

Bayesian Spatially-Adjusted Gini Index Using Poverty Rates for Fine-Grained Inequality Mapping

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Background and Objectives

Income inequality is a persistent challenge for social and economic policy. The **Gini index** is one of the most widely used tools to quantify inequality, offering a **simple and intuitive summary** of income distribution. However, despite its popularity, the Gini index has several limitations—particularly when used to compare **small geographic areas** with very **different socioeconomic contexts**.

In fact, the Gini index often **fails to reflect how inequality affects the most deprived populations** and may be **distorted by extreme high incomes** or **small sample variability**. To address these issues, we propose a simple adjustment: **normalizing the Gini index** using the poverty rate, defined as the proportion of individuals living below **60% of the national median income**.

Our **objectives** were to develop this poverty-adjusted Gini index; to estimate both traditional and **adjusted** versions at the **municipal level** across Spain using **Bayesian methods**; and to assess how this adjustment improves the interpretation of inequality in areas with high levels of deprivation.

Methods

We used a **cross-sectional ecological design** in which the units of analysis were the **8,131 municipalities of Spain**. We considered **two main outcome variables**: the **traditional Gini index** and a **poverty-adjusted Gini index**, where the latter was calculated by **normalising the Gini value with the municipal poverty rate** (defined as the share of the population below 60% of the national median income). This adjustment aimed to capture inequality more meaningfully in areas with high levels of deprivation.

Adjusting poverty

To evaluate the existence of a **geographical pattern in income inequality**, we represented the **smoothed Gini indices** on a map of the region under study (i.e., Spain). To estimate these smoothed values, we specified a **generalized linear mixed model (GLMM)** for the Gini index, without including explanatory variables, but **controlling for extra variability** by incorporating several **random effects** (such as spatially structured and unstructured components) and using the **municipal poverty rate as an offset**.

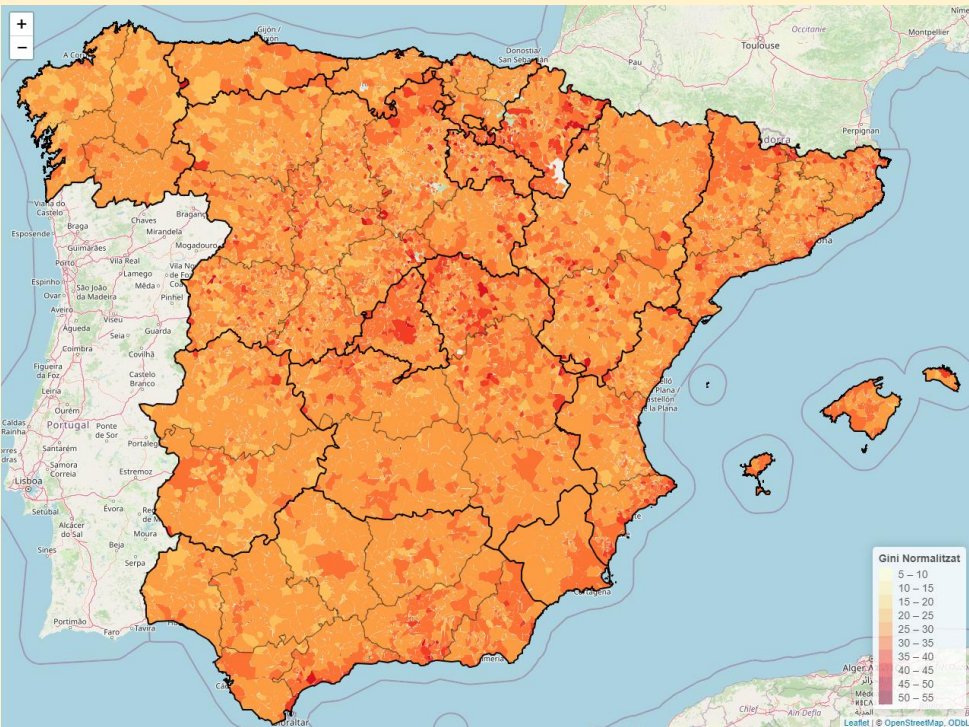
We controlled for unobserved variation, both spatial heterogeneity (using unstructured random effects) and spatial (spatially structured random effects normally distributed with a zero mean and a Matérn covariance function) and temporal dependence (structured random effects, random walk of order one), considering them non-independent but separable. We included the target population as the offset.

Inferences were made following a Bayesian perspective, using the INLA approach. We used priors that penalize complexity (PC priors).

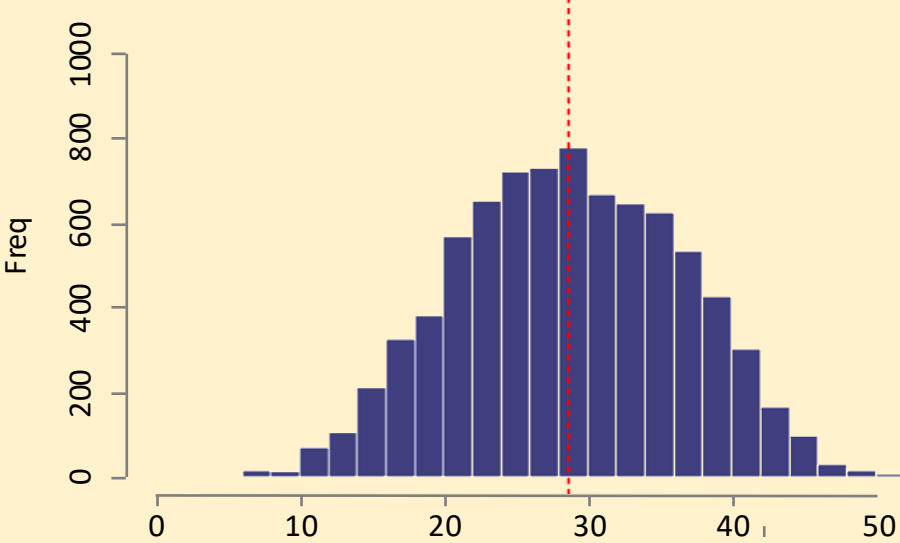
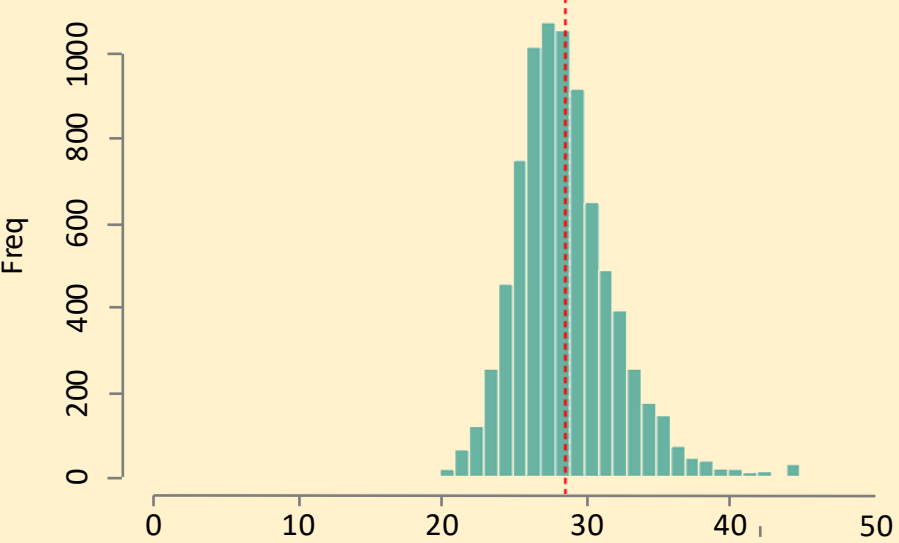
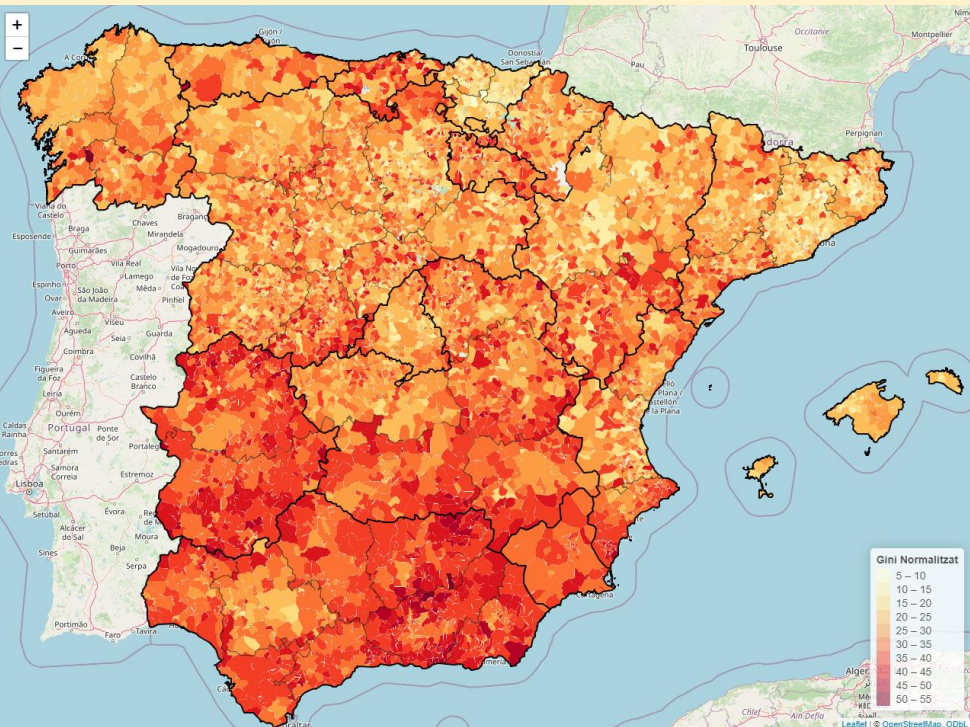
Results

Distribution of the original Gini index (A) and the normalized Gini index (B) in Spain (2022).

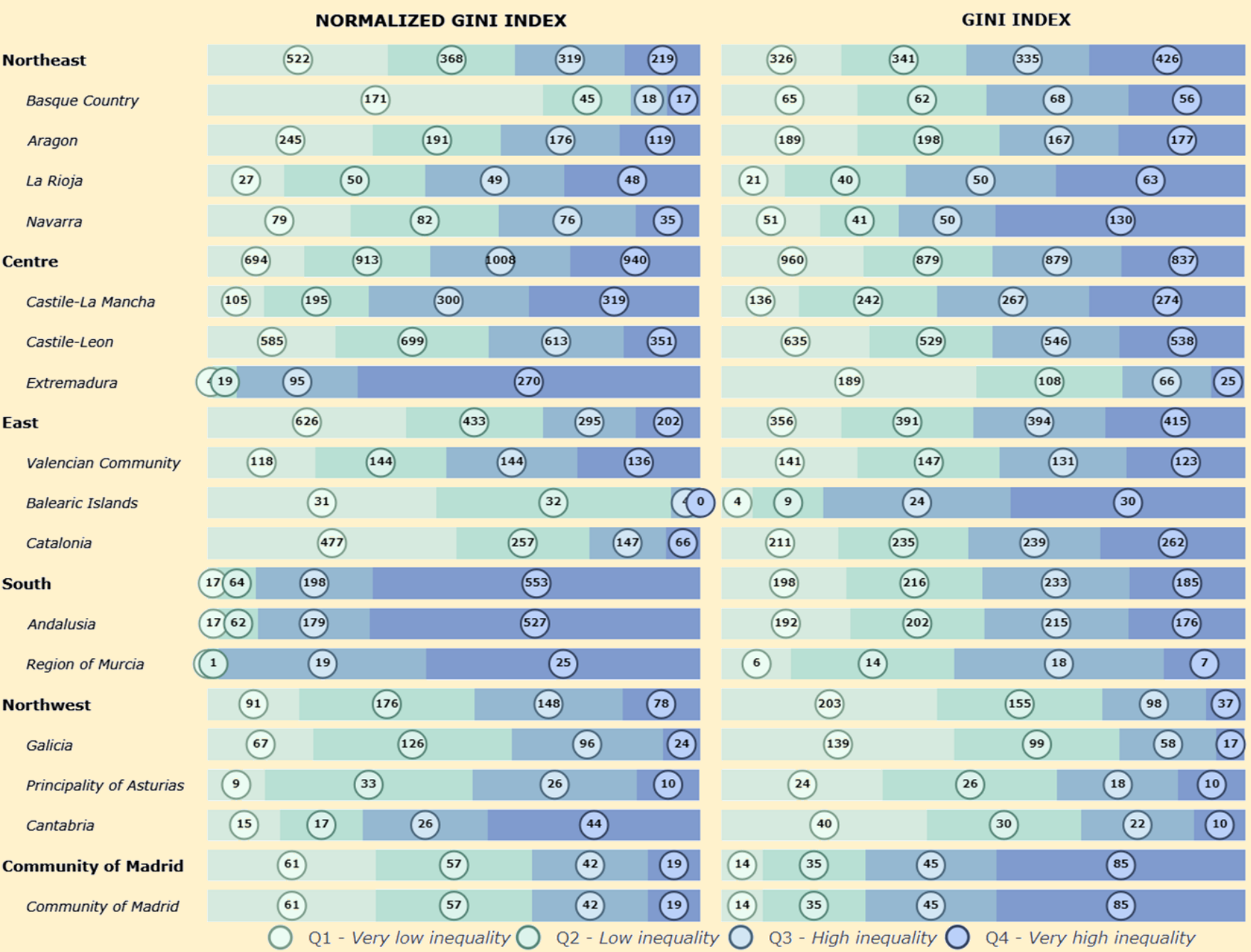
A. Distribution of the original Gini index



B - Distribution of the original Gini index



Distribution of municipalities according to the quartile of inequality at NUTS-1 and NUTS-2 level in Spain (2022).



Conclusions

- The poverty-normalized Gini index with Bayesian spatial modelling delivers more stable, comparable estimates, especially in small, deprived municipalities.
- In Spain, the traditional Gini highlighted high inequality in densely populated urban areas; the normalized measure instead reveals elevated inequality in rural, low-density regions.
- Regions like Extremadura and Murcia emerge as the most unequal after normalization, while Madrid and the Balearic Islands see their rankings decline.
- Nonetheless, it remains a unidimensional metric and should be complemented with multidimensional indicators and validated in other contexts.

Reference

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