majority of rural populations—have seen limited welfare improvements, raising concerns as these zones expand under climate change.
- Market isolation matters: rural populations with poor market access and limited opportunities for agricultural diversification have shown almost no progress in the last two decades.

Other applications ATLAS-AI data

It can be used to assess:

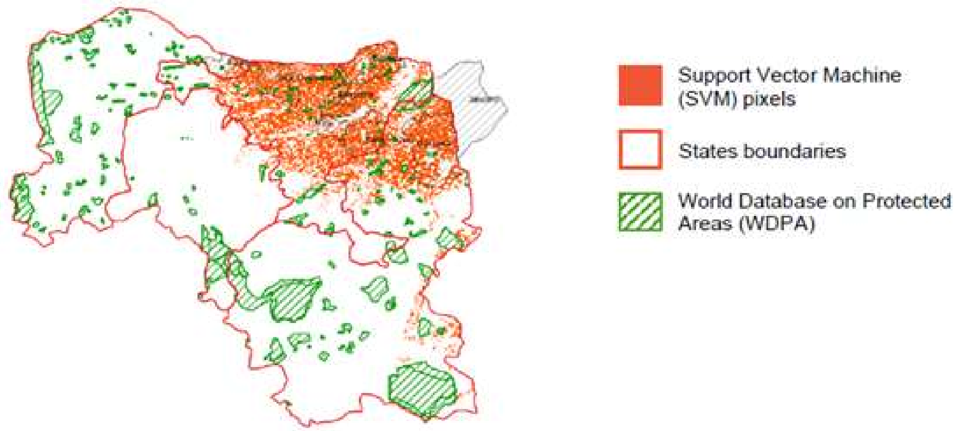
- Climate change impact on wellbeing dynamics in SSA
    - Implications under future scenarios?
- How does exposure to conflict influence wellbeing dynamics (using Violence-ACLED dataset)

It has been used in:

- the HIH initiative (micro-regions) and FAO GEOFIELD rural transformation in India
- FAO SOFA report
- As part of the PSM variables to define IE control groups.
- De la O Campos et al (2023) IE Desertification in North Nigeria
    - SVM is a machine learning algorithm that classified/identified pixels as like the AAD restoration pixels
    - SVM fed with remote sensing data: ATLAS-AI, soil characteristics, elevation, NDVI, land cover, etc.

a. Area of interest for restoration and Action Against Desertification restoration sites

b. Similarity analysis output based on Support Vector Machine modelling. Orange areas denote similar areas to those restored by Action Against Desertification at baseline (year 2016)



Next steps – analysis of ATLAS-AI

- Develop an empirical paper(s) with a subset of the datasets
- To what extent climate and violence shape economic wellbeing (AWI-POV-SP)
- Climate-SPEI constructed for RuLIS project. 13 countries and same adm-div to retrieve potential variables to check mechanism. For other countries, lowest adm-div (level 4)
- Violence-ACLED dataset as in Harari and La Ferrara (2018). In the paper, weather on conflict.
- What else can we add?
  - GAEZ-FS + extra agro variables (heterogeneity)
  - Spatial analysis-correlation (see Azarri and Signorelli, 2020)
  - Market proximity, Infrastructure of telephone companies, road indicators. In Dand and Trinh (2022), temp on POV and vulnerability related with lower access to information
  - SPEI-temp-rainfall at finer resolution than others in the literature

D(0 [@BecerraValbuena, Luis (ESP)] You can also mention that this is only from ESP/ESA side, but that ATLAS-AI data has been used by the HIH initiative (for the creation of the typology of micro-regions in multiple SSA countries) and more recently, in collaboration with GEOFIELD, a research programme on rural transformation in India.
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Thank you

for more information contact:

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find more material online at:

www.fao.org/socioeconomic-research-analysis

Annex

The ATLAS-AI data: sources

Landsat: surface reflectance imagery obtained through Landsat 6, 7, and 8 between 2003 and 2020 to determine land cover.

Shuttle Radar Topography Mission (SRTM): digital elevation data for the year 2000 at a resolution of 1 arc-second.

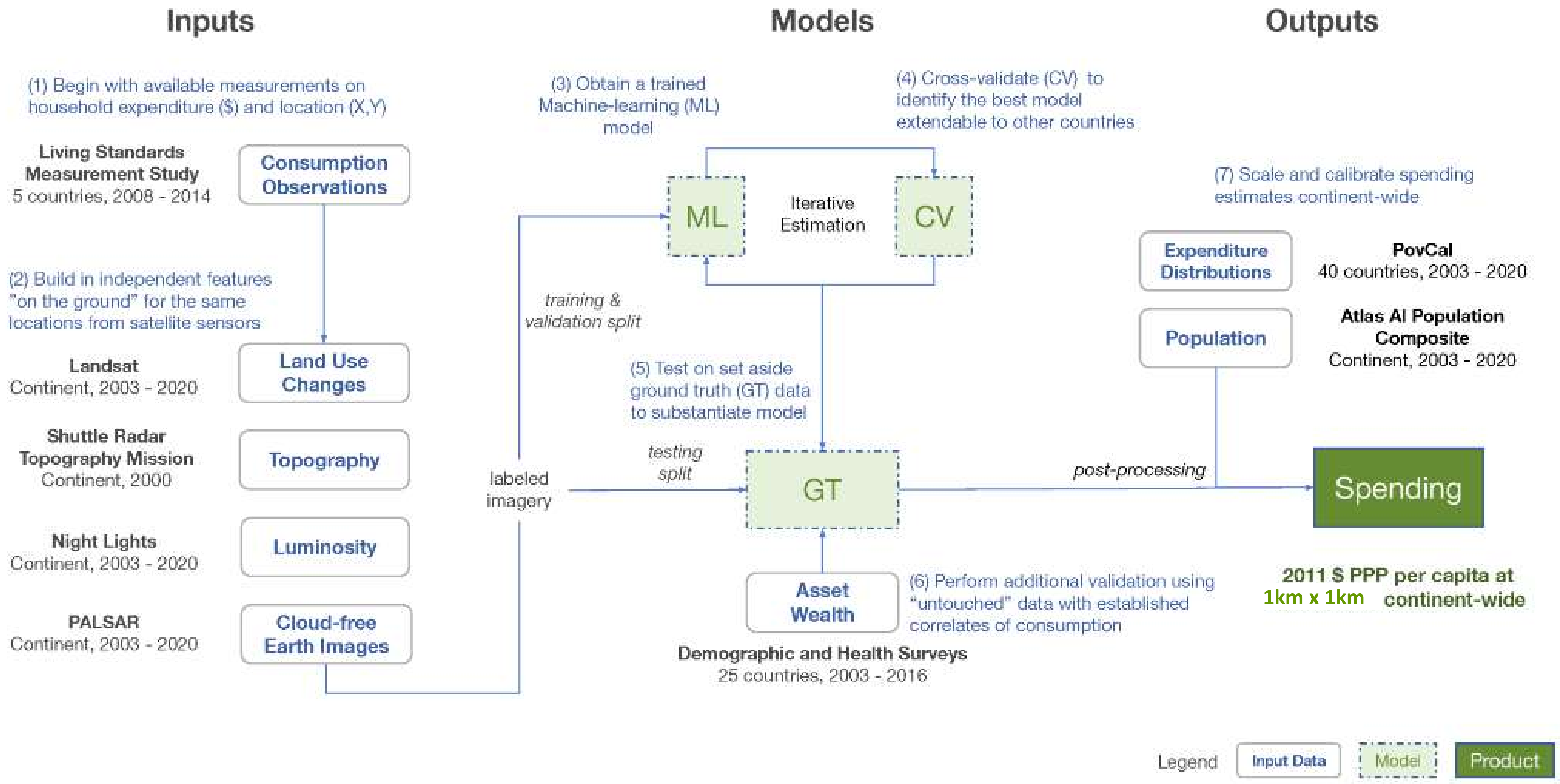
Nighttime Lights (NL): luminosity from the 2004-2005 Defense Meteorological Program (DMSP) median composites, 2010 DMSP median composites, 2014 VIIRS median composite, and the 2015-2020 Visible Infrared Imaging Radiometer Suite (VIIRS).

Phased Array type L-band Synthetic Aperture Radar (PALSAR): 25 meters PALSAR yearly for cloud and weather-free observations.

Demographic and Health Surveys (DHS) Program: 30 countries, for surveys administered between 2003 and 2016.

Global Human Settlement Layer (GHSL) Population Data: 250-meter population grid data from the years 2000 and 2015, and the 1 km settlement grid data.

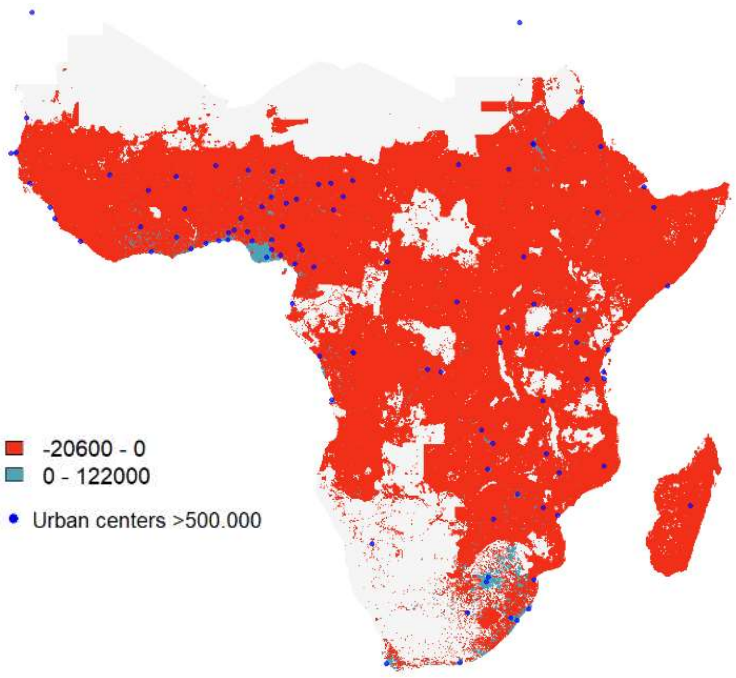
The ATLAS-AI data (SP): in more detail



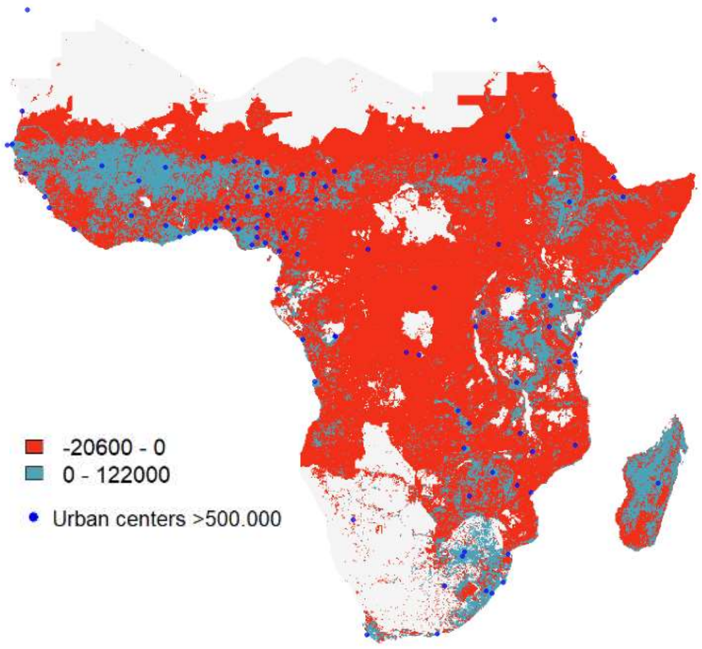
Source: Atlas-AI documentation [here]

Exploratory results (spatial variation)

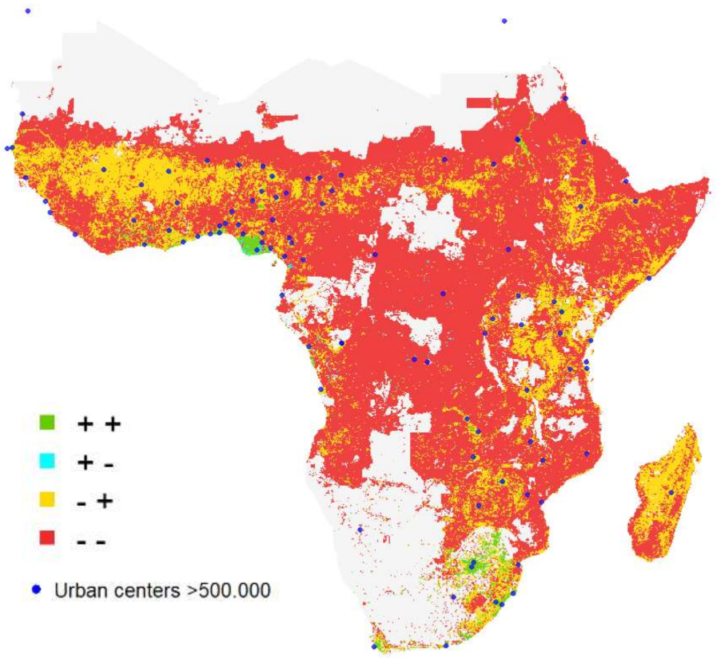
AWI*POP 2003



AWI*POP 2021



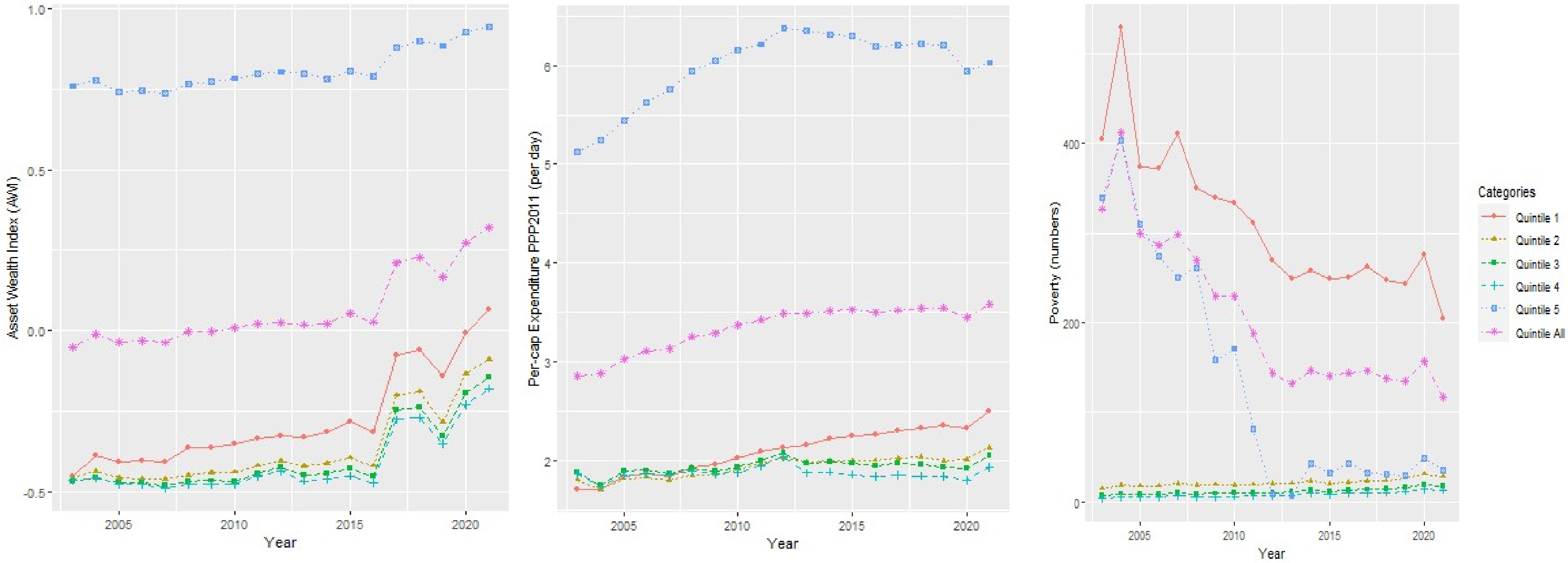
AWI evolution (+/-) 2003 and 2021



i) AWI limited areas maintained above average (green) over time from 2003 to 2021
ii) Improvements in many areas of SSA

Growth and Stagnation: Quintile Analysis

A. Asset wealth B. Per capita expenditure C. Extreme Poverty



QUINTILE (using AWI*POP in 2003):

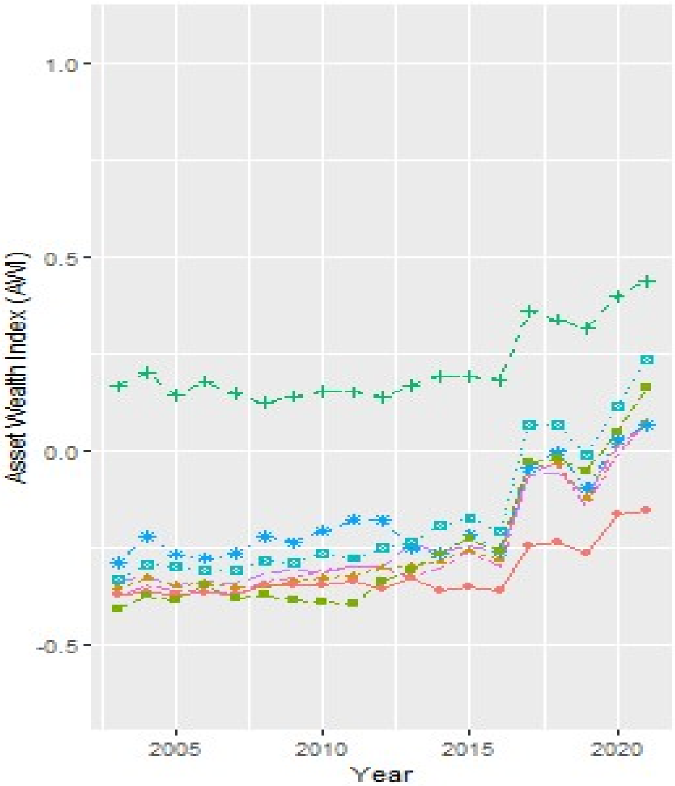
i) Welfare improvement **concentrated in Q1-Q5** (mostly **urban**)

ii) Important POV reductions in Q1-Q5 but numbers still high

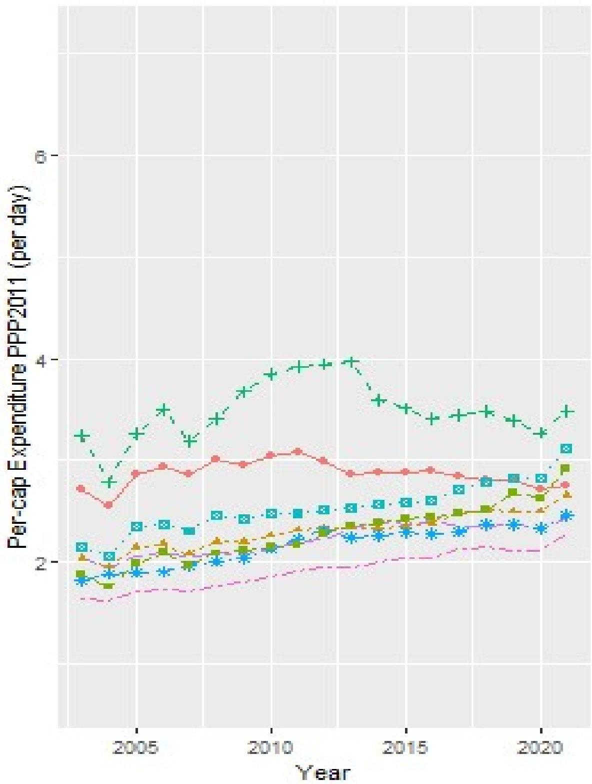
iii) Other quintiles in the middle (highly rural with lower population density) largely stagnated (but smaller POV numbers)

Welfare indicators across main GAEZ

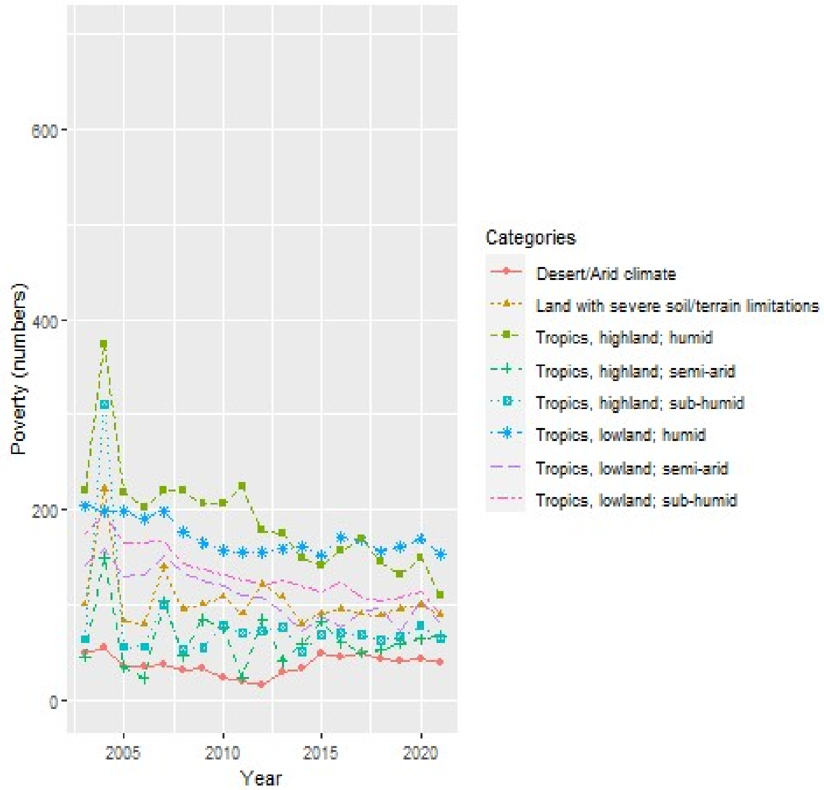
A. Asset wealth



B. Per capita expenditures



C. Extreme Poverty



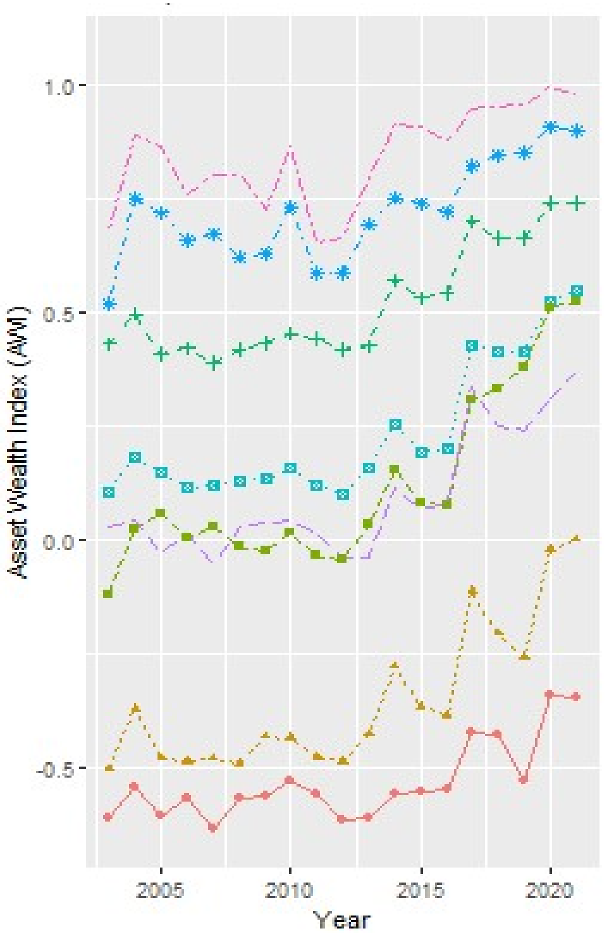
i. **Tropical highlands: better than tropical lowlands** (tropical highland humid exception but achieved a reduction in POV). Opportunities in crop suitability, **exposed to lower temperatures but concentrated in small areas and shrinking.**

ii. **Tropical lowlands struggling and desert and arid** (the lowest AWI, higher SP and lower POV) **stagnated**.

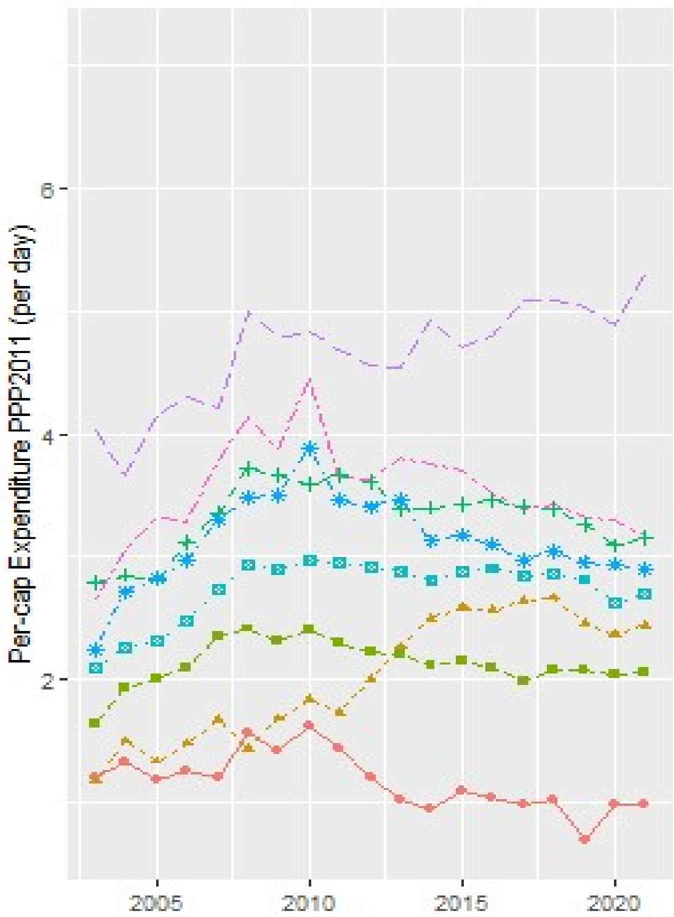
iii. Both **exposed to higher temperature, projected to suffer from climate change, bigger areas, getting bigger.**

Welfare indicators across other GAEZ I

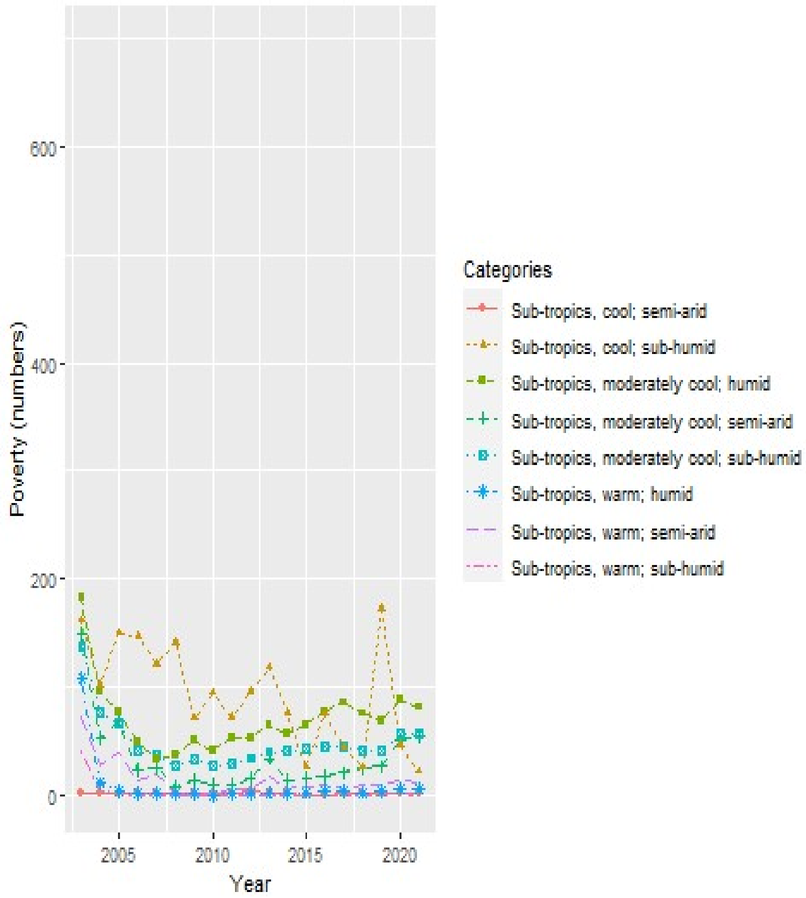
A. Asset wealth



B. Per capita expenditures

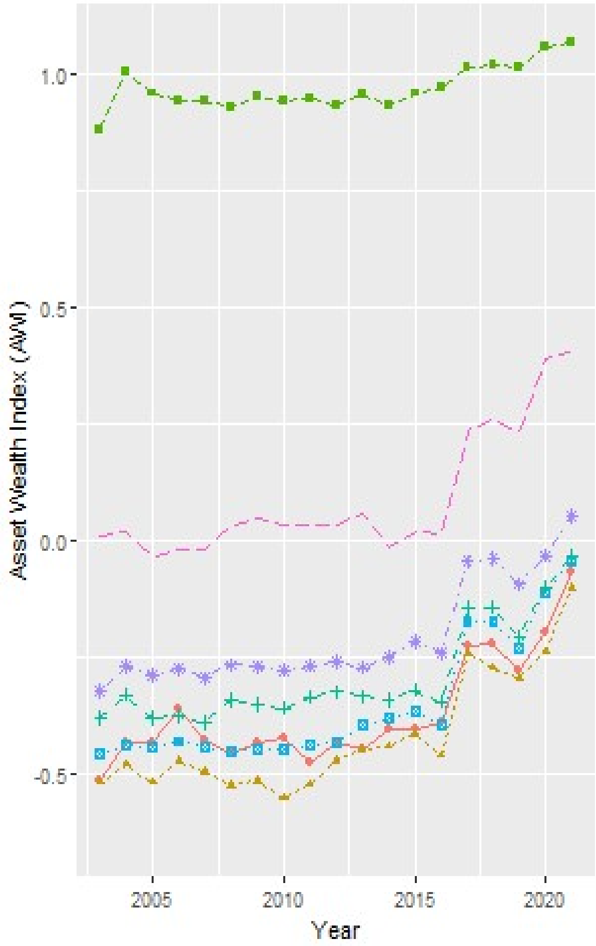


C. Extreme Poverty

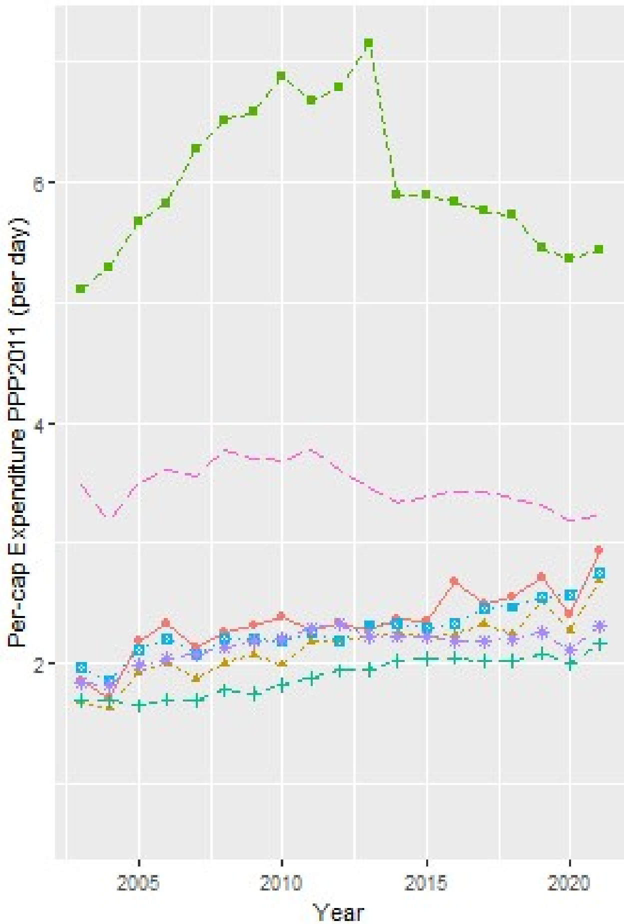


Welfare indicators across other GAEZ II

A. Asset wealth



B. Per capita expenditures



C. Extreme Poverty