Climate and the structure of national urban systems

David Castells-Quintana[a,b], Marcos Sanso-Navarro[c], and María Vera-Cabello[d]

[a]Departamento de Economía Aplicada, Universitat Autònoma de Barcelona

[b]Regional Quantitative Analysis Group (AQR-IREA), Universitat de Barcelona

[c]Departamento de Análisis Económico & IEDIS, Universidad de Zaragoza

[d]Centro Universitario de la Defensa de Zaragoza

February 27, 2026

Abstract

This paper investigates the long-run determinants of cross-country differences in the equality of city size distributions, with a particular focus on climate-related factors. Using a harmonized definition of cities and a balanced panel covering the period 1975–2025, we estimate country-level Pareto coefficients as our main indicator of the equality of national urban structures. We then implement a Bayesian model averaging framework to address model uncertainty in a setting with multiple plausible geographic, socioeconomic, and institutional factors. Our results show that climatic conditions are systematically associated with the internal structure of national urban systems. In particular, mean temperature is positively related to the equality of city size distributions, whereas average precipitation is associated with more uneven urban structures, even after controlling for country and time fixed effects. By contrast, drought intensity does not emerge as a robust determinant. When urbanization rates are considered instead, precipitation remains the only climatic variable displaying a stable association. These findings suggest that persistent climatic conditions influence not only the extent of urbanization but also the degree of urban concentration.

Keywords: Uban centres; Climate change; City size distribution; Bayesian model averaging.

JEL classification: C23, O18, Q54, R12.

1 Introduction

Recent estimates from the World Bank indicate that approximately 56 percent of the global population currently resides in urban areas, which generate more than 80 percent of global Gross Domestic Product GDP, and project that roughly seven out of ten people will live in cities by mid-century (World Bank 2024). This trend reflects a context of sustained and uneven urban growth across countries and regions and has made the analysis of urban systems, and in particular the distribution of city sizes, increasingly central in urban economics. Indeed, this distribution is one of the most extensively studied topics in the field because of its far-reaching theoretical and policy implications. Understanding why some countries exhibit primate city patterns while others display more balanced urban systems is crucial for the design of spatial development strategies aimed at fostering inclusive, efficient, and sustainable urbanization.

Following the seminal contributions of Gabaix (1999) and Eeckhout (2004), much of the literature has focused on testing whether the distribution of city sizes conforms to the rank-size rule, commonly known as Zipf law. This empirical regularity posits that the population of the N-th largest city is inversely proportional to its rank. However, a growing body of evidence shows that Zipf law is not universal, particularly in cross-country settings where urban structures differ markedly (Arshad, Hu, and Ashraf 2018). Historically, comparative analyses have been constrained by inconsistencies in national definitions of what constitutes a city, thereby limiting the scope for reliable cross-country inference. Recent advances in harmonized global definitions of cities, enabled by satellite imagery and remote sensing techniques and promoted by international organizations and academic initiatives such as the Degree of Urbanisation framework, have substantially improved comparability.

Building on these developments, an emerging strand of research shifts the focus from testing Zipf law to identifying the geographic, socioeconomic, and institutional determinants of the city size distribution; see Gomez Osorio and Mykhnenko (2025) and Puente-Ajovin, Sanso-Navarro, and Vera-Cabello (2025), and the references therein. Nonetheless, although geography plays a fundamental role in shaping the location of economic activity through first-nature factors such as the availability of natural resources, topography, and climate (Bosker 2022), existing studies on the determinants of the country-level distribution of city sizes generally do not incorporate climatic variables as potential explanatory factors. Moreover, while the effects of climate shocks have been extensively examined, considerably less attention has been paid to the consequences of persistent, large-scale, and anticipated changes in climate (Lemoine, Hausman, and Shrader 2025).

This paper examines the factors that explain cross-country variation in national city size distributions in the long run, with particular emphasis on climate-related variables. To ensure comparability in the definition and measurement of cities, we exploit the information provided by the most recent release of the Urban Centre Database from the Global Human Settlement Layer (GHSL; Florczyk, Corbane, et al. 2019; Florczyk, Melchiorri, et al. 2019) project; see (Melchiorri et al. 2024; Pesaresi et al. 2024). Following this approach, we construct a balanced panel data set covering the period from 1975 to 2025. Among other indicators, and given the nature of the urban units included in this data set, we focus primarily on the estimated Pareto coefficient derived from country-level rank-size regressions (Gabaix and Ibragimov 2011). In addition, we examine cross-country variation in other measures, such as the urbanization rate and the Herfindahl–Hirschman index.

In line with Wang, Yu, and Sun (2022), we consider three broad categories of determinants of the spatial distribution of economic activity and population: characteristics related to the physical landscape, or first nature; human-related factors and economic incentives, or second nature; and institutions. Beyond the use of a five-decade panel with five-year intervals, the main novelty of our study is the explicit inclusion of climate-related variables among first nature factors. Following Puente-Ajovin, Sanso-Navarro, and Vera-Cabello (2025), and given the wide range of potential determinants of national city size distributions, we address model uncertainty by implementing Bayesian model averaging (BMA) techniques (Raftery, Madigan, and Hoeting 1997). This flexible framework does not require fixing the model size or selecting a specific subset of regressors ex ante and instead provides an integrated approach to model selection, estimation, and inference, enabling us to draw more robust conclusions about the determinants of urban patterns, in general, and the role of climate change, in particular.

We find robust evidence that climatic conditions are systematically associated with cross-country differences in the equality of city size distributions. In particular, higher mean temperatures are linked to more balanced urban systems, whereas greater average precipitation is associated with more uneven city size distributions, even after controlling for country and time fixed effects. When focusing on urbanization rates rather than the internal structure of the urban system, precipitation remains the only climatic variable exhibiting a stable relationship, while temperature does not appear to play a statistically significant role. Moreover, although socioeconomic factors – such as the role of agriculture, population size, and trade openness – continue to matter, their relevance varies depending on whether the outcome of interest is urban concentration or overall urbanization. Taken together, these findings underscore the role of persistent climatic conditions as structural determinants of national urban hierarchies.

The remainder of the paper is organized as follows. Section 2 describes the urban units analyzed, and the potential determinants of their distribution at the country level. Section 3 outlines the empirical strategy, including the estimation of the equality measure under study and the BMA techniques employed. Section 4 provides a preliminary exploratory analysis of the evolution of national urban structures and climatic variables for the countries in our sample, and Section 5 presents the main findings. Finally, Section 6 concludes.

2 Data and variables

The information on city sizes has been extracted from the GHS Urban Centre Database 2025 (Melchiorri et al. 2024; Pesaresi et al. 2024), which provides a harmonized and spatially consistent delineation of urban areas worldwide. This dataset refers to urban centres identified by applying the Degree of Urbanisation (Stage I) methodology to the GHSL population grid (GHS-POP), in line with recommendations for classifying human settlements as urban in both developed and developing countries (World Bank 2008). According to this methodology, urban centres consist of contiguous grid cells with a population density of at least $1,500$ inhabitants per square kilometre of permanent land and a minimum total population of $50,000$. We use population data for the period 1975–2025, measured at five-year intervals. As we compute a regression-based summary indicator of inequality in the distribution of city sizes within each national urban system, we restrict the sample from the outset to countries with at least 10 urban centres at the beginning of the period.

[Insert Table 1 about here]

One of our main objectives is to identify the variables that exhibit a robust relationship with indicators of national urban systems. In line with Wang, Yu, and Sun (2022), we classify the variables that may influence the spatial distribution of economic activity and population into three groups (see Table 1 for a description and sources). The first group comprises characteristics related to the physical landscape, or first-nature factors. This category includes land area, as countries with larger territories may have greater scope for spatial expansion, which could lead to a more concentrated distribution of cities (Sun et al. 2021; Wang et al. 2021). We also consider the shares of land classified as agricultural and arable. These data are obtained from the Food and Agriculture Organization (FAO) of the United Nations (UN).

Among the variables capturing human and economic conditions, we include three indicators reflecting membership in the income groups defined by the World Bank – upper-middle, lower-middle, and low income – based on the expectation that countries with higher levels of development tend to exhibit more uniform city size distributions (Puente-Ajovin, Sanso-Navarro, and Vera-Cabello 2025). Total population and population density are demographic variables that are also likely to be associated with the equality of the city size distribution at the national level (Rosen and Resnick 1980). In addition, they are related to the number of observations available for the rankâsize regressions used to estimate the inequality indicator of national urban systems. Economic structure is measured through the shares of value added in the agricultural and industrial sectors, drawn from the World Development Indicators database. This database also provides data on government final consumption expenditure, education expenditure – which may mitigate regional inequalities through the redistribution of tax revenues (Modica 2017) – and fixed telephone subscriptions. In line with recent contributions, globalization is also considered a potential determinant of equality in the distribution of city sizes. It is proxied by trade in goods and services and net foreign direct investment (FDI) inflows (Puente-Ajovin, Sanso-Navarro, and Vera-Cabello 2025; Sun et al. 2021).

In order to incorporate the recent strand of the literature[1] providing evidence that climate change affects the pace and nature of urbanization, as well as spatial development patterns (Castells-Quintana, Krause, and McDermott 2021, 2023; Helbling and Meierrieks 2023; Zhang and Yan 2022), we include climate-related variables obtained from the WorldClim database. In particular, at the country level and averaged over the previous five years, we consider mean surface air temperature, precipitation levels, and the median historical ensemble of the Standardized PrecipitationâEvapotranspiration Index (SPEI). Given that climate influences both the habitability and the economic potential of specific regions, we hypothesize that it plays a fundamental role in shaping the spatial distribution of cities over time. In particular, adverse climatic conditions – such as rising temperatures and drought episodes – are expected to be associated with accelerated urbanization and significant shifts in national urban structures. These changes may manifest not only through the expansion of urban populations but also via increased spatial fragmentation and altered patterns of city growth.

3 Methods

3.1 Rank-size regressions

The rank–size rule suggests that the city size distribution can be approximated by a Pareto function with a power law exponent equal to one. Accordingly, cross-sectional empirical analyses of Zipf's law typically rely on a log–log linear regression of city rank on city size. To mitigate the small-sample bias of OLS estimations, Gabaix and Ibragimov (2011) propose estimating the following model:

$$\log\left(Rank_i - 0.5\right) = \alpha - \beta \cdot \log(Size_i) + \epsilon_i, \quad i = 1, \ldots, n; \tag{1}$$

where i indexes cities and n denotes the sample size. Zipf law holds when $\beta = 1$.

A coefficient lower (higher) than one indicates that the population is more unevenly (evenly) distributed across the national urban system than predicted by the rankâsize

1. See Helbling et al. (2023) for a critical assessment.

rule. Therefore, this coefficient can be interpreted as a summary indicator of inequality in the distribution of city sizes within a given country. Lower values signal a more balanced urban hierarchy, whereas higher values reflect greater urban primacy or concentration. By focusing on this well-established metric, we capture variations in urban structure that are not readily observable through standard measures of urbanization.

3.2 Bayesian model averaging

Given the wide range of factors that may influence cross-country variability in city size distributions, we follow Puente-Ajovin, Sanso-Navarro, and Vera-Cabello (2025) and implement BMA methods to address model uncertainty. This approach allows the evaluation of multiple regressors by estimating all possible model specifications and computing a weighted average of their results. In doing so, it accounts for uncertainty both within individual models and across alternative model specifications.

Assuming that the estimated coefficient from the rankâsize regression depends linearly on a vector of covariates x, its conditional mean is given by:

$$E(\hat{\beta}c \mid xc) = x_c'\theta, \quad c = 1, \ldots, C; \tag{2}$$

where C denotes the number of countries and θ is a vector of parameters estimated by maximum likelihood.

Model uncertainty arises from the choice of regressors to include in x. Specifically, given a total of q potential explanatory variables, there are 2^q possible models, denoted by M_j for $j = 1, \ldots, 2^q$. Each model M_j is associated with a parameter vector θ^j and has the following conditional posterior density:

$$g(\theta^j \mid \hat{\beta}, M_j) = \frac{f(\hat{\beta} \mid \theta^j, M_j), g(\theta^j \mid M_j)}{f(\hat{\beta} \mid M_j)}; \tag{3}$$

where $f(\hat{\beta} \mid \theta^j, M_j)$ and $g(\theta^j \mid M_j)$ denote the likelihood function and the prior distribution, respectively.

Given a prior model probability $P(M_j)$, the posterior model probability is obtained using Bayes rule:

$$P(M_j \mid \hat{\beta}) = \frac{f(\hat{\beta} \mid M_j)P(M_j)}{f(\hat{\beta})}. \tag{4}$$

Expressions (3) and (4) highlight the need to specify prior distributions for both model parameters and model probabilities, which are then updated using the data. Leamer (1978) assumes that θ is a function of θ^j and derives the posterior density of parameters across all candidate models using the law of total probability. Posterior inclusion probabilities (PIPs) for the q regressors are obtained by summing the posterior probabilities of the models that include each variable. As emphasized by Steel (2020), these PIP and model probabilities represent key advantages of the BMA framework.

To avoid estimating the full set of 2^q models, we apply a Metropolis-coupled Markov chain Monte Carlo sampler. After discarding the first $2,500$ draws as burn in to ensure convergence to the target distribution, the empirical analysis is based on $10,000$ subsequent iterations. We employ a benchmark g prior for model-specific parameters and a beta binomial prior over the model space.

4 Exploratory analysis

Before examining the potential determinants of the distribution of national city sizes, we conduct a description of the countries that are included in our sample, as well as the evolution of their estimated Pareto coefficients and climatic-related variables. Both the minimum threshold of 10 urban centers to estimate rank-size regressions and data availability of the regressors restrict the number of countries to 51, which are highlighted in blue in Figure 1. Broadly speaking, they constitute a globally representative and structurally diverse sample, allowing for the identification of systematic associations between geographic and socioeconomic characteristics, climatic conditions, and the degree of concentration in national urban systems.

[Insert Figure 1 about here]

The sample contains a geographically diverse and socioeconomically heterogeneous group of countries, spanning all inhabited continents. In particular, the sample covers advanced economies, emerging economies, and a broad set of lower-middle- and low-income countries across Sub-saharan Africa, North Africa, South Asia, Southeast Asia, Eastern Europe, and Latin America. These countries range from highly urbanized service-based economies to resource-dependent countries, passing from rapidly industrializing nations, and agrarian economies. Population size also varies substantially, ranging from demographic giants to medium-sized and smaller economies.

From a geographical and climatic perspective, the sample encompasses a broad range of environmental conditions. It includes tropical and equatorial countries characterized by high temperatures and substantial precipitation variability; arid and semi-arid regions exposed to drought risk; temperate European economies; continental and cold-climate countries; as well as monsoon-influenced and climate-sensitive regions in South and Southeast Asia. This climatic diversity is particularly relevant for examining how temperature, precipitation, and drought indicators are associated with patterns of urban concentration. In addition, many of these countries are highly exposed to climate-related risks – such as heat stress, water scarcity, flooding, desertification, and extreme weather events – which may affect internal migration, rural-to-urban flows, and the spatial reorganization of economic activity. In this context, the combination of climatic variability and heterogeneous stages of economic development provides a suitable empirical setting to analyze the relationship between climate-related variables and the Pareto coefficients derived from city size distributions.

[Insert Figure 2 about here]

Figure 2 displays kernel density estimates of the slope parameter in expression (1) at the national level for three different years: 1975, 2000, and 2025. The graph in the upper-left panel includes all countries in the sample and shows that national urban systems have become less equal over time, as indicated by the declining density of values above 1.2. Nonetheless, by the end of the sample period, the distribution exhibits a substantial concentration of density around one. In line with the related literature, this provides evidence of a general fulfillment of Zipf's law in the distribution of city sizes when measured in demographic terms (Düben and Krause 2021; Puente-Ajovin, Sanso-Navarro, and Vera-Cabello 2025). The remaining three panels illustrate the evolution of the distributions by income level. They show that high-income countries have experienced the lowest variability in the degree of equality of their size distributions, while middle-income countries follow a pattern similar to the overall evolution described above. The most significant changes are observed in low-income countries, where the Pareto coefficients have evolved into a bimodal distribution, with two density peaks at values slightly above one and around 1.5.

[Insert Figure 3 about here]

igure 3 presents the temporal evolution of annual mean temperature, precipitation, and the SPEI over the period 1970–2025 for the countries in our sample. In the upper-left panel, the mean annual temperature is shown in blue, together with its 5-year moving average (dashed line). Both series display a persistent upward trend, particularly since the 1990s, with the highest values recorded in the most recent decade. The orange and green lines depict annual maximum and minimum temperatures, respectively, revealing an upward shift across the entire temperature distribution rather than changes confined to one of its tails. The upper-right panel indicates that annual precipitation is characterized by pronounced interannual variability and lacks a clear long-run monotonic trend. Precipitation declined until the mid-1990s and, after reaching a trough, began to increase. This subsequent rise may reflect a growing incidence of extreme weather events, potentially intensifying rainfall episodes and contributing to the recent upward movement in aggregate precipitation levels.

The lower panel displays the SPEI, reflecting the combined influence of temperature and precipitation on drought conditions. Although the index values fluctuate around zero – indicating alternating mildly wet and dry phases – there appears to be a slight tendency toward more frequent or prolonged negative anomalies in recent decades, consistent with rising temperatures increasing evapotranspiration pressures. Overall, Figure 3 documents a robust warming trend alongside variable precipitation dynamics and emerging signs of growing hydroclimatic stress. These evolving climatic conditions may contribute to reshaping the national distribution of city sizes by altering migration incentives, sectoral composition, infrastructure demands, and the relative resilience of large metropolitan areas compared to small and medium-sized cities. In this way, long-term climate change may be linked to patterns of urban concentration and dispersion.

[Insert Figure 4 about here]

Figure 4 presents a series of choropleth maps illustrating the rates of change from 1975 to 2025 in the Pareto coefficient, mean temperature, mean precipitation, and the SPEI. Darker shades of red indicate higher positive growth rates, whereas lighter shades correspond to smaller increases or declines. Several spatial patterns emerge. First, changes in the measure of inequality in city size distributions exhibit clear regional clustering, with particularly pronounced increases in parts of the Southern Hemisphere. Second, temperature trends display a generally positive pattern, consistent with global warming, although the magnitude of change varies across regions. In contrast, precipitation changes are more heterogeneous, with both positive and negative rates unevenly distributed across countries. Finally, the evolution of the SPEI reveals substantial spatial asymmetries, with notable deteriorations in several already arid and semi-arid regions. Taken together, the maps suggest that shifts in climatic conditions and changes in the inequality of city size distributions are spatially structured rather than randomly distributed.

[Insert Figure 5 about here]

Figure 5 presents scatter plots relating the percentage growth of the Pareto coefficient to percentage changes in mean temperature, mean precipitation, and the SPEI over the 1975–2025 period. The association between mean temperature growth and changes in the Pareto coefficient appears, at most, slightly positive, indicating that countries experiencing stronger warming trends tend to exhibit somewhat larger increases in the inequality of their city size distributions. A similar, albeit weak, positive relationship can be observed for the drought index. In contrast, the association between mean precipitation growth and the Pareto coefficient is more clearly negative, with countries experiencing increases in precipitation tending to display declines in the Pareto coefficient. Although the dispersion of observations remains substantial in all three panels, the graphical evidence suggests that precipitation dynamics may be more strongly associated with changes in urban size inequality than temperature or the SPEI. While these unconditional correlations do not establish causality, they provide suggestive evidence consistent with the hypothesis that climate change may be associated with shifts in the internal structure of city size distributions.

5 Results

Table 2 presents the PIPs – which indicate the relative importance of each variable in explaining the data – for the potential determinants of national city size distributions across alternative specifications that either include or exclude climate-related variables, as well as country and time fixed effects. When neither fixed effects nor climatic variables are incorporated (first column), the variables with the highest PIPs are total population, the number of cities in the national sample, the share of arable land, the indicator for upper-middle-income countries, and trade openness, all exceeding 50 percent. The lower panel shows that the sampler visited 556 models, with an average size of 10 covariates, and that 178 models were required to reach a cumulative posterior model probability (CPMP) of 90 percent. The correlation between iteration frequencies and analytical posterior model probabilities is 0.97, indicating a close correspondence between the sampling algorithm and the theoretical posterior distribution. The results reported in the second column indicate that most of the previously relevant regressors retain high PIPs when climatic indicators are included. Among these indicators, mean temperature emerges as the most important factor in explaining cross-country variation in the estimated coefficients from the rank-size regressions, with an inclusion probability of 74 percent.

[Insert Table 2 about here]

The introduction of country fixed effects increases the PIPs of the share of agricultural land (1.00) and the indicator for low-income countries (1.00). Together with trade openness, however, the relationship between the latter and the Pareto coefficient disappears once climate-related variables are included. In this specification, both mean temperature and precipitation exhibit a robust association with the estimated rank-size coefficients, with inclusion probabilities of 100 percent. Relative to the first two specifications, the inclusion of time fixed effects does not meaningfully alter the PIPs of the potential determinants of the city size distribution. Nonetheless, given the pooled cross-sectional nature of our estimations, our preferred specifications are those that incorporate both country and time fixed effects, reported in the last two columns of Table 2. These results closely resemble those obtained when only country fixed effects are included, with the exception of a stronger and more robust relationship between the variable capturing the role of international trade and the degree of equality in the city size distribution, particularly when climatic variables are taken into account.

[Insert Figures 6 and 7 about here]

Figure 6 presents density plots of the regression coefficients for geographical and socioeconomic variables with high PIPs when explaining the cross-country variability of Pareto coefficients, as reported in the last column of Table 3. The results indicate that, on the one hand, the share of agricultural land and population size are inversely associated with the equality of national city size distributions. On the other hand, arable land, the relative importance of the agricultural sector, the number of urban centres, and trade openness are positively associated with the equality of city size distributions. Density plots of the regression coefficients for climate-related variables are displayed in Figure 7. In line with the unconditional relationships shown in the scatter plots in Figure 5, there appears to be a positive relationship between mean temperature and the equality of urban structures. By contrast, average precipitation and the drought index are associated with more uneven city size distributions. Nonetheless, it should be noted that the SPEI receives very low posterior inclusion probabilities.

[Insert Table 3 about here]

Table 3 reports the PIPs obtained when the same BMA exercise is conducted using the urbanization rate as the dependent variable. Our discussion focuses on the specification that includes both country and time fixed effects, as well as climatic variables. As was also the case for the rank-size regression coefficients, the shares of agricultural land and agricultural value added, as well as the number of cities, receive high inclusion probabilities. However, the relationship between the share of arable land, population size, and trade openness and urbanization is much less robust than their link with the equality of the urban system. In this specification, variables related to the level of development appear to be more important in explaining cross-country variability in the urbanization rate. More closely aligned with the main objective of our study, the only variable that displays a robust association with the share of the population living in cities is average total precipitation.

[Insert Figures 8 and 9 about here]

The density plots of the regression coefficients displayed in Figure 8 indicate that urbanization is positively associated with the share of agricultural land and negatively associated with the share of agricultural value added. These signs are the opposite of those observed for national Pareto coefficients. The density plots for the estimated coefficients of the income-group indicators show that lower-middle- and low-income countries tend to exhibit lower urbanization rates. Regarding climatic factors, Figure 9 shows that the estimated coefficients for mean temperature are centered around zero, resulting in a negligible inclusion probability. In contrast to the findings for the rank-size regression coefficients, urbanization is positively associated with average precipitation and the SPEI. However, the latter variable once again receives a very low posterior inclusion probability.

6 Concluding remarks

This paper investigates the long-run determinants of cross-country differences in the equality of city size distributions, with particular emphasis on climate-related factors. Using a harmonized definition of cities from the Global Human Settlement Layer (GHSL) and a balanced panel covering the period 1975–2025, we estimate country-level Pareto coefficients along with complementary indicators of urban structure. To address model uncertainty in a context with multiple plausible geographic, socioeconomic, and institutional determinants, we implement a Bayesian model averaging (BMA) framework. The main contribution of the study is the explicit incorporation of climatic variables – mean temperature, precipitation, and a drought index (SPEI) – into the analysis of national urban systems. In doing so, we move beyond the traditional focus on purely geographic, socioeconomic, or institutional factors and provide systematic evidence on how first-nature climatic conditions are associated with the spatial distribution of population within countries.

Our results indicate that climatic factors are robustly associated with the distribution of city sizes, even after controlling for country and time fixed effects. Mean temperature is positively related to the equality of urban systems, whereas average precipitation is associated with more uneven city size distributions. By contrast, drought intensity exhibits low posterior inclusion probabilities. When urbanization rates are used as the dependent variable, precipitation emerges as the only climatic factor with a stable association, while temperature does not play a statistically meaningful role. These findings suggest that climate affects not only the overall level of urbanization but, more importantly, the internal structure of national urban systems. At the same time, socioeconomic variables – such as the role of agriculture, population size, and trade openness – remain important correlates of urban concentration, although their relevance varies depending on the specific dimension of urban structure under consideration.

These findings have several implications. First, persistent climatic conditions appear to be systematically linked to how population is distributed across cities, pointing to a structural channel through which climate change may reshape urban hierarchies over the long run. Second, the asymmetric effects of temperature and precipitation on urban concentration versus urbanization rates highlight the importance of distinguishing between the size distribution of cities and the overall share of the population living in urban areas. Finally, from a policy perspective, fostering balanced and resilient urban systems requires accounting for country-specific climatic constraints and risks. As climate change intensifies and alters temperature and precipitation patterns, anticipating its spatial consequences will be essential for the design of adaptive infrastructure, regional development strategies, and sustainable urban planning frameworks.

References

Arshad, Sidra, Shougeng Hu, and Badar Nadeem Ashraf. 2018. "Zipf's law and city size distribution: A survey of the literature and future research agenda." *Physica A: Statistical Mechanics and its Applications* 492 (15): 75–92. https://doi.org/10.1016/j.physa.2017.10.005.

Bosker, Maarten. 2022. "City origins." *Regional Science and Urban Economics* 94:103677. https://doi.org/10.1016/j.regsciurbeco.2021.103677.

Castells-Quintana, David, Melanie Krause, and Thomas K. J. McDermott. 2021. "The urbanising force of global warming: The role of climate change in the spatial distribution of population." *Journal of Economic Geography* 21 (4): 531–556. https://doi.org/10.1093/jeg/lbaa030.

———. 2023. "Climate change and the spatial concentration of population." In *The Palgrave Handbook of Global Sustainability,* edited by Robert Brinkmann, 255–272. Cham: Springer International Publishing. ISBN: 9783031019494. https://doi.org/10.1007/978-3-031-01949-4_25.

Düben, Christian, and Melanie Krause. 2021. "Population, light, and the size distribution of cities." *Journal of Regional Science* 61 (1): 189–211. https://doi.org/10.1111/jors.12507.

Eeckhout, Jan. 2004. "Gibrat's law for (all) cities." *American Economic Review* 94 (5): 1429–1451. https://doi.org/10.1257/0002828043052303.

Florczyk, Aneta, Christina Corbane, Daniele Ehrlich, Sergio M. Carneriro Freire, Thomas Kemper, Luca Maffenini, Michele Melchiorri, et al. 2019. *GHSL Data Package 2019.* EUR 29788 EN. Luxembourg: Publications Office of the European Union. https://doi.org/10.2760/290498.

Florczyk, Aneta, Michel Melchiorri, Christina Corbane, Marcello Schiavina, Luca Maffenini, Martino Pesaresi, Panagiotis Politis, et al. 2019. *Description of the GHS Urban Centre Database 2015.* JRC115586. Luxembourg: Publications Office of the European Union. https://doi.org/10.2760/037310.

Gabaix, Xavier. 1999. "Zipf's law for cities: An explanation." *Quarterly Journal of Economics* 114 (3): 739–767. https://doi.org/10.2307/2586883.

Gabaix, Xavier, and Rustam Ibragimov. 2011. "Rank - 1/2: A simple way to improve the OLS estimation of tail exponents." *Journal of Business & Economic Statistics* 29 (1): 24–39. https://doi.org/10.1198/jbes.2009.06157.

Gomez Osorio, Camilo, and Vlad Mykhnenko. 2025. "Extraordinary African cities? Zipfâs law and the emerging African system of cities." *World Development* 195:107108. https://doi.org/10.1016/j.worlddev.2025.107108.

Helbling, Marc, and Daniel Meierrieks. 2023. "Global warming and urbanization." *Journal of Population Economics* 36 (3): 1187–1223. https://doi.org/10.1007/s00148-022-00924-y.

Helbling, Marc, Diego Rybski, Jacob Schewe, Stefan Siedentop, Manon Glockmann, Bastian Heider, Bryan Jones, Daniel Meierrieks, Albano Rikani, and Peter Stroms. 2023. "Measuring the effect of climate change on migration flows: Limitations of existing data and analytical frameworks." *PLOS Climate* 2:1–10. https://doi.org/10.1371/journal.pclm.0000078.

Leamer, Edward E. 1978. *Specification searches: Ad hoc inference with nonexperimental data.* New York: John Wiley & Sons, Ltd. ISBN: 9780471015208.

Lemoine, Derek, Catherine Hausman, and Jeffrey G. Shrader. 2025. *A guide to climate damages.* Working Paper, Working Paper Series 34348. National Bureau of Economic Research. https://doi.org/10.3386/w34348.

Melchiorri, Michele, Ines Mari-Rivero, Pietro Florio, Marcello Schiavina, Katarzyna KrasnodÄbska, Panagiotis Politis, Johannes H. Uhl, et al. 2024. *Stats in the city – The GHSL urban centre database 2025 – Public release GHS-UCDB R2024.* JRC139768. Luxembourg: Publications Office of the European Union. https://doi.org/10.2760/3046391.

Modica, Marco. 2017. "The impact of the European Union integration on the city size distribution of the member states." *Habitat International* 70:103–113. https://doi.org/10.1016/j.habitatint.2017.10.011.

Pesaresi, Martino, Marcello Schiavina, Panagiotis Politis, Sergio Freire, Katarzyna KrasnodÄbska, Johannes H. Uhl, Alessandra Carioli, et al. 2024. "Advances on the Global Human Settlement Layer by joint assessment of Earth Observation and population survey data." *International Journal of Digital Earth* 17 (1): 2390454. https://doi.org/10.1080/17538947.2024.2390454.

Puente-Ajovin, Miguel, Marcos Sanso-Navarro, and María Vera-Cabello. 2025. "The determinants of national city size distributions: A BMA approach." *Cities* 166:106184. https://doi.org/10.1016/j.cities.2025.106184.

Raftery, Adrian E., David Madigan, and Jennifer A. Hoeting. 1997. "Bayesian model averaging for linear regression models." *Journal of the American Statistical Association* 92 (437): 179–191. https://doi.org/10.2307/2291462.

Rosen, Kenneth T., and Mitchel Resnick. 1980. "The size distribution of cities: An examination of the Pareto law and primacy." *Journal of Urban Economics* 8 (2): 165–186. https://doi.org/10.1016/0094-1190(80)90043-1.

Steel, Mark F. J. 2020. "Model averaging and its use in economics." *Journal of Economic Literature* 58 (3): 644–719. https://doi.org/10.1257/jel.20191385.

Sun, Bindong, Tinglin Zhang, Yu Wang, Liangliang Zhang, and Wan Li. 2021. "Are megacities wrecking urban hierarchies? A cross-national study on the evolution of city-size distribution." *Cities* 108:102999. https://doi.org/10.1016/j.cities.2020.102999.

Wang, Yu, Bindong Sun, Sixu Wu, Wan Li, and Tinglin Zhang. 2021. "Can the internet reshape the national city size distribution? Cross-country evidence." *Papers in Regional Science* 100 (5): 1254–1272. https://doi.org/10.1111/pirs.12619.

Wang, Yu, Zhou Yu, and Bindong Sun. 2022. "Equalization or polarization? The effect of the internet on national urban hierarchies across the world, 2000–2018." *Cities* 131:103989. https://doi.org/10.1016/j.cities.2022.103989.

World Bank. 2008. *World development report 2009: Reshaping economic geography.* Washington, DC: The World Bank. ISBN: 9780821376089. https://doi.org/10.1596/978-0-8213-7607-2.

———. 2024. "Urban Development Overview." Accessed February 16, 2026. https://www.worldbank.org.

Zhang, Xinfang, and Bihe Yan. 2022. "Climate change and city size: The role of temperature difference in the spatial distribution of China's population." *Environmental Science and Pollution Research* 29 (54): 82232–82242. https://doi.org/10.1007/s11356-022-21561-8.

Tables and figures

Table 1: Potential determinants of the city size distribution and the urbanization rate at the country level: Description of variables and data sources.

Variable	Description	Source
land	Land area	United Nations
agrland	Agricultural land (% of land area)	United Nations
arable	Arable land (% of land area)	United Nations
UM	Upper-middle income level group indicator	World Bank
LM	Lower-middle income level group indicator	World Bank
LI	Low income level group indicator	World Bank
popul	Total population	United Nations
popdens	Population density (people per sq. km of land area)	United Nations
cities	Number of observations in rank-size regressions	GHS-UCBD
agric	Agriculture, forestry, and fishing, value added (% of GDP)	World Bank
indus	Industry, including construction, value added (% of GDP)	World Bank
phone	Fixed telephone subscriptions (per 100 people)	World Bank
govcons	General government final consumption expenditure (% of GDP)	World Bank
trade	Sum of exports and imports of goods and services (% of GDP)	World Bank
fdi	Foreign direct investment, net inflows (% of GDP)	World Bank
educexp	Government expenditure on education, total (% of GDP)	World Bank
temp	Average mean surface air temperature, last five years (Degrees celsius)	World Bank
precip	Precipitation, last five years (Milimetres)	World Bank
spei	Annual SPEI drought index median historical ensemble, last five years	World Bank

Table 2: Determinants of the city size distribution at the country level: Posterior inclusion probabilities.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
land	0.24	0.05	0.00	0.00	0.08	0.01	0.00	0.00
agrland	0.07	0.03	1.00	1.00	0.01	0.01	1.00	1.00
arable	0.88	0.48	0.96	1.00	0.71	0.28	1.00	1.00
UM	0.71	0.75	1.00	0.02	0.61	0.80	1.00	0.00
LM	0.34	0.10	0.35	0.06	0.19	0.04	0.00	0.00
LI	0.41	0.31	1.00	0.01	0.35	0.15	0.10	0.01
popul	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
popdens	0.22	0.04	0.00	0.00	0.08	0.01	0.02	0.07
cities	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00
agric	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
indus	0.04	0.03	0.00	0.02	0.02	0.01	0.00	0.00
phone	0.12	0.03	0.04	0.00	0.08	0.02	0.04	0.04
govcons	0.03	0.01	0.04	0.02	0.01	0.01	0.02	0.35
trade	0.53	0.45	0.73	0.10	0.32	0.28	0.99	0.60
fdi	0.02	0.01	0.00	0.00	0.00	0.01	0.00	0.00
educexp	0.47	0.24	0.00	0.00	0.37	0.11	0.00	0.00
temp		0.74		1.00		0.78		1.00
precip		0.10		1.00		0.06		1.00
spei		0.04		0.00		0.02		0.01
Country FEs	No	No	Yes	Yes	No	No	Yes	Yes
Time FEs	No	No	No	No	Yes	Yes	Yes	Yes
Observations	561	561	561	561	561	561	561	561
Sampling correlation	0.97	0.99	0.66	0.59	0.97	0.99	0.92	0.63
Models	556	620	481	594	437	393	434	553
CPMP>=0.90	178	160	60	106	97	68	69	95
Av. Size	7.09	6.43	38.67	32.43	5.94	5.67	41.14	35.75

Table 3: Determinants of the urbanization rate at the country level: Posterior inclusion probabilities.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
land	0.07	0.03	0.00	0.00	0.02	0.01	0.00	0.00
agrland	0.61	0.17	0.55	0.40	0.34	0.18	1.00	1.00
arable	0.92	0.73	1.00	1.00	0.48	0.40	0.00	0.00
UM	0.98	0.99	0.00	0.00	0.87	0.93	0.02	0.05
LM	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.86
LI	0.23	0.16	0.39	1.00	0.52	0.38	1.00	1.00
popul	0.95	0.81	1.00	0.31	0.92	0.91	0.21	0.09
popdens	0.35	0.39	0.27	0.31	0.91	0.79	0.24	0.07
cities	0.45	0.24	1.00	1.00	0.18	0.13	0.76	0.77
agric	1.00	1.00	1.00	1.00	1.00	1.00	0.80	0.92
indus	0.28	0.14	1.00	1.00	0.01	0.00	0.00	0.00
phone	1.00	1.00	1.00	1.00	1.00	1.00	0.32	0.11
govcons	0.22	0.53	0.00	0.00	0.15	0.13	0.00	0.00
trade	0.92	0.87	0.00	0.00	0.99	0.97	0.12	0.03
fdi	0.06	0.03	0.00	0.00	0.00	0.00	0.00	0.00
educexp	0.94	0.58	0.00	0.01	0.71	0.68	0.35	0.06
temp		0.09		0.08		0.02		0.00
precip		0.11		0.09		0.17		0.80
spei		1.00		1.00		0.16		0.13
Country FEs	No	No	Yes	Yes	No	No	Yes	Yes
Time FEs	No	No	No	No	Yes	Yes	Yes	Yes
Observations	561	561	561	561	561	561	561	561
Sampling correlation	0.98	0.97	0.43	0.24	0.94	0.92	0.36	0.37
Models	525	837	791	687	860	994	748	636
CPMP>=0.90	161	237	153	58	240	239	132	38
Av. Size	10.02	9.88	30.54	30.83	12.09	11.48	47.77	46.62

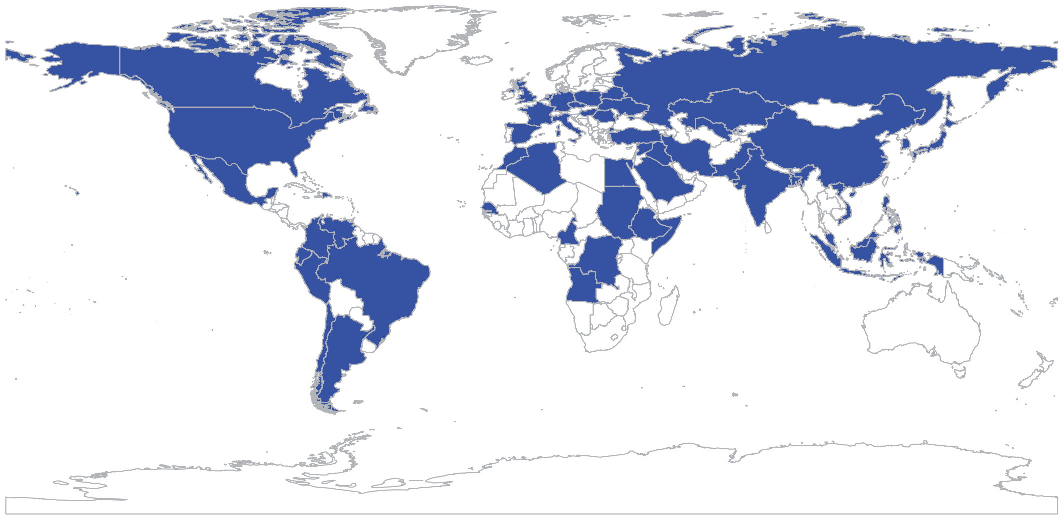

Figure 1: Countries (51) included in the sample.

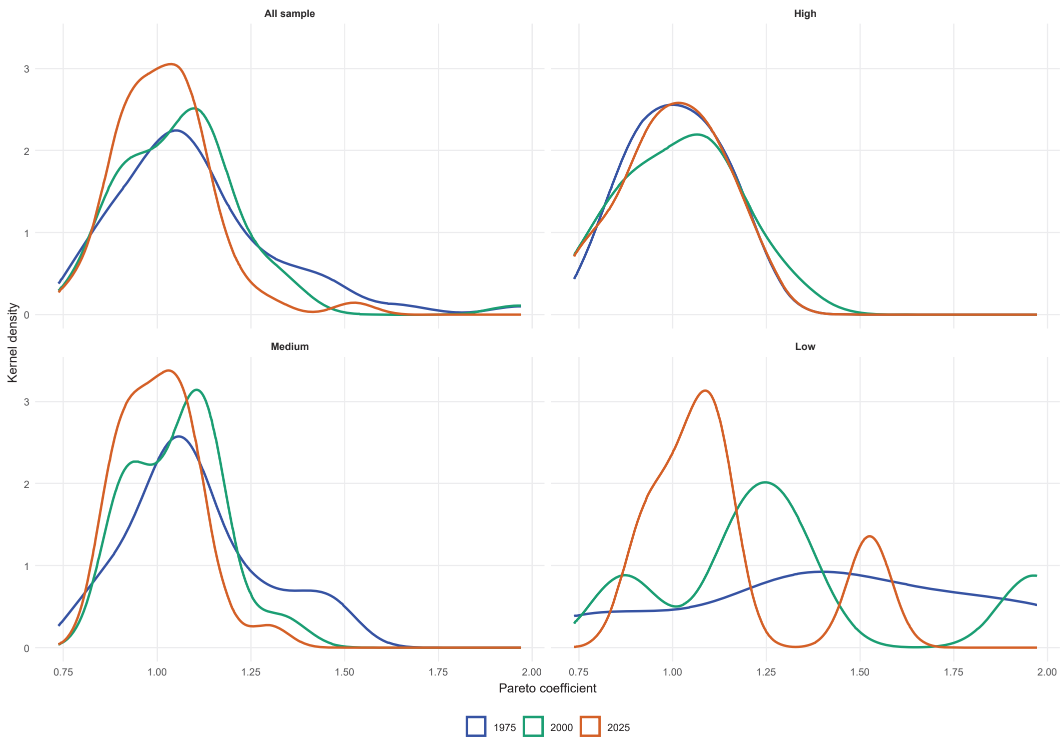

Figure 2: Kernel density estimates of Pareto coefficients from country-level rank-size OLS regressions.

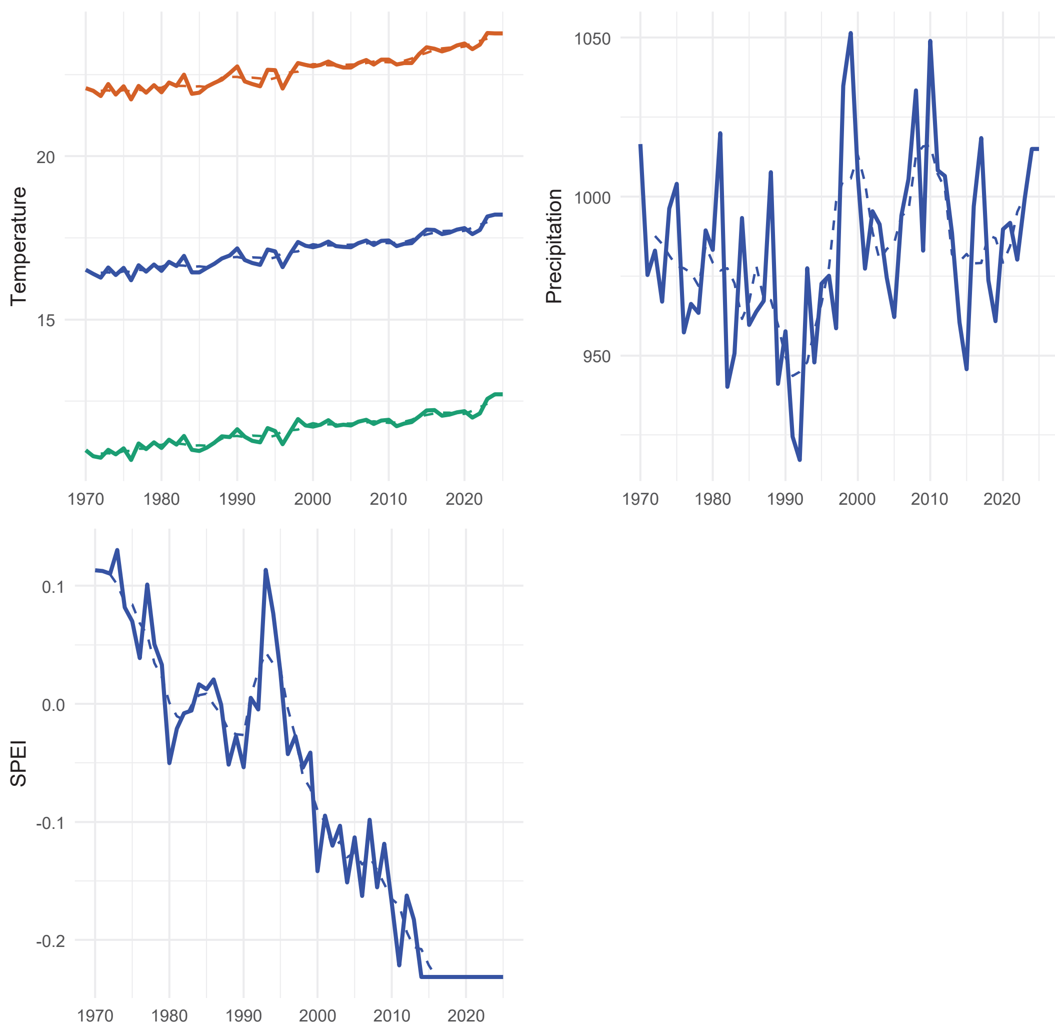

Figure 3: Annual mean of temperature, precipitation, and SPEI for the sample. Blue: mean; dashed: 5-year moving average. Max and min temperatures in orange and green.

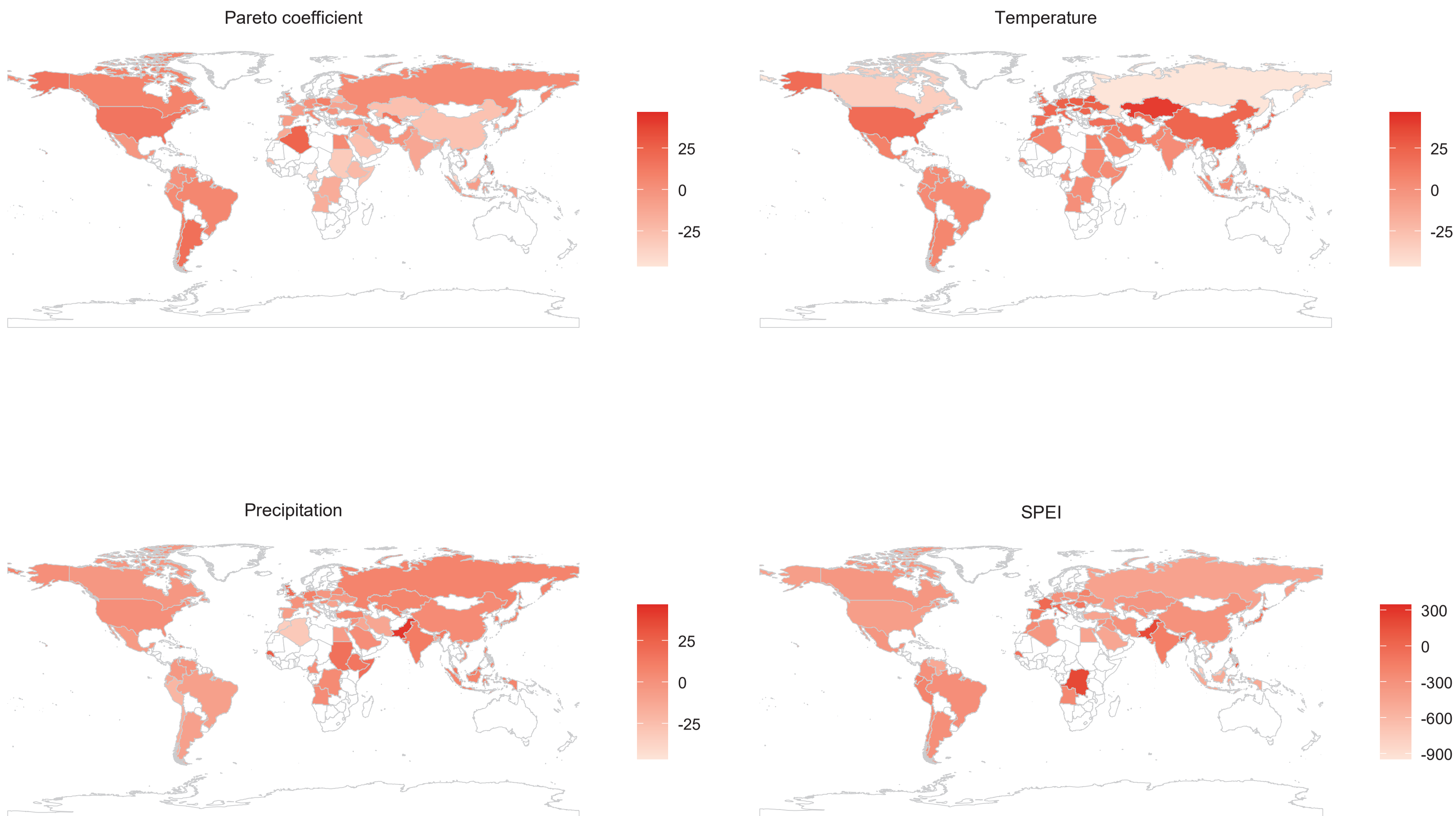

Figure 4: Percentage growth between 1975 and 2025 for Pareto coefficient, temperature, precipitation, and SPEI.

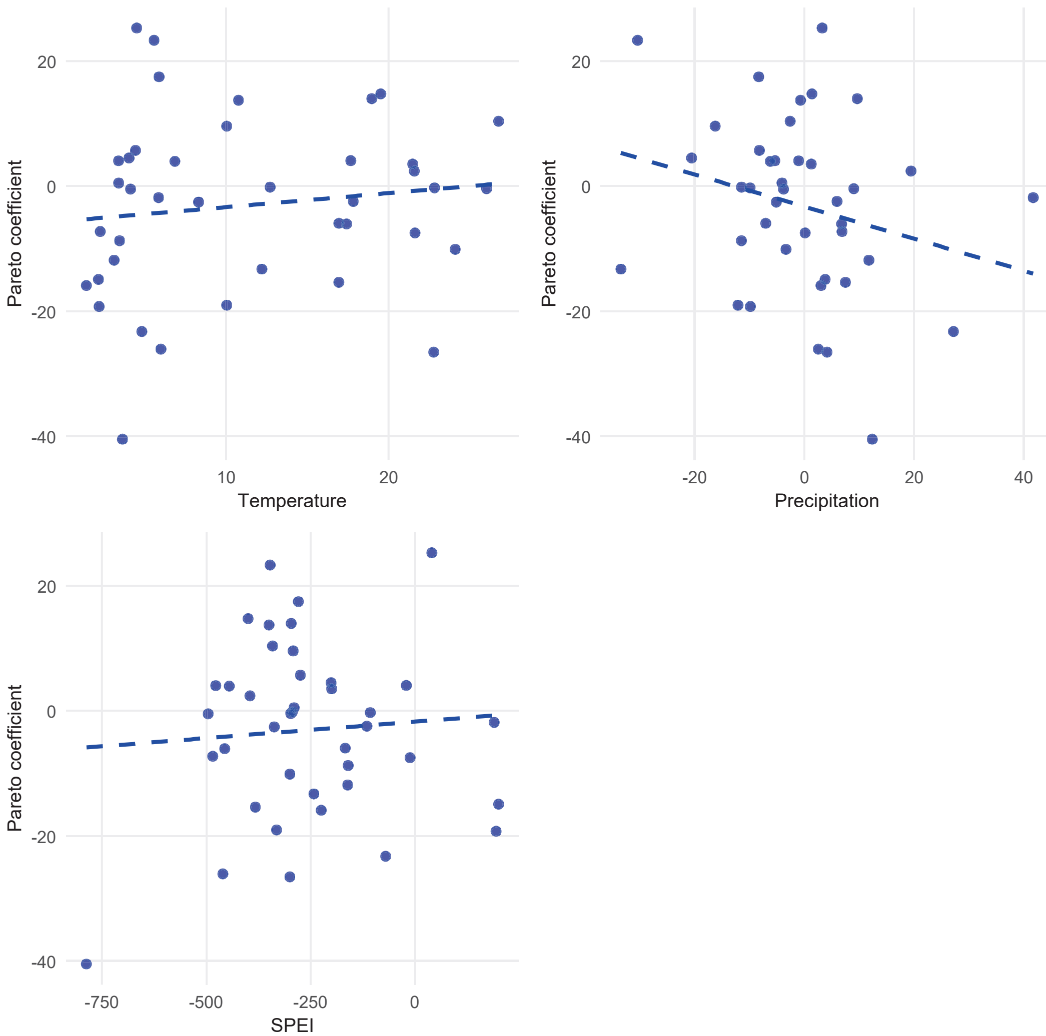

Figure 5: Scatter plots of percentage growth of Pareto coefficient and of temperature, precipitation, and SPEI (1975–2025). Outliers removed for temperature and SPEI (5th–95th percentile).

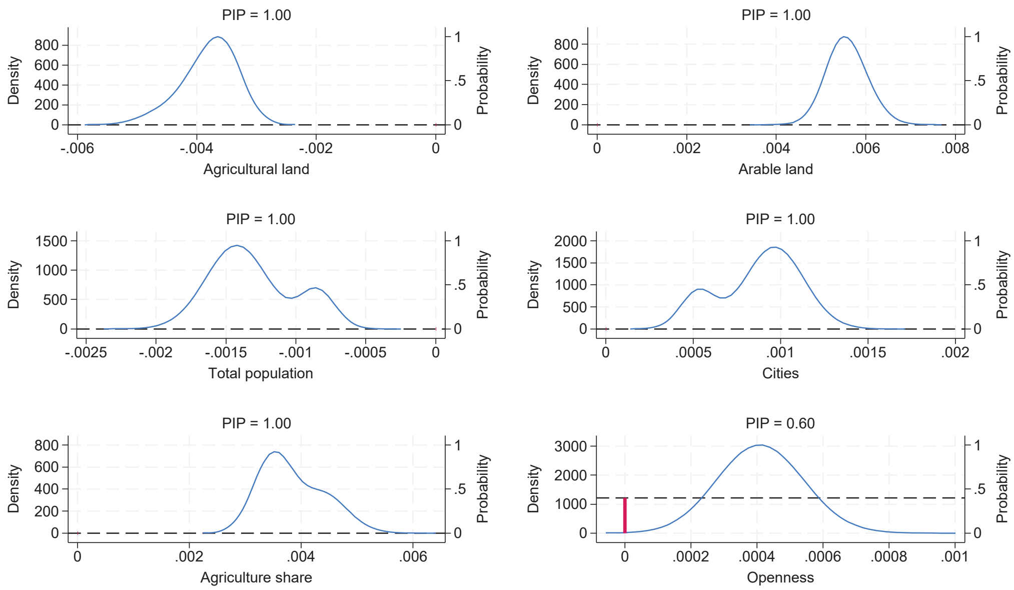

Figure 6: Determinants of city size distribution at the country level: Density plots of regression coefficients for geographical and socioeconomic variables with high posterior inclusion probabilities.

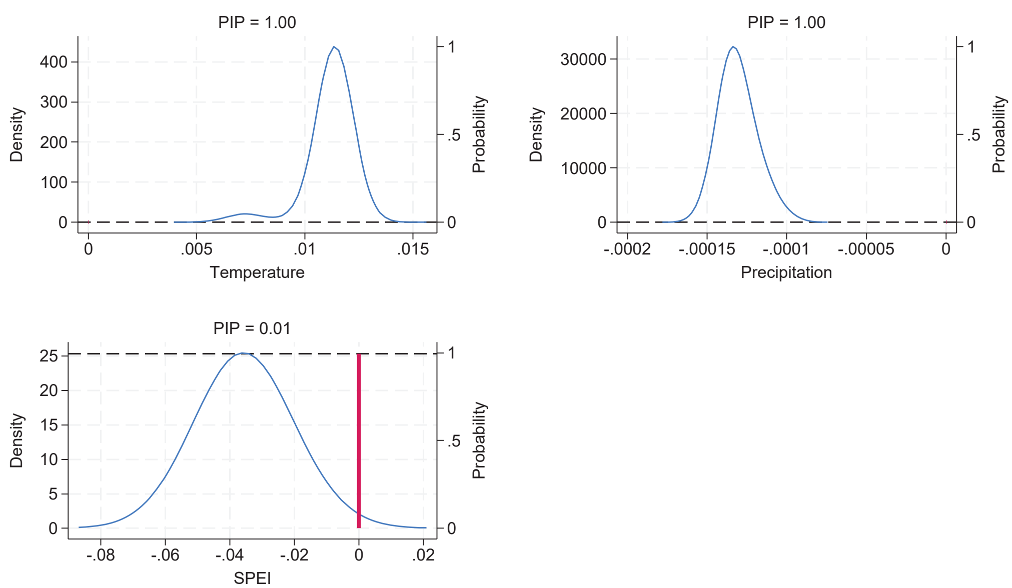

Figure 7: Determinants of city size distribution at the country level: Density plots of regression coefficients for climatic variables.

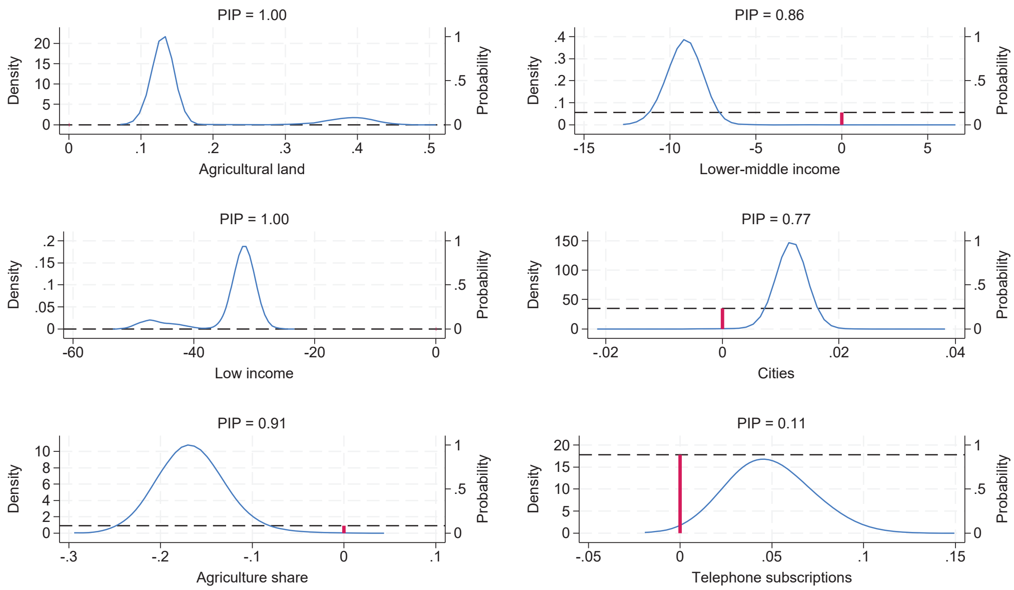

Figure 8: Determinants of urbanization at the country level: Density plots of regression coefficients for geographical and socioeconomic variables with high posterior inclusion probabilities.

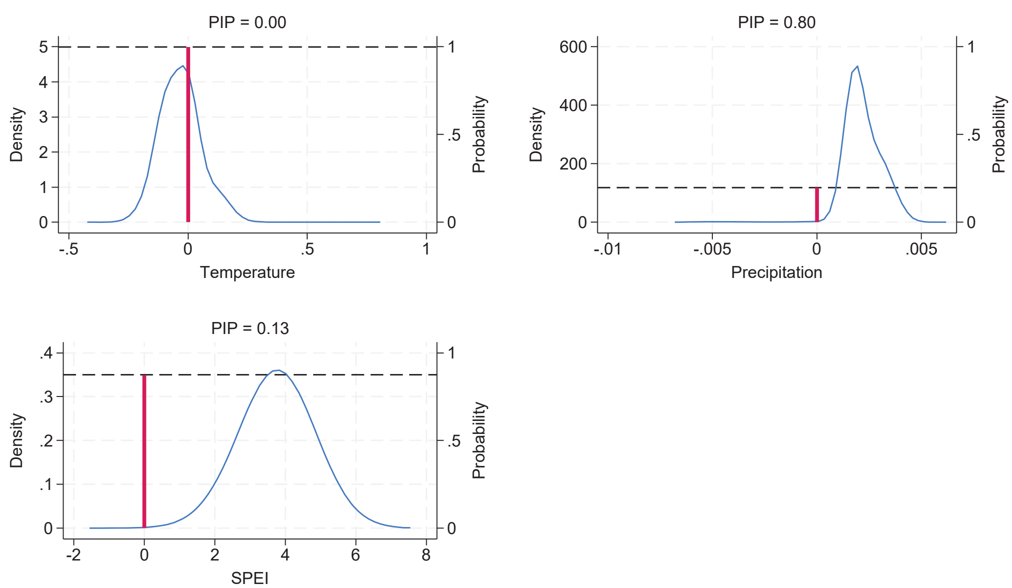

Figure 9: Determinants of urbanization at the country level: Density plots of regression coefficients for climatic variables.