Values and Prices in the Historic City. Divergences and Value Creation

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Abstract. Analyses of the property market in the historic city often reveal heterogeneous, inconsistent or weak results as to the relationship between property characteristics and ask prices, even in homogeneous neighbourhoods. This phenomenon in the historic city is closely related to the existence of an imperfect real estate market, in which properties are often demanded and offered not only by families, but also by tourists as holiday homes and/or by students. The study proposes a model for analysing the residential property market in the historical centre of Syracuse, namely Ortigia, developed with reference to the Theory on sub-markets analysis. The structure of the model is characterised by spatial clustering based on quartiles of property characteristics, an exploration of the relationship between an aggregate quality index and price/sqm based on simple linear regression, spatial clustering based on the aggregate quality index, and fuzzy clustering. The model found a segmentation of the Ortigia property market based on three sub-markets, which provide details on the relationship between property characteristics and price formation, and between groups of property characteristics that contribute to price formation. Fuzzy clustering helped to highlight the dynamics of an imperfect market such as that of the historic centre of Ortigia.

Keywords: Imperfect market · Real estate sub-markets · Fuzzy clustering

1 Introduction

Analyses of the property market in the historic city often reveal heterogeneous, inconsistent or weak results in terms of the relationship between property characteristics and asking prices, even in neighbourhoods that are homogeneous in terms of location and context. In some cases, this is due to the fact that within the same segment, e.g. residential, some properties are intended for personal use, others for productive investment, and still others for speculative investment, thus obscuring the actual market segment to which they refer. These conditions should place these properties in different segments because the preference systems of the economic actors involved are different, which should therefore have different effects on the relationship between the asking price and the characteristics of the property.

This phenomenon, in the historic city, is closely linked to the fact that there is an imperfect property market, in which properties intended as residences are in demanded

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and are offered not only by families but also by tourists as holiday homes and/or by students. This opacity in the true state of properties leads to a blurred characterisation of properties within the same market. In order to achieve a better characterisation of the market, it is necessary to deepen the level of analysis in order to identify potential submarkets.

In other cases, all things being equal, the preferences of the economic actors may be more nuanced and weaker, leading to an overall low significance of the relationship between asking price and property characteristics. This could be tentatively highlighted in the pre-analysis phase of the data with the detection of numerous outliners.

Further research could support the identification of specific sub-markets for the property market under analysis.

There are several methods in the literature to detect significant factors influencing property prices, such as Hedonic models [1] or Automated valuation models (AVM) [2], which can support a robust analysis and characterisation of the market.

There are also numerous filtering models in the literature, developed within the framework of the Theory on sub-markets analysis proposed by William Grigsby, which can support the identification of sub-markets [3].

These models make it possible to identify and characterise sub-markets for apparently homogeneous property markets, i.e. those identified on the basis of spatial segmentation. Due to its complexity the property market in the historic city centre is difficult to describe in terms of sub-markets defined a priori on the basis of its spatial segmentation, since neighbouring units, even if they belong to the same residential segment, can be very different in terms of property characteristics, preference structures of the subjects and actual destination.

The study proposes a model analysis of the residential property market in the historical centre of Syracuse, namely Ortigia, with the aim of identifying and characterising its sub-markets. The model develops several analyses: spatial clustering of properties on the basis on property characteristics; estimation of an aggregate index of overall quality; relationship between aggregate index of overall quality and asking price per square metre; fuzzy clustering. The paper is divided into the following sections: Sect. 2 illustrates the state of the art in the theory of sub-market analysis; Sect. 3 introduces the case study; Sect. 4 illustrates the methodological approach; Sect. 5 reports the results; Sect. 6 proposes some reflections on the results and a summary of the proposed research.

2 Theory on Sub-markets Analysis

“Filterng models”, which aim to study the functioning of local housing systems have been proposed since the 1940s and 1950s [4]. The main assumption of “filtering models” is the existence of real estate submarkets characterised by specific dynamics of house prices, levels of property characteristics and preferences of economic agents.

There is no single concept of property market filtering in the literature [5]. In the field of urban economics, the concept of filtering has developed into two main lines of research: one aimed at analysing processes related to the life cycle of housing units, i.e. changes in the level of property characteristics affecting changes in real house prices;

and another aimed at analysing processes related to the life cycle of households, i.e. changes in their real income level and changes in real house prices.

The empirical research that has developed on the basis of filtering models has mostly focused on analyses aimed at assessing a specific indicator of change: house prices, in order to measure their variation [6], housing turnover [7], household mobility [8]. On the one hand, researchers agree on the existence of real estate submarkets, but on the other hand they do not propose a single empirical dimension to identify them.

A sub-market could be defined on the basis of the location of dwellings in the urban context, creating a spatial sub-market, or on the basis of property characteristics, creating a structural sub-market. Some researchers have found the empirical dimension for the identification of property sub-markets in a division of the market into areas, socio-economic characteristics of households and environmental characteristics [9–11]; others on the basis of neighbourhoods [12–14]; others on the basis of administrative boundaries [15–18]; others on the basis of population data; others identify the sub-market as the result of an in-depth knowledge of the market [19]; others on the basis of property prices defined by professionals [20, 21].

Other researchers consider as a sub-market to includes all properties, regardless of their location in the urban context, that have similar physical characteristics and are identified by economic agents as "close substitutes" [3, 4, 22, 23]. The first researcher to define sub-markets in terms of "close substitutability" of housing was William Grigsby [3]. In terms of strict substitutability, the property sub-market consists of a number n of "close substitutes" that belong to the same group but are "imperfect substitutes" for those belonging to other sub-markets [24–27]. Other research belonging to the nested spatial/structural and demand group-based submarkets sub-markets approach has highlighted the importance of spatial and structural characteristics in definition sub-markets.

Property market analysis aimed at identifying possible sub-markets can be carried out approaches. The academic literature produced over the last few decades has proposed numerous studies on market analysis aimed at the identification of sub-markets on the basis of real estate characteristics.

These studies have highlighted the role played of property characteristics in identifying sub-markets: Rapkin, Winnick and Blanck [3, 28] emphasised the influence of the "unit location within the building" characteristics of properties on the identification of sub-markets; Goodman [21, 29] emphasised the influence of "location and overall accessibility of the building and neighbourhood characteristics" of properties on the identification of sub-markets; Adair, Berry and Mc Greal W.S. [30, 31] emphasised the influence of "location and overall accessibility of the building and neighbourhood characteristics" and "unit location within the building".

Although there is no clear definition of a sub-market in the literature, based on the theoretical framework developed by Grigsby [3] and on the empirical basis that sub-markets can be identified by reference to certain characteristics of properties, several models for identifying and analysing sub-markets have been proposed in the literature: Hedonic pricing models [32, 33]; Factorial Analysis [23]; Cluster analysis [16, 34–36]; Geostatistical Models [37–41]; Hard clustering with the k-means analysis clustering algorithm [42]; Soft clustering with the Fuzzy clustering algorithm [43–48].

3 The Case Study

Situated on the south-eastern coast of Sicily, the island of Ortigia rises a few hundred metres from the mainland and extends into the Ionian Sea, creating two natural harbours, the Small Harbour to the north and the Large Harbour, bordered to the south by the Maddalena Peninsula (Fig. 1).



Fig. 1. Geographical framing of the studied urban context.

The ancient core of the historical centre of Syracuse, Ortigia, covers an area of 45 hectares and is connected to the mainland by two bridges spanning the narrow "Darsena" canal.

The present urban fabric of Ortigia is the result of a complex historical and urban stratification, the fruit of an evolutionary process that has taken place over a long period of time since the Greek colonisation in the 8th century BC. Its millenary history can be seen in the signs and traces that have been preserved over time.

The rebuilding of Ortigia after the devastating earthquake of 1693 in the late Sicilian Baroque style, which that incorporated the remains of previous eras in a harmonious union, has contributed to the creation of an architectural and urban context of absolute value, in which strong identity and cultural characteristics emerge.

On the threshold of the modern age, the Ortigia, still enclosed by the confines of the Spanish fortifications, grew on itself, making hygienic and sanitary conditions critical. From 1870, with the demolition of the fortifications, Ortigia was gradually transformed from the nerve centre of Syracuse to the outskirts.

The city of Syracuse, which had not left the island for many centuries, began to expand on the mainland and the population began to migrate in search of better living conditions. From the second half of the 20th century, the island was abandoned to neglect and decay, with only the poorest classes lived there, leading to progressive social and physical degradation.

Since the end of the last century, however, thanks to an intense process of restoration and improvement that has radically transformed it, Ortigia has once again become a site of primary historical and cultural importance and a strong point in the city's tourist development. In addition, the inscription in the UNESCO World Heritage List-WHL in

2005 has raised Ortigia's profile worldwide, attracting increasing interest from national and international investors.

As a result, a process of gentrification was set in motion, which has transformed Ortigia into a cultural, tourist and leisure centre, but also gradually causing the local population to move to other parts of the city.

In fact, the resident population fell from 27,000 in 1950 to 3,889 in 2020.

The population density is not high and varies according to the tourist season. Ortigia, in fact, is now overcrowded from spring to autumn and depopulated in the winter months.

As for the property market in Ortigia, which was dormant until the early 2000s, it has experienced an unexpected boost since the first decade of the 21st century, with a progressive increase in demand and prices, driven by the presence of a university campus and the development of tourism. The island, now transformed into an "exclusive location", is in fact today the area with the highest unit prices in the city.

4 Method

The methodological approach used to identify and characterise the submarkets for the Ortigia property market consists of the following steps:

- Create a database containing the property characteristics of the sample to be analysed;
- Spatial analysis of the sample of properties based on the quartiles of property characteristics in order to identify sub-markets (spatial segmentation using QGIS);
- Estimation of an aggregate k^* index of the overall quality of properties and spatial analysis of the sample of properties based on its quartiles by using QGIS.
- Analysis of the relationship aggregate k^* index of overall property quality with asking price per square metre.
- Cluster analysis of the property characteristics data of the sample and identification of submarkets (fuzzy clustering).
- Spatial analysis of submarkets identified by fuzzy clustering by using QGIS;
- Local analysis of submarkets.

4.1 Database Real Estate Characteristics

The database, based on the approach of Carlo Forte [49], includes the survey for the sample of the following property characteristics: k_e Location and overall accessibility of the building, and neighbourhood characteristics; k_i Position of the unit within the building; k_t Technological characteristics about building and unit; k_p Income/capital gain; k_a Architectural quality of the building and unit; P_{sqm} Asking price per square metre.

The six real estate characteristics are broken down into sub-characteristics, which are scored on a six points ranging from 1, indicating poor quality, to 5, indicating excellent quality. The main property characteristics are rated based on the aggregation of scores for the sub-characteristics. Table 1 shows the hierarchy of sub-characteristics for the k_e, k_i, k_t, k_p and k_a.

Table 1. Database structure of the property characteristics

k_e- Location and general accessibility of the building and characteristics of the neighbourhood	1. Complexity and urban shape	1. Location and settlement quality; 2. Mix of functions; 3. Social status (occupation type, income level, etc.) of the area; 4. Level of public space maintenance
	2. Urban facilities	1. Public facilities; 2. Public services
	3. Accessibility	1. Mobility to/from the area by private transport; 2. Mobility to/from the area by public transport; 3. Mobility within the neighbourhood
	4. Micro-environmental characteristics	1. Functional and 2. Symbolic characteristics
k_i- Building unit location		1. Panoramic quality; 2. View; 3. Brightness; 4. Orientation; 5. Security;
k_t- Technological characteristics	1. Building	1. Quality of the building structure; 2. Quality of the installations; 3. Quality of the finishes and windows; 4. Maintenance levels
	2. Unit	1. Finish; 2. Quality of the installations; 3. Maintenance levels
k_p- Income / capital gain		1. Income gain; 2. Capital gain
k_a- Architectural quality	1. Building	1. Use suitability; 2. Integration of structure and installations; 3. Finish and technology; 4. Morphological consistency; 5. Space decorum; 6. Maintenance levels
	2. Unit	1. Size, functionality and distribution; 2. Additional surfaces; 3. Quality of finish
$P_{sqm}-$ Asking price		Price per square metre

4.2 Fuzzy Clustering

Cluster analysis is a well-known multivariate statistical technique that can be used to derive a group structure, consisting of several similar units, can be derived from a given

Table 2. Sample of the database.

id	ask price	price/sq	ke	ki	kt	kp	ka
1	400,000	3809.52	4.26	4.35	3.13	5.00	4.06
2	175,000	2333.33	2.03	2.00	3.71	3.50	3.52
3	128,000	2560.00	2.03	2.00	4.31	4.50	3.94
4	150,000	2371.54	2.08	2.30	4.66	4.50	4.44
5	300,000	2857.14	3.17	3.00	3.71	4.50	4.08
6	200,000	2312.14	2.21	4.25	2.17	5.00	3.38
7	215,000	2330.62	1.70	2.60	3.31	4.00	3.92
8	195,000	1361.26	4.37	2.75	1.70	3.00	2.42
9	290,000	2426.78	4.81	4.15	2.42	4.00	3.30
10	308,000	2415.69	3.38	3.05	3.39	3.50	2.78
11	210,000	1564.25	2.03	3.15	1.83	3.00	3.68
12	198,000	2828.57	2.43	2.45	4.48	3.50	4.02
13	130,000	2549.02	2.85	2.40	3.92	3.50	3.60
14	268,000	2977.78	3.06	3.45	1.39	4.00	3.66
...	...	...	...	...	...	...	...
50	540,000	2160	2.515	2.95	4.79	3.5	3.72

population of data. The groups identified are characterised by internal homogeneity and external heterogeneity, assessed with reference to a defined set of variables.

There are several approaches to cluster analysis in the literature, those in which the objects belonging to a given group are selected by similarity, i.e., "similar" objects fall into the same cluster, referred to as hard clustering; those in which the objects belonging to a given group are selected on the basis of modulation of the degree of similarity (even partial), referred to as soft clustering. The fuzzy clustering algorithm belongs to of the soft clustering approaches. Given the imprecision of the data, a soft clustering approach can provide more information than a crisp approach.

There are several approaches to fuzzy clustering, in the literature, hierarchical or non-hierarchical [50]. The latter directly provide an a priori fixed number of clusters using iterative procedures aimed at optimising an objective function [51]. For each solution, an error measure is provided based on the distance between the data and the representative elements of the cluster. Among the fuzzy clustering algorithms proposed in the literature, the one proposed by Kaufman and Rousseeuw [52] is widely used, which proposes the following objective function:

$$C = \sum_{k=1}^{K} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} m_{ik}^2 m_{jk}^2 d_{ij}}{2 \sum_{j=1}^{N} m_{jk}^2} \tag{1}$$

where m_{ik} represents the unknown membership of object i to the cluster k and d_{ij} is the dissimilarity of object i to the cluster i, evaluated as the Euclidean distance or Manhattan distance.

Goodness-of-fit statistics are important in selecting the number of clusters.

The amount of "fuzziness" in a solution can be measured by Dunn's partition coefficient, which measures how to close the fuzzy is to the hard solution. Dunn's partition coefficient is given by the following formula:

$$F(U) = \frac{1}{N} \sum_{k=1}^{N} \sum_{i=1}^{N} m_{ik}^2 \tag{2}$$

This coefficient varies from $1/K$ to 1. Its value is $1/K$ when all memberships are equal to $1/K$. Its value is one when, for each object, the value of a membership is unity. The normalised version of Dunn's partition coefficient, i.e., so that it varies between 0 (completely fuzzy) and 1 (hard cluster, can be represented by the following formula:

$$\mathrm{F_c(U)} = \frac{\mathrm{F(U)} - (\frac{1}{\mathrm{K}})}{1 - (\frac{1}{\mathrm{K}})} \tag{3}$$

Another partition coefficient that helps verify the goodness of the model is the one proposed by Kaufman (Kaufman1990), which can be expressed by the following formula:

$$\mathrm{D(u)} = \frac{1}{\mathrm{K}} \sum\nolimits_{\mathrm{k=1}}^{\mathrm{N}} \sum\nolimits_{\mathrm{i=1}}^{\mathrm{N}} (\mathrm{h_{ik}} - \mathrm{m_{ik}})^2 \tag{4}$$

this coefficient varies in the range from 0(hard clusters) to $1 - (1/K)$ (completely fuzzy).

The normalised version of this coefficient is given by the formula:

$$\mathrm{D_C(U)} = \frac{\mathrm{D(C)}}{1 - \left(\frac{1}{\mathrm{K}}\right)} \tag{5}$$

Dunn's normalised partition coefficient and Kaufman's normalised partition coefficient provide good guidance for identifying the optimal number of clusters, in particular the criterion of selecting the solution with $F_c(U)$ the largest and $D_C(U)$ the smallest.

In this study, we used the NCSS software for fuzzy clustering. It allows us to minimise the objective function C of Kaufman and Rousseeuw [52] and check the goodness of fuzzy clustering, i.e. the number of clusters, based on the values of the normalised partition coefficients of Dunn and Kaufman.

5 Results

We surveyed a sample of 50 properties in the historic centre of Syracuse, i.e. Ortigia, net of outliers.

The property sample data were organised in a database based on the hierarchy identified and presented in the section for the six characteristics: k_e, k_i, k_t, k_p, k_a.and P_{sqm}. A summary of the aggregated data is presented in Table 2.

The spatial analysis of the property sample based on the quartiles of the property characteristics k_e, k_i, k_t, k_p, k_a and P_{sqm} can support an initial exploration of the property market aimed at identifying spatial submarkets. Analysis based on of the quartiles of different property characteristics shows how properties are redistributed according to their level.

Figure 2 shows the spatial distribution of the properties in Ortigia based on the quartiles of property characteristics k_e, and k_i.

For property characteristic k_e, 22% of the properties in the sample belong to the first quartile, 28% to the second quartile, 20% to the third quartile and 30% to the fourth quartile. Properties that fall in the first quartile of k_e are mostly located in the central belt of Ortigia. Those belonging to the second quartile are located partly along the perimeter

but in side streets, and partly in the central strip of Ortigia. Those belonging to the third quartile are mostly located in a perimeter strip that extends inwards to the east and west of the island of Ortigia. Those belonging to the fourth quartile are mostly located along the perimeter strip of the island of Ortigia and along its main street axis, Corso Matteotti.

For the property characteristic k_i, 28% of the properties in the sample belong to the first quartile, 22% to the second quartile, 22% to the third quartile, and 28% to the fourth quartile.

Properties that fall in the first quartile of k_i are mostly located in the central belt of Ortigia. Those in the second quartile are located along the innermost perimeter strip and in the central belt of Ortigia.

Those belonging to the third quartile are mainly located in the central strip and the southern and northern perimeters strip of Ortigia. Those belonging to the fourth quartile are mainly located along the central and western perimeter strip of Ortigia Island.

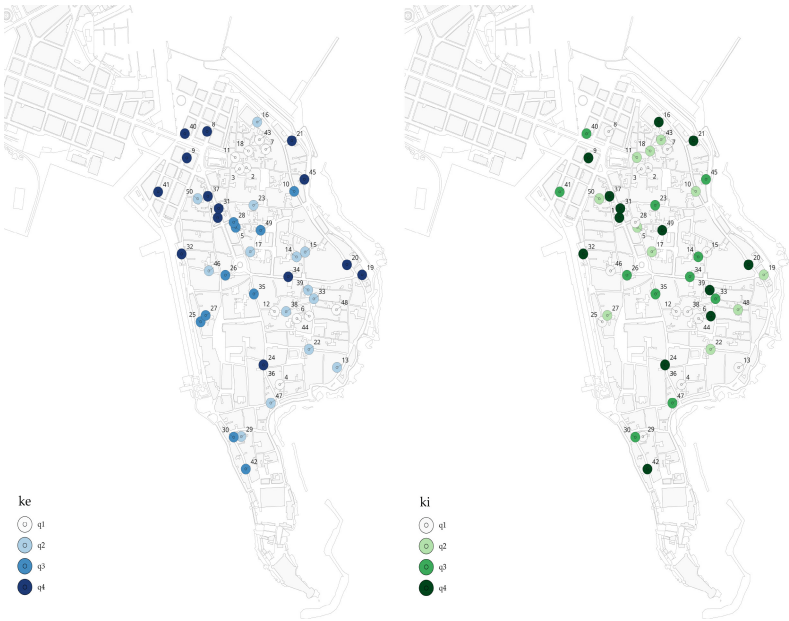


Fig. 2. Spatial distribution of properties in Ortigia based on the quartiles of property characteristics k_e, and k_i.

Figure 3 highlights the spatial distribution of properties in Ortigia based on the quartiles of property characteristics k_t and k_p.

For the property characteristic k_t, 26% of the properties in the sample belong to the first quartile, 22% to the second quartile, 24% to the third quartile and 28% to the fourth quartile. Properties that fall into the first quartile of k_t are mainly located in the central belt of Ortigia.

Those belonging to the second quartile can be found in the northern part of Ortigia. Those belonging to the third quartile ds are mostly found in the northern and southern

areas of the island of Ortigia. Those belonging to the fourth quartile are mostly found along the central strip of the island of Ortigia.

For the property characteristic k_p, 10% of the properties in the sample belong to the first quartile, 28% to the second quartile, 20% to the third quartile and 42% to the fourth quartile. The properties belonging to the the first and second quartiles of k_p are mostly located in the central belt of Ortigia. Those belonging to the third quartile are mostly found along the south-western and northern belts of the island of Ortigia. Those belonging to the fourth quartile are mostly found along the central belt of the island of Ortigia and along the main road axis system.

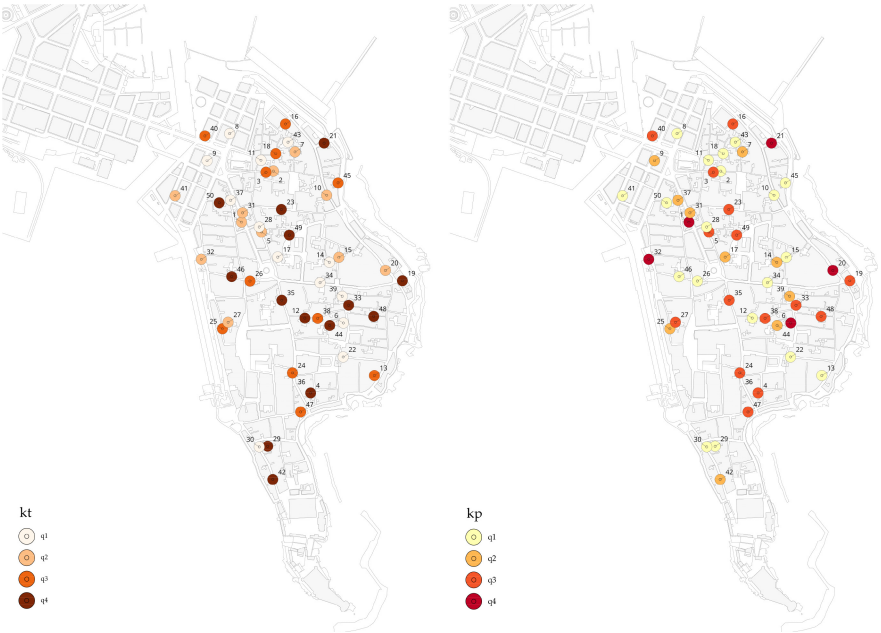


Fig. 3. Spatial distribution of properties in Ortigia based on the quartiles of property characteristics k_t and k_p.

Figure 4 shows the spatial distribution of properties in Ortigia based on the quartiles of property characteristics k_a and P_{sqm}.

For the property characteristic k_a, 26% of the properties in the sample belong to the first quartile, 20% to the second quartile, 28% to the third quartile and 26% to the fourth quartile. Properties in the first quartile of k_a are mainly located in the central belt of Ortigia. Those belonging to the second quartile are mainly located in the central belt of Ortigia and the western perimeter belt. Those belonging to the third quartile are mainly located in the central belt and along the south-western perimeter strip of the island of Ortigia. Those belonging to the fourth quartile are mainly located along the diagonal band in the east-west axis and in the north-western part of the island of Ortigia.

For the property characteristic P_{sqm}, 24% of the sample properties are in the first quartile, 26% in the second quartile, 26% in the third quartile, and 24% in the fourth

quartile. Properties that fall in the first and second quartiles of P_{sqm} are mainly located in the central belt of Ortigia consistent with the spatial analysis of other property characteristics. Those belonging to the third quartile are mainly located in the eastern part of the island of Ortigia. Those belonging to the fourth quartile of P_{sqm} are mainly located in the central and northern areas of the island of Ortigia and along the main axis system.

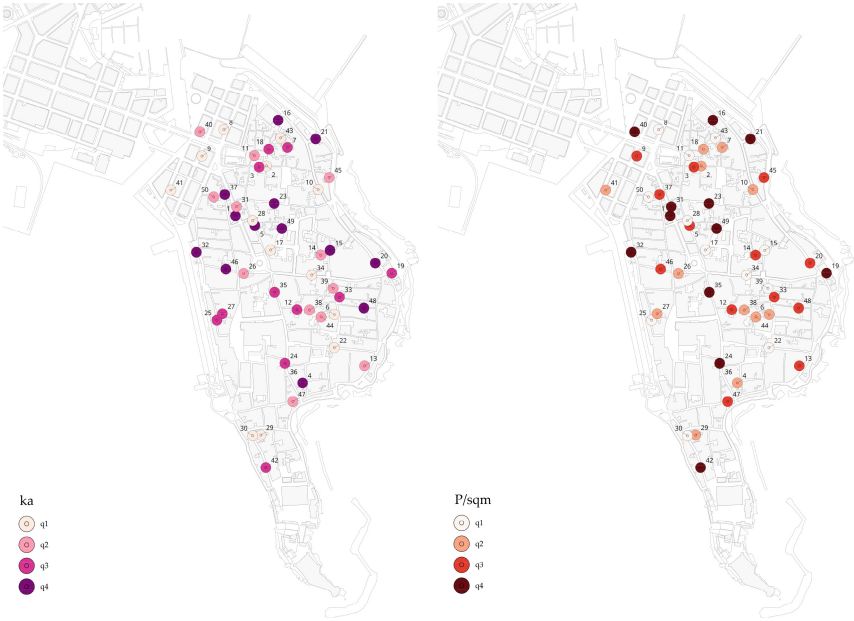


Fig. 4. Spatial distribution of properties in Ortigia based on the quartiles of property characteristics k_a and P_{sqm}.

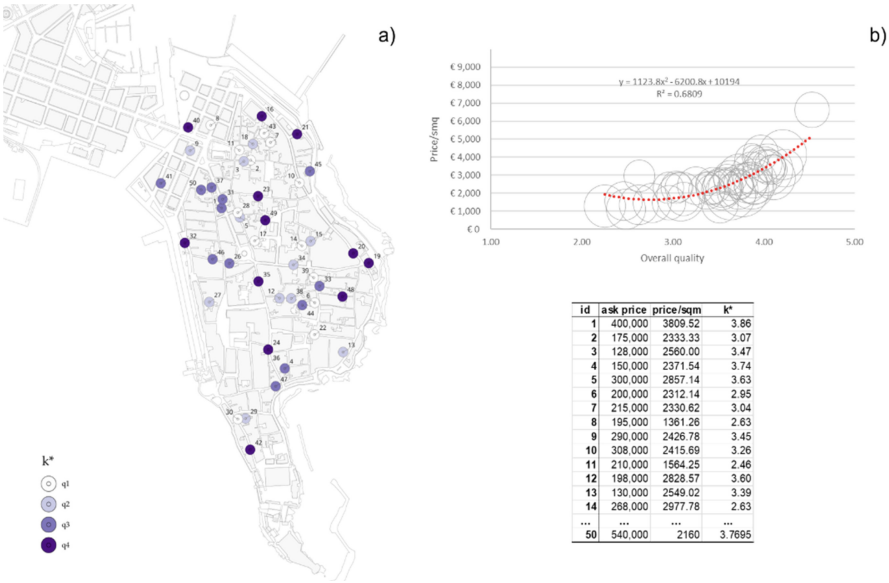
Estimating an aggregate index k^* of property characteristic scores for k_e, k_i, k_t, k_p and k_a provides a measure of overall property quality.

Spatial analysis of the sample of properties based on the quartiles of the aggregate index e k^* provides a map of propriety quality in Ortigia (Fig. 5a). Figure 5a highlights the spatial distribution of properties in Ortigia and the quartiles of the aggregate quality index k^*. For the property characteristic k^*, 26% of the properties in the sample belong to the first quartile, 24% to the second quartile, 24% to the third quartile and 26% to the fourth quartile. Properties in the first quartile of k^* are mainly located in the central belt of Ortigia. Those belonging to the second quartile are present, some along the perimeter but in side streets and and others in the central strip Ortigia.

Those belonging to the third quartile are mainly located in a perimeter strip that extends inwards to the east and west of the island of Ortigia. Those belonging to the fourth quartile are mainly located along the perimeter strip of the island of Ortigia and along its main street axis, Corso Matteotti. Figure 4b highlights a section of the database and the graph showing the relationship between P_{sqm} and overall quality identified by k^*, estimated on the basis of a simple linear regression. The relationship showed in the

graph shows an increase in price as the aggregate quality index k^* increases. The size of the bubble represents the area of each property. The graph shows a smaller bubble for smaller properties, which in most cases corresponds to a lower P_{sqm} and a larger bubble for larger properties, which generally corresponds to a higher P_{sqm}, in line with the typical relationship between P_{sqm} and property quality.

This graph also shows smaller properties with higher P_{sqm} corresponding to higher overall quality, this concerns in some cases buildings of higher historical-architectural value, and therefore consistent with the typical relationship between P_{sqm} and property quality. In other cases the direct proportionality between P_{sqm} is not confirmed even in the face of a pre-analysis led to the identification and removal of outliers based on the R^2 value of the simple linear regression between k^* and P_{sqm} (Fig. 5b). This highlights the likelihood that the sample of properties analysed do not all belong to the same market segment, and thus there is a need to integrate further analysis aimed at identifying and characterising potential submarkets.



id	ask price	price/sqm	k*
1	400,000	3809.52	3.86
2	175,000	2333.33	3.07
3	128,000	2560.00	3.47
4	150,000	2371.54	3.74
5	300,000	2857.14	3.63
6	200,000	2312.14	2.95
7	215,000	2330.62	3.04
8	195,000	1361.26	2.63
9	290,000	2426.78	3.45
10	308,000	2415.69	3.26
11	210,000	1564.25	2.46
12	198,000	2828.57	3.60
13	130,000	2549.02	3.39
14	268,000	2977.78	2.63
...	...	...	...
50	540,000	2160	3.7695

Fig. 5. a) Spatial distribution of properties in Ortigia based on the quartiles of the aggregate index of overall quality k^* state characteristics; b) Relationship between k^* and P_{sqm}.

5.1 Identifying Real Estate Submarkets in Ortigia Based on Fuzzy Clustering

Analyses of the functioning of local housing systems based on filter models aim to identify property submarkets. A sub-market is characterised by properties that can be considered as close substitutes for those belonging to the same group and imperfect substitutes to those belonging to different groups. The identification of sub-markets can be done in terms of spatial characteristics or in terms of property characteristics. Since

our data sample was collected in a relatively small area, the filtering model based on property characteristics is certainly more meaningful. The filtering model proposed in this research is based on fuzzy clustering based on the six property characteristics k_e, k_i, k_t, k_p, k_a. and P_{sqm} of the sample under analysis. In this research, NCSS software was used for fuzzy clustering of the property sample based on the six property characteristics. This software integrates a fuzzy clustering tool that allows us to identify clusters by minimising the objective function C and allows us to identify the significant number of clusters through two goodness-of-fit measures, namely the two normalised Dunn's and Kaufman's partition coefficients. Based on these coefficients we selected the number of clusters, specifically the best configuration is the one that maximises the average Silhouette $F_c(U)$ and minimises the partition coefficient $D_C(U)$. Based on these two selection criteria, three clusters, i.e., three sub-markets, were identified. The presentation of the centroids for the three clusters with reference only to the five property characteristics k_e, k_i, k_t, k_p and k_a, shows that the properties falling in Cluster 3 are those that globally have the highest levels of the six characteristics, the properties falling in Cluster 2 are those with the lowest levels of k_a, k_t and k_p the properties falling in cluster 1 are those with the lowest k_a, k_t (Fig. 6).

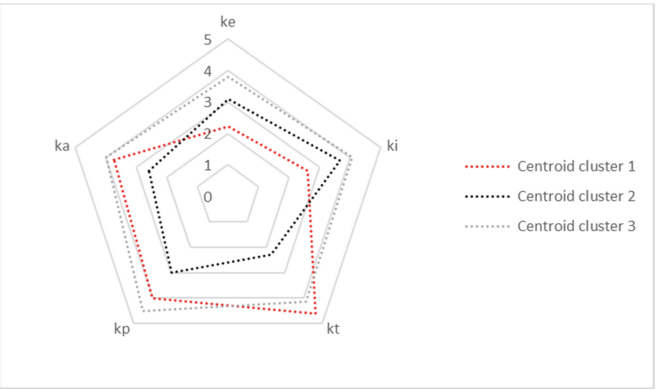


Fig. 6. Comparison between the centroids of the three clusters

The centroid of cluster 1 is represented by the property with id 44 in the data sample, that of cluster 2 by the property with id 30, and that of cluster 3 by the property with id 24. Cluster 1 includes the properties with the following ids. 2, 3, 4, 7, 12, 13, 15, 18, 25, 26, 29, 33, 38, 44, 46, 48 and 50. Cluster 2 contains the properties with the following ids. 6, 8, 9, 10, 11, 14, 17, 22, 28, 30, 34, 39, 41, 43 and 45. Cluster 3 contains the properties with the following ids: 1, 5, 16, 19, 20, 21, 23, 24, 27, 31, 32, 35, 36, 37, 40, 42, 47 and 49. The three clusters identify three sub-markets: the first sub-market identified by cluster 1 is characterised by the properties with lower k_e and k_i, the second sub-market identified by cluster 2 by the properties with lower k_a, k_t and k_p, and the third sub-market identified by cluster 3 by the properties with the best ratings for all six property characteristics. This last submarket is characterised by a slightly higher numerosity than the others, in particularly the numerosity of Cluster 1. The properties

in the original sample are distributed 34% to the submarket of properties with low k_e and k_i identified by Cluster 1, 30% to the submarket with low k_a, k_t and k_p identified by Cluster 2, and 36% to the submarket of properties with one the best ratings for all six property characteristics, identified by Cluster 3. The comparison between the first and second submarkets, shows that properties characterised by a lower level of k_e and k_i and higher level of k_a, k_t and k_p (Cluster 1) have a higher P_{sqm} than those in the submarket characterised by properties with a lower level of k_a, k_t and k_p and higher level of k_e and k_i (Cluster 2). This highlights how economic agents prefer to forego a better location and general accessibility of the building, as well as neighbourhood characteristics or the location of the unit within the building for properties with a higher level of technological characteristics, architectural quality and income/capital gain.

This is consistent with the general characteristics of Ortigia, the historic centre of Syracuse, connected to the mainland only by two bridges. Such a settlement location condition reduces the influence of k_e and k_i characteristics in the formation of the P_{sqm} and increases the influence of k_a, k_t and k_p characteristics in its formation.

The greater importance of k_a characteristic in the formation of P_{sqm} indicates a greater preference for properties with higher historical-architectural value. The greater importance of k_t in the formation of the P_{sqm} indicates a greater preference for properties in good condition and with adequate facilities.

The greater importance of k_p in the formation of the P_{sqm} indicates that the properties are demanded by economic entities for the purpose of production or speculation.

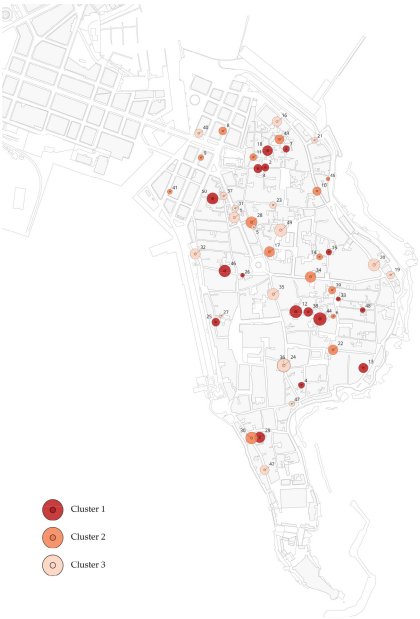


Fig. 7. Spatial analysis of three sub-markets. The size of the bubbles measures the degree to which the element belongs to the cluster.

A local analysis of the three identified submarkets can be carried out on the basis of the membership function of the properties in the clusters.

The spatial analysis of the three clusters shows not only the location of the properties in Ortigia, but also their membership function in the three submarkets, represented by the bubble size in Fig. 7.

The local submarket analysis on the basis of the degree of cluster membership of the properties, shows a more nuanced cluster membership, i.e., below 70% for the Cluster 1 of the properties with id 15, 26, 33 and 48, for the Cluster 2 of the properties with id 6, 8, 9, 11, 14, 39, 41 and 45, for the Cluster 3 of the properties with id 5, 19, 21, 23, 27, 31, 37 and 47.

6 Conclusion and Discussion

The analysis of the residential property market in the historical city of Syracuse, namely Ortigia, was developed in this study with reference to a first spatial clustering of properties based on the quartiles of property characteristics k_e, k_i, k_t, k_p, k_a.and P_{sqm}, which highlighted areas with different characterisation of the levels of property characteristics. A second analysis involving a spatial analysis of properties based on an aggregate index k^*, which highlighted areas with different overall property quality. The study examined the relationship between the aggregate index k^* and P_{sqm}, based on a simple linear regression model, in order to verify not only the robustness of the sample, but also the presence of soft and weak relationships that indicate the need for further research on the Ortigia property market. A third analysis consisted in the fuzzy clustering of the sample of properties on the basis of the six property characteristics k_e, k_i, k_t, k_p, k_a.and P_{sqm}, in order to carry out a more in-depth investigation aimed at highlighting dynamics that were difficult to detect with the previous analyses proposed in this study, which led to the identification of three sub-markets. The three sub-markets highlight information of interest in order to capture the complex dynamics of an imperfect market such as that of a historic city [53]. The sub-market identified by Cluster 3 consists of properties that confirm the natural dynamics between property characteristics and price formation, i.e., a higher level of characteristics k_e, k_i, k_t, k_p and k_a corresponds to a higher P_{sqm}. The two submarkets identified by clusters 1 and 2 provide details on the relationship between property characteristics and price formation, and between groups of property characteristics that contribute to price formation. A comparison of the two submarkets 1 and 2 shows that to the former includes properties with a higher level of k_t, k_p, k_a and P_{sqm} property characteristics and a lower level of k_e and k_i, while the latter includes properties with a lower level of k_t, k_p, k_a and P_{sqm} property characteristics and a higher level of k_e and k_i. These submarkets show a greater dependence on the characteristics k_t, k_p, k_a and a lesser dependence on the k_e and k_i in the formation of P_{sqm}. The lower importance of characteristics k_e and k_i is fully in line with the peculiarities of the property market on the island of Ortigia. It is still possible to highlight a direct relationship between characteristics k_t, k_p, k_a and P_{sqm}, which is confirmed in both sub-markets 1 and 2. This relationship shows a greater preference for properties with a higher historical-architectural value, a greater preference for properties in a good state repair and with adequate facilities, and a greater desirability of such properties for productive or speculative investment [54]. In particular, for the purpose of an in-depth study that highlights

dynamics that are difficult to detect with the previous analyses proposed in this study, the fuzzy clustering has highlighted two sub-markets that can be considered of greatest interest in order to detect the complex dynamics of an imperfect market such as that of a historic city namely Clusters 1 and 2.

These clusters showed fuzzy or inconsistent relationships as to the dynamics between property characteristics and P_{sqm}, and they indicate little apparent consistency in the relationship structure between of economic agents' preferences and P_{sqm}. The identification of fuzzy or opaque dynamics, as well as the identification of submarkets, can improve the quality of property market analyses, especially for historic centre properties. Our data sample consists of data collected through real estate agencies. A pre-analysis this data revealed many outliers, which significantly reduced the number of properties in the sample to be analysed. Comparing the data from real estate agencies with those from some specialised tourist and student websites, we found that in some cases the same properties were offered to different segments. Further research will be carried out to refine the analysis of the property market in Ortigia. The methodological approach proposed in this study can support the analysis of imperfect real estate markets and therefore its implementation can be extended to other contexts with similar characteristics.

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