

Towards a Spatial Approach to Territorialize Economic Data in Urban Areas' Industrial Agglomerations

Diego Altafini(✉) and Valerio Cutini

Dipartimento Di Ingegneria Dell'Energia, Dei Sistemi, Università Di Pisa, del Territorio E Delle Costruzioni, Largo Lucio Lazzarino, 56122 Pisa (PI), Italy
diego.altafini@phd.unipi.it

Abstract. The space matters: beyond a mere background for economic activities placement, it constitutes a crucial element for their overall dynamism. This rationale, however, contravenes more traditional urban and regional economics approaches that interpret space as intangible within their spatial models. In that vein, notable constraints can be found in economic-based methods and spatial units oriented to spatialize the territorial endowments and interpret their role within the urban structure. While economics' methods are limited in their spatial representation, urban and regional planning has otherwise focused in providing instruments that address spatial characteristics of areas where urbanization is predominant. Methods that highlight the configurational properties and the organization of the cityscape structure, could aid economics in its methodological issues. Still, a divide persists between these two fields of research, as neither consistently incorporates the methods and variables considered by the other. In this paper we showcase a method used to create a spatial unit oriented to territorialize economic-based datasets represented at a regional scale within the confines of urban areas' industrial agglomerations. In this proof of concept, variables related to labour – average number of firms, employees, and firm-size; and to installed capital – average real estate prices – are spatialized to outline their patterns distribution across Tuscany's cities. Organized in a GIS-based environment, the representation of such variables within a computerized space and with a proper spatial unit provides a basis that can be associated to the configurational aspects of the territory, being a complementary analysis for urban and regional planning.

Keywords: Spatial models · Territorialization · Economic data

1 Introduction

Since the initial rationales on locational theories [1, 2] and through their development into Urban-Regional Economics [3, 4], space has been regarded as a somewhat intractable notion by economists [5]. From a framework standpoint, it is undeniable that Spatial

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Economics consider space and its organization as an important factor for economic dynamism: for them, the *space matters*. At the same time, however, the overall role and level of detail that spatial representation and territorialization have in economic models recurrently contravene this assumption. It is well-noticed in contemporary economic-based approaches, be in Urban-Regional Economics [6] or in Economic Geography [7], that space, and the territorial endowments that constitute it, tend to be interpreted as "abstracted" and often "intangible" factors [5] – parameters that have influence but are mainly set as a background for more important economic interactions. Thisse [5] states that technical and conceptual issues inherent to analysing the qualities of space led to such "abstracted" interpretation, as few economic models have an approximation with geography – therefore, are not tailored to address in-detail data about territorial organization, while also maintaining a concision in its economic variables and parameters.

While spatial methods used in economics have limitations regarding their accuracy in territorialization, Urban and Regional Planning has been, otherwise, focused on developing instruments to analyse the spatial characteristics of urbanized areas [8, 9]. Methods that integrate datasets and models with different scopes – such as structural [10], morphological [11], and configurational [12] – in computerized environment such as *Geographic Information Systems* (GIS) [13] have become norm on the field. More recently, those methods have taken a step into Spatial Economics – and have been combined with economic variables and datasets to construct multidimensional analyses that prove to address the amount of support given from territorial endowments towards economic activities placement [14, 15]. Still, the same problems regarding economic datasets territorialization that are faced in Spatial Economics also constitute an important limitation for Urban and Regional Planning's integrated analyses. Economic variables – which are mostly available at regionalized scales, and oftentimes, only as numerical data – prevent direct spatialization and territorialization and limit the accuracy and level of detail of spatial information. Even though Urban and Regional Planning have the spatial instruments to address it, the absence of established spatial units and a more tangible dialogue between the fields of research hampers the development of methods that consider their individual requirements.

Awareness of these limitations and issues that pertain Spatial Economics and Urban and Regional Planning current approaches ought to conduce to the development of novel spatial-economic models. Those must be able to address complex spatial behaviours and interactions that may have influence on territorial disparities within urban-regional settings, therefore, diminishing the scales towards the urban. Nevertheless, this outbound step depends first on a transformation on how economics visualize and understand space, as well as create and interpret spatial knowledge; it depends of an integration with methods currently used in Geography and Urban Planning.

With those points in consideration, this paper proposes a method to spatialize economic data, integrating it to a spatial unit – the *macroarea* – that is based on territorial endowments – the built-structures location. The objective is to establish a process to territorialize economic variables available only at regionalized scales and associate them into the areas that pertain to the urban settlements, hence, providing an in-detail notion

of where this data is set on urban space. In this proof-of-concept, made for the Tuscany region territory, we use data from industrial built-structures, to establish spatial units that represent the industrial agglomerations. Those are merged to economic variables related to *labour* (*average firm-size)* and *installed capital (average real-estate value)* to establish their actual position within the territory. The method showcased in this proof-of concept provides a concise procedure to establish and create spatialized economic information which can be reproduced, not only for other urban economic functions such as retail and services, but also for other regionalized economic variables.

2 Datasets and Variables Used in the Proof of Concept

2.1 Datasets for the Construction of a Spatial Unit – the Macroarea

As a manner to territorialize the industrial activities' location and distribution in Tuscany, we conceived a spatial unit defined as a *macroarea* – or a contiguous aggregation of productive spaces (*industrial spaces).* This territorialization of economic activities was conceived, tested, and refined throughout three different publications: in Altafini et al., [16, 17] where *industrial spaces* and macroareas were constructed from the land-use data (manufacture and large retail included); and in Altafini & Cutini [15], where, instead, these spatial units were constructed upon volumetric units that represented the built-structures dedicated to industrial-manufacture uses *(industrial assets).* Both methods resulted in similar territorializations, yet the method using the *industrial assets* provides a greater positional detail. In the present assessment, the same spatial unit constructed in [15] is used, based on data extracted from the Tuscany region built-structures dataset *(Edificato 2k, 10k – 1988–2013)*, obtained from the *Sistema Informativo Territoriale ed Ambientale* (SITA) repository [18].

The *industrial spaces* construction procedure draws a 30 m buffer radius – equivalent to the plot plus the street areas – from each *industrial asset* volumetric unit. Buffered areas are then dissolved into a continuous area. The result, a sole spatial unit (Fig. 1), is then submitted to a negative buffer (30 m), that reduces the excess area created through the positive buffer into the original *industrial assets*' dimensions, while, maintaining the area boundaries and contiguities created in-between them. The resulting *industrial spaces* are then individualized, through their conversion into single parts from the sole territorial unit. A size categorization is then applied in accordance with each *industrial space* area, as well as a corresponding multi-distance buffer radius (Fig. 2, Table 1, p.4) to establish an *area of influence* for each *space.*

Areas created through the multi-distance buffer are then dissolved into a single continuous *macroarea.* The resulting sole spatial unit is then, once again, divided into several single parts based on the presence of spatial contiguities. This results in different-sized *macroareas* that are then categorized in accordance with their size, their *industrial spaces* and their *industrial assets* counts (Table 2).

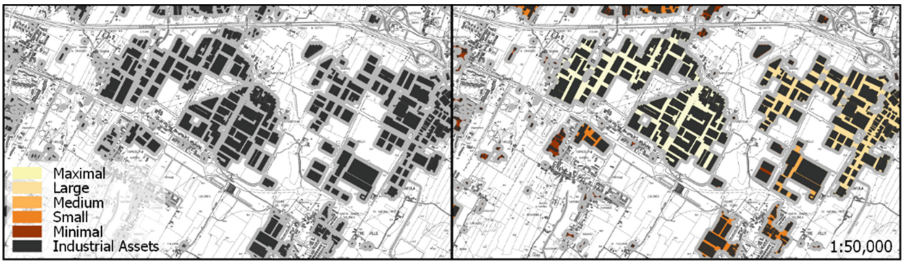

Fig.1. *Industrial assets* conversion in *industrial spaces*: positive (gray) and negative (coloured) buffer results and area categorization

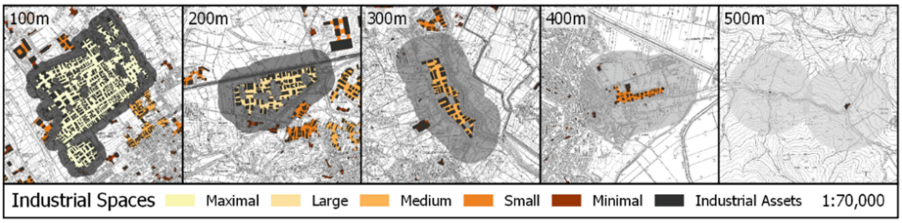

Fig.2. Examples of *industrial spaces* with *categorization* buffer distances applied.

Table 1. *Industrial spaces* classification regarding count, total area, relative multi-distance buffer and total surface after buffer

Classification	Industrial assets count	Industrial spaces count	Total Area [km^2]	Buffer radius [m]	Buffered surface [km^2]
Maximal (>= 0.6 km^2)	2,118	4	4.73	100	9.44
Large (>= 0.2 – <0.6 km^2)	6,914	38	11.98	200	47.29
Medium (>= 0.075–<0.2 km^2)	9,062	128	15.33	300	131.71
Small (>= 0.02–<0.075 km^2)	16,780	623	23.34	400	591.33
Minimal (<0.02 km^2)	45,319	14,901	27.60	500	12,741.37
Total	80,193	15,694	82.98	–	13,521.14

Table 2. *Macroareas* size classification according to industrial spaces count, industrial assets count and area ranges' values

Classification	Industrial assets count	Industrial spaces count	Area range [km^2]	No of macroareas
Isolated macroarea	1	1	<5.00	435
Small macroarea	>1	>1	<5.00	862
Medium macroarea	>1	>1	>= 5.00–<100.00	87
Large macroarea	>1	>1	>= 100.00	3

Table 3. Summary of the different spatial units that compose the industrial agglomerates territorialization

Spatial unit	Spatial unit description	Unit count
Industrial assets	A volumetric unit that represents the total area of an industrial building	80,193
Industrial spaces	Spatial unit that describes the contiguous area occupied by groups of *industrial assets* set in proximity or in the same plots/parcels of land	15,694
Macroareas	Spatial unit that territorializes *industrial assets* based on the overall reach of their contiguous *industrial spaces;* denotes the general occupation, distribution, size, as well as the industrialization degree of an urban area, while also indicating the internal and external displacement logics	1,387

Macroareas are conceptualized to establish a visual representation of the Tuscany's industrial territorial occupation, cohesion, and distribution, informing the industrialization patterns and the dynamics of placement for the *industrial assets* across the territory, above all, in those that are located within urbanized areas (Fig. 3, p. 5).

In the same manner, since the *macroareas* establish the displacement reach through *areas of influence* for the collective *industrial assets* and *spaces*, these spatial units can be used to ascertain spatial correlations of proximity with road-circulation network configurational properties, as performed in the Territorial Exposure Index [15].

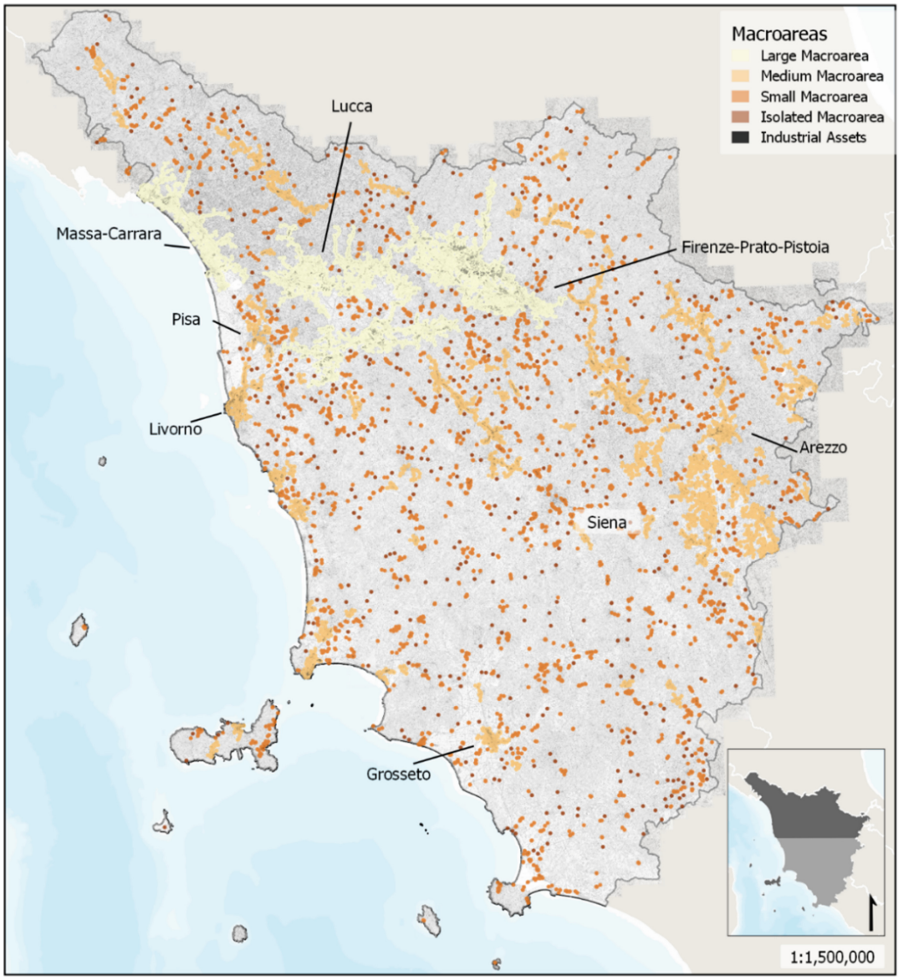

Fig. 3. Macroareas distribution across the Tuscan territory

2.2 Economic Variables and Their Issues of Territorialization

In his firm theory, Robert Lucas Jr. [19] proposes *capital* and *labour* as important economic indicators of firms' overall conditions of operation size and internal dynamism, as the amount of *installed capital* (i.e., buildings and assets) has influence in the allocation of *labour* (i.e., employees). However, by nature, those economic variables tend to be rather intangible when their spatial distribution is considered.

In general, information about *labour* and *capital* is available in a scale of aggregation that is often too extensive to allow a proper territorialization at micro-scales – above all when open data is considered. Moreover, in regionalized assessments even when the smallest spatial units of aggregation are used – as, for example, survey areas or census zones – a distinctiveness persist between the strata of data. The size determination of

survey areas for data collection tends to consider the presence of more or fewer data occurrences, therefore, oftentimes, areas that exhibit sparse information tend to be larger, while areas with more information tend to be smaller, which create misleading spatial contrasts, especially, on urbanized areas' boundaries.

Examples of these territorialization issues can be visualized when the data from the 9th Italian Industrial and Services Census (*Censimenti ISTAT dell'industria e servizi*) [20, 21] is spatialized. The database describes the total number of local units (firms) and the number of employees in the industrial and service sectors for a determined census zone, for the 2011 period. Through the calculation of the ratio between the number of firms and employees we can obtain the average *Firm-Size* – or the amount of *labour* per firm – variable territorialized for this proof of concept (Table 4, Fig. 4). From that, it is possible to spatialize the variable according to their total census zone area to calculate *firm-size density* and provide an overview of where *labour* is distributed across the territory.

Census data are organized in a dual-table system, where a numerical data table (.csv) that contains the local units' and employees' values is associated to a spatial data table (.xls), that possess a locational notation that establishes the census zones within the Tuscany territory. A spatial join must be performed in a GIS-based environment [13] to assemble the numerical table datum to its respective spatial position in the spatial data table, thus allowing variables' spatialization and categorization. Since neither the spatial data table nor the information table possess an entry that attributes the numerical area values to the respective census zones, those had to be independently calculated to attribute the average territorial densities for the local units' and employees' variables. Establishing a density parameter is imperative as, due to the differences in census zones size in urban areas – which are not standardized –, no logical spatial pattern emerges from the dataset spatialization. This greatly affects the overall data territorialization.

Table 4. Local units, employees and firm-size data distribution across the spatial units (census zones) according to their density of occurrences (km^2)

Ranges	Area values - km^2	Local units	Employees	Firm-size
Formulae	–	$\frac{N_{localunits}}{A_{censuszone}}$	$\frac{N_{employees}}{A_{censuszone}}$	$\frac{D_{employees}}{D_{localunits}}$
Very high density	>1,000	3,566	6,724	7,000
High density	<= 1,000 > 500	2,484	2,755	3,516
Medium density	<= 500 > 100	7,488	5,983	6,601
Low density	<= 100 > 20	4,188	2,739	1,039
Very low density	<= 20 > 0	3,730	3,255	3,300
No data	0 or Null	7,378	7,378	7,378
Total census zones	-	28,834	28,834	28,834

Table 5. Definition of the OMI values and OMI zones datum.

Datum	File type	Definition
OMI values	.csv	Real-estate surveyed information for rent and square-meter prices
OMI zones	.kmz	Continuous spatial areas that allocate the OMI values within the territory

Table 6. OMI values ranges, categorization, number of OMI zones and total area

Ranges [€/m^2]	Categorization	Number of OMI Zones	(%)	Total Area [km^2]	(%)
0−200	Very low real-estate value	462	33.55%	11534.06	50.22%
200−400	Low real-estate value	232	16.85%	5737.36	24.98%
400−600	Medium real-estate value	237	17.21%	2224.08	9.68%
600−800	High real-estate value	209	15.18%	1816.85	7.91%
800 - inf	Very high real-estate value	237	17.21%	1656.89	7.21%
Total	–	1377	–	22969.23	–

Even with this spatialization, the *Industrial Census* spatialization does not provide a sufficient differentiation – nor an exact positional information – that indicates the differences in distribution on the boundaries and outside the urbanized areas (Fig. 4). When paired with the *industrial assets* dataset, the *Industrial and Services Census* can provide an overview of the actual number of structures set in each census zone, thus providing a positional information that is absent on the original database (Fig. 4). Nevertheless, it does not solve the issues regarding data territorialization.

Similar spatialization issues can be observed in OMI real-estate quotations *(Quotazioni dell'Osservatorio del Mercato Immobiliare)* [22], a dataset that describes average real-estate prices surveyed within a certain area of the territory for the period between 2002 to 2021. These economic variables can be associated to the amount of *installed capital*, as they convey information about the real-estate prices (€/m^2) across a determined region, important for understanding the dynamics of value within the cities. Its territorialization, even if conceived with the idea to differentiate urban areas according to their position and placement within the cityscape [22, 23], still faces the same problems found in the *Industrial and Services Census* regarding data aggregation, as its regionalized territorial division results in areas with significative differences in size and datum quantity.

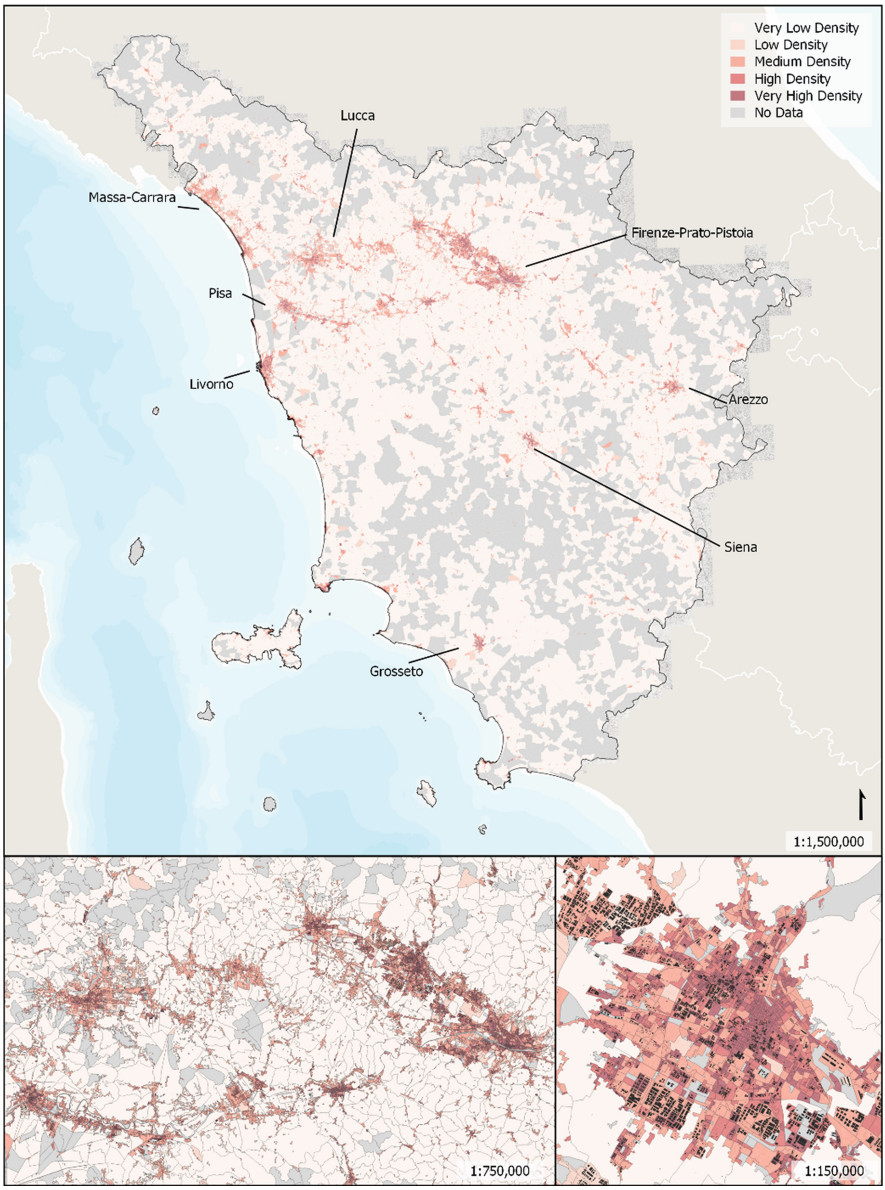

Fig. 4. Spatial distribution of average *firm-size* density in Tuscany

From the methodological standpoint, the OMI datasets spatialization process within a GIS-based environment [13] functions in the same manner as the *Industrial and Services Census*, as data is provided using a dual-table system, where one table represents the OMI values – economic information –, and the other, the OMI zones – surveyed spatial

units As in the census dataset, several adaptations in a GIS-based environment were needed to allow the construction of the average real-estate values.

Spatialized OMI values correspond to a measure of *average installed capital* for a determined OMI zone within Tuscany. OMI values must be joined to OMI zones through a common variable for zone [21]. Since the variable possess sub-categories to differentiate structures' urban functions (24 categories) and their state of conservation (3 categories), the dataset had to organized in columns defined from V1 to V72. "V

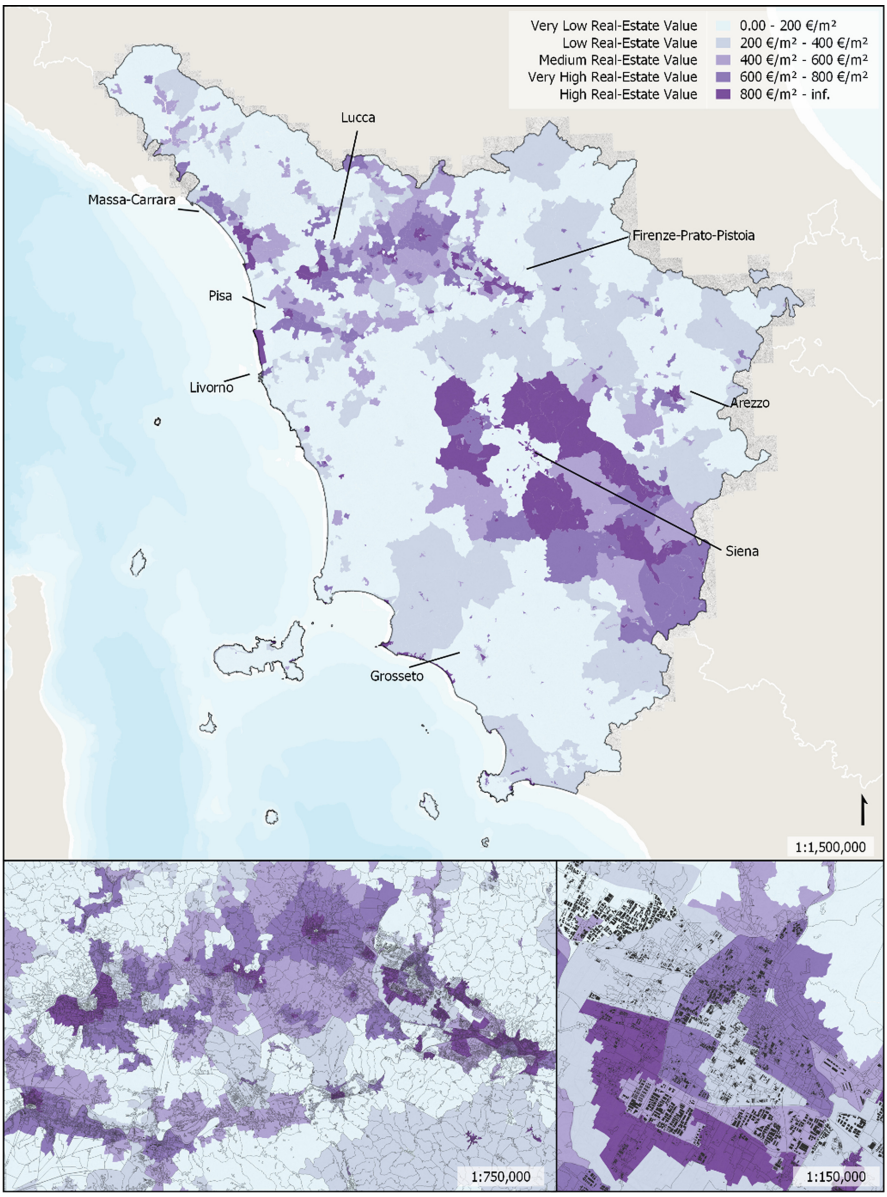

Fig. 5. Spatial distribution of average OMI real-estate values across Tuscany

columns" that corresponded to the industrial urban functions (Warehouses, Industrial Buildings and Laboratories) in all states of conservation were used to calculate the average real-estate values for each OMI zone by considering the minimum and maximum values for prices by square-metre. The results for the OMI dataset are then spatialized and categorized in accordance with their square-meter price range (€/m^2):

Likewise in the *Industrial Census* spatialization, *OMI real-estate values* territorialization provides a limited spatial differentiation, as the data distribution does not provide a precise positional information that indicates the patterns within urbanized areas. In the *OMI values* case (Fig. 5), this issue is even more significative, as territorial divisions have a larger regionalization pattern. While, as in the *Industrial and Services Census*, issues can be mitigated with the addition of the *industrial assets'* dataset, it does not solve the issues in territorialization accuracy regarding location, especially on the areas in the outskirts of urban settlements.

3 A Method for Economic Data Territorialization - Results

As discussed in the previous section, traditional methods for economic data territorialization often face issues regarding their representation accuracy at urban scales. Since data aggregation for those variables tends to be set at larger scales – such as regional – it becomes problematic to identify which information pertains to urbanized areas and which do not, as well as to precise their position within the cityscape. Moreover, the presence of large areas with few data occurrences conceals the real dimension of the phenomena within territories.

Considering these issues, and the imprecisions that it leads to, we propose a method for economic data territorialization that merges the current regionalized datasets with the concept of *macroarea.* As *macroareas* are spatial units whose construction is based on *built-structures* position – in this case, *industrial assets* – they provide a territorialization that encompass areas with effective functional presence. This differs from the regionalized area described in the spatialization using survey zones, as it associates data to areas that are contiguous urban extents – while also highlighting the isolated built-structures within larger survey areas outside urbanized areas borders.

The merge method is rather simple and consists in the intersection between the spatial units made using the join geoprocessing function on a GIS-based environment. In this join, *Macroareas* are applied as an overlay to thr regionalized spatial units that compose the original datasets of the *Industrial and Services Census* and the *OMI Quotations.* Every datum that remains outside the *macroareas'* reach is subtracted from the result (Fig. 6; p.11, Fig. 7., p.11, Fig. 8, p.12, Fig. 9, p.12). This intersection process led to the elimination of most areas within the category "No Data" in the *Industrial and Services Census*, (which were reduced by 92,15%) as well as an overall reduction of the total areas with Very Low Density (80,27%), while preserving the spots where data was present and precising the location of the data where *industrial assets* are placed (Fig. 6 p, 11, Fig. 7, p.11). These differences in terms of area coverage grow in importance in the *OMI Quotations* dataset, as restrictions tend to better reflect the value/location relationships (Fig. 8, p.12), In this case, total areas for each category are extensively reduced (Table 7) and the spatialization now cover only the areas that are adjacent the built-structures (Fig. 9, p.12).

Table 7. OMI values comparison after macroarea reduction

OMI quotations - area (km^2)	Original dataset	Macroarea reduction	$\Delta\%$
Very high avg. real-estate value	1656.89	368.46	−77.76%
High avg. real-estate value	1816.85	561.39	−69.10%
Medium avg. real-estate value	2224.08	684.11	−69.24%
Low avg. real-estate value	5737.36	1270.54	−77.85%
Very low avg. real-estate value	11534.06	1562.81	−86.45%

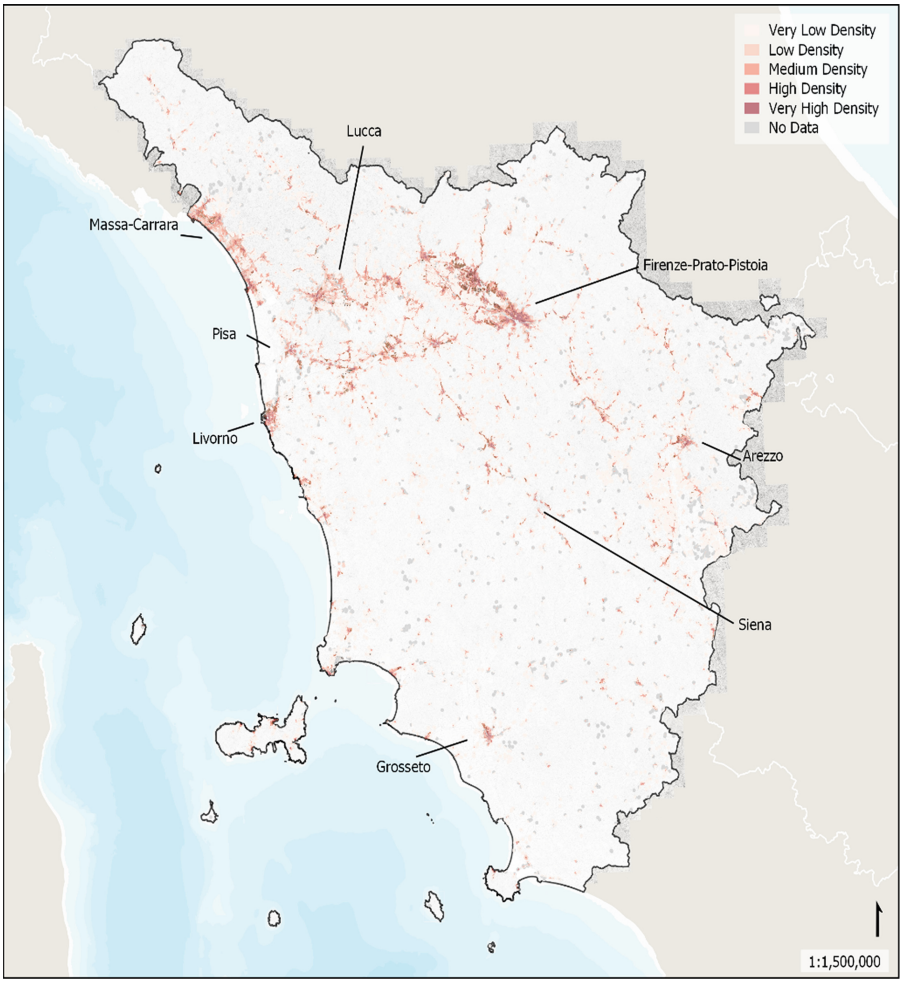

Fig. 6. Spatial distribution of average *firm-size (labour)* combined with macroareas restriction in Tuscany

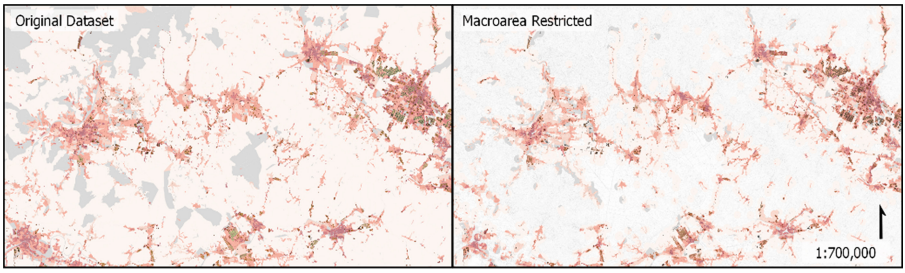

Fig. 7. Comparison between the methods of spatialization for average *Firm Size* in Tuscany

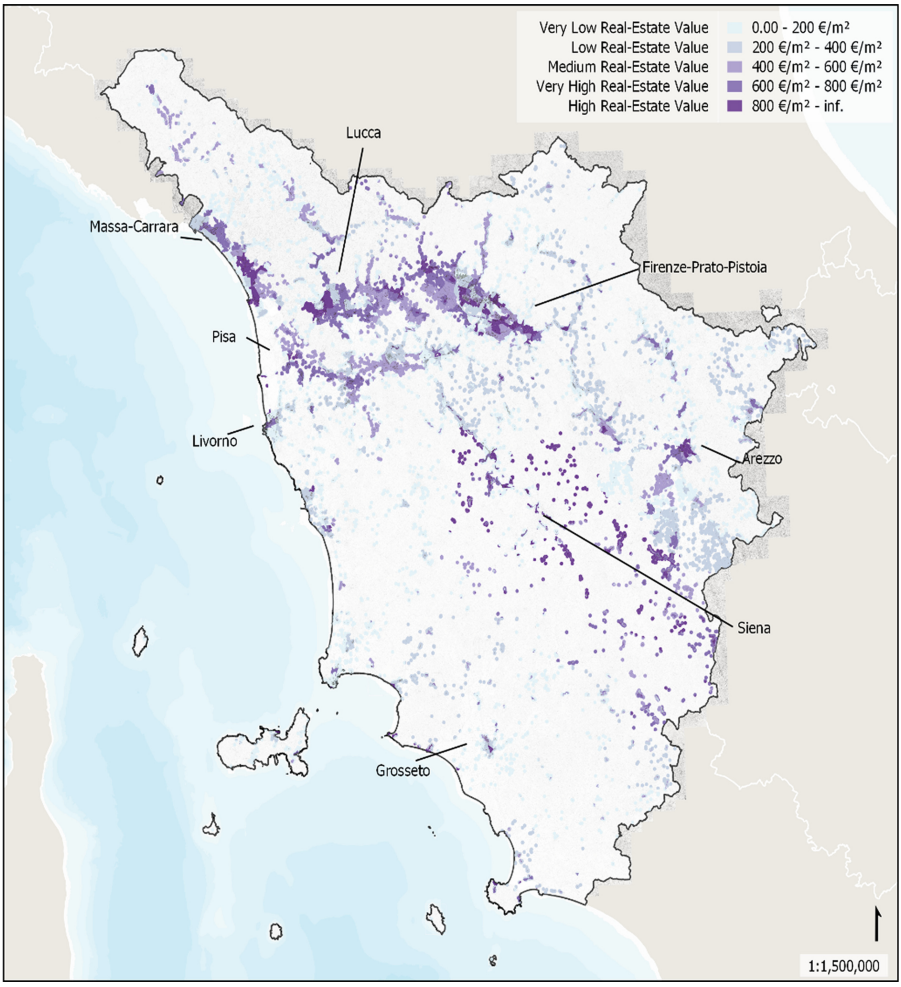

Fig. 8. Spatial distribution of average *OMI real-estate values (installed capital)* combined with macroareas restriction in Tuscany

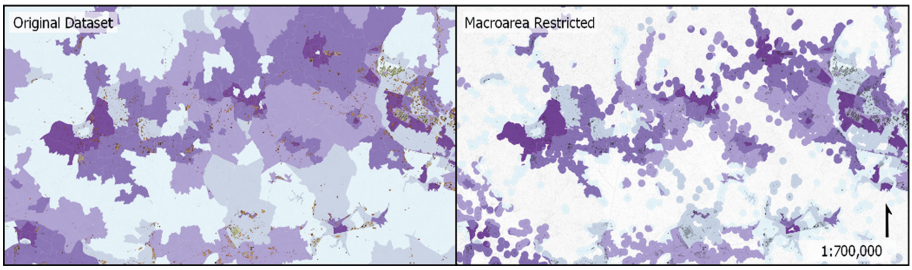

Fig. 9. Comparison between the methods of spatialization for average *OMI real-estate values* in Tuscany

4 Discussion of the *Macroarea-Based* Territorialization Results

Results attained through the *macroarea* restricted territorialization reflect a distinctive concentration pattern for the *average firm-size (labour)*, within septentrional and, to a lesser degree, central Tuscany (Fig. 6, p.11). Those areas correspond to the location of the major urban settlements - the provincial capitals of *Firenze, Livorno, Lucca, Massa-Carrara, Pisa, Prato, Pistoia* – as well as the main conurbations within the region. Moreover, as stated in Altafini & Cutini [15] Northern Tuscany has most of its larger industrial agglomerates under *Low* and *Very Low* Spatial Territorial Exposure, which denotes an adequate territorial support for economic activities there placed.

Although higher ranges of *average firm-size* are predominant within the *macroareas* set on Northern and Central Tuscany, those spaces also possess significative numbers of census zones set under *Low* and *Very Low* ranges, above all, on their hinterlands (Fig. 6, p.11). When compared to the original dataset spatialization method (Fig. 4, p.7) results evidence that most *industrial assets* set on the lower *firm-size* ranges within the Northern and Central *macroareas* are in the boundaries of the large urban settlements. Therefore, located around the census zones within the higher ranges of *average firm-size*, being associated to cityscape continuities (Fig. 7, p.11).

A contrast can be established with Southern Tuscany *macroareas*, where industrial agglomerations effectively follow a hinterland-based spatial distribution. *Industrial assets* tend to be located far from urban centres – as observed in the area between the provincial capitals of *Arezzo* and *Siena* (Fig. 4, p.7, Fig. 7, p.11), and overall *average firm-size* densities tend to be lower. Individuating those territorial patterns is unattainable through the regionalized methods used to spatialize the original datasets (Fig. 7, p.11), which demonstrates the usefulness of the *macroarea* as a spatial unit to improve the overall degree of accuracy in economic variables territorialization.

Concentration patterns for *OMI real-estate values* (Fig. 8 p12) follow similar spatial distributions when compared to the *average firm-size* (Fig. 6, p.11), as areas with higher average prices by square metre (600–800 €/m^2 and above 800 €/m^2) are mostly concentrated in around the provincial capitals in Northern and Central Tuscany. Nevertheless, differences exist as several *macroareas* in Southeast Tuscany hinterlands – between the provincial capitals of *Arezzo* and *Siena* also possess high average prices, as observed in the original dataset spatialization (Fig. 5, p.9).

The *macroarea restriction* reveals a detailed pattern for *real-estate values* distribution (Fig. 8, p.12, Fig. 9, p.12). It demonstrates that, while areas with higher *installed capital* tend to be in proximity to the larger urban centres, the *industrial assets* are mostly placed at the urban settlements' boundaries. Such result can be interpreted as a nod to William Alonso's [3] and Richard Muth's [4] locational theories of urban rent, since patterns of functional distribution assumed in their models tend to be, more-or-less reproduced in the territorial analysis.

Once again, a spatial distribution contrast is observed between Northern and Southern Tuscany (Fig. 8, p.11). The meridional *macroareas* possess a punctual pattern of distribution of *installed capital,* due to its hinterland-based characteristics of industrial placement. Small-localized *macroareas* with high *real-estate values* can be found in smaller and medium settlements, which demonstrate that, as in the North, urban settlements still guide the dynamics of placement to some extent. Southeast Tuscany, however, present a particular characteristic when compared to the Southmost part of the region. While permeated by small *macroareas* with *Low* and *Very Low average firm-size densities* (Fig. 6, p.11), *average real-estate values* are high, which demonstrates that while *industrial assets* tend to be smaller and less contiguous, their *installed capital* and positional value are important (Fig. 8, p.12). In the same manner, ascertain those detailed spatial logics without the use of the *macroarea* is unfeasible, and justifies its usage (Fig. 9, p.12).

5 Concluding Remarks

The territorialization of economic variables is an issue that matters for both Spatial Economics and Urban and Regional Planning. Integrated spatial-economic analysis at urban-regional scales requires a level of detail in spatialization that is unattainable through the sole usage of the traditional regionalized economic variables such as those available through census and surveys. While this kind of territorialization can be reasonably accurate on cities' urban cores, it tends to greatly lose in precisions near the cities' boundaries, due to the increment of the surveyed areas associated to the decrement of the data occurrences. In that aspect, regionalized data can often lead to misjudgements in the assumptions of *what is where* and *why*? In urban settlements.

Acknowledging these issues in territorialization is a first step to solve the problem. In this paper we discussed the characteristics of two regionalized databases, the *Industrial and Service Census* [20] – to describe the distribution of *labour* – and the *OMI Quotations* [22] – to describe the distribution of *installed capital* –, addressing their characteristics of spatialization. Based on that, we proposed a step to merge these datasets to a spatial unit that has been in continuous methodological development – the *macroarea* [15]. The proof-of-concept, made on GIS using data for the Tuscany region, demonstrated the use of a restricted spatial unit based on the built-structures position – the *macroarea* – can mitigate the spatialization problems of regionalized databased, diminishing the overall imprecisions in location. As *macroareas* also establish the reach of each census datum, positioning it within the urbanized spaces, it is a useful variable to analyse dynamics associated to *value*, as well as to establish correlations with other spatial analyses, such as the configurational and morphological. In the same manner, while we establish this

proof-of-concept using *industrial assets*, the same method can be applied to other urban functions such as retail and services, or even to analyse real-estate values evolution for the housing market. Hence, while a simple method, merging the *macroarea* spatial units with the economic datasets can very well increase the level of detail for the analysis and well aid in the explanation and of economic phenomena that pertains the urban environments. Further studies are planned to improve the spatial unit and the methods to associate it to other economic variables Nevertheless, we still believe that a shift on how economic data is made available is also due, given the novel requirements of spatial research.

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