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NEW CHALLENGES FOR XXI CENTURY CITIES

Global warming, ageing of population, reduction of energy consumption, immigration flows, optimization of land use, technological innovation

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The cover image shows older people climbing Via Raffaele Morghen's stairs in Naples (Source: TeMA Journal Editorial Staff).

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Spatial attractiveness towards industrial placement: a parametric index based on spatial-economic territorial exposure metrics

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Abstract

The asymmetrical process of industrial development tends to increase regional disparities and result in different patterns of territorial exposure: the amount of support given to activities placed within industrial agglomerates. Spatial Attractiveness towards industrial placement tends to follow such patterns, as places with lower exposure tend to be more attractive, providing more support to productive activities. Spatial models based in economic methods have issues in precising the nature of Spatial Attractiveness disparities, as their interpretation of space as an abstracted parameter, provides insufficient locational precision to demonstrate these patterns and how those are dependent on relations between production, territorial endowments, and industrial agglomerates' internal organization. Novel spatial-economic models ought to consider and incorporate spatial units reflecting the microfoundations of space while providing an accurate spatialization, crucial aspects to create knowledge useful for decision-making. Hence, the paper showcases spatial models tailored to address the differences in Spatial Attractiveness, based in spatial and economic territorial exposure indexes, to unveil the territorial-imbalances' spatial logics. Organized in a GIS-based environment and using Tuscany as a proof-of-concept, the index-models identified factors of sensitivity or support to firms placed within industrial agglomerates providing an overview of spatial attractiveness within the territory, useful for supporting decision-making practices.

Keywords

Territorial disparities; Spatial attractiveness; Territorial exposure; Urban and regional planning; Industry

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1. Introduction

Urban-regional spaces have industrial areas as one of their fundamental substructures. It is within these spaces of production that the values destined to sustain and reproduce urban economies, the commercial exchanges, and several other services related to city-life, are created (Lefèbvre, 1974). Upon this assumption, it is logical to associate industrial growth or decline to the development or retrogression of other urban functions, such as residential or retail spaces, in a manner that defines these industrial areas as the real and proper drivers of modern-era urban-regional development (Lefèbrve, 1966; 1974).

From this perspective, the industrial agglomerates location within urban-regional territories possess a recursive role regarding their spatial organization: the industrial activities will locate themselves near or within important market and consumption nodes – the cities – and their development will have an influence on the successive industrial agglomeration, conducing to their further growth; plus this expansion will also influence the public policies of investment in infrastructure, resulting in circular and reiterative relationships of growth between cities and industry. Even though desired from a developmental standpoint, these iterations in urban-regional growth also tend to increase the territorial disparities. The asymmetrical regional development patterns may lead to a condition of underuse or straight forward abandonment of potentially productive spaces, that can result in urban-regional environments' exposition to grave socio-economic pressures, such as unemployment and populational decline (Smith, 2008).

While this interdependence between spatial location and development was quite discussed since the Regional Economics introduction as a rationale in the late 19th century, economists' analytical efforts in that matter have been rather restricted to identifying of what is where – and why? at macro-territorial scales; in comparative evaluations of the microeconomic factors regarding costs, production and growth (Weber, 1909; Christaller, 1933; Alonso, 1964; Mills, 1987; Duranton et al., 2015). In that aspect, regional economics maintained a rather unchanging approach – to both theory and space – throughout the 1900-1970 period, firmly based on mainstream economics and its neoclassical theory principles.

The predominance of such overviews, and the historical detachment among economic-based and territorial-geographic-based studies, were in the background of a heated debate regarding the flaws and limitations of the neoclassical synthesis approach (Sraffa, 1925; 1926; 1960; Samuelson, 1947; 1966; Solow, 1956; Lucas, 1976; Pasinetti, 2000). These issues were deemed structural for economics, challenging its very foundations in the period between crisis (1970-1990), enclosing the science in itself, and resulting in limited methodological developments for its marginal fields founded in neoclassical principles, such as regional economics. Hence, few spatial-economic analyses incorporated methods that can describe spaces with sufficient detail, or how the disparities in territorial endowments can affect economic activities placement. In economics, space is more than often defined and interpreted as an abstracted background – or a region that is homogeneous in its innermost territorial characteristics yet, that is assumed to have different economic characteristics from other regions (Altafini & Cutini, 2021; Altafini, 2022).

This abstracted spatial representation of territories can be identified as one of the causes for the discontinuities in spatial-economic models' progress and the production of spatial knowledge in spatial economics and its related fields; present even when the most recent approaches from New Economic Geography are considered (Krugman et al., 1999; Duranton et al., 2015; Altafini, 2022). Paul Krugman (1991) states that this seems to arise from the apparent "neglect" of these branches by mainstream economics – a conclusion which concurs with the hypothesis of a *crisis* in economic thought, following the initial *neoclassical synthesis* consensus. In other hand, Jacques-François Thisse (1998), argue that the economists regarded space – in reality, the territorial characteristics within a region – as intractable in their economic models, given a limitation on spatial-economic methodologies. In that regard, comparative models with limited territorial detail – such as locational quotients (shift-share models) – are still revered, being used on most regional analysis; those, however, tend to ignore the actual territorial setting in which economic activities exist, not because these are considered unimportant, but simply because they are unable to consider it (Thisse, 1998; Altafini, 2022). This issue, associated to economics' reluctance in the adoption of novel instruments and computational methods that interpret space at a greater level of detail – as those developed for Geography, Architecture and Urban and Regional Planning, has left fundamentally unexplored several spatial-economic relations among production systems, the importance of spatial configuration of infrastructural networks, and the organization of economic activities and industrial agglomerates at local scales.

Awareness of these limitations and issues on the current regional economics – and even in Contemporary takes on Economic Geography (Boschma, 2005; 2015), which partakes in the same problems – ought to conduce to novel models capable to assess the complex spatial behaviours and the territorial disparities within industrial agglomerates placed on urban-regional settings. It is necessary then to consider the infrastructural dimensions of space, a transformation that also depends on how economics understand space and create and interpret spatial knowledge. This achieves an unprecedented relevance, as surpassing the analysis limitations of Urban and Regional Economics' spatial models is fundamental to further planning, plus to the successful outcome of post-crisis economic recovery policies.

Based on these issues and foreseeing the future concerns regarding urban-regional analysis, this paper – and the thesis from it derives: Spatial-economic models to evaluate industrial agglomerations: novel instruments for urban-regional analysis (Altafini, 2022); proposes to develop novel spatial-economic methods and models that are more adapted to evaluate the logics of industrial agglomerations, highlighting the motives behind the territorial disparities. Therefore, it is crucial to establish the parameters – or the "spatial microfoundations" – that differentiate the territories and the productive spaces. Based on this premise, this paper discusses the concept of Spatial Attractiveness, and the supporting concept of Territorial Exposure.

Territorial Exposure defines the amount of support given towards the economic activities' placement within the territory, where insufficient support characterizes a degree of exposure to the everchanging economic cycles (Altafini & Cutini, 2021; Altafini, 2022). Exposure can be of spatial nature: given by the organization of territories, the endowments in them (built structures and road-circulation networks); and of economic nature, where the presence of capital and labour contributes to the total amount of support. In other hand, Spatial Attractiveness is interpreted as the sum of positive and negative conditions of Territorial Exposure that will result in the combined support from space and economics – a high overall Exposure will be then equivalent to a low overall Attractiveness. The paper then describes the steps for the construction and an application of the Spatial Attractiveness Index (SAi) a parametric, unweighted general linear model that comprises the partial indices of Spatial and Economic Territorial Exposure Indexes (sTEi and eTEi). The sTEi represents the amount of spatial-derived territorial exposure, associated to the infrastructural support – cohesiveness, agglomeration, and road-network centrality – provided by a territory to the placed economic activities. The eTEi represents, instead, the amount of economic-derived territorial exposure, derived from the distribution of capital and labour in the territory. Those partial indices are also unweighted. The Spatial Attractiveness Index (SAi) then denotes the amount of attractiveness that a territory has towards the placement of industrial activities, given the overall presence or absence of support from the structural-territorial and spatial-economic standpoints.

Formally, the Spatial Attractiveness Index can be defined as:

$$SA_i = sTE_i + eTE_i \tag{1}$$

The paper is structured in four sections: this first introductive part; the section two, that describes and explains the datasets and methods used for the indexes' construction; the section three, that consists of the proof-of-concept, with the application of the SA_i for Tuscany, and the section four, that make the conclusive remarks about the objectives, as well as point out to further research.

2. Datasets and Methods

The datasets used for constructing the Spatial Attractiveness Index (SAi) as well as both Territorial Exposure Indexes (sTEi & eTEi), were organized into a GIS suite (QGIS, 2022), which rendered them suitable for spatial modelling. The section 2.1 describes the used datasets, their pre-processing and extraction methods, as well as the geoprocessing steps. The section 2.2, instead, consists in an overview of the parameters used in the indexes' construction, as well as a brief explanation of the indexes' scoring methods.

2.1 Datasets organization

Part of a multi-domain model, the Spatial Attractiveness Index (SAi) combines a series of spatial and economic parameters defined in the partial indexes that represent Territorial Exposure patterns. Hence, the data used to construct the SAi index can be divided into two groups: spatial-based datasets and economic-based datasets (Altafini, 2022), each with their own particularities.

The spatial datasets comprehend information about Tuscany's territorial endowments – or the characteristics in terms of the morphology and organization of its built structures. Fundamentally, those datasets spatialize Tuscany's industrial assets' distribution and the extension of its road-circulation infrastructure, both used as parameters to construct the Spatial Territorial Exposure Index (sTEi) (Altafini, 2022).

Industrial assets are extracted from Tuscany Region's Built-Structures dataset (Edificato 2k, 10k 1988-2013) (Regione Toscana, 2019a), that outlies the location of all structures set throughout the territory and represent them as volumetric units (polygons) categorized in accordance with their main function. This dataset spans across multiple scales, being assembled from different technical charts (scales 2k and 10k) and is periodic, thus collected over a time-period comprised between 1988 and 2013. For this analysis purpose, only volumetric units categorized under "Industrial" (Industriale) or "Technological Plant" (Impianto Tecnologico) and that are listed as "active" in the post 2013 period are considered as industrial assets. The data was exported from the main dataset and organized in the GIS-suite (Altafini, 2022). The spatial information about the industrial assets is used into the construction of spatial units (Macroareas) – which territorialize the industrial presence within the territory and is used to address aspects related to territorial size and the dynamics of industrial placement and agglomeration. Plus, it serves as basis to enact spatial correlations and incorporate the economic variables (Fig.1).

The road-circulation network dataset employed in the Configurational and Network Analysis derives from the Tuscany Region's Road Graph (Grafo Stradario della Toscana) (Regione Toscana, 2019b), a Road-Centre Line (RCL) graph map that represents the entire regional road-infrastructure. Road-elements were generalized through QGIS integrated Douglas-Peucker algorithm (QGIS, 2022; Altafini & Cutini, 2020) to diminish the total number of vertices and reduce the extensive network modelling time-lapses for Space Syntax' Angular Analysis (Turner, 2001; Altafini, 2022) and for Markov-based network analyses (Altafini et al., 2022; Altafini, 2022).

Angular Analyses can address different kinds of network properties and highlight the urban-regional centralities hierarchies through the configurational measures of Normalized Angular Integration – NAIN (mathematical closeness centrality) and Normalized Angular Choice – NACH (mathematical betweenness centrality) (Hillier et al., 2012) (Tab.1). Those metrics can estimate the movement dynamics within the road system by attributing a value to each road-element and can visualize the local and global patterns of connectivity, accessibility, and proximity within the industrial areas, important for promoting the inter-industrial interactions (Boschma, 2005; Altafini, 2022). Associated to the Space Syntax classic metrics, two novel network measures were developed, based on Markov-Chain principles, to highlight network properties related to the structure of road-elements' importance as connectors within the road-infrastructure: the Normalized Page-Rank Centrality – NPRC and the Normalized Kemeny-based Centrality – NKBC. Based on the properties of strong and weak-ties, (Granovetter, 1973; Altafini, 2022) these metrics visualize the global patterns of road-element importance (NPRC) and overall system redundancy (NKBC) within the network, important aspects regarding Territorial Exposure as the interruption of these elements can lead to a general collapse in terms of accessibility-to-and-within the industrial spaces (Tab.1).

Metric	Formula (Normalized)	Concept	References
Normalized Angular Integration (NAIN)	$NAIN = \frac{Node\ Count^{1.2}}{Total\ Depth}$	Measure the farness between elements in a network; in space syntax, denotes the relative accessibility or movement potential of a road-element, as it informs how close – in topological terms – a road-element is in relation to the others.	Bavelas, 1950; Sabidussi, 1966; Hillier, 2007; Hillier et al, 2012; Altafini, 2022
Normalized Angular Choice (NACH)	$NACH = \frac{\log(Angular\ Choice + 1)}{\log(Total\ Depth + 3)}$	Measures the number of times a certain network element is traversed when moving through the shortest paths from all origin-destination pairs of elements within the network. In *space syntax*, it denotes the hierarchy of *preferential routes* throughout the system.	Freeman, 1977; 1978 Freeman et al.,1979; Hillier, 2007; Hillier et.al, 2012; Altafini, 2022
Normalized Page-Rank Centrality (NPRC)	$PRC_{ij} = \mu_i P_{ij} + \mu_j P_{ij}$ $NPRC = \frac{(PRC * NC) - \wedge(PRC * NC)}{\vee(PRC * NC) - \wedge(PRC * NC)}$	Measures the most important elements within the network, given their own score and the connected elements scores. It denotes the most *strong-tied* road-elements in the network.	Page et al. 1999; Altafini et al., 2022; Altafini et al, 2023
Normalized Kemeny-based Centrality (NKBC)	$KBC_{ij} = k\hat{P} - k(P)$ $NKBC = \frac{KBC' - \wedge KBC'}{\vee KBC' - \wedge KBC'}$	Measures the overall network redundancy, scoring higher the road-elements that establish the weak-ties or bridges between groups of road-elements. NKBC scores the road-elements based on their redundancy, it indicates which elements that, if removed from the network, can lead to a more probable system collapse in terms of connectivity.	Kemeny, Snell, 1960; Altafini et.al. 2022; Altafini et al, 2023

Tab.1 Overview of the configurational and Markov-based network analysis methods

Economic datasets, on the other hand, contain information used to describe the territorial distribution of capital and labour within Tuscany, thus, to construct the Economic Territorial Exposure Index (eTEi). These datasets, while not spatial, can be spatialized through their association to the spatial units used in their data collection – the ISTAT census zones (ISTAT, 2016; Altafini, 2022).

Labour-related variables are obtained from the Italian Industrial and Services Census (Censimenti ISTAT dell'industria e servizi), for the periods of 2001 and 2011 (ISTAT, 2001; 2011; 2016) datasets, and used to address the territorial distribution and density of Local Units (Firms), Number of Employees; plus, the Average Firm-Sizes, this last established from the ratio between Local Units and Employees for each census zone (Altafini & Cutini, 2021b; Altafini, 2022). These datasets are organized in a GIS-based environment (QGIS, 2022) (Fig.1) and, since the data tables (.csv) and their spatial data counterparts (.xls) are placed in different files, a spatial join needs to be performed to assemble the table datum to its respective spatial position, only then permitting variables' manipulation and spatialization. Local Units, Employees and Average Firm-Size variables are used as parameters for the construction of the eTEi attributed to each census zone. The spatialization is further restricted to the Macroareas, to represent only the areas with industrial presence (Fig.1).

The datasets from the Osservatorio del Mercato Immobiliario (OMI) (Agenzia delle Entrate, 2018) are used as a proxy variable to describe the amount of Installed Capital within a certain territory. This variable considers the average real-estate values – in this case, real-estate assets with a productive function – surveyed within a delimited spatial unit and aggregated for the 2002-2020 period. Methodological procedures to construct the OMI values have been described in detail on Altafini et.al. (2021); Altafini & Cutini (2022) and Altafini (2022) and result in the €/m^2 ranges described in section 2.2 (Table 6, p.9), from Very Low to Very High (Fig.1). The OMI values are used as parameters in the eTEi, with their data attributed to each census zone. Likewise, as in the eTEi's Labour component, OMI data is spatially restricted to each Macroarea to represent only the areas with industrial presence within Tuscany.

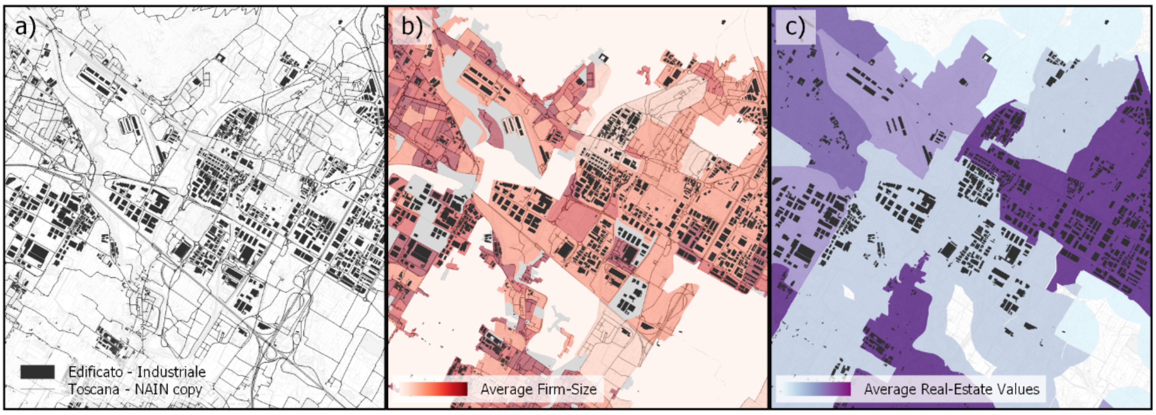

Fig.1 Datasets Spatialization (a) Industrial assets and Road-Circulation Networks; (b) Average Firm-Sizes spatialized into Census Zones and (c) OMI Average Real-Estate values spatialized into a Macroarea restricted representation

Tuscany is an interesting case study, as a representative of the Third Italy (Bagnasco, 1977), which combines larger, medium, and small industrial areas, often scattered throughout the territory. Moreover, it has important road-circulation network differences in terms of density, thus, distinct patterns of infrastructure distribution.

2.2 The Spatial Attractiveness Index structure – sTEi & eTEi methodology

The Spatial Attractiveness Index (SAi) is a General Linear Model (GLM) derived from the unweighted sum of the value ranges established in the Spatial Territorial Exposure Index (sTEi) and Economic Territorial Exposure Index (eTEi). For each TEi, the value ranges are defined from the standardized – unweighted – sum of the modelled parameters that indicate Territorial Exposure (Altafini, 2022). The choice behind using unweighted indices was to provide an unbiased representation of Territorial Exposure, as defined solely by their territorial characteristics without giving a parameter more importance than the reminder.

The sTEi denotes the amount of territorial support that comes from the spatial distribution and organization of the built-structures and road-infrastructure within the territory. This index is derived from the attribution of scores for the following spatial parameters, derived from morphological, configurational, and network structure analysis: The Macroarea Size (Si) and Agglomeration (Ai), which are morphological properties given by the patterns of industrial assets, industrial spaces and macroareas territorial distribution; the NAIN (Ii) and NACH (Ci), configurational properties that indicate the spatial proximity correlations between the macroareas and the highest valued centralities of relative accessibility and preferential routes; and the NPRC (Pi), and NKBC (Ki), Markov-based network properties that indicate the spatial proximity correlation between macroareas and the important road-elements (strong-tied and weak-tied) in the network structure.

Henceforth, the sTEi is defined as (see Tab.2 for value ranges and Tab.3 and 4 for numerical breakdown):

$$sTE_i = S_i + A_i + I_i + C_i + P_i + K_i \tag{2}$$

The numerical ranges for this parametric index sum are set between -6 to 8, allocated in each numerical range through the natural breaks' algorithm (Jenks & Caspall, 1971; Jenks, 1977), which are then standardized between -2 and 2 to correspond to a defined degree of exposure set within the Very Low and Very High ranges (Tab.2). This sTEi iteration differs from the first TEi discussed in Altafini & Cutini (2021a), since here negative values are not defaulted to zero but, instead, considered as they are for the construction of the categorizations.

Categorization – sTEi	Numerical Ranges	Standardized Ranges	Colour Ranges
Very High Territorial Exposure	Inferior or equal to -4	**-2**	**Red**
High Territorial Exposure	Between -4 and 0	**-1**	**Orange**
Moderate Territorial Exposure	Between 0 and 3	**0**	**Yellow**
Low Territorial Exposure	Between 3 and 6	**1**	**Lime**
Very Low Territorial Exposure	Superior or equal to 7	**2**	**Green**

Tab.2 Spatial Territorial Exposure Index (sTEi) – Ranges and Categorization

A breakdown of the parameters, in terms of their distribution within the spatial units (macroareas), and relation with the number of industrial assets and spaces provides an overview of the results attained for each of the partial analyses (Tables 3 and 4). An in-detail analysis regarding the sTEi spatial distribution (Fig.2, p.8), that furthers on the factors behind the spatial patterns can be found on Altafini & Cutini (2021); and Altafini (2022).

Parameter	Scores	Spatial Unit Count	(%)	Industrial Assets	(%)	Industrial Spaces	(%)
Si - Macroarea Size							
Isolated Macroarea	-1	430	31.48%	430	0.54%	430	2.76%
Small Macroarea	0	848	62.08%	8,905	11.17%	2,861	3.59%
Medium Macroarea	1	85	6.22%	23,086	28.95%	4,942	6.20%
Large Macroarea	2	3	0.22%	47,326	59.35%	7,328	47.09%
Ai - Agglomeration Index							
Single Units	-1	584	42.75%	829	1.04%	829	5.33%
Low Agglomeration	0	49	3.59%	353	0.44%	283	1.82%
Medium Agglomeration	1	533	39.02%	8,120	10.18%	3,445	22.14%
High Agglomeration	2	200	14.64%	70,445	88.34%	11,004	70.72%
Ii - Road- Network NAIN							
No - Spatial Correlation	-1	1,148	84.04%	15,714	19.70%	4,805	30.88%
Yes - Spatial Correlation	1	218	15.96%	64,033	80.30%	10,756	69.12%
Ci - Road- Network NACH							
No - Spatial Correlation	-1	261	19.11%	609	0.76%	406	2.61%
Yes - Spatial Correlation	1	1105	80.89%	79,138	99.24%	15,155	97.39%
Pi - Road- Network NPRC							
No - Spatial Correlation	-1	117	8.57%	211	0.26%	159	1.02%
Yes - Spatial Correlation	1	1,249	91.43%	79,536	99.74%	15,402	98.98%
Ki - Road- Network NKBC							
No - Spatial Correlation	-1	271	19.84%	815	1.02%	459	2.95%
Yes - Spatial Correlation	1	1,095	80.16%	78,932	98.98%	15,102	97.05%

Tab.3 Spatial Territorial Exposure Index (sTEI) – scores, macroareas count, number of Industrial Assets and number of Industrial Spaces for each parameter

Spatial Territorial Exposure Index	Macroarea Count	(%)	Total Area [km²]	(%)
Very High Territorial Exposure	120	8.78%	100.89	2.28%
High Territorial Exposure	383	28.04%	356.50	8.04%
Moderate Territorial Exposure	556	40.70%	903.60	20.38%
Low Territorial Exposure	285	20.86%	1,339.64	30.22%
Very Low Territorial Exposure	22	1.61%	1,732.69	39.08%

Tab.4 Spatial Territorial Exposure Index (sTEI) – Macroareas count and total territorial area.

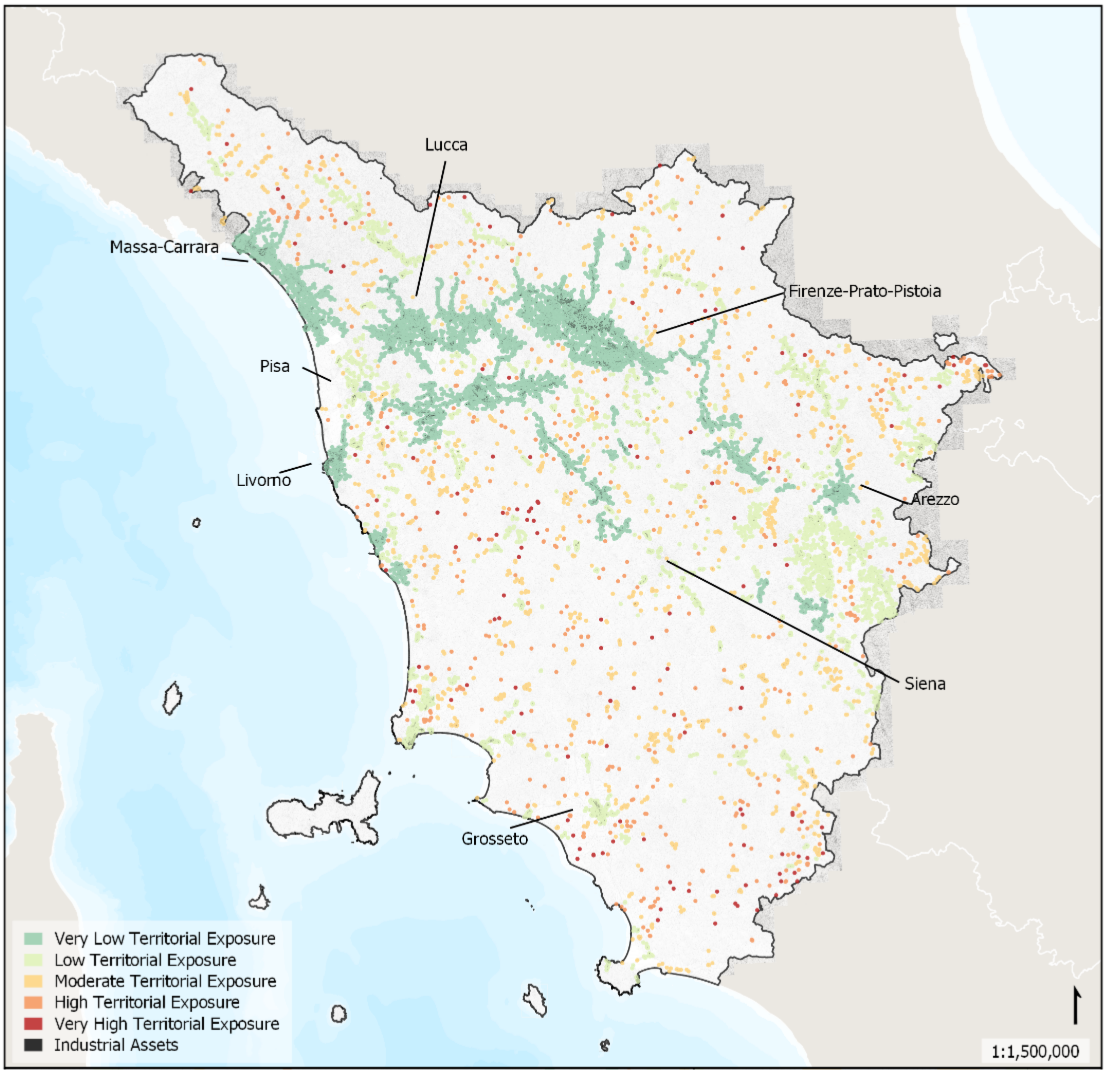

Fig.2 Spatial Territorial Exposure Index (sTEi) distribution patterns within the Tuscany region

The eTEi denotes the amount of territorial support that comes from the economic conditions, related to labour and capital distribution, within the territory. This is assembled though the attribution of scores for the following economic parameters: the Territorial density of Local Units (Firms) (Fi), Territorial density of Employees (Ei), Average Firm-Size Density (Zi), all associated to labour; and the average real-estate values given by the OMI real-estate values (Oi), that represent a proxy for the installed capital throughout the region.
Henceforth, the eTEi is defined as (see Tab.5 for value ranges and Tab. 6 and 7 for numerical breakdown):

$$eTE_i = F_i + E_i + Z_i + O_i \tag{3}$$

The value ranges for this parametric index slightly differ from its spatial counterpart being set from -8 to 8, allocated in each numerical range through the natural breaks' algorithm (Jenks & Caspall, 1971; Jenks, 1977), yet they are also standardized between -2 and 2, to correspond to defined degrees of exposure that range from Very Low to Very High.
Another important aspect, particular to the eTEi is that several spatial units do not possess observations – due to the lack of census data, hence a category of "No Data" had to be created. The categorizations for the eTEi are defined as (Tab.5, p.9):

Categorization – eTEi	Numerical Ranges	Standardized Ranges	Colour Ranges
No Data	Null values	-	Grey
Very High Territorial Exposure	Inferior or equal to -3	**-2**	**Red**
High Territorial Exposure	Between -3 and 0	**-1**	**Orange**
Moderate Territorial Exposure	Between 0 and 3	**0**	**Yellow**
Low Territorial Exposure	Between 3 and 6	**1**	**Lime**
Very Low Territorial Exposure	Superior or equal to 7	**2**	**Green**

Tab.5 Economic Territorial Exposure Index (eTEi) – Ranges and Categorization

Parameter	Scores	Spatial Unit Count	(%)	Industrial Assets	(%)	Industrial Spaces	(%)
Local Units (Firms) – Fi							
No Data	-	6,448	17.50%	3,894	4.88%	1,289	8.29%
Very Low Density	-2	9,181	24.92%	10,030	12.58%	4,067	26.15%
Low Density	-1	4,690	12.73%	13,587	17.04%	2,872	18.47%
Medium Density	0	9,431	25.60%	38,773	48.64%	5,595	35.98%
High Density	1	3,033	8.23%	8,704	10.92%	1,046	6.73%
Very High Density	2	4,057	11.01%	4,727	5.93%	683	4.39%
Number of Employees – Ei							
No Data	-	6,514	17.68%	3,894	4.89%	1,289	8.29%
Very Low Density	-2	7,808	21.19%	6,213	7.80%	3,072	19.76%
Low Density	-1	3,350	9.09%	4,402	5.53%	1,590	10.23%
Medium Density	0	7,221	19.60%	16,235	20.38%	3,957	25.46%
High Density	1	3,603	9.78%	15,261	19.16%	2,455	15.79%
Very High Density	2	8,344	22.65%	33,661	42.25%	3,181	20.46%
Firm-Size (Average) – Zi							
No Data	-	6,514	17.68%	3,943	4.95%	1,297	8.34%
Very Low Density	-2	8,615	23.38%	8,833	11.08%	3,956	25.44%
Low Density	-1	1,590	4.32%	8,543	10.72%	1,769	11.37%
Medium Density	0	8,620	23.40%	38,860	48.75%	5,781	37.17%
High Density	1	4,021	10.91%	10,100	12.67%	1,490	9.58%
Very High Density	2	7,480	20.30%	9,436	11.84%	1,259	8.10%
OMI Values (Capital) – Oi							
No Data	-	0	0.00%	0	0.00%	0	0.00%
Very Low Real-Estate Value	-2	9,928	26.95%	10,458	13.12%	3,238	20.82%
Low Real-Estate Value	-1	8,155	22.14%	21,078	26.44%	4,003	25.74%
Medium Real-Estate Value	0	5,526	15.00%	17,254	21.64%	3,331	21.42%
High Real-Estate Value	1	6,494	17.63%	17,429	21.86%	2,730	17.55%
Very High Real-Estate Value	2	6,737	18.29%	13,496	16.93%	2,250	14.47%

Tab.6 Economic Territorial Exposure Index (eTEI) – scores, macroareas count, number of Industrial Assets and number of Industrial Spaces for each parameter

A breakdown of the parameters, in terms of their distribution within the spatial units (census zones), provides an overview of the results attained for each of the partial analyses (Tab.6 and 7).

A further breakdown of the spatial relation of labour and capital with the number of industrial assets and spaces can be found on Altafini (2022). The spatialization of the eTEi is displayed on Fig.3 (p.10).

Economic Territorial Exposure Index	Spatial Unit Count	(%)	Total Area [km2]	(%)
No Data	8,104	22.00%	830.33	18.87%
Very High Territorial Exposure	9,899	26.87%	2,870.33	65.25%
High Territorial Exposure	5,316	14.43%	285.77	6.50%
Moderate Territorial Exposure	6,361	17.27%	286.15	6.50%
Low Territorial Exposure	4,684	12.71%	102.26	2.32%
Very Low Territorial Exposure	2,476	6.72%	24.26	0.55%

Tab.7 Economic Territorial Exposure Index (eTEI) – Spatial units count and total territorial area

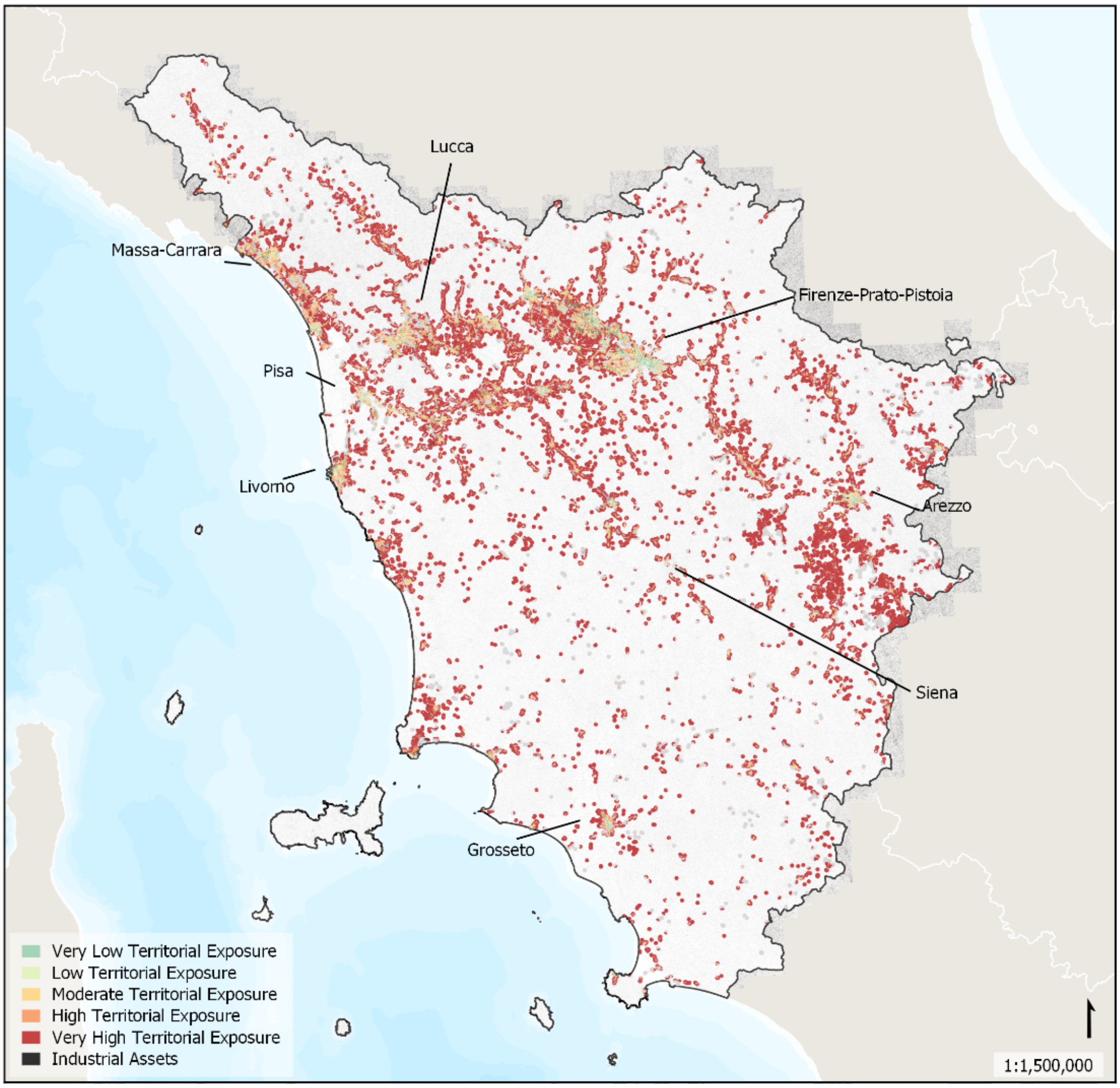

Fig.3 Economic Territorial Exposure Index (eTEi) distribution patterns within the Tuscany region

2.3 The Spatial Attractiveness Index methodology

In a similar manner to the previous indicators, the SAi is assembled through the attribution of scores that, in this case, are derived from each category of territorial exposure.

For the SAi, scores are standardized within the range between -2 to 2, a result from the sum between the sTEi and eTEi.

Henceforth, SAi definition is the following, as stated in Equation 1:

$$SA_i = sTE_i + eTE_i \tag{1}$$

The resulting index corresponds to a defined degree of spatial attractiveness, that ranges from Very Low to Very High. These ranges are inverse in relation to the TEi's, meaning that areas with Very Low Territorial Exposures will have Very High Spatial Attractiveness.

Since the fundamental spatial unit for the SAi the census zones, likewise as in the eTEi, some spatial units have no observations, which require the addition of a category for "No Data". With this in consideration, the categorizations are defined as (Tab.8):

Categorization – SAi	Standardized Ranges	Colour Ranges
No Data	-	Grey
Very Low Spatial Attractiveness	-2	Red
Low Spatial Attractiveness	-1	Orange
Moderate Spatial Attractiveness	0	Yellow
High Spatial Attractiveness	1	Lime
Very High Spatial Attractiveness	2	Green

Tab.8 Spatial Attractiveness Index (SAi) – Ranges and Categorization

The datasets relationships and the methodological processes that result in the sTEi and eTEi, and then in the SAi are summarized in Fig.4:

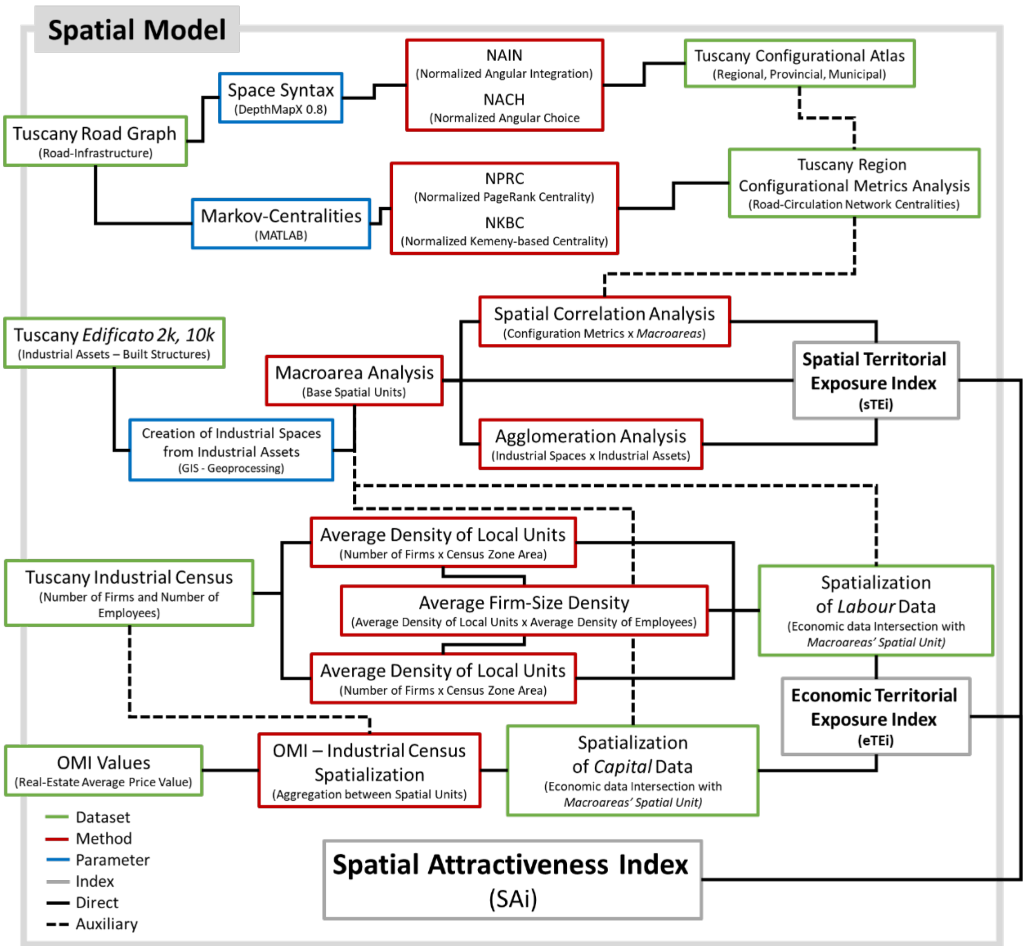

Fig.4 Datasets relationship and methodological scheme for the index construction

3. Results and Discussion

Significative territorial disparities are revealed through the SA_i spatialization, that shows the patterns of Spatial Attractiveness distribution within Tuscany (Fig.5). The results attained by the SA_i improve and refine – in terms of territorial detail – those obtained through the spatialization of the individual indexes of Spatial Territorial Exposure ($_sTE_i$) (Altafini & Cutini, 2021) and Economic Territorial Exposure ($_eTE_i$) (Altafini, 2022). A data breakdown for the SAi (Tab.9 and 10) demonstrates the numbers for spatial units, occupied total area, total industrial assets, and total industrial spaces, as well as how those are distributed within the several ranges of spatial attractiveness.

Spatial Attractiveness Index	Spatial Unit Count	(%)	Total Area [km2]	(%)
Very High Spatial Attractiveness	6,240	16.94%	109.55	2.49%
High Spatial Attractiveness	10,140	27.52%	473.95	10.77%
Moderate Spatial Attractiveness	4,849	13.16%	1,039.28	23.62%
Low Spatial Attractiveness	6,324	17.17%	1,648.90	37.48%
Very Low Spatial Attractiveness	1,183	3.21%	297.09	6.75%
No Data	8,104	22.00%	830.33	18.87%

Tab.9 Spatial Attractiveness Index (SAi) – Spatial units count and total territorial area

Spatial Attractiveness Index	Number of Industrial Assets	(%)	Number of Industrial Spaces	(%)
Very High Spatial Attractiveness	14,398	16.17%	1,583	11.19%
High Spatial Attractiveness	37,826	42.47%	5,286	37.36%
Moderate Spatial Attractiveness	8,956	10.06%	2,448	17.30%
Low Spatial Attractiveness	12,944	14.53%	1,410	9.96%
Very Low Spatial Attractiveness	2,450	2.75%	357	2.52%
No Data	12,486	14.02%	3,066	21.67%

Tab.10 Spatial Attractiveness Index (SAi) – Number of Industrial Assets and Spaces

From a quantitative standpoint, it can be observed that most spatial units are set within the High SAi ranges (27.52% - 5,286), that also hosts most of the industrial assets (42.47% - 37,826) and industrial spaces (37.36% - 5,286) (Tab.9 and 10). These results, plus the pattens that emerge from the spatialization (Fig.5 p.13), are in line with economic theory assumptions regarding capital and labour, and how the presence of those factors reinforce general tendencies of spatial agglomeration and attractiveness of a territory towards industrial placement. Even though not as predominant regarding the spatial units when compared to the High Spatial Attractiveness range with just 6,240 (16.94%) spatial units, the Very High Spatial Attractiveness range hosts the second highest quantity of industrial assets, with 16.17% (14,398) of the total. In effect, the spatial distribution differences of labour associated factors (i.e, local units, employees, and firm-size) are the main attributes that differentiate the High and Very High ranges of attractiveness, as areas that have greater values for these parameters are set in the upper range. When spatial units' total occupied area is considered, however, both higher ranges correspond to a rather small territory, with an aggregate covering just about 13.26% of the regional total (circa 583.5 km^2) (Tab.9).

The spatialization emphasizes that the territories within the highest ranges of attractiveness are comprised of industrial spaces with a limited extension, with industrial assets placed in a compact pattern, as observed in Fig.5 (p.13) and in Fig.6 (p.14).

This reinforces the previously attained results for the $_sTE_i$, in its first iteration (Altafini & Cutini, 2021) suggesting that agglomeration is an important factor in reducing the overall condition of territorial exposure from a spatial standpoint. Hence, the model's spatialization demonstrates the economic assumption, that the spatial proximity among the firms tends to improve the overall spatial attractiveness of a territory to economic activities placement. Moreover, in the specific case of Tuscany, the SAi spatialization (Fig.5) reveals important territorial differences that highlight the current divide amongst northern and southern areas of the region – that is similar to the north-south divide in development that exist in Italy. Still, while these differences are noticeable, their causes are only revealed through the exploration of the Territorial Exposure Indexes (Altafini, 2022). It is observed that the differences in infrastructure – especially in terms of road-circulation networks – among northern and southern hinterlands are the main cause of exposure, as the lack of proximity to those road-elements mark the differences among macroareas with higher and lower support (Fig.6).

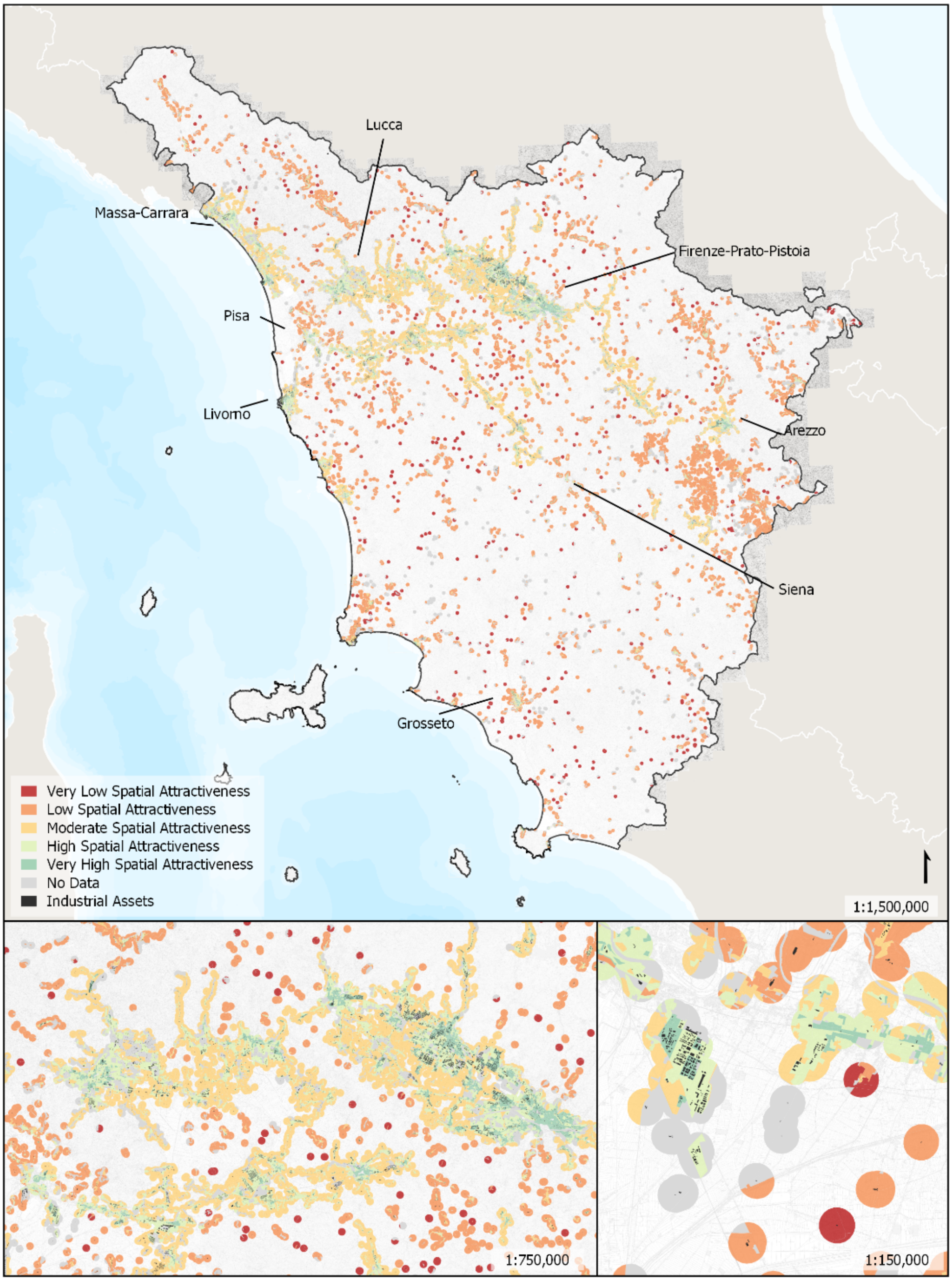

Fig.5 Spatial Attractiveness Index (SAi) distribution patterns within the Tuscany region

The Moderate Spatial Attractiveness range assume a rather distinctive spatial pattern as, although they occupy the second largest area overall 1,039.28 km^2 (23.62%) (Tab.9, p.11, Fig.5, p.13), they comprise just 13.16% (4,849) of the spatial units and only 10.06% (8,956) of the total of industrial assets (Tab.9 and 10).
As a rule, the areas that comprise the Moderate Spatial Attractiveness ranges are located near the boundaries of the macroareas that are set in the Spatial Territorial Exposure's (sTE_i) Very Low ranges (Fig.5, Fig.6).

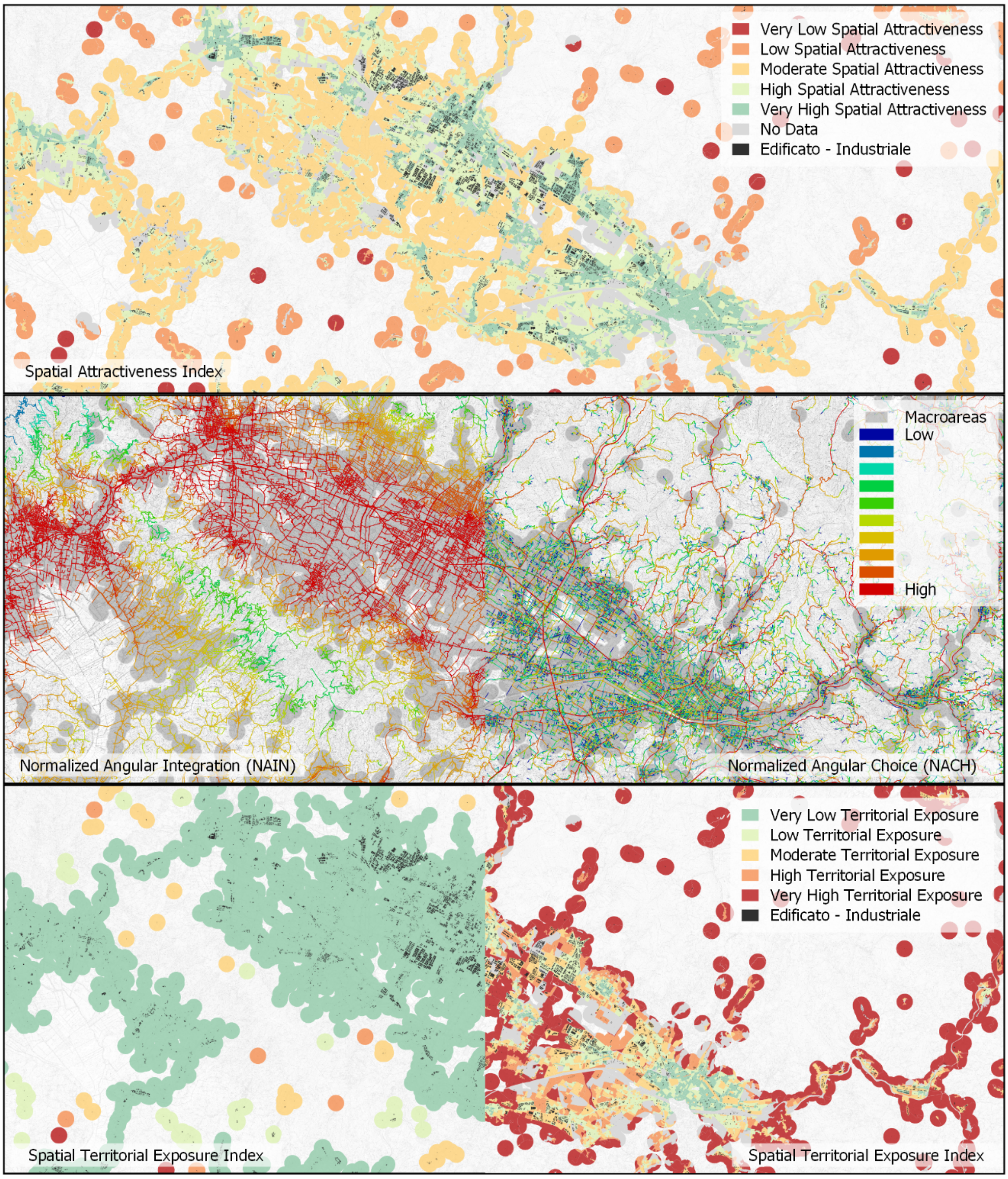

Fig.6 Spatial Attractiveness Index (SAi) – comparison with the Spatial Territorial Exposure (sTEi), the Economic Territorial Exposure (eTEi), the Normalized Angular Integration (NAIN) and the Normalized territorial distribution patterns – Firenze, Prato and Pistoia Area

Although not noticeable at a first glance, the result highlights the importance of road-circulation network centrality patterns in the overall spatial attractiveness, above all, of the relative accessibility (Integration), property described by the Normalized Angular Integration (NAIN), a component of sTE_i's R_i parameter (Altafini & Cutini, 2021; Altafini, 2022). An in-depth analysis (Fig.6) demonstrates that the high values for relative accessibility cause the most differentiation between the ranges of sTE_i, diminishing the overall degree exposure. Therefore, a high degree of accessibility compensates a local absence of capital and labour, as the nearness to areas that do have a concentration of these factors is improved, thus increasing the spatial attractiveness of these boundaries to economic activities placement.

These findings are in accordance with the conclusions of Froy (2021) on the importance of relative accessibility in the underlying urban spatial structure that supports the industrial agglomerates' organization – suggesting that many firm-to-firm relationships are dependent on the spatial proximity of those firms, and that efficient road-circulation network connections are determinant factors to placement, agglomeration, and the overall industrial environment (Altafini, 2022).

Still, even though relative accessibility has a role in establishing the local patterns of spatial proximity amongst industrial assets, it becomes a less important factor when regional connections are to be considered, since closeness patterns, at this scale, tend to be restricted to a compact core that comprehends the larger urban settlements. In that aspect, regional connections between the industrial spaces are better represented by the preferential routes in the road-circulation network – defined by the Normalized Angular Choice (NACH) component in the Ri parameter (Atafini, 2022).

Preferential routes, have a role in supporting the industrial spaces within the higher ranges of territorial exposure (Fig.6, p.14), establishing linkages or bridges between those and the larger industrial agglomerations. This lowers the overall degree of territorial exposure of these peripheral areas as it provides to the industrial assets located far from the relative accessibility core, access to areas that concentrate economic factors: firms, capital, and labour (Altafini & Cutini, 2022b). Hence, proximity to these routes improves the overall spatial attractiveness to industrial placement (Altafini, 2022).

The effects of a higher degree of territorial exposure in spatial attractiveness can be observed within the Low and Very Low Sai ranges (Fig.5; Fig.6). Those ranges correspond to an aggregate 20.38% (7,507) of the total spatial units, with several industrial spaces and industrial assets equivalent to, respectively, 17.28% (15,394) and 12.48% (1,767) of the regional totals (Tab.9 and 10, p.11).

Nevertheless, combined, the Low and Very Low Sai ranges occupy the largest territorial extent within Tuscany, with circa 44.23% (1,945.99 km^2) of the total macroareas territory.

The spatial distribution of the lower ranges of Spatial Attractiveness informs a remarkable pattern regarding territorial disparities; those are predominant throughout Tuscany's hinterlands (Fig.5, p.12) and located in smaller macroareas that are set beyond the relative accessibility core at regional scale (Fig.6, p.14). While the innermost spatial units within those areas tend to present higher degrees of Spatial Attractiveness – with Sai values ranging from Moderate to High, depending on the amount of industrial assets, capital, or labour – the outer boundaries tend to offer less territorial support and attractiveness to placement when compared to what is verified in the larger macroareas. The disparities between macroareas with boundaries in Moderate Sai ranges and those with boundaries in Low-Very Low Sai ranges are, however, not just dependent on their hinterland placement and the consequential decreases on the regional relative accessibility; in effect, differences among these two cases can be attributed to the overall cohesiveness and agglomeration of the industrial areas.

These patterns can be verified when the Sai, sTEi and eTEi spatialization results for Pisa (Fig.7, p.16) and Livorno greater areas (Fig.8, p.16) are analysed.

Lower SAi values found for Pisa and Livorno can be attributed to differences both in sTEi's parameters of macroareas' sizes (Si) and agglomeration (Ai). Therefore, despite the presence of internal spatial units with a good amount of economic support, as indicated in the eTEi spatialization, as well as other factors related to a lower territorial exposure – such as support of the road-circulation network –, it is the low internal cohesiveness of these areas that contributes the most to the increase in overall territorial exposure.

Macroareas that present higher degrees of agglomeration (Ai) (green in sTEi), also exhibit Moderate Spatial Attractiveness near their boundaries, while areas that present lower agglomeration – represented in lime and yellow in the sTEi, have instead boundaries with Very Low Spatial Attractiveness (Fig.7 and 8).

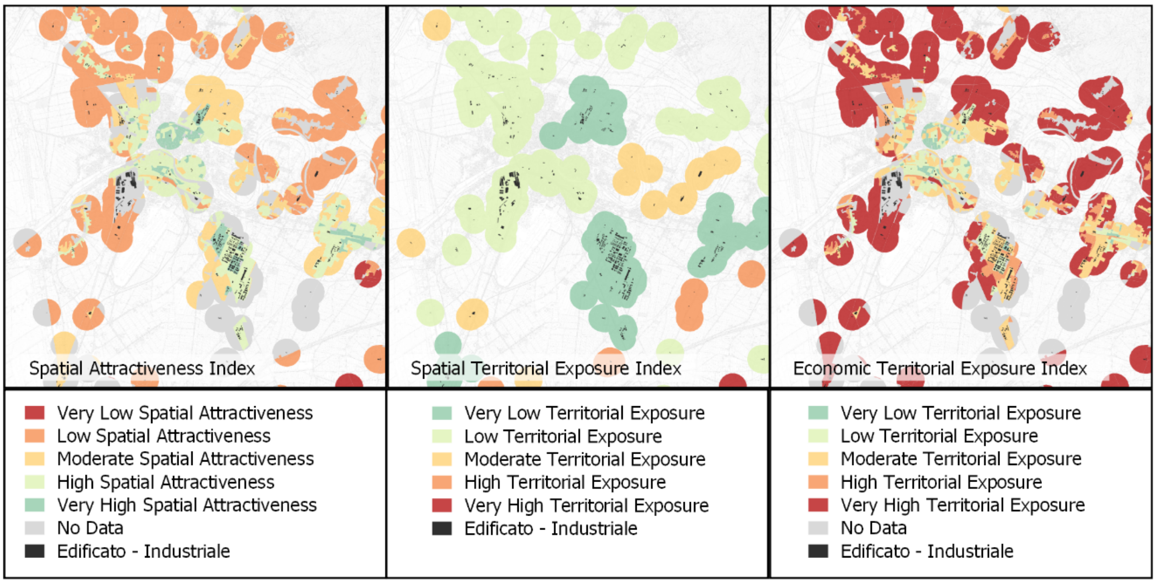

Fig.6 Spatial Attractiveness Index (SAi) – comparison with the Spatial Territorial Exposure (sTEi) and the Economic Territorial Exposure (eTEi) territorial distribution patterns for the Pisa urban area

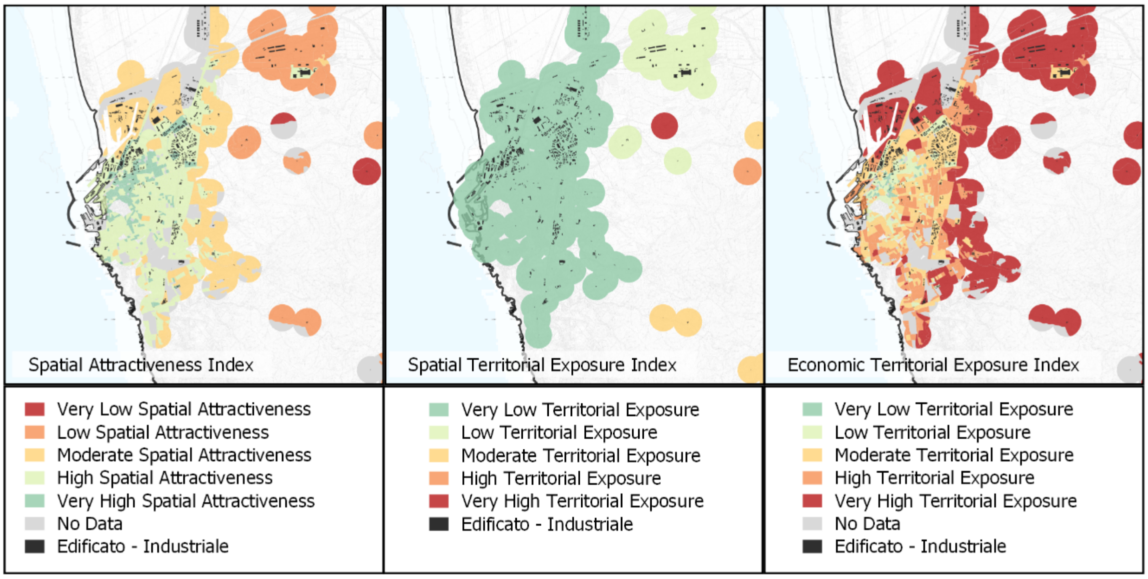

Fig.7 Spatial Attractiveness Index (SAi) – comparison with the Spatial Territorial Exposure (sTEi) and the Economic Territorial Exposure (eTEi) territorial distribution patterns for the Livorno urban area

The assembled Spatial Attractiveness Index (SAi) can provide a novel dimension for spatial-economic based territorial analysis. It is tailored to consider parameters derived both from the territorial endowments, such as the disposition of the built-structures, and the centralities of the road-circulation network, as well as from the economic structure, associated to labour, capital, and firm-size. A distinctive of this model is that it considers those aspects at a level of detail and within a scale that goes beyond what is usually addressed in the fields of Regional Economics and Economic Geography. Nevertheless, are limitations in what the model can currently explain, not related to its structure, which designed to be flexible, but related to data quality and availability. A more granular dataset regarding the industrial functions, with sector specialization and type/intensity of the activities, could be used to integrate this approach to the network-based approach proposed by Froy (2021). This would lead to a better depiction of the inner configuration of the industrial areas, from a relational

standpoint, while also merging it with the conditions that allow those relationships to happen. This could be a next step for this research towards understanding other kinds of territorial imbalances.
The relevance of the road-circulation network patterns and of the road-infrastructure can be attested in the results for the spatial attractiveness model, hence, the configurational properties of these networks reveal themselves as determinants for interpreting territorial disparities' patterns among the economic activities' distribution at localized scales in the regional continuum, which can contribute to improving competitiveness, and working towards providing evidence for a rebalance of the industrial systems, as part of decision-making strategies (Gargiulo & Sgambati, 2023). These attributes, more than often, are mis-considered both by Regional Economists and Economic Geographers and must be part of the digitalization efforts oriented to understand vulnerable territories (Garau et al., 2023) and support the novel smart cities, in an integrated approach (Barresi & Pultrone, 2013; Pultrone, 2023). While by no means we disregard the approaches made in these fields, especially, since the Evolutionary branch of the Economic Geography is walking towards this direction, we propose that the general abstraction of the spatial component, ever-present in current economic-based analysis, is to be shifted towards a broader overview that considers the real characteristics – or the variables that constitute the spatial microfoundations – within the territories. As proved by both the Spatial and Economic Territorial Exposure Indexes, as well as by the Spatial Attractiveness Index, we already in possess of the technical knowledge and the instruments to do so.

4. Conclusive remarks

Throughout this research, we identified that there was a certain distance amid the interpretations from Urban and Regional Planning and from Spatial Economics about "what is space?". As discussed in the introduction, this gap seems to arise from the apparent "neglect" (Krugman, 1991) of the spatial economics' branches by the mainstream economics, as the crisis of the first neoclassical consensus in the 1970-1990's period contested the methodological foundations of the spatial models developed within economics. While space is undoubtedly considered as an important factor in economics, it is well-noticed in their approaches – be in Urban-Regional Economics or in Economic Geography – that regions and territories tend to be interpreted from an abstracted standpoint – meaning that their internal characteristics or disparities are often deemed as intangible factors (Thisse & Walliser, 1998). Hence, the spaces will constitute themselves of a mere background, with a set of homogeneous qualities on where the different dynamics take place; certainly, a contrast in relation to the in-detail overviews found within more territorial-planning-based disciplines and approaches.
It can be stated, then, that the spatial models developed in economics possess – here inspired in Robert Lucas' (1976) critique on the neoclassical synthesis – rather unsolid "microfoundations", thus, a limited understanding of what characteristics present on space can influence in location, support, and resilience to economic trends. In that matter, abstracting details on the representation of space leads to its interpretation as a mere structural component – an invariant – when space is neither structural, nor invariant; on the contrary, it changes its structure in accordance with fluctuations in the physical, economic, and historical contexts. Under this argument we identified a significant shortcoming of the spatial-economic theories and models in general. Nevertheless, can be addressed through considering principles and instruments that became ubiquitous in urban and regional planning, such as the use of Geographic Information Systems and the creation of Digital Twins, that are based on virtually reproducing the real dynamics between material and economic factors, allowing to interpret those as tantamount determinants to understand – "what is really where, and why?". It is through this approximation between the disciplines, which must surpass the "intangibilities of space" that assumed by the economics. This will allow a movement of transition towards to a second renaissance of Urban-

Regional Economics' and the Economic Geography's spatial-economic models, and the creation of more effective instruments to address the dynamics that occur in the real world.

This paper – and the thesis in which it was based – were structured within these *lacunae.* While its main result is the Spatial Attractiveness Index (SAi), its construction is derived from a combined set of spatial and economic analyses – the indexes of Spatial and Economic Territorial Exposure (sTEi & eTEi). Even if those indexes can be interpreted independently, when worked in conjunction they contribute towards the general objective that is rupturing with the paradigms of an "intangible space" and proposing novel methodological instruments and spatial models capable to support an in-depth analysis of space and its territorial disparities, applicable for urban and regional planning, but foremost, to economics. These approaches novelty consists in incorporating territorial variables associated to infrastructure (i.e. built-structures position and the road-circulation networks) while creating spatial units that allow to interpret their configurational and morphological characteristics along economic variables (i.e. capital and labour) to understand their combined support towards the placement of economic activities. Challenges remain, above all, regarding the incorporation of more economic variables to this analytical framework. Although datasets are available that can help assess the economic vitality of industrial agglomerates, such as sector, firm size, productivity, and revenues, there are spatialization issues since the data is collected at the firm level and may reveal sensitive information about the productive activity that could lead to identification. Additionally, research costs are a concern since many of these databases are privately owned and require significant funds for a comprehensive data acquisition at a regional scale. These could be the next steps in terms of understanding the territorial imbalances.

Despite these limitations, the proposed spatial model and framework, based on real spatial representations, can clearly identify territorial disparities in industrial agglomerates throughout a region, as seen in the proof-of concept for Tuscany. Moreover, it demonstrates how the presence and placement of territorial endowments can affect their economic dynamism within the different parts of a same region. Therefore, the SAi and the Territorial Exposure Indexes provide more detailed territorial representations than the spatial models typically used Urban and Regional Economics studies and comprehend a step towards an economic analysis based on Digital Twins.

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