nature sustainability

Resource

https://doi.org/10.1038/s41893-025-01689-4

Rising income inequality across half of global population and socioecological implications

Received: 29 November 2024

Accepted: 20 October 2025

Published online: 05 December 2025

Check for updates

Daniel Chrisendo[1,2,8], Venla Niva[1,8], Roman Hoffmann[3], Sina Masoumzadeh Sayyar[1], Juan Rocha[4], Vilma Sandström[5,6], Frederick Solt[7] & Matti Kummu[1,8]

Income inequality is one of the most important measures to indicate socioeconomic welfare and quality of life, and has implications for the environment. Yet, especially at the subnational level, comprehensive global data on income distribution are widely missing. Such data are essential for assessing patterns of inequality within countries and their development over time. Here we created seamless global subnational Gini coefficient and gross national income purchasing power parity per capita datasets for the period 1990–2023 and used these to assess the status and trends of income inequality and income, as well as their interplay. We show that while gross national income has increased for most people globally (94%), inequality has also increased for around 46–59% (depending on the national dataset used) of the global population, while it has decreased for 31–36% and has not shown a significant trend for 10–18%. We illustrate heterogeneities in inequality trends between and within countries, analyse plausible confounding factors related to inequality, and highlight the broad utility of the datasets through a case study that investigates correlations with terrestrial ecological diversity. Our dataset and analyses provide valuable insights for relevant stakeholders to direct future research and make informed decisions at the global, national and subnational levels, addressing societal, economic and environmental challenges caused by inequality.

Income has been widely used as an economic metric to measure a nation's wealth and standard of living[1]. For many years, particularly in the second half of the twentieth century, utilitarian economic growth and increased national income were the primary focus of development and inequality was seen as an acceptable trade-off necessary for poverty reduction[2]. A nation could be highly unequal, characterized by a big gap in wealth between the rich and the poor, while at the same time being generally wealthy[3]. However, recent evidence suggests that inequality poses a threat to long-term economic development[4]. It plays a vital role in how much economic growth alleviates (absolute) poverty since, in a highly unequal society, only a tiny share of growth accrues to those experiencing poverty[2].

Beyond economic considerations, income inequality foresees the level of social justice and stability of a country, as countries with less income disparity have been shown to have a higher quality of government, higher level of democracy, lower corruption and more laws and

[1]Water and Development Research Group, Aalto University, Espoo, Finland. [2]Department of Land Economy, University of Cambridge, Cambridge, UK. [3]International Institute for Applied Systems Analysis (IIASA), Wittgenstein Centre for Demography and Global Human Capital (IIASA, VID/OeAW, University of Vienna), Laxenburg, Austria. [4]Stockholm Resilience Centre, Stockholm University, Stockholm, Sweden. [5]Faculty of Agriculture and Forestry, Department of Economics and Management, and Helsinki Institute of Sustainability Science (HELSUS), University of Helsinki, Helsinki, Finland. [6]Finnish Environment Institute, Helsinki, Finland. [7]University of Iowa, Iowa City, IA, USA. [8]These authors contributed equally: Daniel Chrisendo, Venla Niva, Matti Kummu. e-mail: dc951@cam.ac.uk; matti.kummu@aalto.fi

regulations promoting social justice and ensuring fair opportunities for all[4,5], as was observed in the Nordic countries[6]. On the contrary, high inequality is linked to lower quality of life, as a high gap in income often leads to poorer health outcomes[7], lower life expectancy[8], lower levels of education[9], higher crime rates[7] and eventually lower level of happiness and well-being[10] because it restricts access to essential resources and services for the poorer sections of society[4]. From an environmental perspective, high income inequality is linked to various environmental degradations, including increased carbon emissions[11] and biodiversity loss[12].

Those examples show that examining income inequality becomes essential, and focusing solely on income to track a country's performance does not provide a complete picture. On that note, the United Nations (UN) has prioritized the fight against inequality in its sustainable development goals (SDGs) (goal 10: reduce inequality within and among countries), highlighting the need to 'leave no one behind'[13]. An organization such as the World Bank acknowledges its importance and translates it into an ambitious goal to specifically promote income growth for the poorest 40% of the population across countries, regardless of the country context[9].

Despite the decreasing trend in inequality between countries, albeit with some disagreements following the COVID-19 pandemic[14], inequality within countries has increased in many regions[15,16]. The root causes of this trend and its effects vary across different settings[4]. Subnational data over a long period are, therefore, needed when analysing changes in inequality and the resulting implications to provide policy-relevant evidence. For example, the challenges and policy strategies to increase human welfare appear very different for a country with highly concentrated poverty in specific areas compared with one where it is more evenly spread geographically[17]. Nevertheless, such analyses remain few, and no comprehensive subnational dataset exists globally, let alone over several decades. There are high-quality national datasets[18–20] and two subnational datasets[17,21] for selected countries ($n = 134$ for ref. 21; $n = 26$ for ref. 17), but these cover only restricted periods (varying from 1999 to 2018, depending on the country, in the case of ref. 21; 2010 for ref. 17).

Here we fill this gap by creating a global subnational Gini coefficient (SubNGini) dataset—a widely used measure of inequality in the literature[19]—as well as a seamless subnational gross national income (GNI) at purchasing power parity (PPP) per capita (SubNGNI) dataset. Both have annual data for more than the last three decades (34 years; 1990–2023). We harmonized the subnational datasets against two different reported national datasets, in which we filled the missing years using interpolation and extrapolation (Methods).These datasets together enable us to map the status of these two important development indicators for any given year, assess the trend in each administration area and visualize their (co)evolution side by side. The data can be visualized and explored with an online tool at https://wdrg.aalto.fi/income-inequality-explorer/ and the data are available via Zenodo at https://doi.org/10.5281/zenodo.14056855 (ref. 22).

We further investigate the linkages between inequality and income over time, explore plausible confounding factors of heterogeneities in inequality trends and demonstrate how the data can be used in socioecological studies. Our findings offer useful insights into trends in income inequality, providing valuable information to evaluate goal 10 of the SDGs and empower policy-makers to make informed decisions. Furthermore, the SubNGini and SubNGNI datasets offer various possibilities for other researchers to use for global or regional spatiotemporal analysis, such as vulnerability and risk assessments.

Results

Dataset creation

For the SubNGini (income inequality dataset), we first produced two gap-filled national datasets; one based on the standardized world income inequality database (SWIID)[19] and the other based on the world inequality database (WID)[18] data (Methods). In both datasets, we identified countries that were missing in either one but exist in the other ($n = 195$ for SWIID and $n = 216$ for WID). We then used neighbouring countries that have data in both datasets to derive data for a few countries with missing values in one dataset (Methods and Extended Data Table 1). Then, we interpolated and extrapolated the missing years. This resulted in complete datasets for both SWIID and WID, covering the period from 1990 to 2023, for 207 countries.

We then collected the subnational (administration 1-level) Gini coefficient from various sources, including income databases of harmonized microdata Luxembourg income study database (LIS)[23] and economic research forum database provided by LIS (ERF-LIS)[24] as well as readily calculated Gini coefficient data from global data lab (GDL)[25], global subnational poverty atlas (GSAP)[21], national censuses and literature (Extended Data Figs. 1 and 2). Altogether, our dataset includes Gini data for 2109 subnational areas (covering 151 countries, where 94.2% of the global population lived in 2023) and 16,241 distinct entries (administration area–year combinations).

The subnational data originate from various sources and might not be fully comparable. Therefore, instead of using the subnational Gini coefficient values directly, we followed the approach that Kummu et al.[26] used for gross domestic product (GDP) per capita. We calculated the ratio between subnational and national data, where the national data were from the same source as the subnational data. Using the ratio allowed us to combine datasets from different sources without introducing potential inconsistency between them. We then interpolated the ratio between reported years, while for the missing data in the head and tail of the reported subnational dataset we used the ratio from the closest reported year (assuming that the ratio between national and subnational values remained unchanged, similarly to ref. 26 for GDP per capita). At the end, we multiplied the ratios by the national dataset, resulting in harmonized subnational data against two distinct global datasets (SWIID and WID) (Methods). In the main text, we present the results using data from the SWIID national dataset, which includes error estimates and thus it was possible to perform an uncertainty analysis using only that dataset.

For the SubNGNI (income per capita dataset), we first collected national data from the UNDP[27] and the World Bank[20], resulting in a GNI per capita PPP (in 2021 international $) dataset for 207 countries. For the subnational data, we used an existing subnational database from the GDL[28]. The dataset includes subnational data for 1,801 subnational areas, as illustrated in Extended Data Fig. 3 (covering 166 countries, where 98.3% of the global population lived in 2023) and comprises a total of 55,293 distinct entries (administration area–year combinations). We followed a procedure similar to that used for the SubNGini data to obtain the combined interpolated and extrapolated subnational and national data (Methods).

Geographical distribution and trends of income inequality

In 1990, the lowest inequality was observed in Northern Europe, Central Europe and some parts of Russia, with varying income levels (Fig. 1a,b). In 2023, countries in Europe have among the highest levels of income and the lowest levels of inequality, although the Gini coefficients are higher than those of 1990 (Fig. 1c,d). Other areas with high income were found in North America, Saudi Arabia, Australia, Japan and in some parts of Russia, where low and high inequality were observed. For example, Saudi Arabia had a very high income in both years, but the inequality was also very high. Meanwhile, the highest levels of inequality in 1990 and 2023 were found in Sub-Saharan Africa and the tropical parts of Latin America. Worryingly, in Africa, this was aggravated by a very low per capita income. The pattern is very similar in the data based on the other national data (WID), particularly in Central Asia and Central America, where WID-based data show relatively higher inequality, although some differences also exist (Extended Data Fig. 4a–d).

https://doi.org/10.1038/s41893-025-01689-4

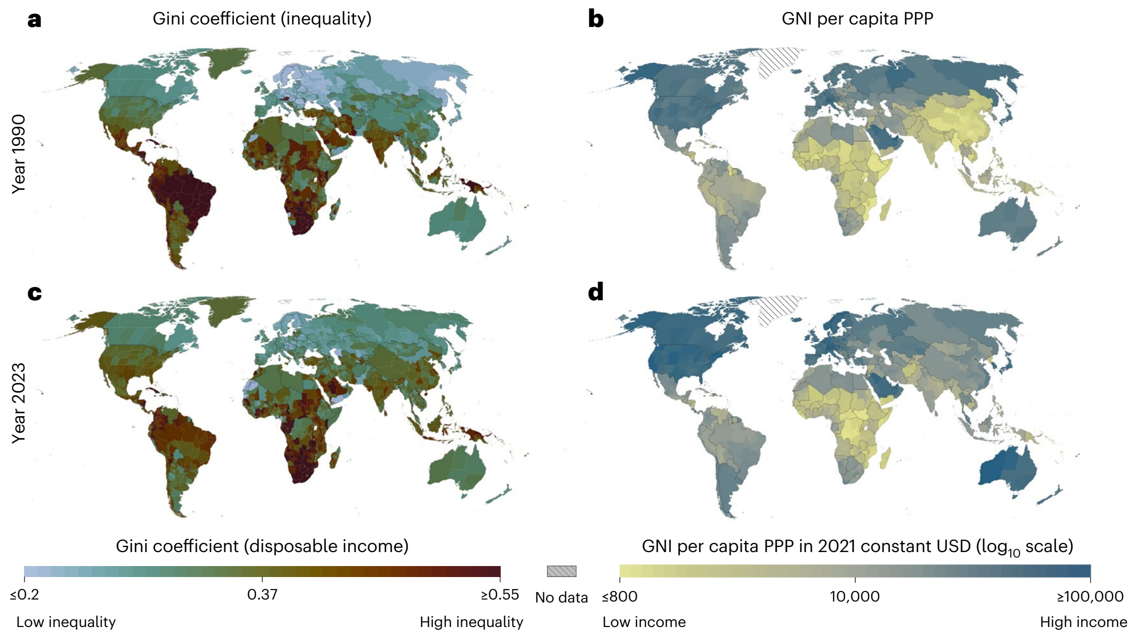


Fig. 1 | Gini coefficient and GNI per capita for 1990 and 2023. a, Gini coefficient, as calculated based on disposable income, for 1990. **b**, GNI per capita PPP for 1990. **c**, Gini coefficient, based on disposable income, for 2023. **d**, GNI per capita PPP in 2021 constant US$ ($\log_{10}$ scale; for 2023). Colour bar in **c** also relates to **a**, and colour bar in **d** also relates to **b**. Gini coefficient based on SWIID national data is used here; see maps for the dataset based on WID national values in Extended Data Fig. 4. See the uncertainty analysis results in Supplementary Note and Supplementary Fig. 4. Basemaps from Natural Earth (https://www.naturalearthdata.com/).

The subnational-level datasets reveal the spatial heterogeneity in inequality and income within countries, especially in large countries such as the USA, Brazil, India and Russia, which would remain hidden when analysing only country-level data (Extended Data Figs. 5–7). The highest within-country variability in the Gini coefficient (using the year 2023 and measured with a coefficient of variation) can be found in various countries in Sub-Saharan Africa, South America and Asia (Extended Data Fig. 8a). Meanwhile, the highest variability in GNI per capita can also be found in Sub-Saharan African countries; however, values are also high in China, Russia, Turkey, Papua New Guinea and certain parts of Eastern Europe (Extended Data Fig. 8b).

While income has generally increased in many parts of the world, the trend of inequality has shown more variation (Figs. 2 and 3). To assess in more detail how income and income inequality have changed over the past 34 years, we classified the world according to the magnitude of change in both indicators (Figs. 2a and 3). In the Americas, the most favourable development occurred in Latin America (Figs. 2a and 3c,i), where income inequality decreased (see Fig. 2 for statistical breaks). However, the inequality in the region was exceptionally high in 1990 and has remained at a high level despite the improvements (Fig. 1a). On the other hand, North America and other wealthy countries, such as Australia, Norway, Germany and other European countries, experienced increases in inequality (Figs. 2a and 3b,h,m). In Europe, the increasing inequality has been primarily driven by the substantial income gains among the top 10% of earners, while the income share of the bottom 50% has either stagnated or declined[29]. Several factors were found to influence this, such as tax systems that have become less progressive in some European countries, thus reducing the tax redistributive effects, as well as reductions in welfare programmes[7,30]. China, on the other hand, is quite distinct. Across the country, income and income inequality increased or strongly increased (Figs. 2c and 3d). The inequality in Sub-Saharan Africa shows the most considerable variation, with a decrease in Western Africa and an increase in Eastern and Southern Africa (Figs. 2a and 3l).

The contrasting trends can also be observed within individual countries. Indonesia, Spain, Egypt and Ethiopia are some of the countries where both increasing and decreasing inequalities are observed in different regions within each country. For example, the eastern part of Indonesia, the northern part of Spain, the southern part of Egypt and the southwestern part of Ethiopia experienced a decreasing trend in inequality, while the rest of those countries saw an increase in inequality (Fig. 2a).

When comparing the subnational trends based on the SWIID national dataset to those derived from the other national data (WID), they mostly agree, particularly in South America, Sub-Saharan Africa and Europe (Extended Data Fig. 4e,f). However, there are some distinct differences, as the direction of trend contradicts in large parts of Mexico, India and France (in these countries, the national-level correlation between these datasets is also very low or negative, as shown in Supplementary Fig. 1)—this is probably due to the different input data they rely on.

The results generally highlight that the global positive development in income between 1990 and 2023 (Fig. 2b) did not correspond with a similarly positive trend in inequality reduction (Fig. 2a). In fact, our results show that in 2023, around half (46% in SWIID base data and 59% in WID-based data) the people in the world lived in areas where inequality had increased (measured with a statistically significant—$P < 0.1$—positive slope using Siegel repeated medians) and more than half (58%) in places where income had strongly increased. On the other hand, only about one-third (31% in WID-based data and 36% in SWIID-based data) of the population lived in areas where inequality had decreased since 1990 (Fig. 2d). As much as 23% of the global population in 2023 lived in areas where both income and income inequality had strongly increased since 1990.

The interplay of income and income inequality

To analyse the interplay between inequality and income, we classified the world's subnational regions into 16 combinations on the basis of their GNI per capita and Gini, both for 1990 and 2023 (Fig. 4a,b). We distinguished between regions with low (<US$1,045), lower-middle (US$1,046–4,095), upper-middle (US$4,096–12,695) and high (US$>12,695) income (based on 2021 classification by the World Bank[31],

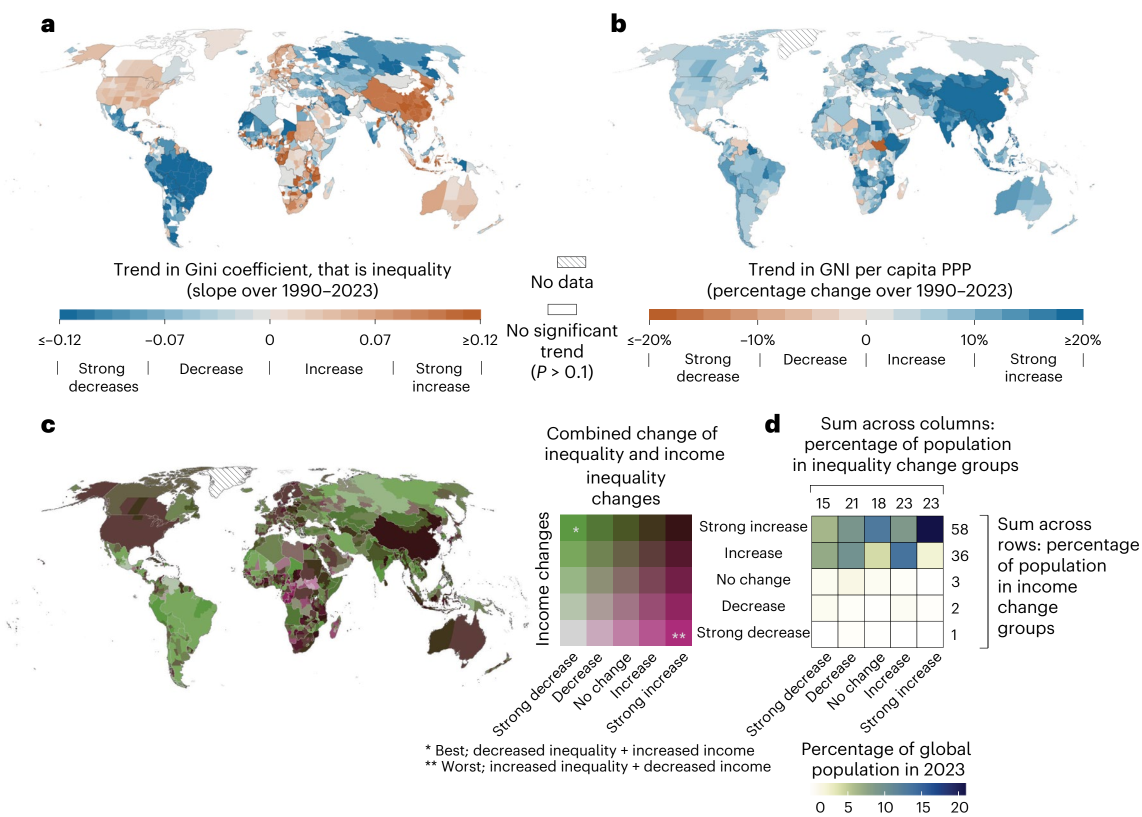


Fig. 2 | Combined change of income and income inequality. **a**, Change in inequality between 1990 and 2023 using subnational data based on the SWIID national dataset; trend for the dataset where the WID national dataset is the base is shown in Extended Data Fig. 4. We used the quantiles to determine the breakpoints, choosing the largest (absolute, as there were negative values) of the 25th and 75th quantiles for the breakpoints on both the negative and positive sides between strong decrease and strong increase, and 0 was used as the breakpoint in the middle. This resulted in the following classes: strong decrease (trend ≤ −0.07), decrease (−0.07 < trend ≤ 0), increase (0 < trend < 0.07) and strong increase (trend ≥ 0.07). **b**, Change in income between 1990 and 2023. For income (GNI), the classes were: strong decrease (trend ≤ −10%), decrease (−10% < trend ≤ 0%), increase (0% < trend < 10%) and strong increase (trend ≥ 10%). **c**. Combined change in inequality and income. Each bin illustrates a situation with a different combination of changes in inequality and income, for example, the bottom-right corner depicts a situation where income had a strong decrease while inequality had a strong increase. The map is a spatial representation of the heatmap. **d**, Relative population (percentage of global population) in different combinations in 2023. Row and column-wise sums represent the share of the global population living in each income (rows) and inequality change group (columns). For example, in 2023, 58% of the global population lived in areas where income had a strong increase between 1990 and 2023. The sum across rows exceeds 100% as a result of rounding up. Slopes were calculated with Siegel repeated medians (mblm R package) and only statistically significant slopes ($P < 0.1$) are reported. The associated P value tests the null hypothesis of a zeroslope using a two-sided hypothesis test without adjustments for multiple comparisons. See the uncertainty analysis results in Supplementary Note and Supplementary Fig. 4. Basemaps in **a**–**c** from Natural Earth (https://www.naturalearthdata.com/).

as our data are based on 2021 international $, a hypothetical currency that has the same purchasing power parity as the US$) as well as those with relative equality (Gini of 0–0.3), adequate equality/reasonable income gap (0.3–0.4), big income gaps (0.4–0.5) and severe inequality (0.5–1), based on UN classification[32].

The results illustrate that many areas in Latin America, which experienced severe inequality combined with relatively high incomes in 1990, managed to move towards less inequality by 2023 (Fig. 4). At the same time, the income level remained the same in the high-income regions of the world while the degree of inequality worsened. The global hotspots in 1990 and 2023 for both low income and high inequality were mostly located in the central parts of Sub-Saharan Africa.

Interestingly, in 1990, the largest shares of the global population (20%) lived in areas with relatively low income (low–middle) but adequate levels of equality (Fig. 4c). By 2023, the demographics had changed so that the largest share of the global population (33%) lived in places with high income and adequate levels of equality (Fig. 4c), a drastic increase from 1990 when only 9% lived within this class and thus indicating a total 24%-point increase in people in these regions (Fig. 4c). This is explained by both unequal population growth rates worldwide and the changing conditions regarding income and income inequality. However, in general, more people tend to live in areas with a large income gap, while fewer live in areas with relative equality (Fig. 4c), indicating a trend towards a more unequal society.

The interplay of income equality and ecological diversity

To illustrate the value of the SubNGini and SubNGNI datasets to socioecological studies, we consider the relationships among progress towards SDG 8 ‘Decent work and economic growth’, SDG 10 ‘Reduced inequalities’ and SDG 15 ‘Life on land’. To date, global analyses of interactions between income, income inequality and environmental changes have been conducted mostly on the national level[11]. Here we show how our data can be used within the socioecological sphere by performing a subnational analysis to explore trends in income and income inequality and comparing them with trends in terrestrial ecological diversity[33] over the past three decades (Methods). There are several links between income, income inequality and ecological diversity. First, higher income inequality may be correlated with increased natural resource exploitation, which in turn reduces the natural habitats for biodiversity[12]. Higher income inequality was also found to push the poorer part of society to occupy vulnerable lands, such as areas close to forests[12]. Lastly, rich populations in high-income countries

 https://doi.org/10.1038/s41893-025-01689-4

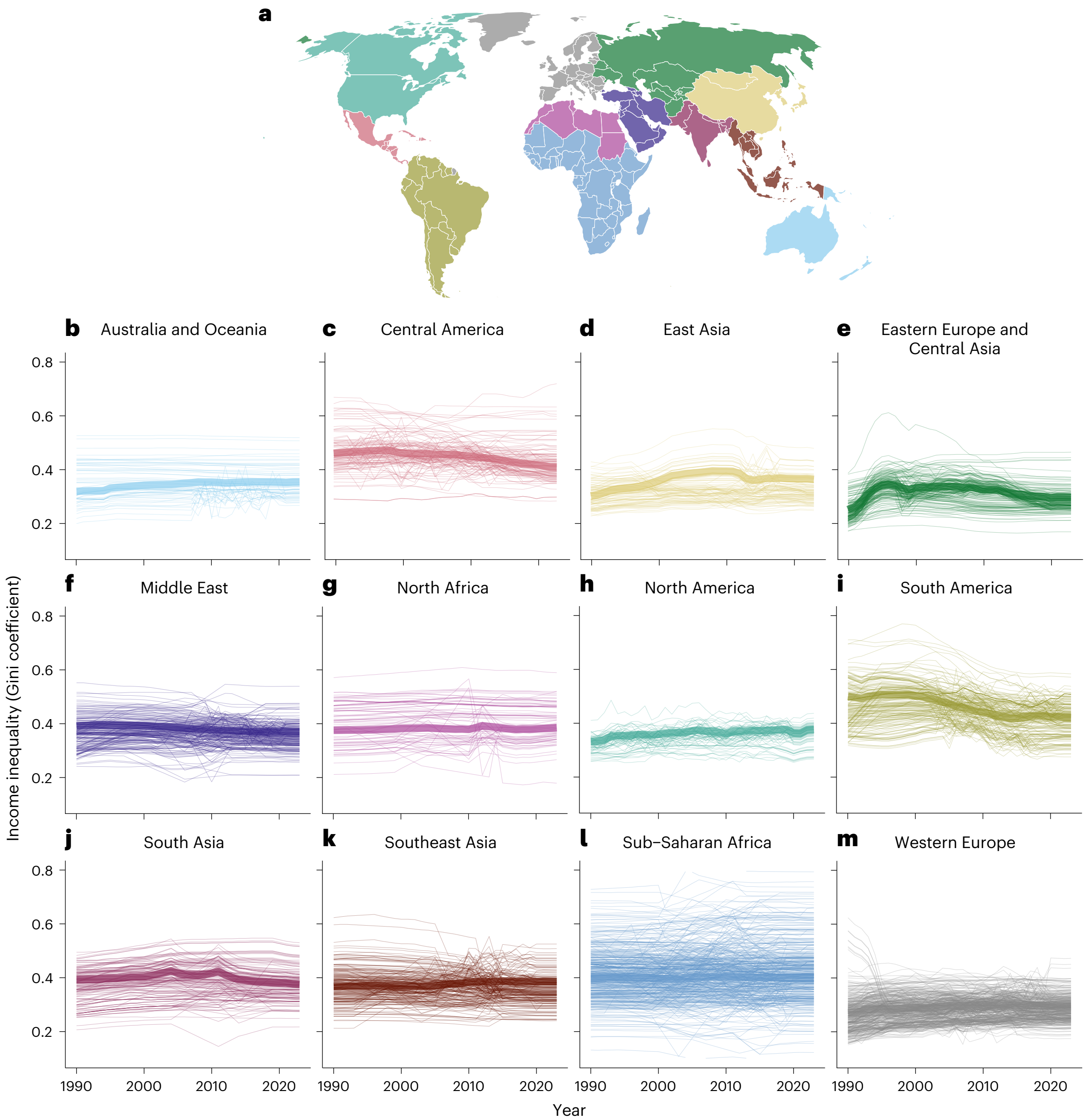


Fig. 3 | Regional and subnational time series for the Gini coefficient from 1990 to 2023. a, Map of the regions. **b**–**m**, Time series for each region: Australia and Oceania (**b**), Central America (**c**), East Asia (**d**), Eastern Europe and Central Asia (**e**), Middle East (**f**), North Africa (**g**), North America (**h**), South America (**i**), South Asia (**j**), Southeast Asia (**k**), Sub–Saharan Africa (**l**), and Western Europe (**m**). Thick lines are population-weighted regional average and thin lines are subnational time series (when available, otherwise national). The subnational Gini coefficient data based on the SWIID national data are used here. Note that 0.2 indicates relative equality and 0.8 indicates severe inequality. Basemap in **a** from Natural Earth (https://www.naturalearthdata.com/).

may drive global demand for products (such as palm oil, soy, beef and timber) that often contribute to habitat loss and biodiversity decline in low-income countries[34].

We found that a few bright spots exist where all three indicators are moving in a positive direction (higher income, higher equality and higher ecological diversity) (Fig. 5a). However, the level of progress is not expected to meet global aims by 2030, such as the SDGs. The considerable concentrations of bright spots are located in Russia, areas in Eastern Europe, Malaysia and Iran, as well as in some areas of Western Europe, South America and New Zealand. The countries with all administration areas in the bright spot category were Austria, Jamaica and Moldova, while there are a handful of countries where over 50% of the administration areas belong to this category (Fig. 5a). Dark spots (negative trends in all indicators), in turn, are common in the African continent, particularly in central Africa, Libya, parts of South Africa, Namibia and Madagascar. Outside Africa, dark spots are also observed in Chiapas, Mexico (Fig. 5a).

Most areas have mixed trends in these three indicators. Europe, the USA and China are dominated by the combination of increased ecological diversity and income but decreasing equality (higher Gini coefficient) (Fig. 5a). However, elsewhere, the dominant classes are either decreasing ecological diversity and equality with increased income (dominating in Canada, Australia, India and large parts of Africa; *n* of administration areas is 615) or decreasing ecological diversity and rising income and equality (dominating Latin America, Central Asia and Northwestern Africa; *n* = 695).

In general, the distribution of the average values of these three indicators (Fig. 5b) shows that bright spots appear in areas where low ecological diversity (compared with the natural stage; ref. 33) is combined with high income and relatively high equality (a low Gini

https://doi.org/10.1038/s41893-025-01689-4

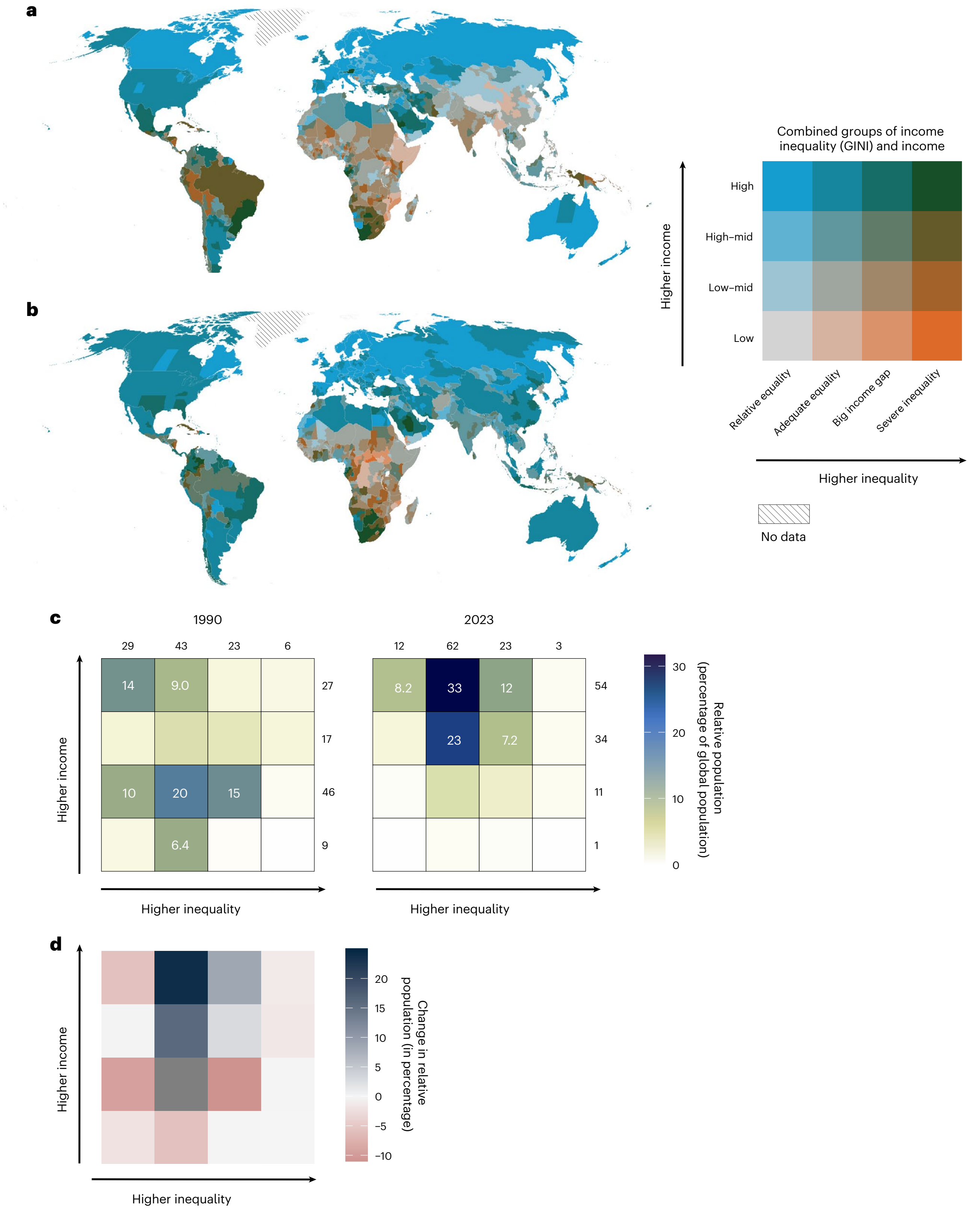


Fig. 4 | Combined groups of income and income inequality. a,**b**, Global classification of income and inequality in 1990 (**a**) and 2023 (**b**) using the 2021 World Bank income groups (high income >US$12,695; upper-middle (mid) income US$4,096–12,695; lower-middle income US$1,045–4,095; low income <US$1,045) and the Gini coefficient range by UN[32] (relative equality (0–0.3); adequate equality/reasonable income gap (0.3–0.4); big income gap (0.4–0.5) and severe inequality (0.5–1)). **c**, Relative population, presented as percentage of the global population, in each inequality–income group in 1990 and 2023. **d**, The change in population between 1990 and 2023 in %-units. The subnational Gini coefficient data based on SWIID national data are used here. Basemaps in **a** and **b** from Natural Earth (https://www.naturalearthdata.com/).

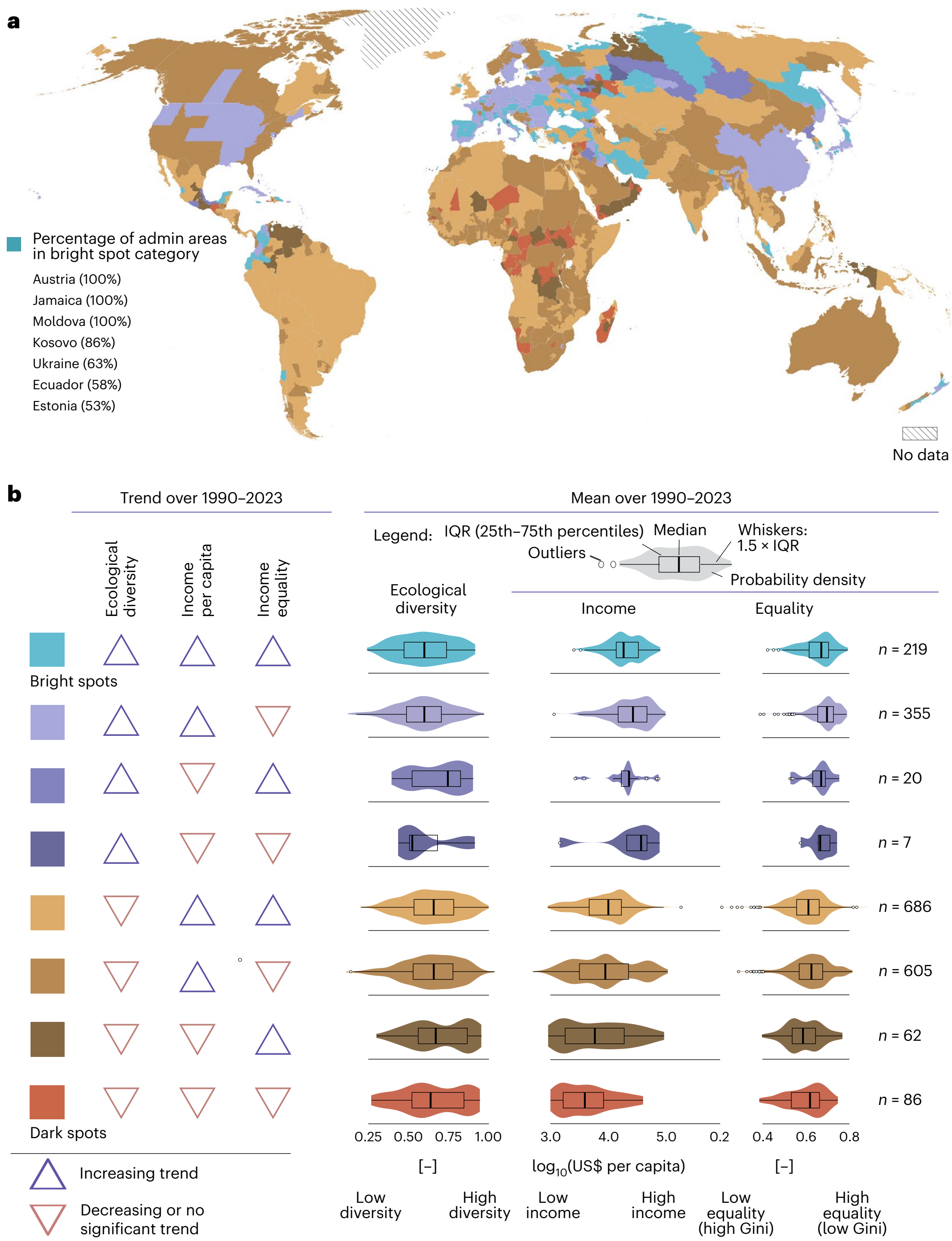


Fig. 5 | The interplay of ecological diversity, income and income equality. **a**, A map showing the combinations of trends in ecological diversity, income and income equality (1 − Gini coefficient) over 1990–2023. Bright spots (all trends positive) and dark spots (all trends negative) are highlighted. **b**, The distributions of average values (over 1990–2023) of each indicator in each trend combination class. In the last column, the *n* corresponds to the number of administration (admin) 1 areas in each trend combination class. Slopes were calculated with Siegel repeated medians (mblm R package) and only statistically significant slopes ($P < 0.1$) are reported. The subnational Gini coefficient data based on SWIID national data are used here. IQR, interquartile range. Basemap in **a** from Natural Earth (https://www.naturalearthdata.com/).

coefficient). For areas with increased ecological diversity and income but decreased equality, income and equality are the highest among all classes. For areas with a negative trend in ecological diversity, the income is lower and the equality has smaller differences with similar direction (compared with areas with a positive trend in ecological diversity) (Fig. 5b). The dark spots have the lowest income and equality and high (but decreasing) diversity. As a rough conclusion, high-income and high-equality countries have exploited their natural resources but are slowly restoring them, whereas low-income countries have done the opposite.

Discussion

Previously, global analyses of income inequality have relied primarily on national-level Gini coefficients, often limited by short time series and sparse coverage. While such data have enabled broad assessments of inequality across countries and facilitated international comparisons, they have not captured inequalities at a finer spatial and temporal resolution. As our analysis demonstrates, these subnational variations can be substantial: trends in income inequality at the subnational level frequently diverge from national averages, sometimes even moving in opposite directions (Extended Data Figs. 5–7).

To address this gap, we developed a globally harmonized dataset of subnational Gini coefficients (SubNGini) and gross national income per capita (SubNGNI), covering more than three decades of annual data. These datasets provide an unprecedented level of spatial and temporal resolution for income inequality and economic well-being. They enable us not only to assess the overall trajectory of inequality but also to identify where and for whom it has increased or declined, offering valuable information for policy-making, as well as tracking progress towards SDG 10. Despite global economic growth during the study period, our results indicate that subnational income inequality has increased for half the world's population, with notable geographic variation.

Various policies have been proposed globally to reduce inequality and promote inclusive and balanced economic growth, including, for example, progressive taxation, expanded social protection and improved access to quality healthcare, education and basic services, which can be important tools to address inequality[7,9,30]. While a complete evaluation of their effectiveness is beyond the scope of this study, we highlight selected policy measures and developments that may help explain some of the patterns and trends observed in our subnational data.

The role of historical developments and policies

Many countries, especially low- and middle-income countries, have experienced growing national and subnational inequality over the past few decades, primarily due to unequal income growth, as well as population dynamics and movements[2,3]. Generally, policies aimed at reducing inequality have targeted two main areas: (1) increasing incomes among the poorest population groups through, among others, social welfare and protection programmes, cash transfers, minimum wage laws and educational investments; and (2) redistributing wealth from top to bottom via progressive taxation and subsidies. Below, we examine illustrative cases of countries that have followed different trajectories in their income and inequality trends, as well as their policy strategies.

China represents a notable case of sustained economic growth and large-scale poverty reduction since the 1990s, driven by market-oriented reforms and an open-door policy. In 1990, almost 72% of the population lived below the World Bank's poverty line of international $2.15 per day; by 2023, this share had dropped to just 0.1% (ref. 35). Income increases were observed across all subnational regions (Fig. 2b), with coastal and urbanized areas experiencing the most rapid gains. At the same time, these regions also experienced rising local inequalities (Extended Data Fig. 7), which can be attributed to China's household registration system, the Hukou and rural–urban migration[36]. Hukou is a registration mechanism that classifies Chinese citizens as either urban or rural residents, tying their access to public services, such as education, healthcare, housing and social security, to their registered locality. When people from rural China migrate to cities, especially towards the economically advanced east, they often cannot access urban public services because they do not hold an urban Hukou. This has intensified subnational disparities—both within cities, where rural migrants often face structural disadvantages and between regions, as urban hubs continue to concentrate economic opportunities[36,37]. In response to these trends, the Chinese government has implemented regional development programmes aimed at reducing disparities between provinces and bridging rural–urban income gaps[38]. Additional measures include supporting internal migrants, relaxing Hukou restrictions, expanding education, strengthening social protection systems, reforming personal income taxation and fiscal redistribution that provides transfers from richer to poorer regions to improve public services and infrastructure[38].

India is another compelling example that illustrates the value of subnational analysis. While national-level data suggest relative stability in inequality over time (Extended Data Figs. 5–7), disaggregated patterns reveal significant regional divergence. In particular, northern India has experienced stagnant inequality, whereas southern states have made more inclusive progress[39]. This relative success in the south, which has long been a stronghold of the Indian left, is linked to sustained investments in public health, education, infrastructure and economic development that have benefited the local population more broadly[40]. These differences highlight the importance of moving beyond national averages to uncover the underlying dynamics of inequality and identify the drivers of inclusive growth (Extended Data Figs. 5 and 6).

Brazil, another emerging economy, exemplifies common patterns of inequality observed across Latin America, where many countries have experienced rapid economic development in recent decades. Unlike China, Brazil has seen a decrease in income inequality, although from a high initial level. Historically, Brazil's high inequality stemmed from a large wealth gap as well as the segregation and discrimination of disadvantaged population groups[41]. Between 1990 and 2023, Brazil's Gini coefficient declined from 0.57 to 0.45, showing notable progress. The recent reduction in inequality across Brazilian regions is attributed to several factors. One of the most influential initiatives in reducing poverty has been Bolsa Família, a conditional cash transfer (CCT) programme that provides financial assistance to low-income families. Recognized as the largest CCT programme in the world, Bolsa Família aims to reduce short- and long-term poverty by requiring families to meet health and education conditions to receive support[42,43]. Beyond poverty reduction, the programme has led to improvements in school attendance, reduced dropout rates[42], enhanced food security and diet quality[43] and decreased crime and suicide rates[44,45]. Similar programmes have taken place in Mexico and Chile[46], with similar effects on income inequality. The increase in the minimum wage in Brazil has also played a important role in reducing income inequality, particularly by raising the incomes of the lowest-paid workers and those in the informal sector[47]. However, despite improvements in income and inequality, there are still differences at the subnational level. Similar to coastal areas in China, Brazil's southern and coastal regions are more developed and offer greater economic opportunities than the northern parts and rural Amazonas[48], as reflected in the higher GNI in these areas (Fig. 1).

Germany, like many other high-income countries in Europe (such as France, Spain and parts of the Nordic countries), illustrates a context in which income inequality has increased despite relatively modest growth in average incomes (Fig. 2). Particularly after the reunification of East and West Germany in 1990, both interregional and intraregional disparities widened[49]. The economic transformation of the eastern states initially led to substantial investment and modernization, but structural differences in productivity, employment opportunities and infrastructure have persisted. Over time, capital accumulation, rising real estate and asset prices and the transmission of wealth through inheritance have contributed to a growing concentration of income and wealth at the top[29,49]. Meanwhile, many low-income households have experienced stagnating or even declining real wages, compounded by labour market flexibilization and the expansion of precarious forms of employment[50]. The German government has sought to mitigate these trends through interstate fiscal transfers, minimum wage legislation and sustained investments in public education and vocational training. Yet these efforts have so far been insufficient to reverse broader inequality trends in the country.

Finally, some regions in our dataset exhibit conditions of high inequality and low income levels (Fig. 4). This is particularly evident in conflict-affected areas, such as parts of Niger, Sudan, South Sudan and the Central African Republic. Sociopolitical tensions not only harm economic growth but can also exacerbate inequalities, especially when

 https://doi.org/10.1038/s41893-025-01689-4

conflicts disproportionately affect specific regions or population groups[51]. Conflicts can also lead to migration, with implications for both subnational income and inequalities[52]. High levels of inequality can also be a driver of conflict, potentially creating a vicious cycle[9]. Beyond restoring peace, governments and the international community have advocated for policies aimed at promoting inclusive economic growth, reducing discrimination and strengthening social cohesion.

The economic growth–urbanization–inequality nexus

Urbanization plays a vital role in explaining some of the income growth and inequality trends observed across countries and regions in our dataset. Development and planning policies often favour more metropolitan areas and urban populations, leading to higher income growth in these areas[53]. As a result, this drives rural-to-urban migration as individuals seek better economic opportunities and improved living standards[9].

However, rapid urban growth frequently outpaces planning and service provision. In many low- and middle-income countries with high population growth, such as those in Africa or South Asia, this has resulted in the expansion of informal settlements, where low-skilled migrants face limited access to infrastructure, social services and formal employment opportunities[53]. These dynamics not only reinforce sociospatial segregation but also contribute to rising intra-urban inequality. In densely populated urban centres, the coexistence of extreme wealth and poverty increases overall inequality levels, a trend visible in many countries included in our dataset.

At the same time, urbanization can also contribute to reducing inequality, particularly in the national context. In some of the least developed countries, urbanization has been associated with rural–urban income convergence, facilitated by processes such as agricultural transformation, remittance flows from urban to rural areas and the return migration of skilled individuals[54]. These mechanisms can strengthen rural livelihoods and narrow income disparities.

Notably, the inequality-reducing potential of urbanization appears more pronounced in small and medium-sized cities, where urban expansion is often more manageable and inclusive[55]. For instance, several Latin American countries have experienced declining subnational inequalities (Fig. 2) alongside the growth of secondary cities. Similar patterns are evident in North Africa and Western Asia. Nevertheless, in many of these regions, inequality was exceptionally high in the 1990s and recent improvements represent a return to more moderate levels rather than a complete reversal of structural disparities.

Looking ahead, the fastest rates of urbanization are projected in regions currently characterized by high levels of inequality, particularly in Sub-Saharan Africa[53]. This highlights the critical importance of urban planning and governance. Our findings underscore the need for further research on how well-managed urbanization can promote equitable development, reduce rural–urban disparities and mitigate subnational income inequality.

Limitations and way forward

While our dataset provides insights into income levels and inequality trends at the subnational scale, it faces several limitations that are important for interpreting the results. First, the data are derived from a combination of publicly available sources, which vary in quality, coverage and methodology across countries and over time. This introduces potential measurement issues and inconsistencies that may affect the comparability of our estimates. Second, the definition and boundaries of the subnational units considered differ across countries, which likewise complicates direct cross-country comparisons. The spatial scale of analysis inherently shapes inequality measurements: a too-fine spatial disaggregation can obscure inequalities that exist within countries, while a too-broad spatial aggregation may overlook local heterogeneity[56]. Finally, although we highlight associations between observed trends and potential policy drivers, our study remains descriptive. Causal inferences about the effectiveness of specific interventions cannot be drawn without more detailed, context-specific analysis and stronger identification strategies, which are outside our scope.

Given the well-documented adverse effects of inequality on social cohesion, political stability and individual well-being, narrowing income gaps—both between and within subnational regions—remains a key priority for sustainable development. Our analysis highlights the importance of considering context-sensitive and inclusive approaches. At the local level, tailored solutions (for example, access to basic services) should be implemented on the basis of the unique needs of each community locality. The national government should redistribute resources to poorer areas and ensure equality across regions. Meanwhile, the international community can support national and local efforts through funding, expertise, policy advice and cross-border cooperation. Our high-resolution longitudinal dataset can support more targeted research and policy experimentation, helping to identify strategies that foster more equitable growth and enhance inclusivity.

Methods

National data for subnational Gini coefficient

We first collected national (administration 0 level) Gini coefficient data from two sources: SWIID[19] and WID[18]. These both provide better coverage than the national-level dataset compiled by the World Bank. SWIID has data for 195 administration 0 areas, WID for 216 areas and the World Bank for 168 areas.

We compared the SWIID and WID national datasets by selecting countries with at least ten overlapping observations. A direct comparison was not possible, as the methods used to generate these products differ: the SWIID produces comparable Gini coefficients by statistically adjusting existing data across various sources. The WID, however, constructs its Gini coefficients by integrating diverse data, with tax records serving as a key source for robust estimation of top incomes. Thus, for each country, we first normalized the Gini time series by dividing each entry by the national average over time. Then, we computed the correlation and root mean square error. While for most countries the correlation was high, there were some distinct differences as well (Supplementary Fig. 1). Therefore, we decided to compile two distinct datasets, one based on SWIID national data and the other based on WID national data.

For those countries for which SWIID data were not available but there were data in WID ($n = 6$; Extended Data Table 1), WID data were used. Similarly, for countries where there were data in SWIID but not WID ($n = 3$; Extended Data Table 1), SWIID data were used. For both SWIID and WID, data from GDL[25] for Western Sahara were used. Owing to the differences between the national datasets, we did not directly adapt the data from the other dataset. Instead, we used data from neighbouring countries that have data for both SWIID and WID (or GDL) to scale the values from the dataset. Specifically, we used the time-series trend for the country in question from the dataset that had data for this country. We then scaled that trend using a neighbouring country that had a similar level and trend of Gini coefficient and for which data were available in both the SWIID and WID datasets. Further, we used data from mainland France to its overseas departments (Guadeloupe, Martinique, French Guiana, Réunion and Mayotte) in both datasets, for which data did not exist at the administration 0 level. This resulted in a national dataset containing data for 207 countries.

The gaps for missing years in national data were filled via linear interpolation and extrapolation methods developed by Chrisendo et al.[57] and Kummu et al.[26]. Shortly, this extrapolation method addresses missing data in country-level time series by first categorizing countries based on data completeness. For countries with nearly complete data, missing values were estimated by creating linear models with full-data countries, selecting the best-fitting and geographically closest counterpart and then scaling the modelled time series on the basis of the ratios of the first and last reported values of the target country to the modelled values. This expanded dataset (complete and nearly complete) then served as the basis for extrapolating data for countries with more limited data, using the same linear modelling and scaling approach. Finally, countries with very few data points were filled by scaling the time series of their geographically closest counterpart from the combined complete and nearly complete dataset, again using ratios derived from their limited available data points. To capture the potential uncertainty due to the extrapolation, we conducted a comprehensive uncertainty analysis for it (Supplementary Note and Supplementary Fig. 2).

Subnational data for subnational Gini coefficient

In the next step, we collected subnational (administration 1 level, that is, provincial) data from harmonized microdata LIS[23] and ERF-LIS[24] as well as readily calculated Gini coefficient data from GDL[25], GSAP[21], national censuses and other literature. Altogether, our dataset includes Gini data for 2,109 subnational areas (covering 151 countries, where 94.2% of the global population lived in 2023) and altogether 16,241 distinct entries (administration area–year combinations). The origin and temporal extent of the subnational data are shown in Extended Data Fig. 2 and detailed information on the sources for each country is given in Supplementary Table. The areas with only a few years of subnational data (Extended Data Fig. 2b) combined with a short range of data availability (Extended Data Fig. 2c), such as various countries in Central Asia and Eastern Africa, should be considered with caution. This is also shown in the uncertainty analysis we conducted on the SWIID dataset (being the only dataset with error estimates) (Supplementary Fig. 4).

As the subnational data originate from different sources, we did not use the values directly. To ensure the comparability between the sources, we calculated the ratio between the subnational-level value and the national-level value, both from the same data source, following the approach by Kummu et al.[26]. To get the national values from LIS and ERF-LIS, we used their databases to calculate the Gini coefficient for both subnational (administration 1 level) and national (administration 0 level) levels. For data from GDL and national censuses, we used the reported Gini coefficient for these two administration levels. For countries where national data were not available from the same source as subnational data, we calculated the population-weighted mean national Gini coefficient.

To give an example: if Gini coefficients for subnational areas for a given year were 0.45, 0.37 and 0.42 and the national value was 0.41 (based on the same source), the ratios for subnational areas were 1.098 (0.45/0.41), 0.902 and 1.024. We then used this to multiply, for example, the SWIID national value. Let us assume that the SWIID national value would have been 0.35 for that year and thus the final subnational values for SWIID were:

subnational area 1: $1.098 \times 0.35 = 0.3843$
subnational area 2: $0.902 \times 0.35 = 0.3157$
subnational area 3: $1.024 \times 0.35 = 0.3584$

And assume that the WID would have had a national Gini coefficient of 0.48 for that country in question, then the subnational values would have been:

subnational area 1: $1.098 \times 0.48 = 0.5270$
subnational area 2: $0.902 \times 0.48 = 0.4330$
subnational area 3: $1.024 \times 0.48 = 0.4915$

Therefore, the subnational values in the final dataset are harmonized with the national data in question.

Finally, to fill the gaps between reported values, we used interpolation. For the missing values at either the beginning or end of the study period, we used the latest reported Gini ratio value, that is, we assumed that the ratio between national and subnational values remained unchanged in the years before the first subnational value and after the last subnational value (similarly to ref. 26 for GDP per capita).

We then used the reported national data to get the final value for subnational areas by multiplying the subnational Gini ratio by the reported national value. We used the subnational ratio to minimize the impact of different procedures when estimating the Gini coefficient in various datasets. It ensured that the subnational data were aligned with the national values. The overall workflow is illustrated in Extended Data Fig. 1.

Data for subnational GNI per capita PPP

The subnational income data are based on tabulated subnational GNI per capita PPP data from refs. 26,28. Their data were used to create a gridded and gap-filled subnational GNI per capita dataset for each year from 1990 to 2023, at 5-arcmin resolution. We used a similar method to fill in missing years and rasterize the data as Kummu et al.[26] used in their gridded GDP per capita PPP data. This is shortly described below.

We first collected national-level (administration 0) GNI per capita at PPP data from the UNDP Human Development Index database[27] (in 2021 international $) and the World Bank Development Index database[20] (in 2021 international $), preferring the UNDP data. For years with missing data, we filled the gaps using linear interpolation and an extrapolation method developed by Kummu et al.[26] and Chrisendo et al.[57]. Subnational-level (administration 1) data were obtained from ref. 28, where detailed information on the origin and extent of the reported data is also provided. The temporal extent of the subnational data is illustrated in Extended Data Fig. 3, which shows that the temporal coverage for subnational GNI per capita data is generally very good.

To reconcile the national and provincial data, we calculated the ratio between the administration 1-level GNI and the administration 0-level GNI per capita (the latter being estimated from the subnational values weighted by population data). This allowed us to derive a subnational GNI ratio by dividing the administration 1-level GNI by the calculated national GNI (see the previous section on 'Subnational Gini coefficient').

We then interpolated these subnational GNI ratios using linear interpolation to fill gaps between years with reported values. For the leading and trailing missing values, we used the latest available subnational GNI ratio. These interpolated and extrapolated subnational GNI ratios were multiplied by the reported national-level data to estimate the subnational GNI per capita (PPP).

Classifying groups of income inequality and income

We classified the world into 16 groups based on the level of GNI and Gini in 1990 and 2023. We used the World Bank's grouping, based on 2021 thresholds (as the GNI is given in 2021 constant international $): high income >US$12,695; upper-middle income US$4,096–12,695; lower-middle income US$1,045–4,095; and low income <US$1,045. For the Gini coefficient, we used the range by the UN[32], which is consistent across different countries and regions: relative equality (0–0.3); adequate equality/reasonable income gap (0.3–0.4); big income gap (0.4–0.5); and severe inequality (0.5–1). After classification, it was possible to calculate the number of people (we used the GHS population data[58]) living in each group.

We also classified the world into 16 groups based on the magnitude of change in GNI (percentual change) and Gini (slope) between 1990 and 2023. For Gini, we used the slope over the study period calculated with Siegel repeated medians (mblm R package) and only statistically significant slopes ($P < 0.1$) were considered. In the slope, a positive value indicates increasing inequality and a negative value indicates improvement, that is, a decrease in inequality. For both GNI and Gini, we used the quantiles to determine the breakpoints so that the largest (absolutely, as there were negative values) of the 25th and 75th quantiles were chosen for the breakpoint in both negative and positive sides between strong decrease (increase) and 0 was used as the breakpoint in the middle. This resulted in the following grouping:

Gini: strong decrease, change ≤ −0.07; decrease, −0.07 < change ≤ 0; increase, 0 < change < 0.07; strong increase, change ≥ 0.07.

GNI: strong decrease, change ≤ −10%; decrease, −10% < change ≤ 0%; increase, 0% < change < 10%; strong increase, change ≥ 10%.

Variation of Gini and GNI within countries

To estimate the variation in subnational Gini and GNI per capita values within each country, we used the coefficient of variation calculated from the subnational values of each country for which data were available. We calculated this for the year 2023 (Extended Data Fig. 8).

The interplay of income equality and ecological diversity

Here we combined the trends from 1990 to 2023 of three indicators to explore whether reducing inequality, increasing income and protecting the environment are mutually exclusive. We used the trends for income and equality (1 − Gini coefficient), as introduced above. In the case of income trend, we aggregated the trend to Gini administration 1 areas using the population-weighted mean.

For ecological diversity, we used data from ref. 33, which represent changes in average local terrestrial diversity (including animal, plant and fungal species) caused by land use relative to the natural stage (Extended Data Fig. 9). The data are a combination of modelling and observations. The decadal values (1990–2030; post-2020 are estimates) were first linearly interpolated within each 0.25° grid cell. We then aggregated annual data to Gini administration 1 areas using area-weighted mean.

To classify each administration 1 area, we used binary values for each indicator. Areas with statistically significant ($P < 0.1$) positive trends, calculated using Siegel repeated medians (mblm R package), were classified as positive trends, while areas with no significant trend ($P > 0.1$) or a significant negative trend ($P < 0.1$) were classified as having a negative trend. We combined the neutral and negative trends to limit the number of combinations of three indicators from 27 to 8. We then mapped these eight different trend combinations (Fig. 5a).

Finally, we calculated the mean of each indicator for each administration 1 unit and plotted the distribution of these for each of the eight trend combination classes (Fig. 5b).

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All the data used in this study are publicly available or are available open access via Zenodo at https://doi.org/10.5281/zenodo.14056855 (ref. 22). These include the following datasets: national and subnational Gini coefficient for 1990–2023 (gridded with 5-arcmin resolution, a polygon gpkg file and tabulated csv file); national and subnational GNI per capita PPP for 1990–2023 (gridded with 5-arcmin resolution, a polygon gpkg file and a tabulated csv file); input data (raw reported data and so on) for both (Gini coefficient and GNI per capita) datasets. Data are visualized in an online tool at https://wdrg.aalto.fi/income-inequality-explorer/. The data underlying the web application are available in the repository with all other data.

Code availability

The analysis was performed using RStudio (R v.4.3.2). The code is available at the following repositories: subnational Gini coefficient data, https://github.com/mattikummu/subnatGini; subnational GNI per capita data, https://github.com/mattikummu/subnatGNI; and analyses of this paper, github.com/mattikummu/gini_gni_analyses.

References

1. Capelli, C. & Vaggi, G. Why gross national disposable income should replace gross national income? *Dev. Change* **47**, 223–239 (2016).
2. Ravallion, M. Income inequality in the developing world. *Science* **344**, 851–855 (2014).
3. Hamann, M. et al. Inequality and the biosphere. *Annu. Rev. Environ. Resour.* **43**, 61–83 (2018).
4. Ferreira, I. A., Gisselquist, R. M. & Tarp, F. On the impact of inequality on growth, human development, and governance. *Int. Studies Rev.* **24**, viab058 (2022).
5. Rau, E. G., Stokes, S., Bermeo, N. & Roberts K. Income inequality and the erosion of democracy in the twenty-first century. *Proc. Natl Acad. Sci. USA* **122**, e2422543121h (2024).
6. Martela, F., Greve, B., Rothstein, B. & Saari, J. in *World Happiness Report* (eds Helliwell, J. F. et al.) 128–146 (Wellbeing Research Centre at Univ. Oxford, 2020).
7. Polacko, M. Causes and consequences of income inequality—an overview. *Stat. Politics Policy* **12**, 341–357 (2021).
8. Kessels, R., Hoornweg, A., Thanh Bui, T. K. & Erreygers, G. A distributional regression approach to income-related inequality of health in Australia. *Int. J. Equity Health* **19**, 102 (2020).
9. *Poverty and Shared Prosperity: Taking on Inequality* (World Bank, 2016); https://www.worldbank.org/en/publication/poverty-and-shared-prosperity-2016
10. Buttrick, N. R., Heintzelman, S. J. & Oishi, S. Inequality and well-being. *Curr. Opin. Psychol.* **18**, 15–20 (2017).
11. Baloch, M. A., Danish, K. S. U. D., Ulucak, Z. Ş. & Ahmad, A. Analyzing the relationship between poverty, income inequality, and CO_2 emission in Sub-Saharan African countries. *Sci. Total Environ.* **740**, 139867 (2020).
12. Kubiszewski, I., Ward, C., Pickett, K. E. & Costanza, R. The complex relationships between economic inequality and biodiversity: a scoping review. *Anthropocene Rev.* **11**, 49–66 (2024).
13. *Transforming Our World: The 2030 Agenda for Sustainable Development* (UN, 2030); https://sdgs.un.org/2030agenda
14. Deaton, A. COVID-19 and global income inequality. *LSE Public Policy Rev.* **1**, 1 (2021).
15. Wu, T. et al. Triple bottom line or trilemma? Global tradeoffs between prosperity, inequality, and the environment. *World Dev.* **178**, 106595 (2024).
16. Milanovic, B. The three eras of global inequality, 1820–2020 with the focus on the past thirty years. *World Dev*. **177**, 106516 (2024).
17. Piacentini, M. *Measuring Income Inequality and Poverty at the Regional Level in OECD Countries* (OECD, 2014); https://doi.org/10.1787/5jxzf5khtg9t-en
18. *World Inequality Database* (WID, accessed 13 November 2024); https://wid.world/data/
19. Solt, F. Measuring income inequality across countries and over time: the standardized world income inequality database. *Soc. Sci. Q.* **101**, 1183–1199 (2020).
20. *World Bank Open Data* (World Bank, accessed 13 November 2024); https://data.worldbank.org
21. *Global Subnational Poverty Atlas (GSAP)* (World Bank, accessed 13 November 2024); https://datacatalog.worldbank.org/search/dataset/0042041/International-Poverty-Line–Subnational-Poverty
22. Kummu, M. et al. Global subnational Gini coefficient (income inequality) and gross national income (GNI) per capita PPP datasets for 1990–2023. *Zenodo* https://doi.org/10.5281/zenodo.14056855 (2025).
23. *Luxembourg Income Study Database* (LIS, accessed 13 November 2024); https://www.lisdatacenter.org/our-data/lis-database/
24. *ERF-LIS Database* (LIS, accessed 13 November 2024); https://www.lisdatacenter.org/our-data/erf-lis-database/

25. *Gini Coefficient Wealth Inequality* (Global Data Lab, accessed 13 November 2024); https://globaldatalab.org/areadata/metadata/gini/
26. Kummu, M., Kosonen, M. & Masoumzadeh Sayyar, S. Downscaled gridded global dataset for gross domestic product (GDP) per capita PPP over 1990–2022. *Sci. Data* **12**, 178 (2025).
27. *Human Development Report 2025—A Matter of Choice: People and Possibilities in the Age of AI* (UNDP, 2025); https://hdr.undp.org/system/files/documents/global-report-document/hdr2025reporten.pdf
28. Smits, J. & Permanyer, I. Data descriptor: the subnational human development database. *Sci. Data* **6**, 190038 (2019).
29. Morgan, M. & Neef, T. *What's New About Income Inequality in Europe (1980–2019)?* (WID, 2020); https://wid.world/document/whats-new-about-income-inequality-in-europe-1980-2019/
30. *Developments in Income Inequality and the Middle Class in the EU* (EU, 2024); https://doi.org/10.2806/84980
31. Hamadeh, N., Van Rompaey, C. & Metreau, E. *New World Bank Country Classifications by Income Level: 2021–2022* (World Bank, 2021).
32. Ibarra, L. et al. *The World Bank's New Inequality Indicator: The Number of Countries With High Inequality* (World Bank, 2024); https://documents1.worldbank.org/curated/en/099549506102441825/pdf/IDU1bd155bac16d78143af188331f87564a9d6c8.pdf
33. Purvis, A. & Hill, S. *Local Terrestrial Diversity (PREDICTS)* (German Centre for Integrative Biodiversity Research, 2022); https://doi.org/10.25829/5yq9t7
34. Wiebe, R. A. & Wilcove, D. S. Global biodiversity loss from outsourced deforestation. *Nature* **639**, 389–394 (2025).
35. *Poverty and Inequality Platform* (World Bank, accessed 5 June 2024); https://pip.worldbank.org/home
36. Zhu, Y. & Österle, A. Rural–urban disparities in unmet long-term care needs in China: the role of the Hukou status. *Soc. Sci. Med.* **191**, 30–37 (2017).
37. Li, L., Ma, S., Zheng, Y. & Xiao, X. Integrated regional development: comparison of urban agglomeration policies in China. *Land Use Policy* **114**, 105939 (2022).
38. Jain-Chandra, S. et al. *Inequality in China—Trends, Drivers and Policy Remedies* (IMF, 2018); https://www.imf.org/en/Publications/WP/Issues/2018/06/05/Inequality-in-China-Trends-Drivers-and-Policy-Remedies-45878
39. Sridhar, K. S. & Reddy, A. V. Investment and economic opportunities: urbanization, infrastructure and Governance in the North and South of India. *Asia-Pac. Dev. J.* **18**, 1–46 (2011).
40. Roy, S., Majumder, S., Bose, A. & Chowdhury, I. R. The rich–poor divide: unravelling the spatial complexities and determinants of wealth inequality in India. *Appl. Geogr.* **166**, 103267 (2024).
41. Souza, P. H. G. F. A history of inequality: top incomes in Brazil, 1926–2015. *Res. Soc. Stratif. Mobil.* **57**, 35–45 (2018).
42. Reynolds, S. A. Brazil's Bolsa Familia: does it work for adolescents and do they work less for it? *Econ. Educ. Rev.* **46**, 23–38 (2015).
43. Neves, J. A. et al. The Brazilian cash transfer program (Bolsa Família): a tool for reducing inequalities and achieving social rights in Brazil. *Glob. Public Health* **17**, 26–42 (2022).
44. Machado, D. B. et al. Relationship between the Bolsa Família national cash transfer programme and suicide incidence in Brazil: a quasi-experimental study. *PLoS Med.* **19**, e1004000 (2022).
45. Chioda, L., De Mello, J. M. P. & Soares, R. R. Spillovers from conditional cash transfer programs: Bolsa Família and crime in urban Brazil. *Econ. Educ. Rev.* **54**, 306–320 (2016).
46. Soares, S. et al. *Conditional Cash Transfers in Brazil, Chile, and Mexico: Impacts Upon Inequality* (UNDP, 2007); http://www.undp-povertycentre.org
47. Sotomayor, O. J. Can the minimum wage reduce poverty and inequality in the developing world? Evidence from Brazil. *World Dev.* **138**, 105182 (2021).
48. de Mendonça, H. F. & Esteves, D. M. Income inequality in Brazil: what has changed in recent years? *CEPAL Rev.* **112**, 107–123 (2014).
49. Albers, T. N. H., Bartels, C. & Schularick, M. *Wealth and Its Distribution in Germany, 1895–2018* (IFO, 2022); https://www.ifo.de/sites/default/files/docbase/docs/cesifo1_wp9739.pdf
50. Bartels, C. Top incomes in Germany, 1871–2014. *J. Econ. Hist.* **79**, 669–707 (2019).
51. Buhaug, H., Cederman, L. E. & Gleditsch, K. S. Square pegs in round holes: inequalities, grievances, and civil war. *Int. Stud. Q.* **58**, 418–431 (2014).
52. Abel, G. J., Brottrager, M., Crespo Cuaresma, J. & Muttarak, R. Climate, conflict and forced migration. *Glob. Environ. Change* **54**, 239–249 (2019).
53. *Inequality in a Rapidly Changing World* (UN, 2020); https://www.un.org/development/desa/dspd/wp-content/uploads/sites/22/2020/02/World-Social-Report2020-FullReport.pdf
54. Wan, G., Zhang, X. & Zhao, M. Urbanization can help reduce income inequality. *npj Urban Sustain.* **2**, 1 (2022).
55. Castells-Quintana, D. & Royuela, V. Are increasing urbanisation and inequalities symptoms of growth? *Appl. Spat. Anal. Policy* **8**, 291–308 (2015).
56. Wong, D. W. S. in *WorldMinds: Geographical Perspectives on 100 Problems* (eds Janelle, D. G. et al.) 571–575 (Springer, 2004).
57. Chrisendo, D., Piipponen, J., Heino, M. & Kummu, M. Socioeconomic factors of global food loss. *Agric. Food Secur.* **12**, 23 (2023).
58. Schiavina, M., Freire, S., Carioli, A. & MacManus, K. *GHS-POP R2023A—GHS Population Grid Multitemporal* (1975–2030) (GHSL, 2023); https://doi.org/10.2905/2FF68A52-5B5B-4A22-8F40-C41DA8332CFE

Acknowledgements

This study was funded by the European Research Council (ERC) under the European Union Horizon 2020 research and innovation programme (grant agreement no. 819202), the Research Council of Finland Flagship Programme under project Digital Waters (grant no. 359248), Strategic Research Council (SRC) through project 'Water–Food Futures' (grant no. 365512) and Maa- ja vesitekniikan tuki ry (grant no. 43481). R.H. acknowledges further funding through an ERC grant (2C-RISK, grant no. 101162653) and Horizon Europe grant (SPES, grant no. 101094551). V.S. acknowledges funding from the Research Council of Finland profile building area Resilient and Just Systems (RESET) (grant no. 353218). J.R. acknowledges support from FORMAS grant 2020-00454. We are grateful for access to the data from the LIS (Luxembourg Income Study Database), the ERF-LIS (Economic Research Forum database provided by LIS), and the statistical offices of the Netherlands and New Zealand. Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. Neither the European Union nor the granting authority can be held responsible for them. P. Pulli is greatly acknowledged for developing the online income inequality explorer tool.

Author contributions

M.K., D.C. and V.N. designed the research with support from J.R. and F.S. Data collection and processing were led by M.K. with help from S.M.S., V.N. and F.S. Analyses were performed by D.C., V.N. and M.K. with help from J.R. V.S. created the online data explorer. V.N. and M.K. created the illustrations. All authors discussed the methods and results, and helped shape the research and analysis. D.C., R.H. and M.K. took the lead in writing and revising the paper with important contributions from all authors.

Funding
Open Access funding provided by Aalto University.

Competing interests
The authors declare no competing interests.

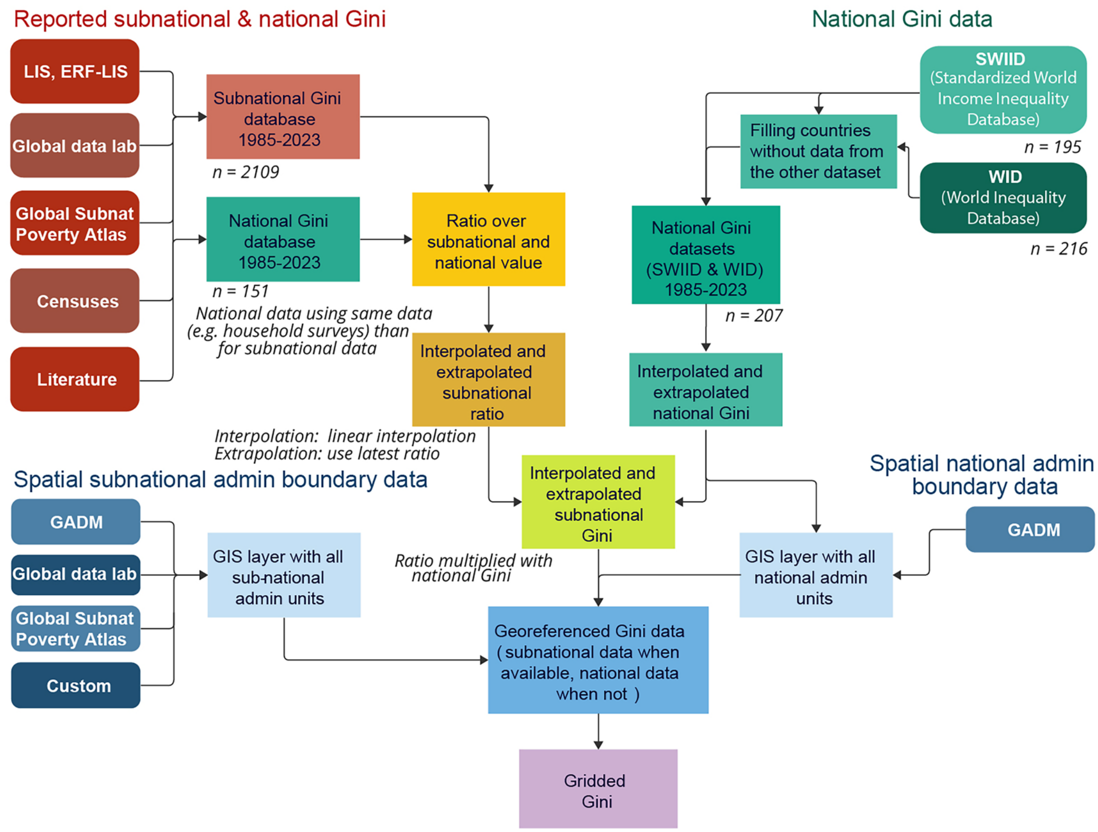
Additional information
Extended data is available for this paper at https://doi.org/10.1038/s41893-025-01689-4.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41893-025-01689-4.

Correspondence and requests for materials should be addressed to Daniel Chrisendo or Matti Kummu.

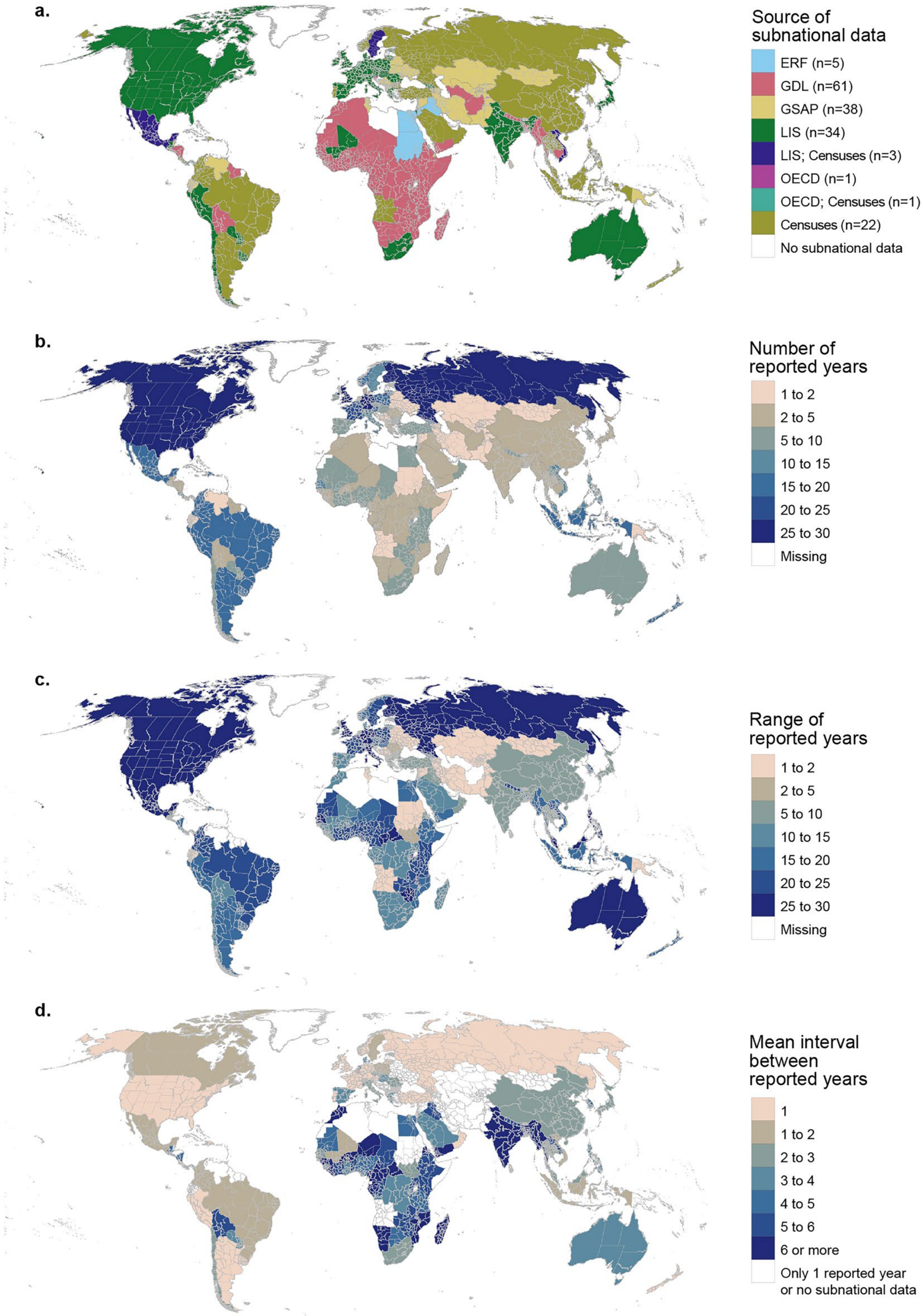
Peer review information *Nature Sustainability* thanks Yuli Shan and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

 https://doi.org/10.1038/s41893-025-01689-4



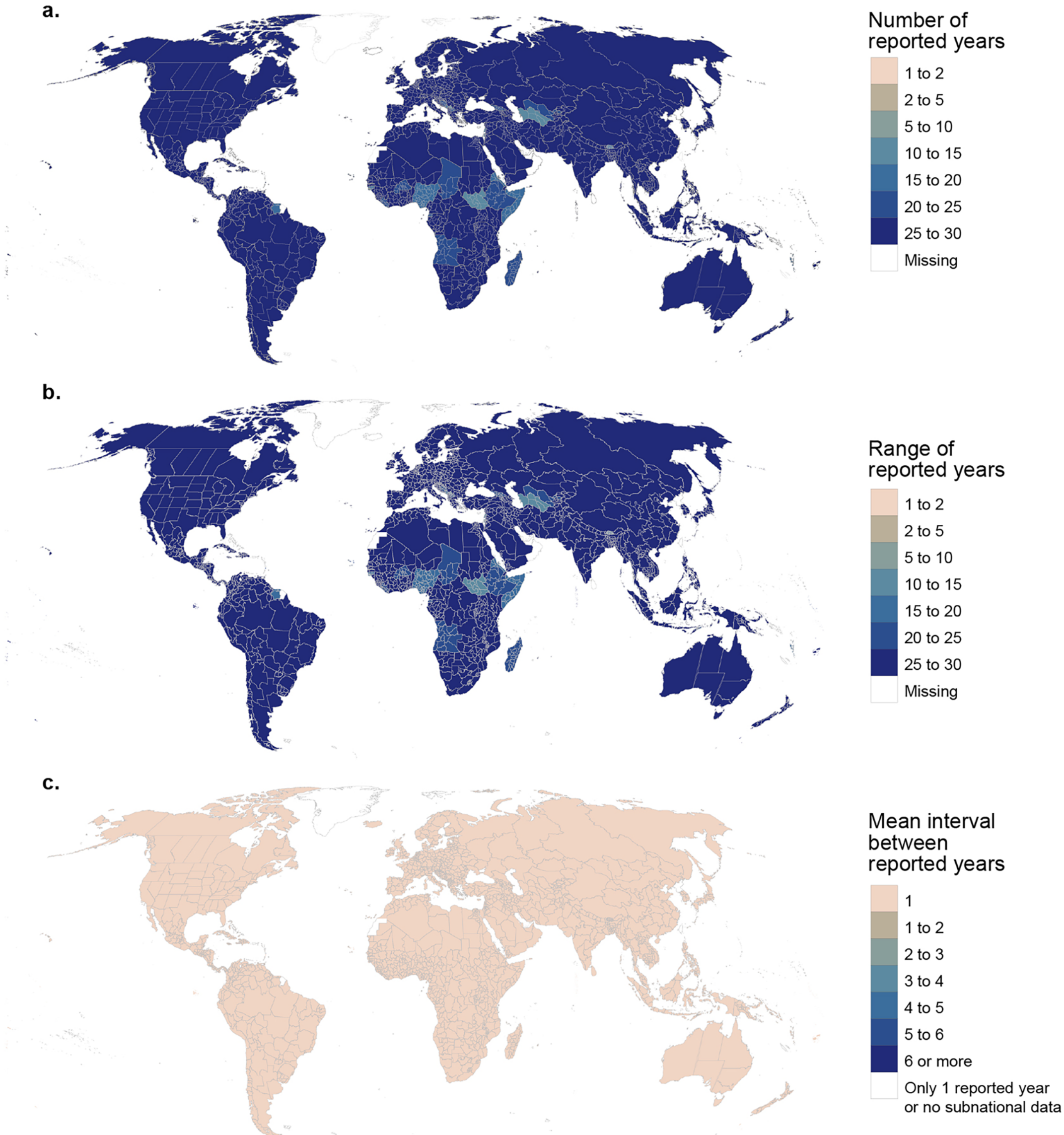
Extended Data Fig. 1 | Schematic outline of the Gini coefficient dataset creation. Data sources and workflow for creating subnational and national Gini coefficient datasets.

https://doi.org/10.1038/s41893-025-01689-4

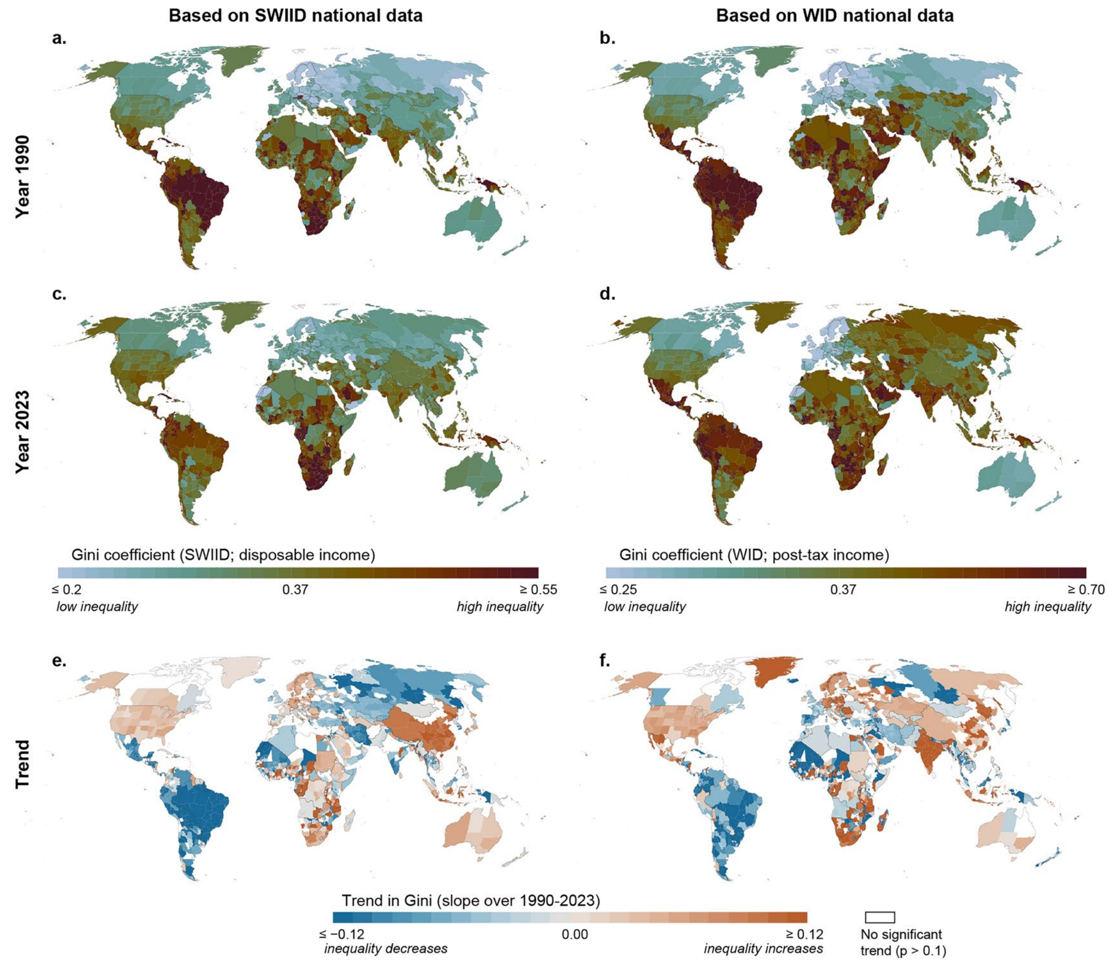


Extended Data Fig. 2 | Origin and temporal extent of the data for the subnational Gini coefficient database. a. source of each subnational data (see Supplementary data table for more details), **b.** number of years of reported subnational data in each country, **c.** range of reported years (that is, if there were data for 2000, 2005, and 2010, then the range would be 11 years) for each administrative area, and **d.** mean interval of reported years (that is, if there were data for 2000, 2005, and 2010, then the mean interval would be 5 years). Basemaps from GADM (https://www.gadm.org/).

 https://doi.org/10.1038/s41893-025-01689-4

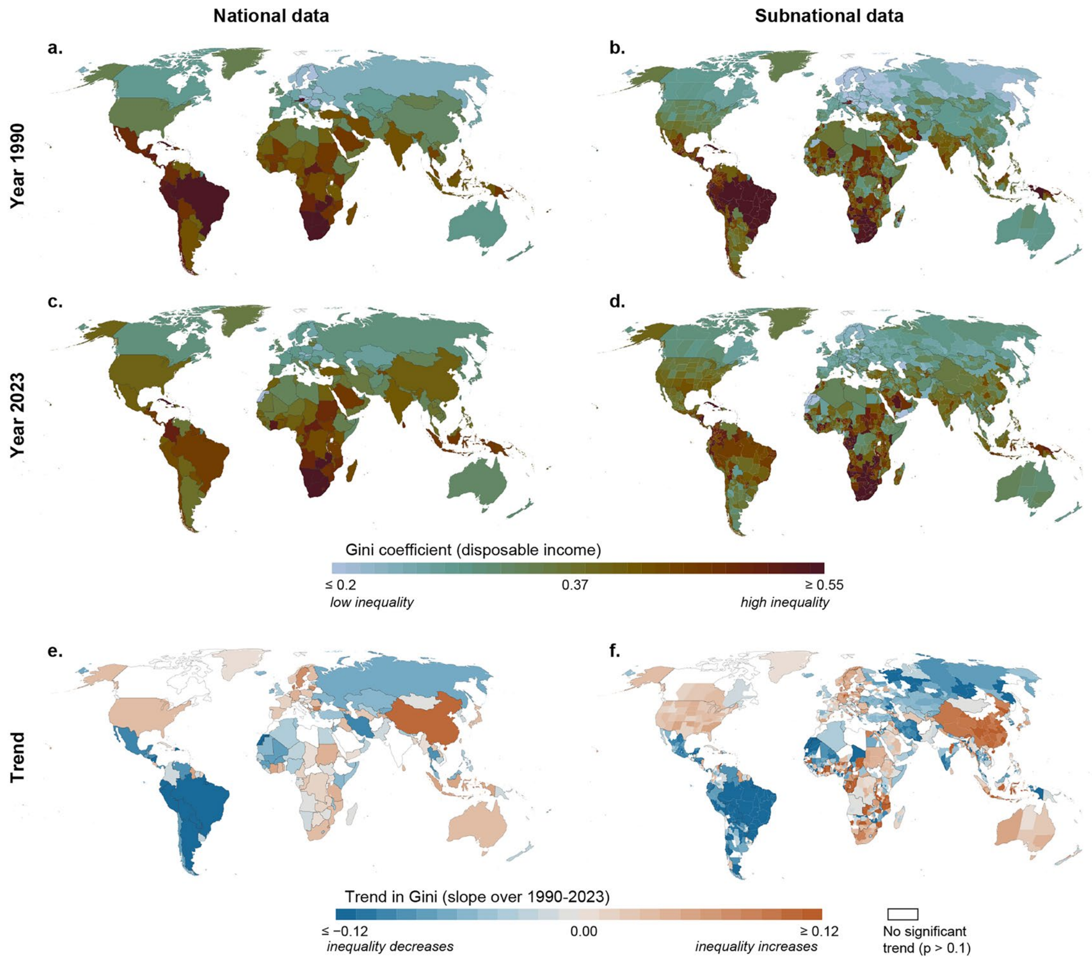


Extended Data Fig. 3 | Temporal extent of the data for the subnational gross national income (GNI) per capita database. a. number of years of reported subnational data in each country, **b**. range of reported years (that is, if there were data for 2000, 2005, and 2010, then the range would be 11 years) for each administrative area, and **c**. mean interval of reported years (that is, if there were data for 2000, 2005, and 2010, then the mean interval would be 5 years). Basemaps from GADM (https://www.gadm.org/).



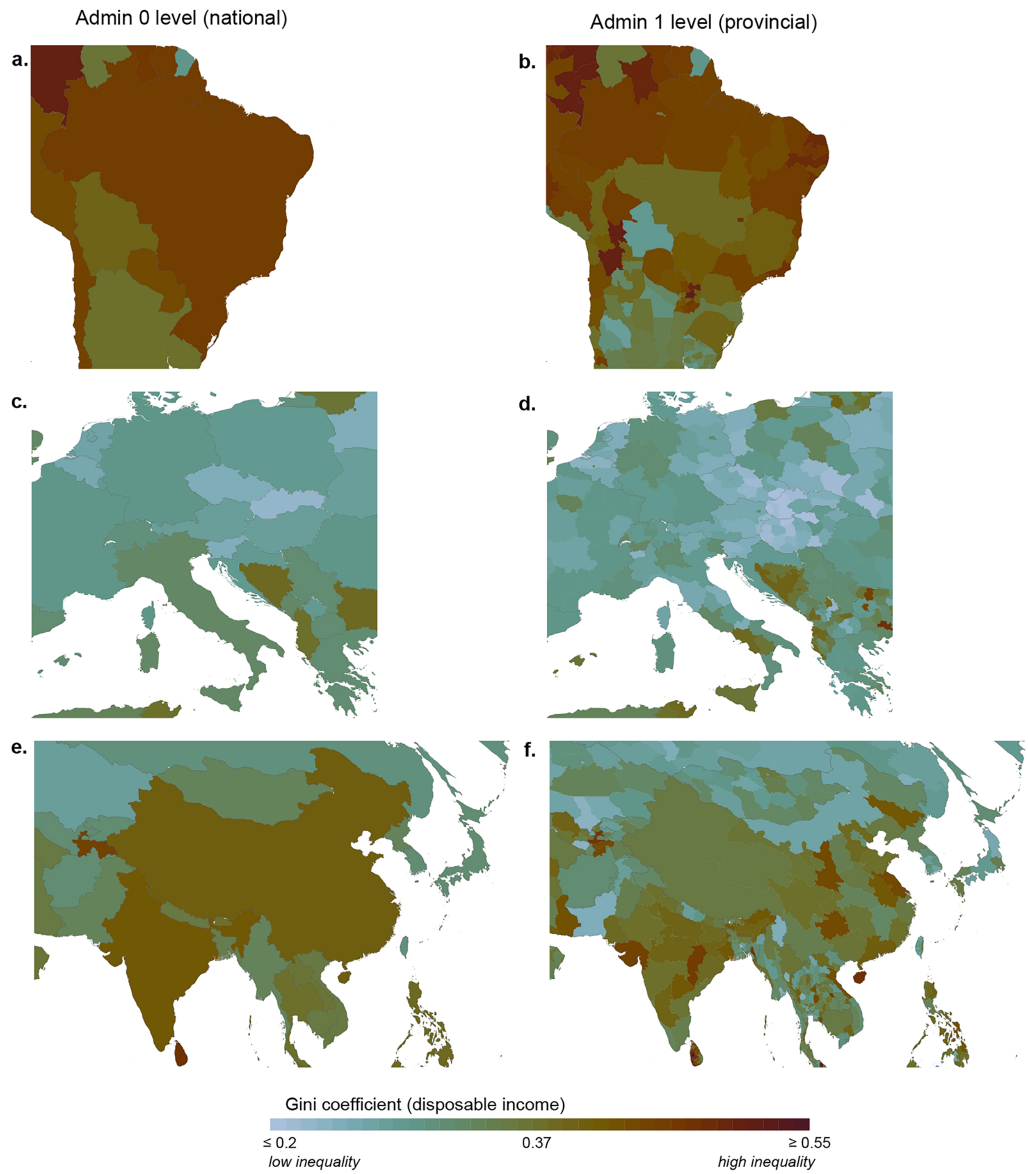
Extended Data Fig. 4 | Comparison of two datasets based on different national level data. The subnational data based on SWIID national data are presented in the left column: **a**) showing status in 1990; **c**) showing status in 2023; and **e**) trend. The subnational data based on WID national data are presented in the right column: **b**) showing status in 1990; **d**) showing status in 2023; and **f**) trend. Slopes were calculated with Siegel repeated medians (mblm R package), and only statistically significant slopes ($p < 0.1$) are reported. The associated p-value tests the null hypothesis of a zeroslope using a two-sided hypothesis test without adjustments for multiple comparisons. Note: Different scales for SWIID and WID Gini coefficients. Basemaps from Natural Earth (https://www.naturalearthdata.com/).

 https://doi.org/10.1038/s41893-025-01689-4



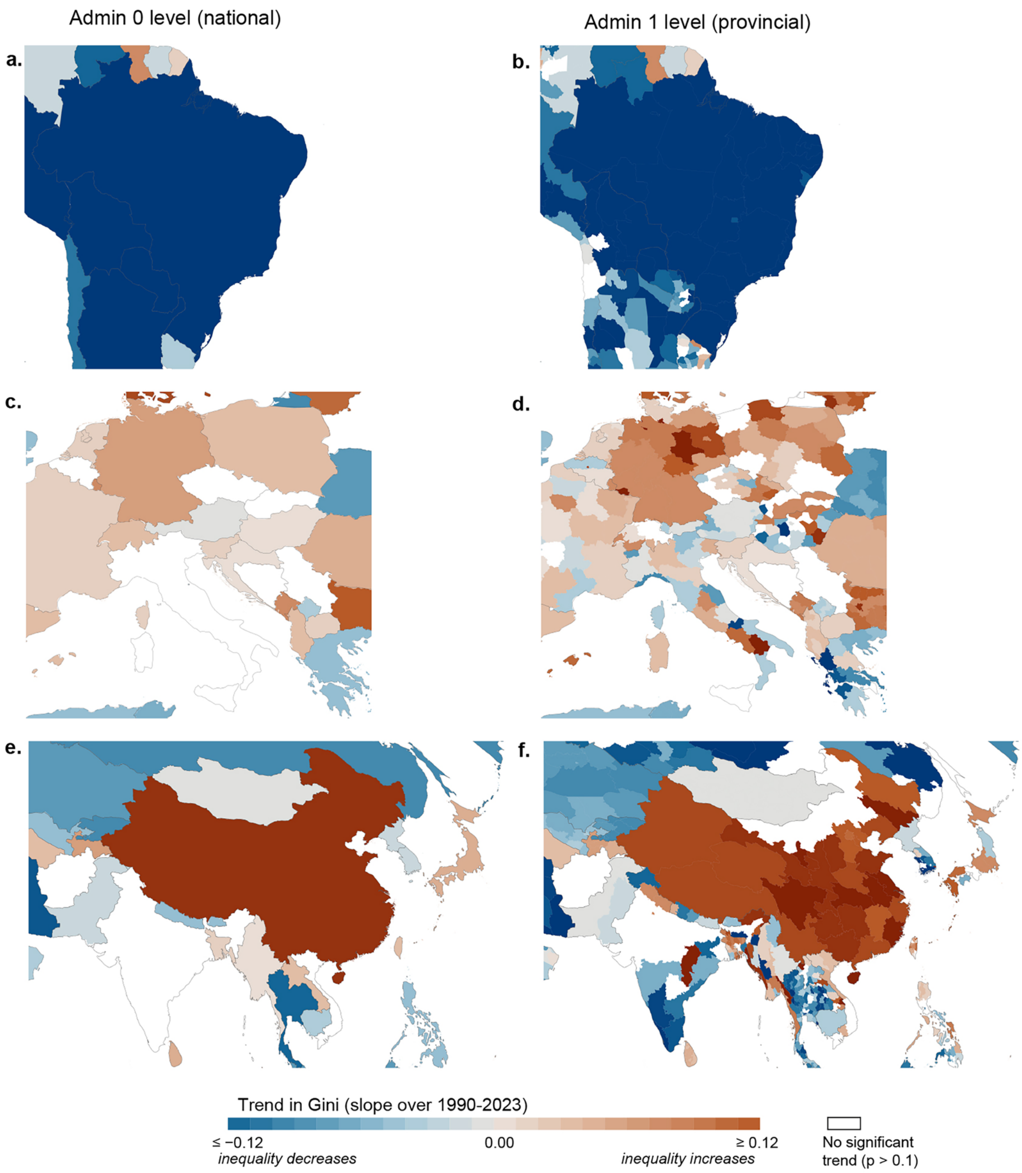
Extended Data Fig. 5 | Gini coefficient for national and subnational levels for the years 1990 and 2023, as well as the trend on both scales. The national data based on SWIID are presented in the left column: **a**) showing status in 1990; **c**) showing status in 2023; and **e**) trend. The subnational data based on SWIID national data are presented in the right column: **b**) showing status in 1990; **d**) showing status in 2023; and **f**) trend. We used the Gini coefficient based on disposable income. Slopes were calculated with Siegel repeated medians (mblm R package), and only statistically significant slopes ($p < 0.1$) are reported. The associated p-value tests the null hypothesis of a zeroslope using a two-sided hypothesis test without adjustments for multiple comparisons. Note: The Gini coefficient based on SWIID national data is used here. Basemaps from Natural Earth (https://www.naturalearthdata.com/).

 https://doi.org/10.1038/s41893-025-01689-4



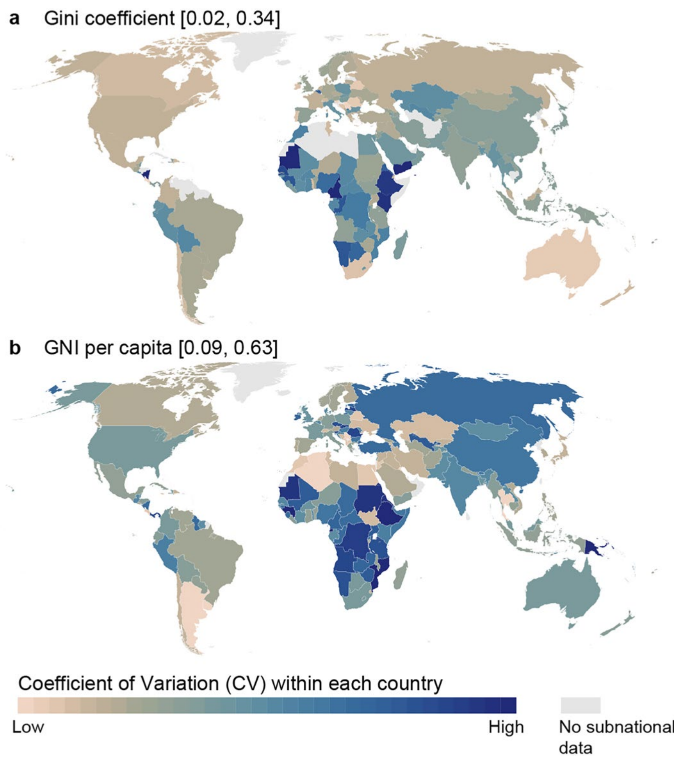
Extended Data Fig. 6 | Gini coefficient for national and subnational levels for 2023 for selected geographical locations. **a**. admin 0 level for Brazil, **b**. admin 1 level for Brazil, **c**. admin 0 level for Central Europe, **d**. admin 1 level for Central Europe, **e**. admin 0 level for China and India, and **f**. admin 1 level for China and India. We used the Gini coefficient based on disposable income. Note: The Gini coefficient based on SWIID national data is used here. Basemaps from Natural Earth (https://www.naturalearthdata.com/).

https://doi.org/10.1038/s41893-025-01689-4



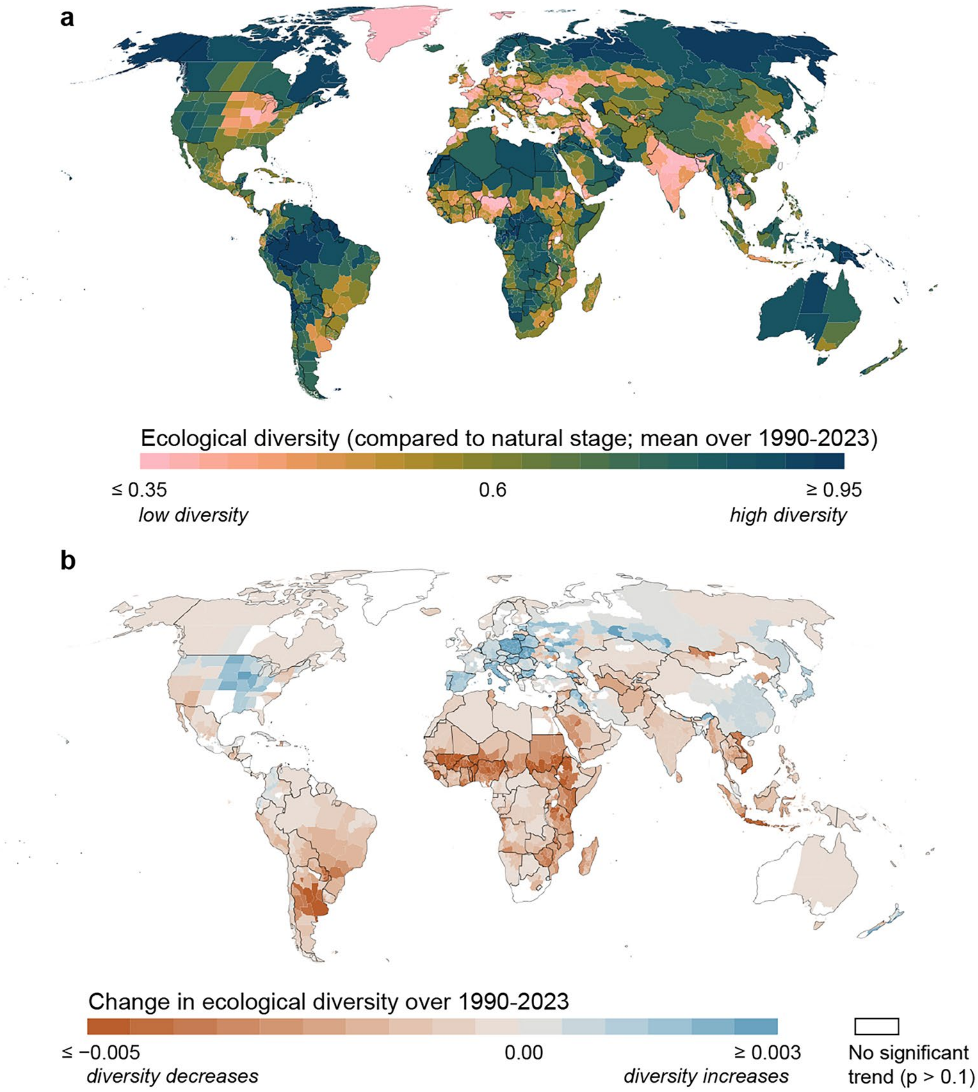
Extended Data Fig. 7 | Trend of Gini coefficient for national and subnational levels (1990-2023) for selected geographical locations. a. admin 0 level for Brazil, **b**. admin 1 level for Brazil, **c**. admin 0 level for Central Europe, **d**. admin 1 level for Central Europe, **e**. admin 0 level for China and India, and **f**. admin 1 level for China and India. We used the Gini coefficient based on disposable income. Slopes were calculated with Siegel repeated medians (mblm R package), and only statistically significant slopes ($p < 0.1$) are reported. The associated p-value tests the null hypothesis of a zeroslope using a two-sided hypothesis test without adjustments for multiple comparisons. Note: The Gini coefficient based on SWIID national data is used here. Basemaps from Natural Earth (https://www.naturalearthdata.com/).

https://doi.org/10.1038/s41893-025-01689-4



Extended Data Fig. 8 | Coefficient of variation (CV) within each country for the Gini coefficient and gross national income (GNI) per capita. a. CV for Gini coefficient, and **b**. CV for GNI per capita. Values are calculated from the 2023 data. The range of values (2.5th - 97.5th percentile) is given in the title of each tile. Note: The subnational Gini coefficient data based on SWIID national data are used here. Basemaps from Natural Earth (https://www.naturalearthdata.com/).

 https://doi.org/10.1038/s41893-025-01689-4



Extended Data Fig. 9 | Ecological diversity. a. Mean of ecological diversity compared to the natural stage over 1990-2023, and **b**. Change in ecological diversity over 1990-2023. Change was calculated with Siegel repeated medians (mblm R package), and only statistically significant slopes ($p < 0.1$) are reported. The associated p-value tests the null hypothesis of a zeroslope using a two-sided hypothesis test without adjustments for multiple comparisons. Basemaps from Natural Earth (https://www.naturalearthdata.com/).

https://doi.org/10.1038/s41893-025-01689-4

Extended Data Table 1 | Countries without data in the national datasets, along with their neighbouring countries used to estimate the data

	Countries without data	Neighbouring countries
SWIID (filled from WID)	Brunei	Malaysia
	Cuba	Haiti
	Eritrea	Djibouti
	Macao	Hong Kong
	Monaco	France
	North Korea	Korea (Republic of)
SWIID (filled from GDL)	Western Sahara	Morocco
WID (filled from SWIID)	Côte d'Ivoire	Mali
	Namibia	South Africa
	Kosovo	Serbia
WID (filled from GDL)	Western Sahara	Morocco

nature portfolio

Corresponding author(s): Daniel Chrisendo, Matti Kummu

Last updated by author(s): Oct 6, 2025

Reporting Summary

Nature Portfolio wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Portfolio policies, see our Editorial Policies and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☒	☐	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☒	☐	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☒	☐	A description of all covariates tested
☒	☐	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☐	☒	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	We collected the data from various sources, such as the Standardised World Income Inequality Database, the World Inequality Database, the Global Data Lab, the Luxembourg Income Study Database, the Economic Research Forum, the Global Subnational Poverty Atlas, Smits & Permanyer (2019), UNDP, World Bank, Purvis and Hills (2022), national censuses, and other literature. We did not use any specific software to extract or collect the data from these sources.
Data analysis	We used R version 4.3.2 to produce the Results for the analysis in the manuscript. The analysis code is available on GitHub: https://github.com/mattikummu/gini_gni_analyses

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

The data used in this study are openly available on Github: https://github.com/mattikummu/subnatGini (subnational GINI coefficient data) and https://github.com/mattikummu/subnatGNI (subnational GNI per capita data)

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	We did not have human research participants
Reporting on race, ethnicity, or other socially relevant groupings	We did not have human research participants
Population characteristics	We did not have human research participants
Recruitment	We did not have human research participants
Ethics oversight	We did not have human research participants

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	In this study, we produced income and income inequality data at subnational level and provided relevant analyses. The study is using mixed-methods (quantitative and qualitative).
Research sample	We do not have research sample, instead we use all available data. When necessary, we created data points by using intrapolation and extrapolation methods.
Sampling strategy	We did not do sampling, instead we use all available data.
Data collection	We collected the data from various sources, such as the Standardised World Income Inequality Database, the World Inequality Database, the Global Data Lab, the Luxembourg Income Study Database, the Economic Research Forum, the Global Subnational Poverty Atlas, Smits & Permanyer (2019), UNDP, World Bank, Purvis and Hills (2022), national censuses, and other literature. The data were acquired in a digital form.
Timing	We collected historical GNI and GINI data at national and subnational levels from 1990-2021.
Data exclusions	We did not exclude any data
Non-participation	Not applicable
Randomization	Not applicable

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Clinical data
☒	☐ Dual use research of concern
☒	☐ Plants

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Plants

Seed stocks	Not applicable
Novel plant genotypes	Not applicable
Authentication	Not applicable