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Abstract

This study introduces the Social Growth Index (SGI), an integrated framework for assessing socioeconomic resilience at the municipal level across Italy. The SGI builds on the idea that a territory is resilient if it can sustain long-term growth despite exposure to external shocks—both positive, such as large-scale public investments under the National Recovery and Resilience Plan (PNRR), and negative, such as the COVID-19 pandemic. These events represent structural tests for local systems, revealing their ability to adapt, recover, and convert temporary disturbances into lasting development trajectories.

Using harmonized data for 2010–2022, the SGI integrates three standardized variables—GDP density (GDP per m^2), GDP per capita, and population density—that jointly capture productive intensity, individual prosperity, and demographic vitality within a consistent spatial structure.

To obtain the SGI, we design a methodological framework integrating Fixed Rank Kriging (FRK) for the spatial downscaling of Gross Domestic Product (GDP) with Copeland aggregation for multi-criteria ranking. FRK enables spatially coherent GDP estimates at fine resolution, while the Copeland method aggregates municipalities' relative performance without imposing arbitrary weights.

Results reveal a persistent North–South divide, with higher resilience levels in Northern and Central Italy and lower values in Southern, Sicilian, and inland Sardinian areas. Temporal analysis indicates structural persistence in highly resilient urban and industrial systems alongside localized improvements around regional capitals. Comparison with ISTAT's Municipal Fragility Index (IFC) exhibits consistency among indicators measuring intersecting economic aspects. Future extensions include developing a spatio-temporal FRK model and incorporating additional drivers—such as employment, innovation, and environmental sustainability—to enhance temporal coherence and policy relevance.

Keywords: Socioeconomic Resilience, Copeland Method, Fixed Rank Kriging, Spatial Downscaling, Social Growth Index, Territorial Disparities

1 Introduction and Literature Review

In economic and regional sciences, resilience is commonly defined as the ability of territories to resist, absorb, and recover from external shocks while maintaining long-term growth trajectories (Martin, 2010; Pendall et al., 2010; Bristow, 2014). This interpretation extends the ecological foundations of resilience (Holling, 1973; Folke, 2006), integrating them with spatial and institutional dimensions relevant to human settlements and economic systems. More recent studies emphasize that resilience is not a static property but a dynamic process reflecting both resistance to disruption and the capacity for structural transformation (Davoudi, 2012; Simmie and Martin, 2010).

A large body of empirical research has sought to operationalize resilience through composite indicators. The OECD (OECD, 2014) and the European Commission (European Commission, DG REGIO, 2020) emphasize its multidimensional nature, encompassing economic, social, demographic, and environmental components. At the European level, indices such as the Regional Economic Resilience Index (Faggian et al., 2018) and the Resilience Capacity Index (Foster, 2007) combine economic performance with social and infrastructural indicators. In Italy, ISTAT's Municipal Fragility Index (IFC, Indice di Fragilità Comunale) (ISTAT, 2023a) provides a complementary view by mapping local vulnerabilities in demographic structure, education, labor, and social cohesion.

Several other frameworks have been developed internationally. The City Resilience Index by Arup (Arup International Development, 2015) integrates dimensions of health, well-being, governance, and environment, while the Baseline Resilience Indicators for Communities (Cutter et al., 2014) and the Community Disaster Resilience Index (Peacock et al., 2010) focus on social, economic, environmental, and institutional capacities related to disaster risk. The Economic Resilience Index proposed by Rose and Krausmann (Rose and Krausmann, 2013) adopts a more strictly economic perspective, yet may underrepresent social and institutional aspects that are crucial for adaptive capacity. In Italy, Graziano and Rizzi (Graziano and Rizzi, 2016) proposed a framework that separates vulnerability and resilience dimensions, allowing a dynamic interpretation of causes and responses, although data heterogeneity limits its applicability across all territories.

From this literature, two main challenges emerge. First, the availability and comparability of data across spatial and temporal scales are often limited, hindering consistent and reproducible assessments of resilience. Socioeconomic indicators are frequently collected at heterogeneous administrative levels, updated at irregular intervals, or defined according to different methodological standards, making cross-regional and longitudinal comparisons difficult (OECD, 2014; Eurostat, 2018). Such inconsistencies in data collection and harmonization frameworks represent a key limitation for reproducible territorial analyses, as highlighted by international statistical institutions, which emphasize the need for coherent spatial and temporal definitions of indicators to enable meaningful comparison across administrative boundaries. As a result, many studies remain confined to regional or provincial analyses, since harmonized data at the municipal level are rarely available. Among the few indices produced at this finer scale, the IFC (ISTAT, 2024) developed by ISTAT represents a valuable reference;

however, it does not explicitly account for spatial dependence between municipalities and is available only for the years 2018, 2019, and 2021. This limits its ability to capture how local conditions evolve over time and how inter-municipal dynamics contribute to resilience or fragility within broader territorial systems. Second, most existing indices and empirical frameworks neglect the spatial interdependence that characterizes socioeconomic phenomena (Briguglio et al., 2009). Local territories are not isolated entities but are interconnected through flows of labor, capital, and innovation that generate spatial spillovers and regional interdependencies. Ignoring these relationships can obscure how shocks propagate through space and how clusters of vulnerability or resilience emerge, ultimately reducing the explanatory and policy relevance of resilience assessments.

Recent advances in spatial statistics have introduced multiscale spatial modeling and frameworks capable of more effectively capturing territorial heterogeneity (Cressie and Wikle, 2015; Zammit-Mangion and Cressie, 2021). Among these, the Fixed Rank Kriging (FRK) approach has proven particularly suitable for socio-economic applications, as it enables the disaggregation of aggregate indicators—such as GDP—onto finer spatial units while preserving statistical coherence (Sainsbury-Dale et al., 2024).

Based on this literature, the present study proposes the Social Growth Index (SGI), a composite measure that integrates the FRK-estimated GDP at the municipal level with demographic information and aggregates results using the Copeland method (Saari and Merlin, 1996). By employing FRK, the SGI explicitly accounts for spatial dependence in economic structures, ensuring that GDP estimates for each municipality are informed by the behavior of neighboring areas. This spatial coherence represents a key methodological advance compared to existing indices — such as ISTAT's IFC — that, while valuable, do not explicitly model inter-municipal relationships. The SGI therefore provides a complementary perspective, capturing how resilience emerges within interconnected local systems rather than isolated administrative units. Its aggregation through the Copeland method provides an interpretable and transparent framework that can be easily understood and applied by policy makers and other stakeholders. Indeed, we compared SGI with IFC to assess its empirical consistency and demonstrate its relevance for territorial policy analysis and resilience.

The remainder of the paper is structured as follows. Section 2 describes the data sources, coverage, and harmonization procedures. Section 3 presents the methodological framework, including index construction, the FRK downscaling model, and the Copeland aggregation. Section 4 reports the main results and comparison with the IFC, while Section 5 concludes with policy implications, limitations, and perspectives for future research.

2 Data

This section describes the datasets and the harmonization procedures employed in the analysis, ensuring transparency and reproducibility of the results. All information comes from publicly accessible and open-source repositories maintained by official statistical institutions, namely Eurostat (2023a), ISTAT (2023b), and the Italian Ministry of Economy and Finance (MEF, 2025). The resulting data set covers the period

2010–2022 and integrates three key socioeconomic variables—Gross Domestic Product (GDP), GDP per capita and Population—selected for their central role in measuring local economic performance and individual well-being.

Data on GDP at constant prices (base year 2015) was retrieved from Eurostat's data *set Economy at regional level* (code `nama_10r_3gdp`), which provides harmonized annual regional accounts for all NUTS 2 and NUTS 3 regions of the European Union (Eurostat, 2023a). The population refer to the resident population as of 1 January of each year and were obtained from the official municipal registers published by ISTAT (2023b). All datasets are distributed under open-data licenses, consistent with the transparency and reuse principles adopted by Eurostat and ISTAT. Data were collected September 2025 and are fully aligned with the 2021 NUTS classification (Regulation EU 2016/2066).

The observation period spans from 2010 to 2022, providing thirteen annual cross-sections that capture both long-term structural dynamics and short-term shocks, including the socioeconomic effects of the COVID-19 pandemic. The geographical coverage encompasses the entire Italian territory, comprising 20 NUTS 2 regions and 107 NUTS 3 provinces, which were later downscaled to 7,901 municipalities (Local Administrative Units, LAU). Each observation corresponds to a unique spatial–temporal pair (i, t), where i denotes the administrative unit and t the reference year. GDP and GDP per capita are expressed in millions of euros at constant 2015 prices, while Population represents the resident stock as of 1 January of each year.

To ensure comparability over time and across space, all variables were harmonized through a rigorous multi-step preprocessing pipeline. Monetary quantities were first converted into constant 2015 euros by deflating nominal GDP values using regional price indices (deflators) at the NUTS 2 level, following the methodological guidelines of the Eurostat (2013). This procedure was necessary because neither Eurostat nor ISTAT directly provide real (inflation-adjusted) GDP series at the provincial level. The use of regional deflators ensures internal coherence with the European System of Accounts and allows for spatially consistent comparisons of real economic activity across provinces and over time. Administrative boundaries were then harmonized with the 2021 NUTS revision and the official ISTAT geometries, guaranteeing spatial alignment across all years. GDP per capita for each municipality and year was computed according to:

$$\text{GDP per capita}_{i,t} = \frac{\text{GDP}_{i,t}}{\text{Population}_{i,t}}, \tag{1}$$

where $\text{GDP}_{i,t}$ represents real GDP and $\text{Population}_{i,t}$ the resident population of administrative unit i in year t. As GDP data are not directly available at the municipal scale, local estimates were obtained using the FRK spatial downscaling model, which interpolates GDP values from higher administrative levels while capturing spatial dependence and heterogeneity in the economic structure.

Additionally, area-based indicators were computed to enhance spatial comparability across territories of different sizes. GDP density (GDP/Area) and population density (Population/Area) were derived using the official ISTAT territorial surface data (in m^2) (ISTAT, 2023c). These transformations allow for meaningful comparisons of economic performance and demographic concentration across heterogeneous spatial units, providing a coherent empirical foundation for the subsequent modeling of municipal-level indicators and for the construction of the Social Growth Index.

3 SGI Index Construction

The construction of the Social Growth Index (SGI) builds on the idea that a territory is resilient if it can sustain long-term growth despite exposure to external shocks—both positive (large-scale public investments under the Piano Nazionale di Ripresa e Resilienza (PNRR)), and negative (the COVID-19 pandemic). These events represent structural tests for local systems, revealing their capacity to adapt, recover, and convert temporary disturbances into lasting development trajectories.

The SGI is designed to capture this multidimensional nature of territorial resilience by integrating economic performance, demographic activity, and individual well-being within a consistent analytical framework. The index assumes that a territory can be considered resilient if it maintains or improves its capacity for growth and adaptation over time, regardless of the type of external shock it faces.

To operationalize this concept, three variables were selected that jointly describe the main dimensions of socioeconomic resilience: GDP, GDP per capita, and Population. These variables provide complementary perspectives on the functioning of local systems. GDP measures the productive capacity of an area, GDP per capita reflects the average level of prosperity experienced by residents, and Population expresses the demographic scale and potential of the local community.

GDP represents the total monetary value of goods and services produced within an economy over a specific period. It remains the most widely used indicator of economic performance, reflecting both the productive capacity and the cyclical dynamics of a system. As highlighted by the International Monetary Fund (Fund, 2020), GDP provides a comprehensive picture of aggregate output, although it does not directly measure social welfare or income distribution. The World Bank (Bank, 2022) stresses that GDP captures the scale of economic activity, serving as a benchmark for international comparisons and policy evaluation. Similarly, the Organisation for Economic Co-operation and Development (OECD) (OECD, 2014) frames GDP growth as one of the pillars of economic resilience, since regions with higher productive capacity tend to better withstand and recover from adverse shocks. In the context of resilience, GDP is therefore interpreted as an indicator of the overall functioning of the local economy, measuring the ability to generate output and sustain economic cycles despite external disturbances.

GDP per capita (GDPpc) is defined as the ratio between the total GDP of a territory and its resident population. It provides a synthetic measure of the average economic output available per inhabitant and is widely used as a proxy for the material standard of living of a community (International Monetary Fund, 2023; World Bank, 2024; Eurostat, 2023b). In practice, GDPpc allows meaningful comparisons across territories of different size, complementing total GDP (which reflects productive scale) and Population (which reflects demographic capacity). A higher GDPpc is typically associated with greater economic resources available on average to residents, and thus with higher potential levels of well-being and resilience. At the same time, GDPpc has important limitations: it does not account for income distribution, non-market activities, environmental costs, or other dimensions of quality of life (OECD, 2020). For this reason, international organizations often interpret it as one pillar of socioeconomic assessment, to be complemented by other dimensions when evaluating well-being or resilience (United Nations Development Programme, 2024).

Population measures the number of people residing in a given administrative unit. While simple in definition, it provides critical information on the demographic health and vitality of a community. Population size and dynamics are central to understanding resilience, as they influence the capacity of a territory to sustain local services, maintain labor supply, and foster social capital (OECD, 2023; United Nations, Department of Economic and Social Affairs, Population Division, 2022). In regional studies, population growth is often interpreted as a signal of attractiveness and socio-economic vitality, whereas population decline or rapid ageing pose risks to long-term resilience (OECD, 2021). In this context, a stable or expanding population base supports local service provision, intergenerational knowledge transfer, and economic adaptability. Conversely, demographic shrinkage or rapid ageing can undermine welfare sustainability, reduce market size, and exacerbate vulnerability to external shocks (UN-Habitat, 2022). Within this analytical framework, Population acts as a proxy for human capital and social potential, completing the economic dimensions of the index with a demographic perspective.

The three variables—GDP, GDP per capita, and Population—are conceptually interconnected and together define the structural balance between economic output, individual prosperity, and demographic resources. Their relationship is expressed by the fundamental identity (World Bank, 2024; Eurostat, 2023b):

$$\text{GDP} = \text{GDP per capita} \times \text{Population}. \tag{2}$$

This relationship correctly expresses the total output of an area as the product of individual productivity and the number of residents. However, when comparing administrative units of very different sizes—such as large urban areas versus small municipalities—absolute values of GDP and Population are not directly comparable, as they scale with the size of the territory. To obtain measures that allow a meaningful comparison between territories, we normalize each term of the equation by the surface area of the administrative unit (in m^2). Dividing both sides by the same quantity yields to:

$$\frac{\text{GDP}}{\text{Area}} = \text{GDP per capita} \times \frac{\text{Population}}{\text{Area}}. \tag{3}$$

We define the formal indicator GDP Density = GDP/Area. This transformation introduces three interpretable and spatially comparable indicators: (1) GDP/Area, representing the economic density or the amount of economic output generated per unit of land; (2) GDP per capita, capturing the average wealth or productivity per resident; and (3) Population/Area, indicating the population density or concentration of human capital.

Expressing the identity in area-normalized terms enables a consistent assessment of territories with heterogeneous size and structure. This ensures that differences in economic performance and demographic intensity are analyzed on a comparable spatial scale. This transformation thus provides a coherent foundation for subsequent analyses of socioeconomic resilience, which depend not only on total magnitudes but also on the spatial concentration and intensity of economic and demographic phenomena. These normalized variables form the empirical basis of the Social Growth Index, which integrates economic scale, individual prosperity, and demographic strength into a coherent and spatially consistent measure of local resilience and long-term growth potential.

After deriving spatially consistent measures of GDP density, individual wealth, and demographic concentration, the final step involves aggregating these three dimensions into a single, interpretable measure of territorial performance. To this end, the Copeland method (Saari and Merlin, 1996) is adopted, providing a transparent and non-parametric approach to synthesize multidimensional information without imposing arbitrary weights.

The Copeland method is a well-established procedure in social choice theory and multi-criteria decision analysis, designed to produce an ordinal ranking based on pairwise comparisons among units. Its main advantage lies in evaluating relative performance across multiple criteria while maintaining interpretability and robustness to scale differences.

Let $A = \{a_1, \ldots, a_n\}$ denote the set of n municipalities, each evaluated on the criteria set $L = \{l_1, l_2, l_r\}$ with size r. For each ordered pair of municipalities (a_i, a_k), we define the dominance function:

$$S(i,k) = \sum_{l \in L} \begin{cases} +1, & \text{if } a_{il} > a_{kl}, \\ 0, & \text{if } a_{il} = a_{kl}, \\ -1, & \text{if } a_{il} < a_{kl}. \end{cases} \tag{4}$$

The resulting score $S(i, k)$ represents the number of dimensions in which municipality i outperforms municipality k. Summing across all comparisons yields the *Copeland score* for unit i:

$$C_i = \sum_{k \neq i} S(i,k), \tag{5}$$

which captures the overall dominance of municipality i within the system. Higher C_i values indicate stronger relative performance, interpreted here as higher levels of socioeconomic resilience.

The resulting copeland score, denoted as the Social Growth Index (SGI), expresses the relative socioeconomic resilience of each municipality, integrating productive capacity, individual prosperity, and demographic vitality into a unified measure.

This procedure establishes the conceptual framework for evaluating local resilience through the Social Growth Index. Yet, because official GDP data are observed only at regional and provincial levels, an additional modeling step is necessary to infer municipal-scale estimates. The following section describes the spatial downscaling process based on the Fixed Rank Kriging model, which enables the estimation of

GDP for all Italian municipalities while preserving statistical coherence across spatial hierarchies.

3.1 Fixed Rank Kriging

To investigate economic resilience at the municipal level, we perform a downscaling of GDP density data (GDP per unit area) observed at the provincial and regional levels to a municipal scale. The core of the methodology is the Fixed Rank Kriging (FRK) (Cressie and Johannesson, 2008), a hierarchical spatial mixed-effects framework designed to model multiscale and non-stationary processes of Gaussian data. Following the formulation in (Sainsbury-Dale et al., 2024), we implement a FRK model which accomodates the non-Gaussian nature of GDP density data.

Specifically, we consider as observations the GDP density values for all provinces and regions across Italy, denoted by Z_i for $i = 1, \ldots, m$, where m is the total number of observed spatial units. Since GDP densities are strictly positive, we assume that they are independent and distributed according to a Gamma, conditionally on a hidden process Y controlling their means and modeled within the FRK framework.

The process Y is constructed as a mixed effect model defined over a computational grid of n units, referred to as Basic Area Units (BAUs), covering the entire Italian spatial domain D. Let $\{\mathbf{s}_j\}_{j=1}^n$ denote the centroids of the BAUs. The process Y is then specified as

$$Y(\mathbf{s}_j) = \mathbf{t}(\mathbf{s}_j)^\top \boldsymbol{\alpha} + \nu(\mathbf{s}_j) + \xi(\mathbf{s}_j), \quad j = 1, \ldots, n, \tag{6}$$

where:

- $\mathbf{t}(\mathbf{s}_j) \in \mathbb{R}^q$ is a vector of q observed covariates at location $\mathbf{s}_j$ (e.g., population, employment, financial indicators),
- $\boldsymbol{\alpha} \in \mathbb{R}^q$ is a vector of regression coefficients to be estimated,
- $\nu(\mathbf{s}_j)$ is a zero-mean, spatially structured, random effect capturing "medium to large-scale" spatial correlation,
- $\xi(\mathbf{s}_j)$ is a zero-mean "fine-scale" error term.

Model (6) captures the fixed effects of known predictors by means of the term $\mathbf{t}(\cdot)^\top \boldsymbol{\alpha}$ while the residual spatial heterogeneity, which cannot be explained through the covariates, is represented by the combined process $\nu(\cdot) + \xi(\cdot)$.

To model $(\nu(\mathbf{s}_1), ..., \nu(\mathbf{s}_n))^\top$ we use a Spatial Random Effects (SRE) representation:

$$\nu(\mathbf{s}_j) = \boldsymbol{\Phi}(\mathbf{s}_j)^\top \boldsymbol{\eta} = \sum_{\ell=1}^{r} \phi_\ell(\mathbf{s}_j)\, \eta_\ell, \quad j = 1, \ldots, n,$$

where $\boldsymbol{\eta} = (\eta_1, \ldots, \eta_r)^\top$ is a zero-mean Gaussian random vector whose precision matrix $Q \in \mathbb{R}^{r \times r}$ has *fixed rank*, and $\boldsymbol{\Phi}(\cdot) = (\phi_1(\cdot), \ldots, \phi_r(\cdot))^\top$ denotes a set of predefined spatial basis functions defined on D. In this work, we select a Gaussian basis system spanning two spatial resolutions, enabling the model to better capture multiscale structure and nonstationary spatial variation. Moreover, as in (Sainsbury-Dale et al., 2024), the precision matrix Q is sparsely parametrized and block-diagonal so that coefficients of basis functions belonging to different levels are independent. Finally, we assume the fine-scale errors $\xi(\mathbf{s}_1), ..., \xi(\mathbf{s}_n)$ to be independent and identically distributed Gaussian with zero mean and variance σ^2_ξ; moreover these errors are independent of $(\nu(\mathbf{s}_1), ..., \nu(\mathbf{s}_n))^\top$.

Let $\mathbf{\Phi}$ denote the matrix of basis functions $\mathbf{\Phi}(\cdot) = (\phi_1(\cdot), \dots, \phi_r(\cdot))^\top$ evaluated at locations $\{\mathbf{s}_j\}_{j=1}^n$ of the BAUs. The variance-covariance matrix of $(Y(\mathbf{s}_1), ..., Y(\mathbf{s}_n))^\top$ is thus:

$$\mathbf{\Phi}^\top Q^{-1}\mathbf{\Phi} + \sigma^2_\xi I.$$

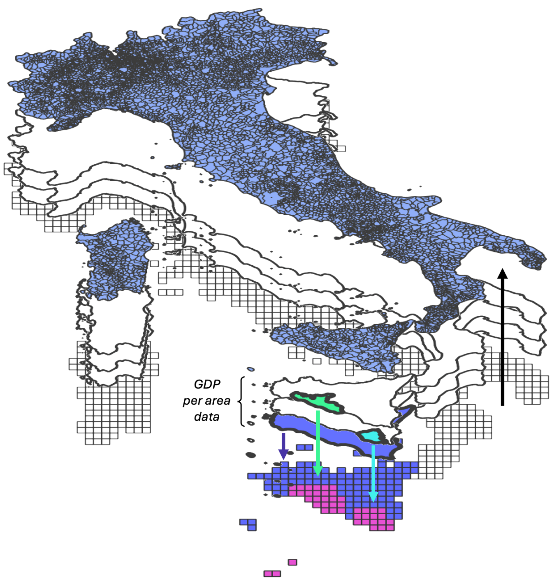


Fig. 1: The diagram illustrates the hierarchical structure of the Fixed Rank Kriging framework. The lowest level consists of the computational grid of Basic Areal Units (BAUs). The intermediate layers shows the heterogeneous observational supports, or footprints; for example, the case of the Sicily region highlights how provincial and regional data may overlap. The uppermost layer corresponds to the prediction support, here represented by municipalities.

We now define the mean process $\boldsymbol{\mu} = (\mu(\mathbf{s}_1), ..., \mu(\mathbf{s}_n))^\top$ of the GDP densities evaluated at the level of the BAUs, by setting

$$g(\mu(\mathbf{s}_j)) = Y(\mathbf{s}_j),\ j = 1, ..., n$$

where the link function g is set to be the logarithm. Let $\boldsymbol{\mu}_Z = (\mu_{Z_1}, ..., \mu_{Z_m})^\top$ denote the vector obtained by aggregating the BAU means $\mu(\mathbf{s}_1), ..., \mu(\mathbf{s}_n)$ at the level of the m observed units (i.e., provinces and regions); in fact, define $C_Z \in \mathbb{R}^{m\times n}$ to be the linear operator (a non-random matrix) mapping $\boldsymbol{\mu}$ to $\boldsymbol{\mu}_Z$, whose entries are such that BAUs are aggregated consistently with the administrative geometry.

The model is completed by assuming that, given the latent $\boldsymbol{\mu}$ spatial process, the observations Z_i's are conditionally independent, each Z_i being conditionally distributed according to a Gamma with rate parameter ψ, shape parameter $\psi * \mu_{Z_i}$, and therefore mean μ_{Z_i}.

Thus, the model becomes:

$$
\begin{gathered}
g(\mu(\boldsymbol{s}_j)) = \mathbf{t}(\mathbf{s}_j)^\top \boldsymbol{\alpha} + \boldsymbol{\Phi}(\mathbf{s}_j)^\top \boldsymbol{\eta} + \xi(\mathbf{s}_j), \quad j = 1, \dots, n, \\
\boldsymbol{\eta} \sim \mathrm{N}_r(\mathbf{0}, Q^{-1}) \\
\xi(\mathbf{s}_1), ..., \xi(\mathbf{s}_n) \sim^{i.i.d.} \mathrm{N}_1(0, \sigma_\xi^2) \\
\boldsymbol{\mu}_Z = C_Z \boldsymbol{\mu} \\
Z_i | \boldsymbol{\mu}_Z \sim \mathrm{Gamma}(\psi * \mu_{Z_i}, \psi) \quad i = 1, \dots, m
\end{gathered}
\tag{7}
$$

The resulting unknown parameters, to be estimated using the methods and the algorithms provided in (Sainsbury-Dale et al., 2024), are $\boldsymbol{\theta} = (\boldsymbol{\alpha}^\top, Q, \sigma_\xi^2, \psi)^\top$, which determine the fixed effects, the covariance of the vector $\boldsymbol{\eta}$, and the variance of the $\xi(\mathbf{s}_j)$'s.

Let us finally conclude this section by stressing how the FRK model described in (7) embodies the hierarchical structure of spatial levels illustrated in Figure 1 and briefly summarized below:

1. Observed data layers: corresponds to the areal GDP density data, possibly characterized by heterogeneous and overlapping supports across multiple administrative levels. In the FRK terminology these are called *footprints*;
2. Computational grid layer: consists of the Basic Areal Units. This layer represents the highest-resolution grid, where the latent spatial process controlling the means of GDP densities is defined. Indeed, this process is hidden and cannot be directly observed, as both data and covariates are aggregated over the coarser lattice of administrative units;
3. Prediction layer: corresponds to the set of municipalities, where predictions are obtained by integrating the means of GDP densities estimated on the BAUs.

In the next Section, we incorporate the FRK algorithm depicted above in (3.1) into the general framework for constructing municipal indicators, applying it to the dataset presented in Section 2.

4 Results

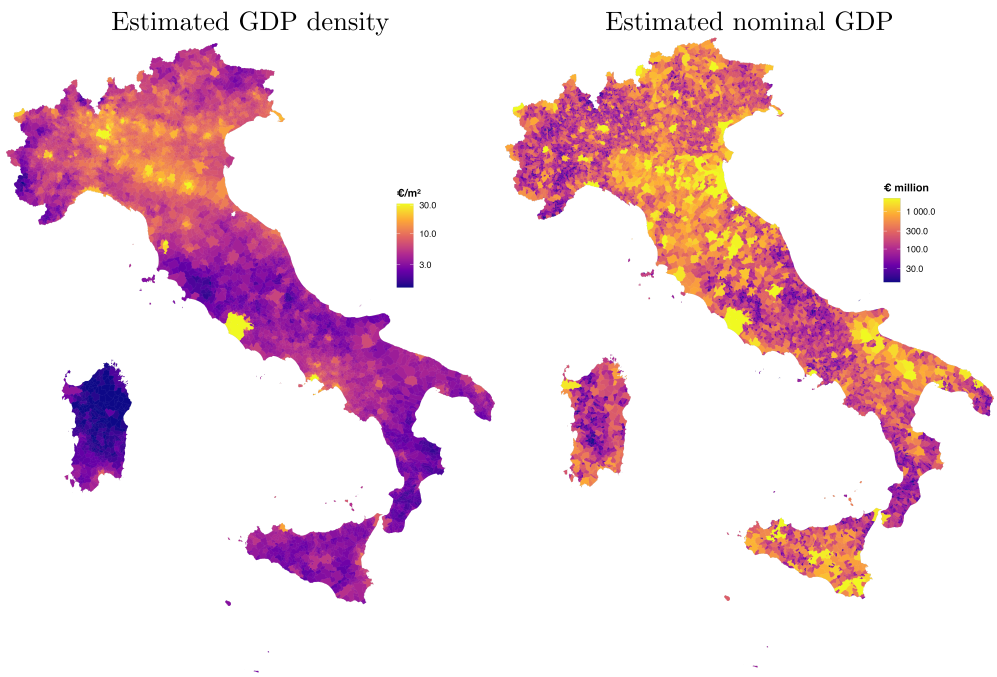
We apply the Fixed Rank Kriging methodology described in the previous section to downscale the spatial indicator GDP Density defined in (3), by exploiting spatial multiscale dependence. Our dataset is constituted by province-level GDP data as observed values and municipality-level covariates as predictors. The selected covariates are: (i) Population size (ISTAT), representing the total number of residents in each municipality; and (ii) Income per capita (MEF), defined as the ratio between the total declared income of residents and the number of taxpayers within each municipality.[1] Both covariates are available at the municipal level for the entire period of analysis and were selected for their economic relevance, interpretability, and spatial completeness. The correlation between the two predictors decreases over time, ranging from 0.258 in 2010 to 0.195 in 2022, suggesting that they capture complementary aspects of local socioeconomic structure.

The choice of FRK is motivated not only by its computational tractability but also by its ability to represent the spatial dependence structure typical of socioeconomic phenomena. The spatial smoothing inherent in FRK enables the reconstruction of unobserved GDP values at the municipal level in a principled manner, informed by neighbouring areas and by the selected covariates. This step bridges the data gap between observed provincial GDP and the finer municipal scale, providing spatially coherent and economically interpretable estimates that form the empirical basis of the SGI. The FRK model yields continuous spatial predictions of GDP density as defined in (3) (i.e., GDP per unit of surface area), capturing the underlying productive intensity across the territory. The nominal GDP of each municipality is subsequently obtained by multiplying the predicted density values by the corresponding municipal surface area.

In our analysis, we employ a computational grid of $n = 13{,}170$ Basic Areal Units (BAUs) with a 5 km cell size and 81 Gaussian-shaped basis functions distributed over two resolution levels. The simulations are performed in R using the package FRK v2 (Zammit-Mangion and Cressie, 2021), specifically designed for handling non-Gaussian data (Sainsbury-Dale et al., 2024).

Figures 2a and 2b display, respectively, the spatial distribution of FRK-estimated GDP density (GDP per m^2) and nominal GDP for the reference year 2022. The spatial pattern of GDP density reveals pronounced territorial heterogeneity: the highest values are concentrated in major metropolitan and industrial areas—such as Milan, Turin, Bologna, and Rome—while peripheral and inner regions exhibit markedly lower levels. The nominal GDP distribution follows a similar gradient, confirming the internal coherence between extensive (total GDP) and intensive (GDP per m^2) measures of economic activity.

[1] According to the Italian Ministry of Economy and Finance (MEF — Dipartimento delle Finanze), income per capita corresponds to the average taxable income per resident taxpayer, derived from annual income tax declarations (Modello Unico, 730, Certificazione Unica).



(a) GDP density (GDP per m^2). (b) Nominal GDP (million €).

Fig. 2: Spatial distribution of FRK-estimated GDP density and nominal GDP at the municipal level (year 2022).

The two indicators convey complementary perspectives: nominal GDP reflects the overall economic scale and is naturally higher in large urban centers such as Milan, Rome, Turin, Bologna, and Naples; in contrast, GDP density highlights the intensity of production relative to land area, revealing how smaller municipalities surrounding major cities—particularly around Milan, Bologna, and Florence—often display high productivity per unit of land despite lower aggregate GDP levels. This contrast underscores the different spatial meanings of the two indicators and anticipates their role within the SGI framework: GDP density will be used directly as one of the key variables, while nominal GDP will serve as the basis for computing GDP per capita, thus linking economic and demographic dimensions of resilience.

Building on the conceptual framework introduced in Section 3, we compute the SGI of each Italian municipality as its rank position in the ordering derived from the Copeland scores. Municipalities are compared according to the criteria $L = \{\text{GDP density, GDP per capita, Population density}\}$; see (4).

The Copeland method is a transparent and non-parametric procedure widely used in multi-criteria analysis. In our setting, the Copeland score is computed with respect to the joint set of criteria L. Lower Copeland scores identify municipalities with lower resilience, whereas higher scores denote progressively better resilience conditions. The resulting SGI therefore provides a synthetic and interpretable representation of the relative socioeconomic resilience of Italian municipalities.

Figure 3 illustrates the spatial distribution of the SGI for the years 2010 and 2022, highlighting a persistent territorial gradient across the Italian peninsula. As depicted in the 2010 map on the left, the highest-resilience municipalities—corresponding to the top decile of the Copeland scores distribution—were predominantly located in Northern and Central Italy, particularly across Lombardy, Emilia-Romagna, Veneto, and Tuscany, whereas Southern regions, together with parts of Sicily and inland Sardinia, exhibited systematically lower scores. The 2022 map on the right confirms the persistence of this North–South divide, although several localized improvements emerge around medium-sized urban systems and regional capitals such as Bari, Cagliari, and Catania. The continued concentration of high-SGI municipalities in Northern Italy, which constitutes the most resilient part of the country, reflects a structural and persistent territorial advantage rooted in long-standing economic and demographic conditions. At the same time, upward transitions observed in several intermediate areas indicate emerging patterns of local adaptation and recovery, particularly in territories that historically exhibited lower resilience levels, many of which are located in Southern Italy.

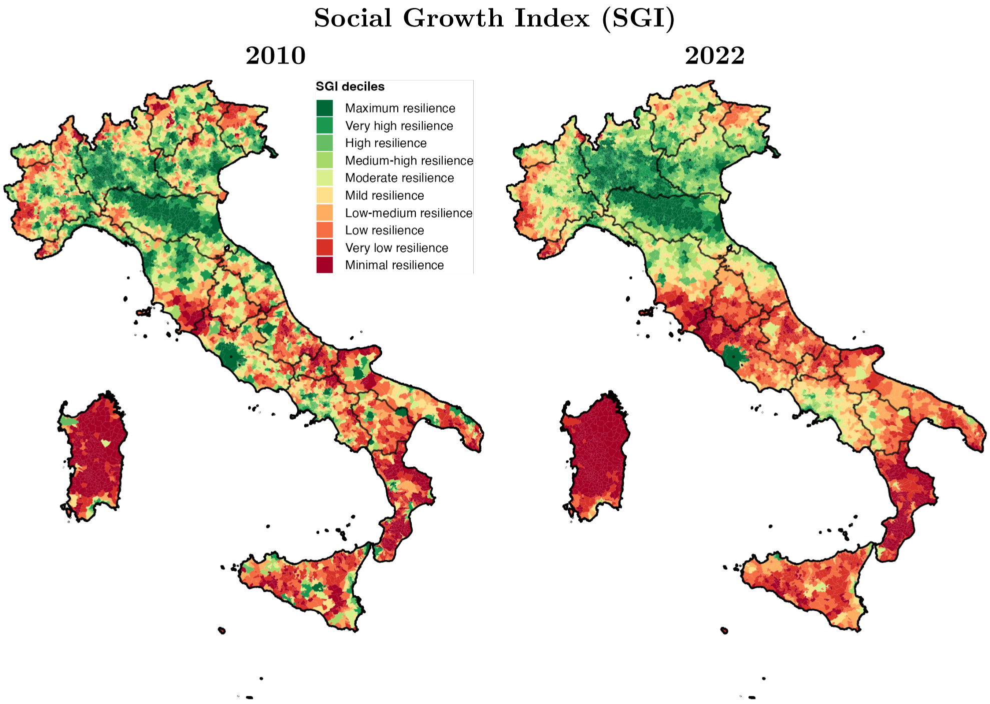


Fig. 3: Spatial distribution of the Social Growth Index (SGI) at the municipal level in 2010 (left) and 2022 (right). The indicator is displayed in deciles: darker green areas correspond to the Maximum resilienc class (top decile), while orange and red areas represent the Minimum resilience class (bottom decile). The comparison highlights the persistent North–South divide, with localized improvements emerging in selected areas of Southern Italy.

To further investigate temporal evolution, we analyze changes in the SGI and the associated spatial autocorrelation patterns. Figure 4 compares the variation in municipal SGI between 2022 and 2010 with the corresponding clusters of spatial association identified through the Local Indicator of Spatial Association (LISA) (Anselin, 1995).

We examine the difference between the SGI deciles for the years 2010 and 2022, denoted as $\Delta\text{SGI} = \text{Decile}_{2022} - \text{Decile}_{2010}$. The spatial distribution of ΔSGI exhibits a clear regional pattern. Several municipalities in Northern Italy, particularly in the North-East and parts of Emilia–Romagna, record improvements in their SGI decile (green areas), while many municipalities in Central and Southern Italy display declines (red areas), consistent with long-standing structural vulnerabilities. Local gains are nonetheless visible around selected regional capitals and coastal areas of Apulia, Calabria, and Sicily, suggesting processes of targeted economic and demographic adjustment.

The LISA clusters confirm that these variations are spatially structured rather than random. Low–Low clusters identify groups of municipalities jointly experiencing significant declines in SGI, while High–High clusters correspond to areas where improvements are spatially concentrated. High–Low and Low–High configurations capture spatial outliers whose local trajectories diverge from those of the surrounding municipalities. Overall, the evidence suggests that resilience dynamics in Italy evolve through interconnected spatial systems rather than isolated municipal changes.

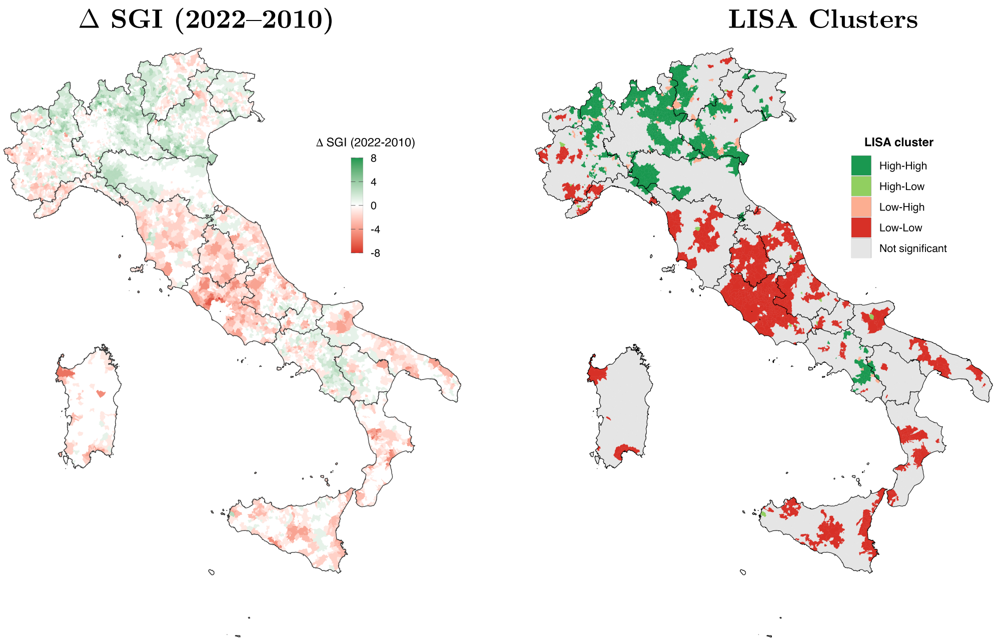


Fig. 4: Spatial variation and local spatial autocorrelation of the Social Growth Index (SGI) at the municipal level. The left panel reports the change in SGI deciles between 2010 and 2022 (ΔSGI), where red shades indicate a shift toward lower resilience deciles (worsening conditions) and green shades denote movement toward higher resilience deciles (improvement). The right panel displays the corresponding LISA clusters of spatial association (Anselin, 1995). Low–Low clusters identify neighbouring municipalities jointly experiencing significant declines in resilience, while High–High clusters highlight areas of shared improvement. High–Low and Low–High configurations indicate spatial outliers, where local dynamics differ from those of surrounding municipalities.

4.1 Comparison with the Municipal Fragility Index (IFC)

To assess the interpretative consistency of the SGI, we compare it with the Municipal Fragility Index (IFC) developed by ISTAT, which is available for the years 2018, 2019, and 2021. Figure 5 displays the decile maps of both SGI and IFC, with more resilient areas represented in green and more fragile areas in red.

The IFC measures municipal fragility: higher values indicate higher fragility, and the index is provided in deciles. The first decile, which includes the lowest 10% of IFC values, corresponds to the municipalities that are least fragile, shown in dark green in Figure 5. Conversely, the SGI is a measure of resilience: higher SGI values indicate higher municipal resilience. For comparability, we also use a decile representation. In this case, the first decile, which includes the lowest 10% of SGI values, identifies the least resilient municipalities, highlighted in dark red in Figure 5.

Taken together, the two indices offer complementary perspectives on territorial conditions. The SGI captures the intensity and balance of local economic and demographic structures, whereas the IFC reflects structural vulnerabilities and socio-demographic weaknesses. A consistent spatial pattern emerges from the comparison.

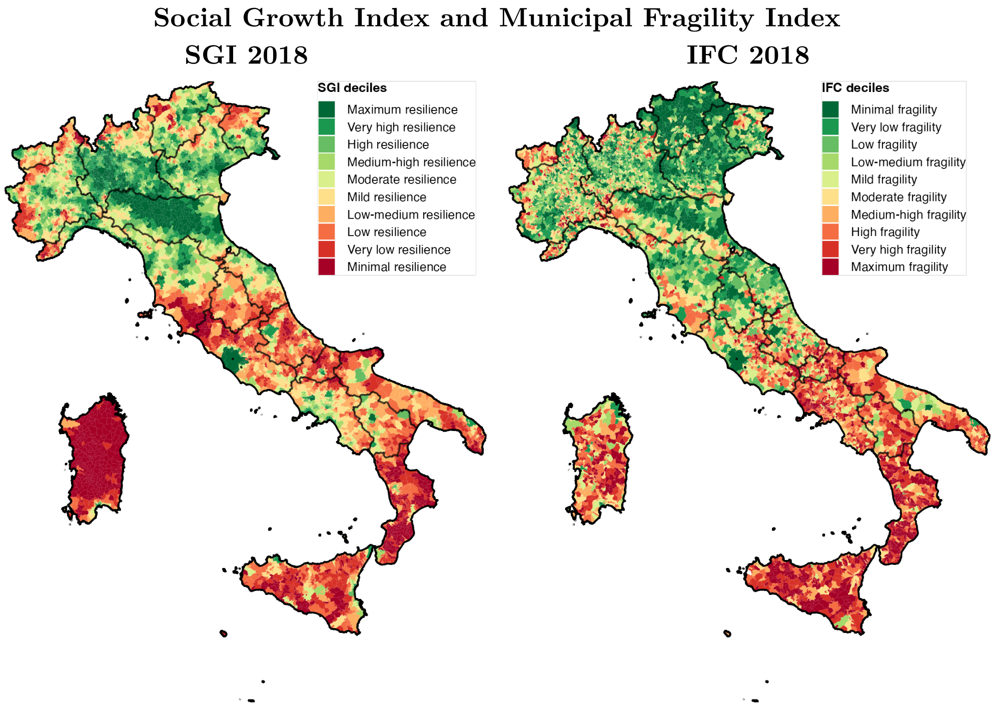


Fig. 5: Spatial comparison between SGI and IFC for 2018. Northern and Central Italy exhibit higher resilience, whereas Southern regions display lower resilience.

Indeed, the spatial comparison highlights a strong concordance between the SGI and IFC representations of Italian territorial conditions. Both measures consistently identify the same macro-patterns: municipalities in Lombardy, Emilia–Romagna, and Veneto show the highest resilience levels, while Southern regions, inland Sardinia, and parts of Sicily display lower resilience. These results confirm the persistence of long-standing socio-economic disparities across Italian territories.

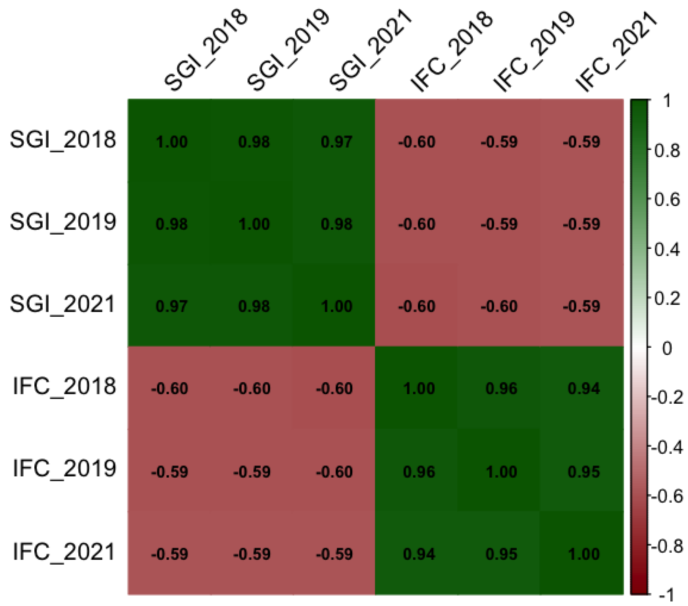


Fig. 6: Correlation matrix between the SGI deciles and the IFC deciles for the years 2018–2021. The IFC series is available only for 2018, 2019, and 2021. The highlighted block shows the cross-index correlation ($r \approx -0.6$), indicating a significant negative relationship between the two measures of resilience.

The correlation matrix in Figure 6, derived from decile values for both SGI and IFC, further supports the agreement between the two indices. Both indices exhibit strong temporal stability, with intra-index correlations exceeding 0.9. Moreover, consistent cross-index correlations emerge. When computing correlations across deciles, values around -0.6 are obtained, as expected given that the SGI measures resilience and the IFC measures fragility. All pairwise correlations are significant at the 0.001 level, confirming that the observed associations are robust and unlikely to occur by chance.

Overall, these findings indicate that the SGI provides a coherent and synergic representation of territorial well-being within the Italian context.

5 Discussion and Conclusions

This study introduced an integrated framework for assessing socioeconomic resilience at the municipal level across Italy, combining spatial statistical modeling with multi-criteria aggregation methods. The proposed approach leverage on Fixed Rank Kriging, used for the spatial downscaling of GDP, and the Copeland ranking method, to synthesize multiple indicators into a coherent and interpretable ordinal measure. Through this integration, the study addresses one of the main challenges in resilience analysis—namely, the lack of harmonized, fine-grained data capable of reflecting both spatial dependence and multidimensional socioeconomic structures. The resulting Social Growth Index (SGI) provides a synthetic, spatially consistent representation of territorial resilience, capturing how economic performance, demographic vitality, and individual prosperity jointly contribute to a territory's capacity to adapt and sustain growth over time. By leveraging FRK's ability to infer local economic patterns from aggregated data and Copeland's transparent ranking mechanism, the SGI establishes a reproducible and policy-relevant framework for comparing resilience across municipalities and tracking its evolution within broader regional systems.

The results revealed a persistent spatial divide in resilience across Italy. Northern and Central municipalities consistently exhibit higher SGI scores, reflecting diversified and productive economies, whereas Southern regions, parts of Sicily, and inland Sardinia remain characterized by lower resilience levels. Temporal comparisons between 2010 and 2022 confirmed both the structural persistence of resilient urban and industrial areas and localized improvements around regional capitals and medium-sized urban systems.

The comparison with the Municipal Fragility Index IFC supported the ability of SGI to depict municipalities resilience. Spatial maps and correlation analysis showed how SGI is a parsimonious yet capable measure of territorial well-being. Whereas the IFC emphasizes vulnerability and socio-demographic weakness, the SGI highlights local economic and demographic strengths, providing a forward-looking measure of growth potential and adaptive capacity. Moreover, unlike the IFC—which is currently available only for three cross-sections (2018, 2019, and 2021)—the SGI can be computed for the entire 2010–2022 period at the municipal level. Its construction relies exclusively on harmonized variables (GDP, GDP per capita, and population) that are systematically released by Eurostat and ISTAT, making the index replicable and easily extendable to other spatial contexts. In principle, the same methodological framework could be applied to the European scale, using Eurostat regional accounts (GDP at NUTS-2 and NUTS-3 levels) as the upper-layer observations for downscaling and local resilience assessment.

Despite its robustness and reproducibility, the proposed framework presents some notable limitations. The main constraint lies in the ordinal nature of the SGI: in fact, it allows for consistent comparisons of positions between territories and years, but not for the direct measurement of how much resilience changes over time in absolute terms. This limits the possibility of quantifying temporal variations in resilience intensity and of expressing them as pure numerical differences.

Moreover, while the spatial disaggregation of GDP through FRK improves the territorial granularity of economic information, it currently relies on year-by-year estimations. Future developments could extend this approach toward a spatio-temporal FRK model, allowing for the joint estimation of GDP across both space and time and a more coherent reconstruction of resilience trajectories.

Overall, the Social Growth Index provides a robust and interpretable framework for monitoring territorial resilience, bridging economic and demographic dimensions within a unified spatial model. Its consistency with national fragility measures suggests that the SGI can serve as a valuable complement for public policy evaluation, regional planning, and the allocation of development resources. Further research will integrate additional drivers, such as employment, innovation, or environmental sustainability, and explore advanced frameworks to enhance the temporal consistency and interpretability of resilience assessments.

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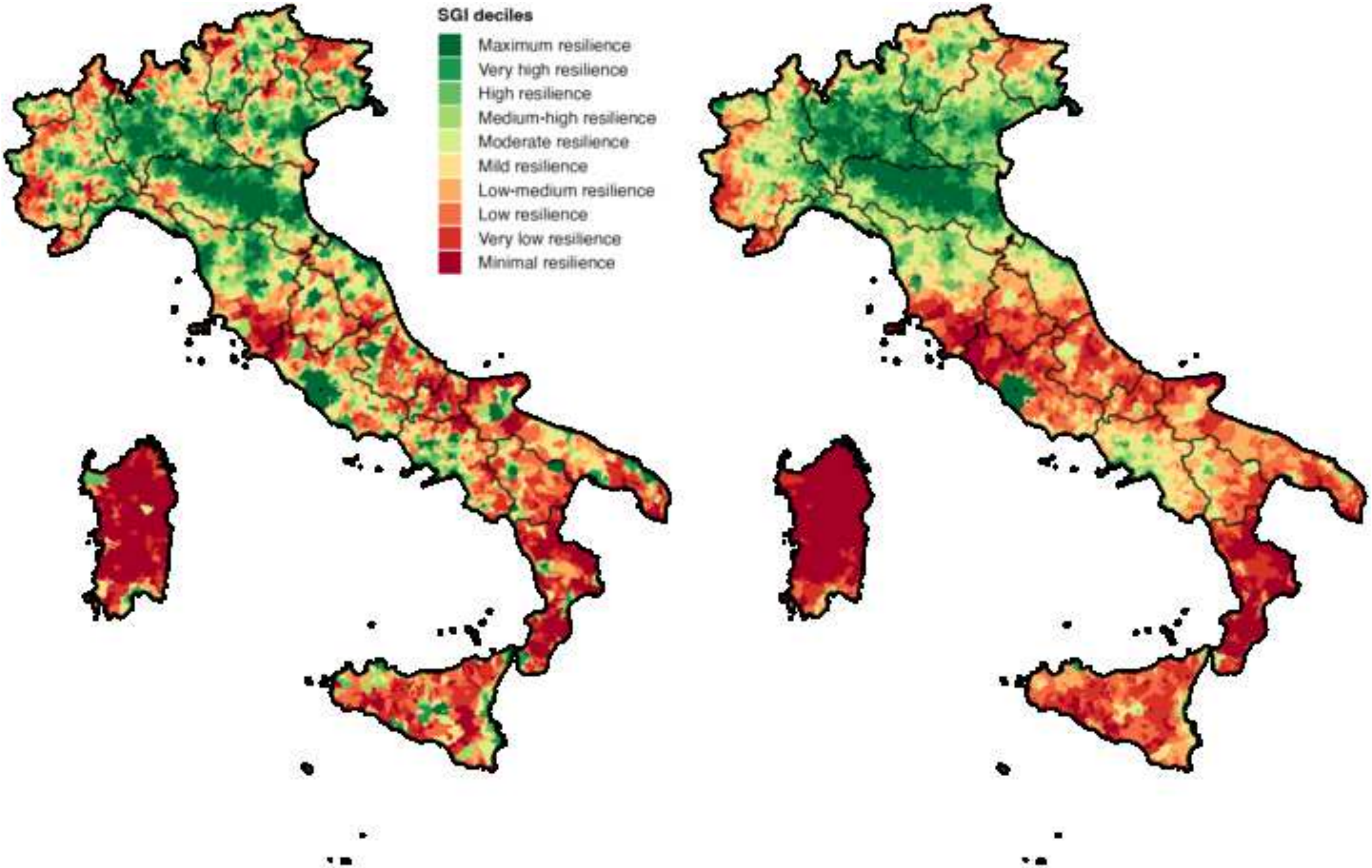

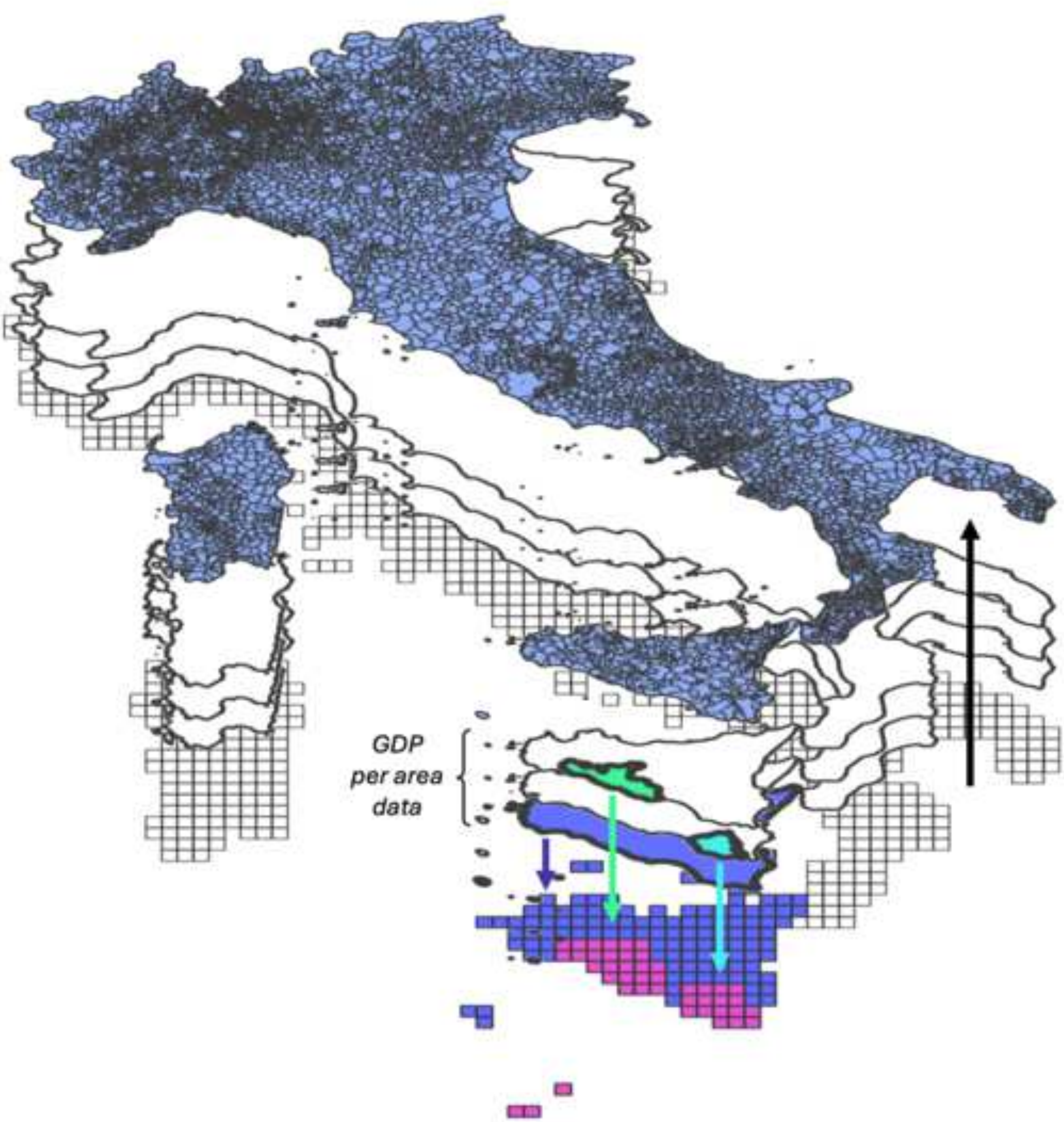
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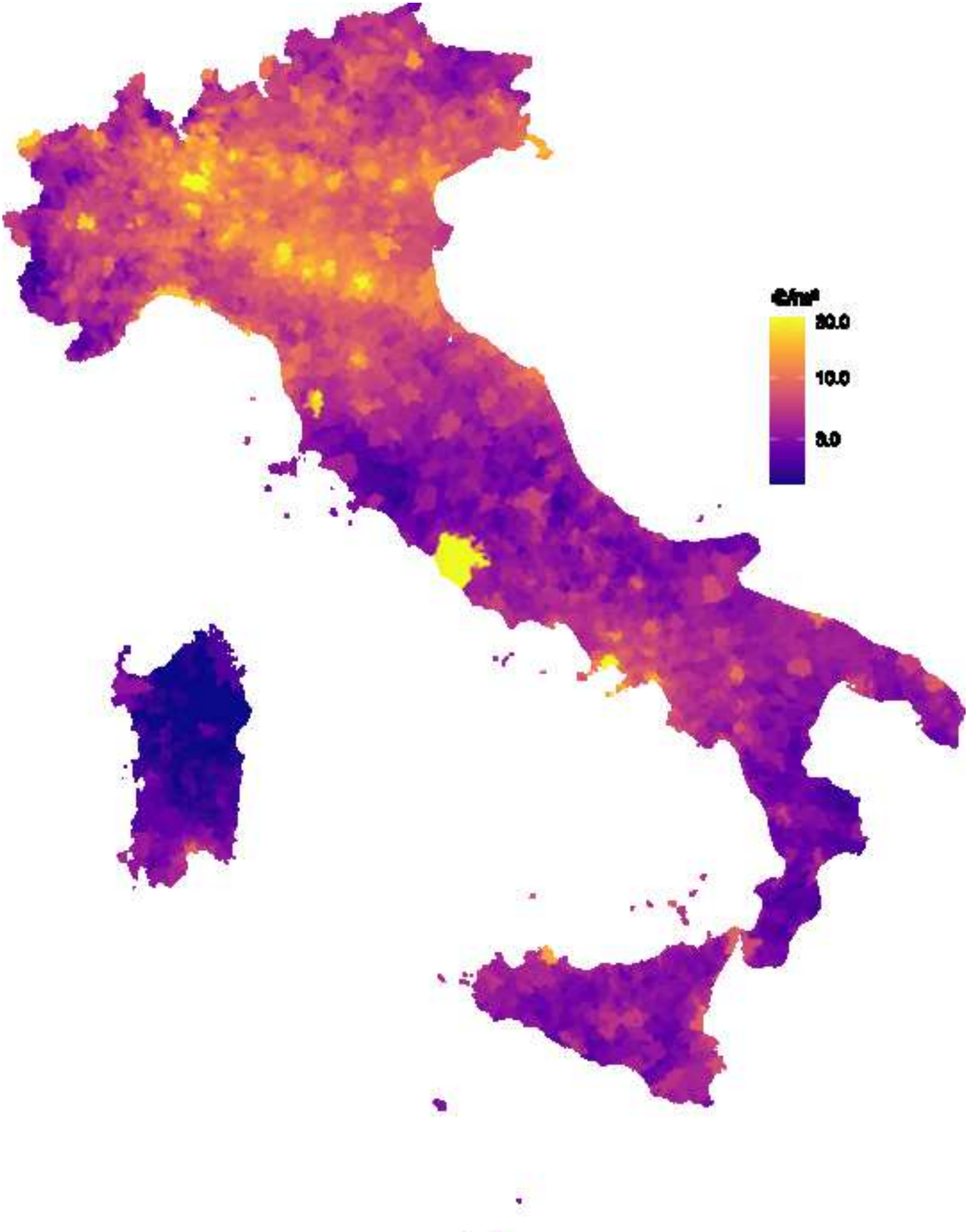

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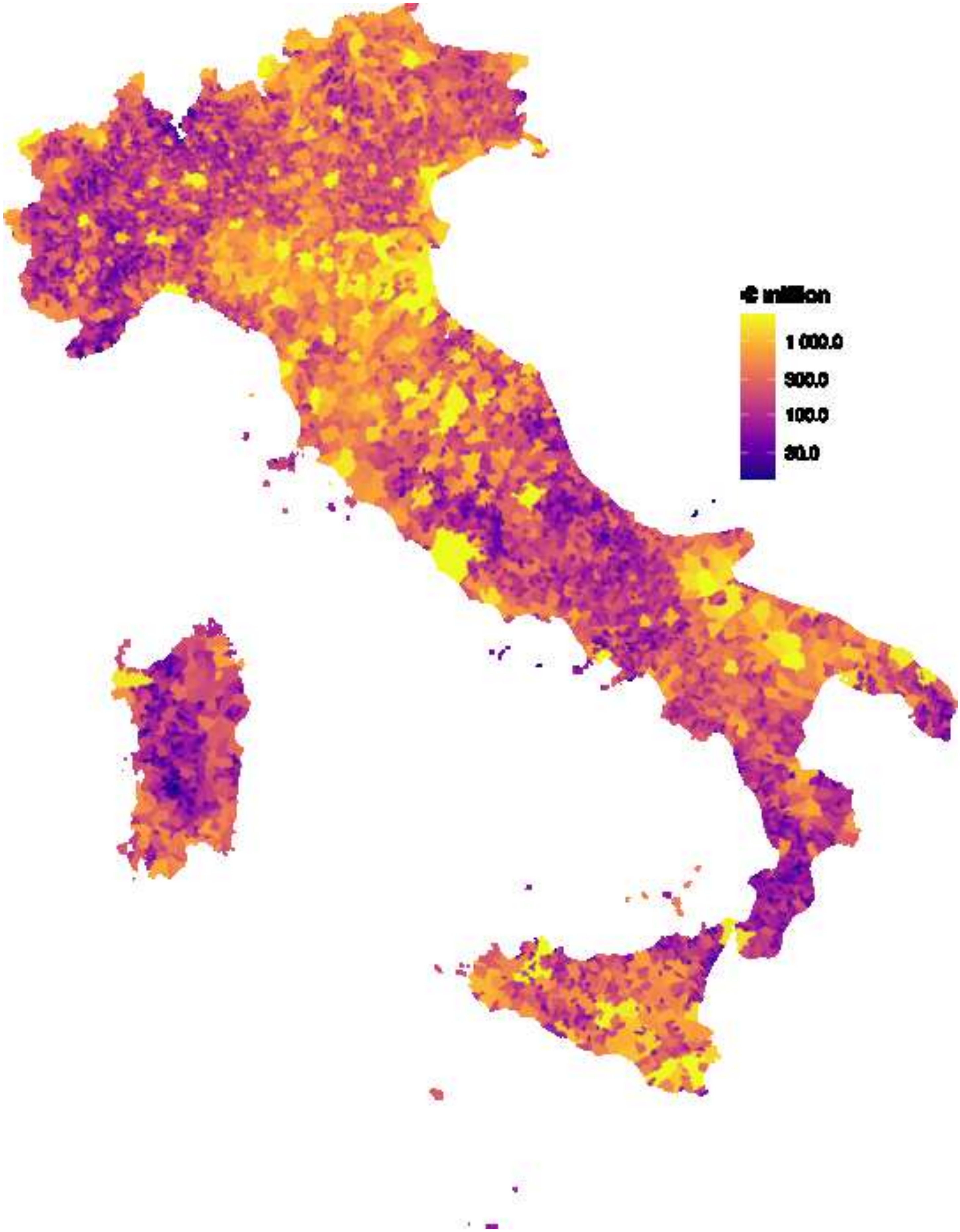

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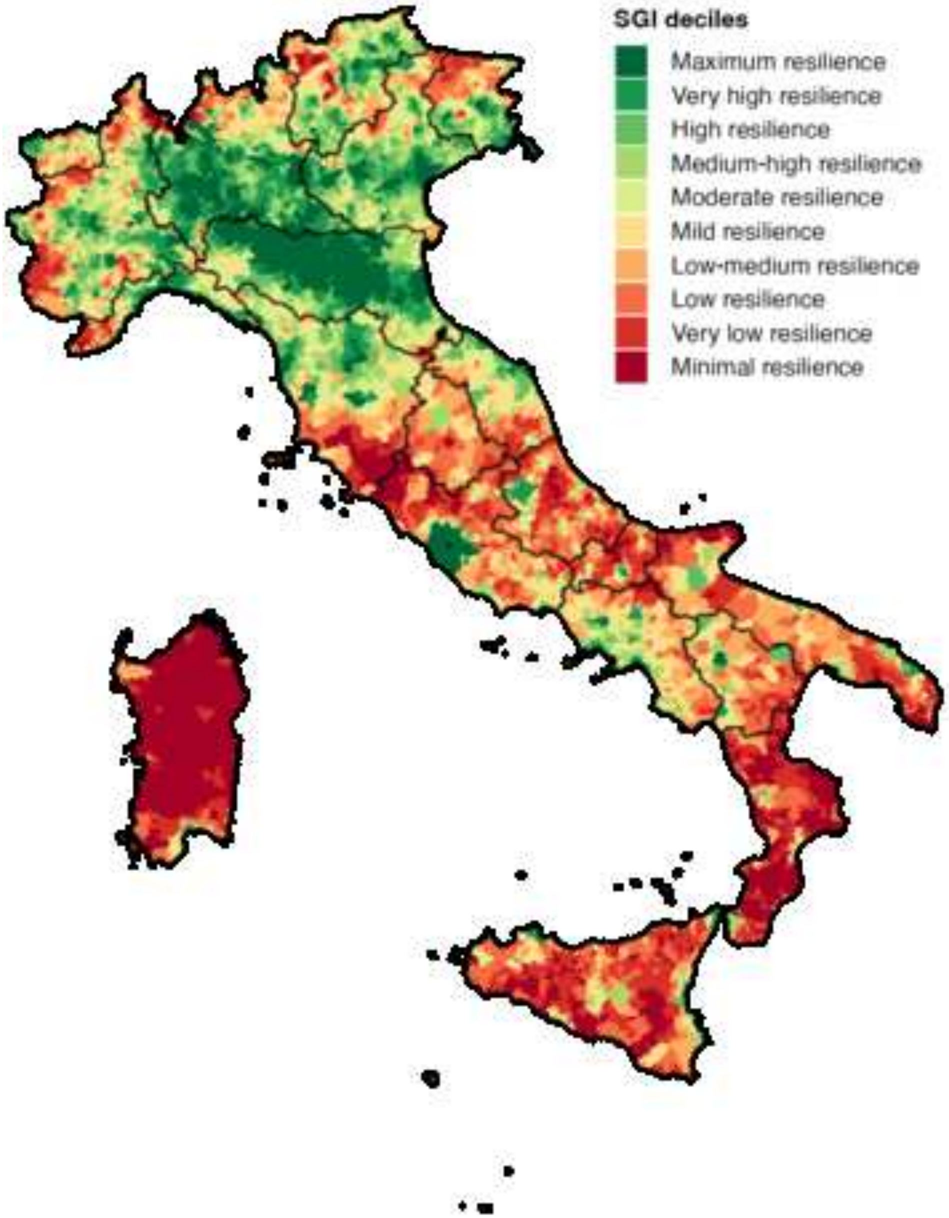

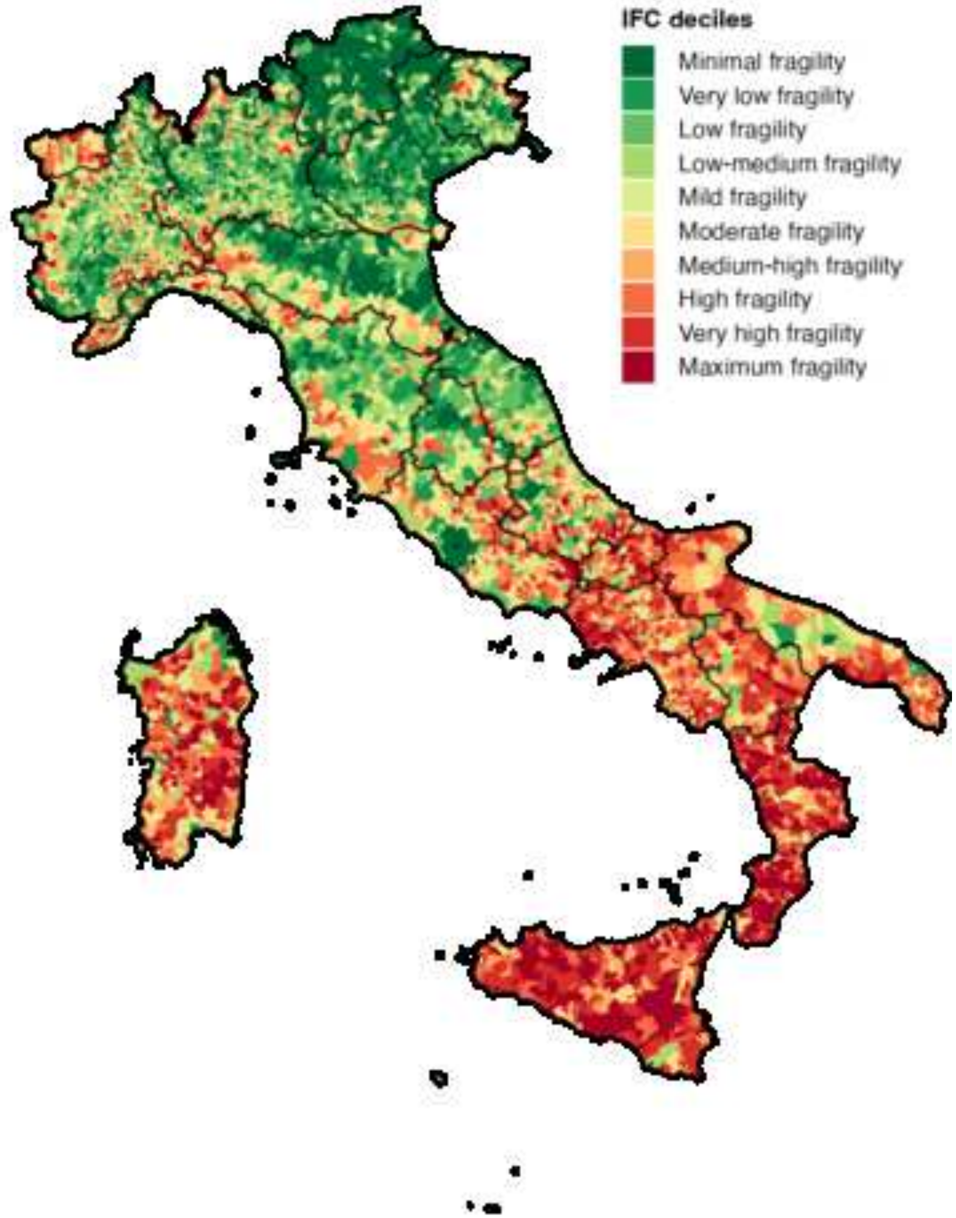

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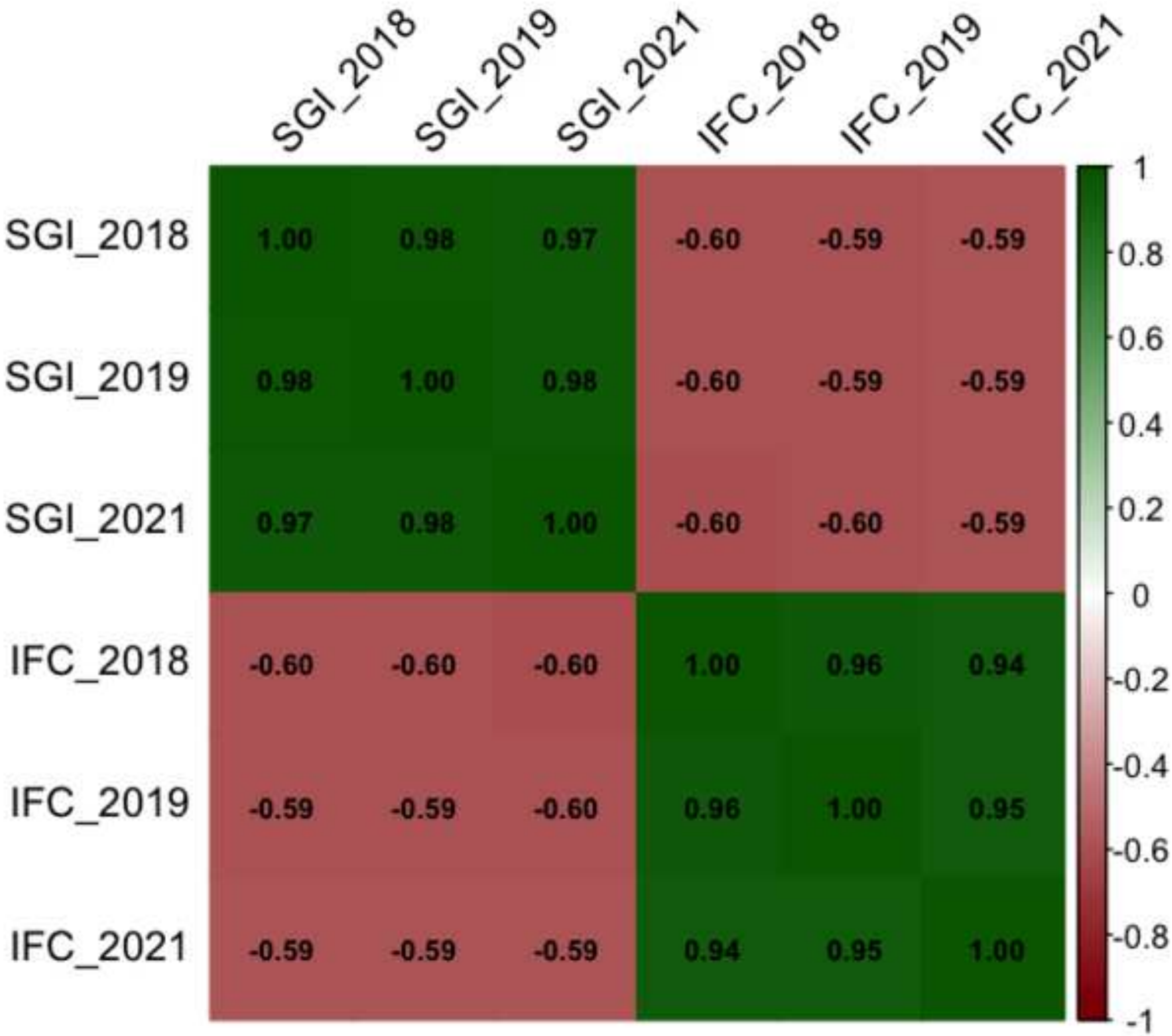

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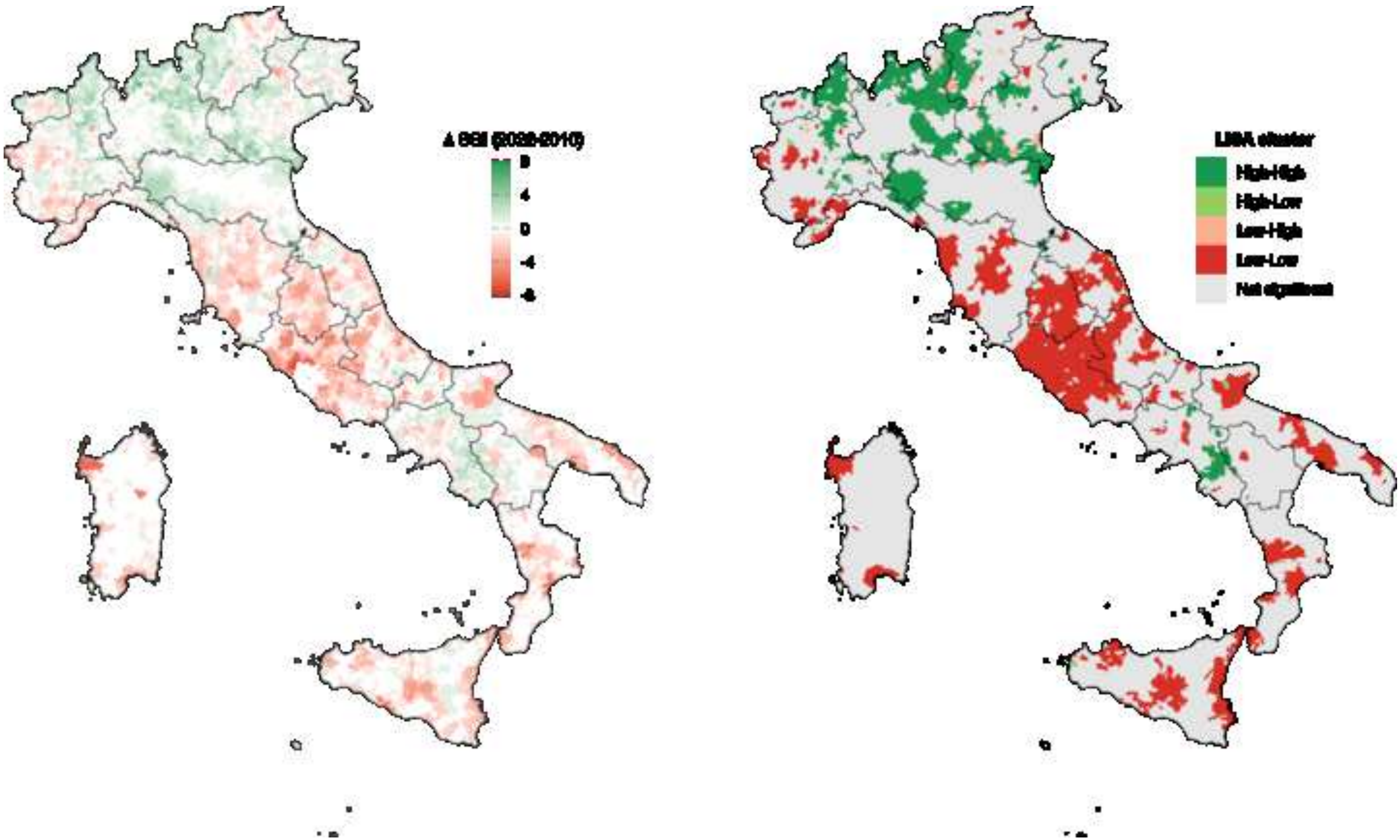

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