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Article

A new fuzzy rule-based model to partition a complex urban system in homogeneous urban contexts

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Abstract: We present a new unsupervised method aimed to obtain a partition of a complex urban system in homogenous urban areas, called urban contexts. The area of study is initially partitioned in microzones, homogeneous portion of the urban system, that are the atomic reference elements for the census data. With the contribution of domain experts, we identify the physical, morphological, environmental and socio-economic indicators need to identify synthetic characteristics of urban contexts and create the fuzzy rule set necessary to determine the type of urban context. We implement the set of spatial analysis processes necessary to calculate the indicators for microzone and apply a Mamdani fuzzy rule system to classify the microzones. Finally, the partition of the area of study in urban contexts is obtained by dissolving continuous microzones belonging to the same type of urban context. Tests are performed on the Municipality of Pozzuoli (Naples - Italy); the reliability of out model is measured by comparing the results with the ones obtained by detailed analysis.

Keywords: urban system; urban context; microzone, fuzzy rule set; Mamdani fuzzy system; spatial database; GIS

1. Introduction

An urban system is a complex entity, composed of various elements with physical, morphological, environmental and socio-economic characteristics, related to each other. Often, in order to analyze the area of study related to urban analysis problems, is useful partition it in a set of areas homogeneous with respect to specific characteristics. In literature there are various studies in which unsupervised methods are proposed to segment the area of study in homogeneous zones in order to analyze specific problems. Various authors propose automatic classification methods to partition urban areas and elements from raster remote sensing data. In [19] a genetic algorithm is applied in order to extract automatically classification rules of urban areas from remote sensing data. In [9] a is applied a framework modeling the expert knowledge in order to segment coastal areas in raster remote sensing data. In [12] a new method based on unsupervised change detection focused on individual buildings is applied to very-high resolution remote sensing imageres to extract elements in urban systems. In [4] a hierarchical object-oriented model is proposed to classify objects in an urban area from high resolution satellite images. In [8] a multiple-kernel learning model is proposed to classify urban areas from spectral and LiDAR raster data. A review of classification methods proposed to classify urban land cover by using raster LiDAR remote sensing images is presented in [19].

Recently, the aviability of various thematic data at different scales from different institutional sources together with the use of socio-demographic census data, allows to implement methods for the unsupervised classification of urban systems that take into consideration the knowledge of the urban system and the expert knowledge of the analyzed problem. In [5] the area of study is partitioned in homogeneous zones based to morphological and soil characteristics in order to analyze the vulnerability of aquifer to pollution; a fuzzy algebraic structure is applied in order to assess the aquifer vulnerability in any zone. In [15] a multiple level association rule mining method is applied on spatiotemporal socio-economic and land cover datasets based on a hierarchical classification scheme to extract relations between objects in the area of study and classify them.

In [3] a simulated annealing method is applied to partition an area of study in homogeneous zones based on socioeconomic characteristics. In [6] a partition of the urban system in census zones is performed in order to study the spatial distribution of socioeconomic characteristics. In [1] a multi-objective approach is applied in order to partition into microregions the municipalities of the region of Parana in Brazil; this approach maximize the population homogeneity and the medical procedure used in any microregion and minimize inter-microregion traveling.

In this research we propose a novel model based on a Mamdani fuzzy rule system [13,14] aimed to partition an urban system in homogeneous zones, called *urban contexts*; each urban context is labeled with a specific urban class based on a specific taxonomy related to the studied problem.

Our approach is independent of the analyzed problem; initially we partition the area of study in homogeneous zones given by census atomic elements called *microzones*. We follow the Italian Presidential Decree n. 138 of 1998 that in the Article 1 defines *a microzone* as a homogeneous portion of the urban system, which may include one municipality, a portion thereof, or groups of municipalities, characterized by similar environmental and socio-economic characteristics. The microzone represents a portion of the municipality or, in the case of areas consisting of groups of municipalities, an entire municipal territory homogeneous in terms of urban, historical-environmental and socio-economic characteristics, as well as in the provision of urban services and infrastructure. For example, in each microzone buildings are predominantly uniform for construction features, construction period and residential/industrial/commercial use.

The first step of our method concerns the acquisition of different not normalized thematic data from various institutional sources, including of the last microzone census database.

Subsequently, a homogeneous knowledge base of the analyzed urban system is created, in order to extract a set of synthetic indicators representing characteristics of the urban system related to the analyzed problem. These indicators express the input variables of a fuzzy rule set extracted by domain experts in which the output variable expresses an urban class.

A Mamdani fuzzy rule system is applied to classify the microzones assigning them a specific class; finally, a dissolve spatial operator is used to aggregate microzones spatially contiguous classified in the same urban class in urban contexts; in addition, we assess a membership degree of each urban context to its class, given by a weighted average of the membership degrees to this category calculated in any microzone include in the urban context. This membership degree represents the uncertainty in the attribution of the urban context to its urban class and provides an evaluation of the reliability of the classification.

The main advantages of the proposed model are the independence of it from the analyzed problem and its usability. In fact, our framework can be applied to any type of problems involved analysis of urban systems and streamlines and make more efficient the construction of the knowledge transferred by the domain experts. Finally, the assessment of the membership degree of the urban contexts to their urban classes allows the analyst to evaluate the reliability of the resultant partition.

In next section is described in detail the proposed model; in order to show the ways in which the components of our model are applied, a case study concerned with partitioning an urban system in contexts in which urban classes are typified by different residential density is explored.

In section 3 are described the area of study and the institutional datasets used in our experiments; in section 4 are shown the results of our experiments. Final considerations are reported in section 5.

2. The proposed model

Our model is composed by a set of 5 phases, as in fig. 1.

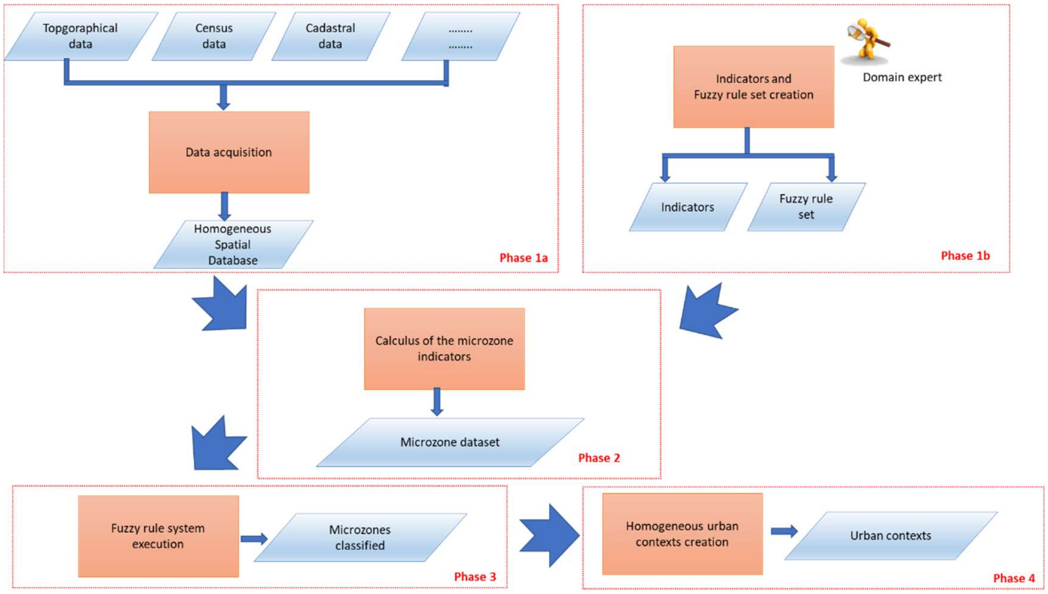

Figure 1. Scheme of the phases of the model.

The phases 1a and 1b are executable in parallel.

The phase 1a (*Data acquisition*) concerns with the acquisition of the datasets from Institutional sources. A set of staging procedures are necessary to provide the reconciliation of these inhomogeneous data (for example, to carry out the transformation and conversions of spatial data in a unique coordinate system and to correct spatial topological errors) and the creations of relations between the various datasets. Output of this phase is given by the homogeneous spatial database of the area od study.

In the phase 1b (*Indicators and fuzzy rule set creation*) are defined the various physical, environmental and socio-economic indicators and is created the fuzzy rule set; this phase is executed with the contribution of domain experts. To model the expert knowledge and construct the fuzzy rules, we create a fuzzy partition of the domain of each indicator in which any fuzzy set is assigned by using a triangular or semi-trapezoidal fuzzy number and is titled with a linguistic label assigned by the domain expert.

In the phase 2 (C*alculus of the microzone indicators*) are implemented the spatial analysis processes need to calculate the indicators. Each indicator represents a summarize of specific characteristics of the microzone; it is calculated by applying the formulas created in the phase 1b and by using a set of geoprocessing and statistical operators applied on entities and characteristics in the spatial database.

In the phase 3 (*Fuzzy rule system execution*) for each microzone is executed the Mamdani fuzzy rule system in order to assign the microzone to a specific urban class. The indicators are fuzzified by a fuzzification component; then the fuzzy inference component is applied by using the Mamdani min and max operators; the urban class assigned to the microzone is given by the consequent of the fuzzy rule with greatest strength.

In the phase 4 (*Homogeneous urban contexts creation*) the adjoining microzones belonging to the same urban class are dissolved and is created the thematic map of the urban contexts of the area of study.

2.1. Phase 1.a - Data acquisition

In this phase the data on the area of study are acquired from various institutional sources. Output of this phase is a spatial database implementing the homogenous knowledge base of the area of study. A spatial dataset to acquire is given by the microzone census data, including the polygon spatial data corresponding to the microzones. Other datasets are need to extract the synthetic

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indicators, related to different information layers as population, buildings, roads, urban green, schools, infrastructures.

A set of geo-processing activities are necessary in order to normalize the spatial datasets; all datasets must be converted in a unique coordinate system and a topological check it needs to verify the integrity of the dataset. Other geoprocessing activities could be carried out to extract and normalize the thematic data, as, for examples:

- extracting themes from a dataset in various format;
- merge of datasets correspondent to a theme and distributed per tiles and clipping it on the area of study;
- apply spatial operators to relate to any feature of the theme information inserted as annotation texts (for example the road name to assign to any polyline of a road network).

A data cleaning activity on the data fields it needs in order to verify their integrity and accuracy, to delete outliers and correct inconsistent data and redundancies.
Finally, all themes and tables are imported in a spatial database and the relation between them are created.

2.2. Phase 1b. – Indicators and fuzzy rule set creation

The indicators need to classify the microzones are evaluated by domain experts. In our experimentation the experts consider 14 indicators related to various thematic layers that characterize the area of study and are necessary to evaluate to which urban class the microzone belongs. In Tab. 1 are described all the indicators; to each indicator is assigned an identify and are reported the type of indicator, i.e. the thematic layer to whom it is referred, a brief description and its unit of measure.

Table 1. Indicators used to classify the microzones of the area of study

Indicator	Type	Description	Unit of measure
I_1	buildings	Mean square meters of residential buildings for resident	Square meters
I_2	buildings	Percent of industrial areas with respect to total built areas	Percent
I_3	urban green	Mean square meters of green areas for resident	Square meters
I_4	urban green	Percent of green areas with respect to area of the microzone	Percent
I_5	roads	Percent of the overall length of district urban roads[1] with respect to the overall length of roads in the microzone	Percent
I_6	roads	Percent of overall length of the district urban roads with width less than 7 m. with respect to the overall length of all district urban roads in the microzone	Percent
I_7	population	Number of residents per square kilometer	(Square kilometers)$^{-1}$
I_8	buildings	Percent of the number of residential buildings built before 1945 with respect to all residential buildings	Percent
I_9	buildings	Mean number of dwellings with at least one resident in the residential buildings	

[1] *Urban district road*: single carriageway with at least two lanes, paved quays and sidewalks.

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I_{10}	buildings	Percent of residential buildings with at least 16 dwellings with respect to all residential buildings	Percent
I_{11}	schools	Accessibility and proximity of schools in the microzone	Percent
I_{12}	public transportation	Usability of public transport networks	Percent
I_{13}	coastal/marine zone	Coastal/marine area	Percent
I_{14}	large public infrastructure	Presence of large public infrastructures	Percent

After defining the indicators, the domain experts create a fuzzy partition of any indicator by using triangular and semi-trapezoidal fuzzy numbers to create the fuzzy sets. The fuzzy partitions of the indicators in Tab.1 are shown in Tab.2. in which are reported the identifier of the indicator, a label assigned to any fuzzy sets, the inf, mean and sup values of the fuzzy number and the type of fuzzy set (ST = Semi-Trapezoidal, TR = Triangular).

Table 2. Fuzzy partitions of the indicators

Indicator	Label	inf	mean	sup	Type of fuzzy set
I_1	Scanty	0	10	30	ST
	Mean	20	30	50	TR
	Discrete	40	60	80	TR
	High	70	100	∞	ST
I_2	Null	0	10	20	ST
	Mean	10	30	50	TR
	Discrete	40	50	70	TR
	High	60	70	100	ST
I_3	Scanty	0	10	40	ST
	Mean	30	50	70	TR
	Discrete	60	80	90	TR
	High	90	200	∞	ST
I_4	Null	0	10	30	ST
	Mean	10	30	50	TR
	Discrete	30	50	70	TR
	High	50	70	100	ST
I_5	Null	0	20	30	ST
	Mean	15	40	50	TR
	Discrete	40	50	70	TR
	High	60	70	100	ST
I_6	Null	0	10	20	ST
	Mean	10	30	50	TR
	Discrete	40	50	70	TR
	High	60	70	100	ST
I_7	Scanty	0	100	1000	ST
	Mean	100	1000	5000	TR
	Discrete	1000	5000	10000	TR
	High	5000	10000	∞	ST
I_8	Null	0	10	20	ST
	Mean	10	30	50	TR

	Discrete	40	50	70	TR
	High	60	80	100	ST
I_9	Scanty	0	5	10	ST
	Mean	5	20	30	TR
	Discrete	30	40	60	TR
	High	40	60	∞	ST
I_{10}	Null	0	10	20	ST
	Mean	10	30	50	TR
	Discrete	40	60	80	TR
	High	60	80	100	ST
I_{11}	Null	0	10	20	ST
	Mean	10	30	50	TR
	Discrete	50	70	90	TR
	High	70	90	100	ST
I_{12}	Null	0	10	20	ST
	Mean	10	30	50	TR
	Discrete	40	50	70	TR
	High	60	70	100	ST
I_{13}	Null	0	10	30	ST
	Mean	30	50	70	TR
	High	60	90	100	ST
I_{14}	Null	0	10	20	ST
	Mean	10	50	70	TR
	Discrete	50	80	90	TR
	High	60	90	100	ST

In order to extract the fuzzy rules, the experts define the taxonomy of the urban area classes. In our experimentation are considered the following set of urban area classes in which any class characterize a type of residential or rural zone of the urban system.

Table 3. Urban area classes

Urban area class	Description
Residential old town	Residential agglomeration of ancient or recent formation characterized by historical, artistic and environmental goods even if tampered with or degraded or not present at the same time
Comfortable residential zone	Dwelling place equipped with comfortable and modern/contemporary dwellings, infrastructures, sports facilities and green spaces
Downtrodden residential zone	Dwelling place equipped with uncomfortable dwellings and poor of infrastructures, sports facilities and green spaces
Industrial zone	Zone with prevalent or mixed industrial areas
Coastal residential zone	Area inclusive of a border with sea or great lakes with mainly maritime services
Fragmented Rural/wooded zone	Area mainly rural or wooded with reduced settlement development
Sprawl	Informal modern/contemporary urban settlement

Each class in Tab. 3 is correspondent to a fuzzy set of an output linguistic variable Z defined in the domain [0,1] and representing, following an increasing order from 0 to 1, the impact of residential settlements to the area. The first fuzzy set is a semi-trapezoidal fuzzy set representing a predominantly rural or wooded area; the last fuzzy set is a semi-trapezoidal fuzzy set representing a compact residential old town. The intermediate fuzzy sets are triangular. These fuzzy sets are defined in tab 4 and are graphically shown in fig. 2.

Table 4. Fuzzy partitions of the urban area classes

Urban area class	inf	mean	sup	Type of fuzzy set

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Fragmented rural/wooded zone	0	0.2	0.3	ST
Industrial zone	0.2	0.3	0.4	TR
Sprawl	0.3	0.4	0.5	TR
Coastal residential zone	0.4	0.5	0.6	TR
Comfortable residential zone	0.5	0.6	0.7	TR
Downtrodden residential zone	0.6	0.7	0.8	TR
Residential old town	0.7	0.8	1	ST

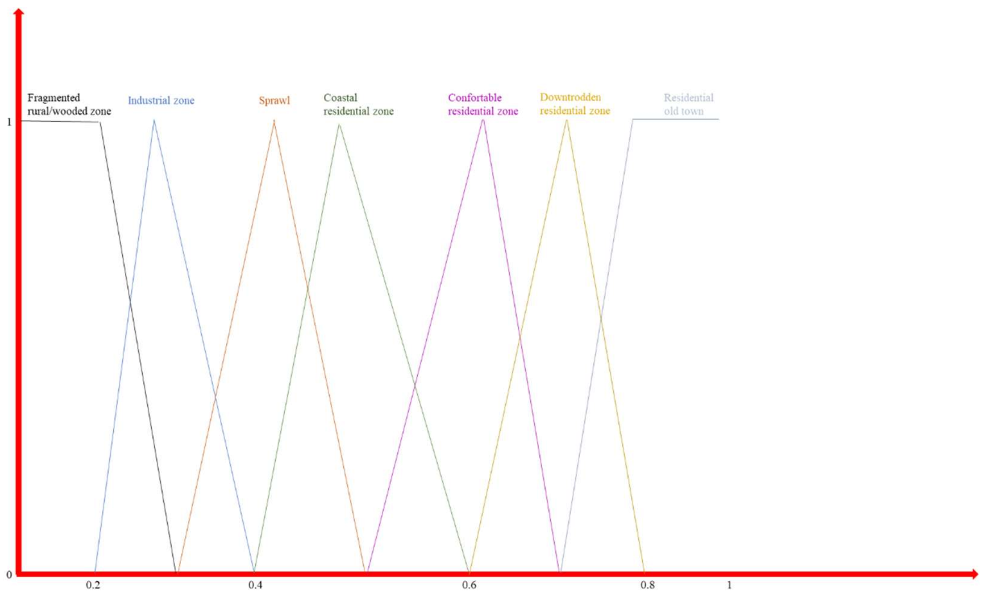

Figure 2. Plotting of the output variable fuzzy sets.

Based on their knowledges, the experts extract the set of fuzzy rules need to evaluate the urban class to whom belongs any microzone. In our experimentation the 14 indicators are used as input variables in the antecedent of each rule and the output variable Z is used in the consequent, labeled as in tab. 3. The fuzzy rule set is composed by fuzzy rules extracted by the experts written in the form:

$$R_k\text{: } \mathbf{IF}\ (I_1 = I_{1k})\ \Delta_1\ (I_2 = I2_k)\ \Delta_2\ \ldots\ \Delta_n\ (I_n = I_{nk})\ \mathbf{THEN}\ (Z = Z_k) \quad (1)$$

where I_1, I_2, I_n, are input variables given by the linguistic labels of the fuzzy sets of the indicators and Z is the output variable. The operator Δ_i (i=1,…,n) is given by an AND or an OR connectives. We construct the fuzzy rule set considering only AND connectives, splitting rules in which there are OR connectives in the antecedent. To show the splitting process of the rules, we take into consideration the following subset of fuzzy rules created by the experts.

IF (I_4 == *Null*) AND (I_6 == *Discrete* OR I_6 == *High*) AND (I_7 == *High*) **THEN** Z == *Residential old town*
IF (I_1 == *Discrete* OR I_1 == *High*) AND (I_3 == *Discrete* OR I_3 == *High*) AND (I_8 == *Null*) AND (I_{12} == *High*) **THEN** Z == *Comfortable residential zone*
IF (I_2 == *Null*) AND (I_7 == *Scanty* OR I_7 == *Mean*) AND (I_{12} == *High*) AND (I_{14} == *Discrete* OR I_{14} == *High*) **THEN** Z == *Comfortable residential zone*
IF (I_2 == *Discrete* OR I_2 == *High*) AND (I_6 == *Null*) AND (I_7 == *Scanty*) THEN Z == *Industrial zone*

After the rule splitting process we obtain the following final fuzzy rules:
R_1: **IF** (I_4 == *Null*) AND (I_6 == *Discrete* OR I_6 == *High*) AND (I_7 == *High*) **THEN** Z == *Residential old town*
R_2: **IF** (I_4 == *Null*) AND (I_6 == *High*) AND (I_7 == *High*) **THEN** Z == *Residential old town*
R_3: **IF** (I_1 == *Discrete*) AND (I_3 == *Discrete*) AND (I_8 == *Null*) AND (I_{12} == *High*) **THEN** Z == *Comfortable residential zone*

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R_4: **IF** (I_1 == *High*) AND (I_3 == *Discrete*) AND (I_8 == *Null*) AND (I_{12} == *High*) **THEN** Z == *Comfortable residential zone*

R_5: **IF** (I_1 == *Discrete*) AND (I_3 == *High*) AND (I_8 == *Null*) AND (I_{12} == *High*) **THEN** Z == *Comfortable residential zone*

R_6: **IF** (I_1 == *High*) AND (I_3 == *High*) AND (I_8 == *Null*) AND (I_{12} == *High*) **THEN** Z == *Comfortable residential zone*

R_7: **IF** (I_2 == *Null*) AND (I_7 == *Scanty*) AND (I_{12} == *High*) AND (I_{14} == *Discrete*) **THEN** Z == *Comfortable residential zone*

R_8: **IF** (I_2 == *Null*) AND (I_7 == *Mean*) AND (I_{12} == *High*) AND (I_{14} == *Discrete*) **THEN** Z == *Comfortable residential zone*

R_9: **IF** (I_2 == *Null*) AND (I_7 == *Scanty*) AND (I_{12} == *High*) AND (I_{14} == *High*) **THEN** Z == *Comfortable residential zone*

R_{10}: **IF** (I_2 == *Null*) AND (I_7 == *Mean*) AND (I_{12} == *High*) AND (I_{14} == *High*) **THEN** Z == *Comfortable residential zone*

R_{11}: **IF** (I_2 == *Discrete*) AND (I_6 == *Null*) AND (I_7 == *Scanty*) THEN Z == *Industrial zone*

R_{12}: **IF** (I_2 == *High*) AND (I_6 == *Null*) AND (I_7 == *Scanty*) THEN Z == *Industrial zone*

2.3. Phase 2. – Calculus of the microzone indicators

To calculate the indicators in any microzone are applied specific spatial analysis functions. For example, the indicator I_1 in Tab. 1 is calculated by selecting the residential buildings in the area of study and extracting the total surface area covered by residential buildings and the number of residents per microzone. Finally, for any microzone the ratio between this total surface area and the number of residents is calculated.

A hierarchy of spatial analysis processes could be need in order to calculate the value of an indicator. In our experiment, to calculate the indicators I_{11}, I_{12}, I_{13} and I_{14} is necessary to calculate further parameters, labeled II level indicators, described in the following table.

Table 5. II level Indicators used to classify the microzones of the area of study

Indicator	II level Indicator	Type	Description	Unit of measure
I_{11}	I_{11a}	schools	Percent ratio between the service area (500m radius around the primary school) and the extension of the microzone	Percent
	I_{11b}	schools	Percent ratio between the service area (500m radius around the lower secondary school) and the extension of the microzone	Percent
	I_{11c}	schools	Percent ratio between the service area (500m radius around the secondary school) and the extension of the microzone	Percent
I_{12}	I_{12a}	public transportation	Percent ratio between the bus stop service area (100m radius around the bus stop) and the extension of the microzone	Percent
	I_{12b}	public transportation	Percent ratio between the railway/subway station service area (300m radius around the railway/subway station) and the extension of the microzone	Percent
I_{13}	I_{13a}	coastal/marine zone	Coastal area (1 if the microzone is a coastal area; 0 otherwise)	{0,1}

	I_{13b}	coastal/marine zone	Maritime terminal (1 if it is present in the microzone; 0 otherwise)	{0,1}
I_{14}	I_{14a}	large public infrastructures	Presence of public large sport facilities (1 if large sports facilities are present in the microzone; 0 otherwise)	{0,1}
	I_{14b}	large public infrastructures	Presence of public hospitals (1 if it hospitals are present in the microzone; 0 otherwise)	{0,1}

The indicator I_{11} is obtained as a weighted mean of the indicators I_{11a}, I_{11b} and I_{11b} where the weights, are, respectively, the residents with age between 5 and 9 years, the residents with age between 10 and 14 years and the residents with age between 15 and 19 years.

Formally, let $n_{5\text{-}9}$ be the number of residents in the microzone with age in the range 5-9 years, $n_{10\text{-}14}$ the number of residents in the microzone with age in the range 10-14 years and $n_{15\text{-}19}$ the number of residents in the microzone with age in the range 15-19 years.

The indicator I_{11} is given by the formula:

$$I_{11} = \frac{I_{11a} \cdot n_{5-9} + I_{11b} \cdot n_{10-14} + I_{11c} \cdot n_{15-19}}{n_{5-9} + n_{10-14} + n_{15-19}} \tag{2}$$

The indicator I_{12} is obtained as a weighted mean of the indicators I_{12a} and I_{12b}.

$$I_{12} = \frac{I_{12a} \cdot w_{12a} + I_{12b} \cdot w_{12b}}{w_{12a} + w_{12b}} \tag{3}$$

where w_{12a} and w_{12b} are the weights assigned, respectively to the indicators I_{11a} and I_{11b}. The experts set w_{12a} = 3 and w_{12b} = 7 considering the influence of railway/subway station services to be greater than the bus services one.

The indicator I_{13} is calculated as:

$$I_{13} = \begin{cases} 0\% & \text{IF } \mathrm{I}_{13a} = 0 \\ 50\% & \text{IF } \mathrm{I}_{13a} = 1 \text{ AND } \mathrm{I}_{13b} = 0 \\ 100\% & \text{IF } \mathrm{I}_{13a} = 1 \text{ AND } \mathrm{I}_{13b} = 1 \end{cases} \tag{4}$$

The indicator I_{14} is calculated as:

$$I_{14} = \begin{cases} 0\% & \text{IF } \mathrm{I}_{14a} = 0 \text{ AND } \mathrm{I}_{14b} = 0 \\ 50\% & \text{IF } \mathrm{I}_{14a} = 1 \text{ AND } \mathrm{I}_{14b} = 0 \\ 80\% & \text{IF } \mathrm{I}_{14a} = 0 \text{ AND } \mathrm{I}_{14b} = 1 \\ 100\% & \text{IF } \mathrm{I}_{14a} = 1 \text{ AND } \mathrm{I}_{14b} = 1 \end{cases} \tag{5}$$

2.4. Phase 3. – Fuzzy rule system execution

In this phase a Mamdani fuzzy rule-based system is used to classify the microzones.

In Fig. 2 is schematized the fuzzy rule-based system used.

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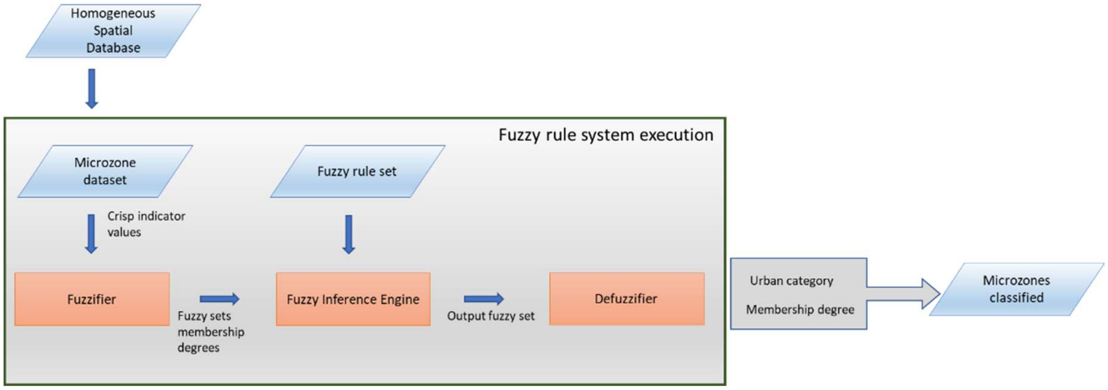

Figure 3. *Scheme of the fuzzy rule based system*

From the spatial database constructed in the previous phase is extracted the microzone dataset containing the crisp values of the indicators calculated for any microzone. The *Fuzzifier* component imports these indicator values and assign to any indicator the membership degrees to its fuzzy sets. Then, the *Fuzzy Inference Engine* component reads the membership degree of the fuzzy sets related to any indicator and performs the inference process calculating the strength of any fuzzy rule in the fuzzy rule set.

The min operator is applied to the AND connectives in the antecedent of the fuzzy rule to calculate its strength. The Fuzzy Inference Engine realizes the aggregation process to construct the output final fuzzy set. Aggregation is the process by which the truncated output fuzzy sets in each rule are combined into a single fuzzy set that represents the output aggregated fuzzy set.

In order to show the aggregation process, we consider a system formed by two fuzzy rules in the form:

$$\begin{cases} R_1: & \text{IF } (I_1 \text{ is } \mathrm{A}_1) \text{ AND } (I_2 \text{ is } \mathrm{B}_1) \quad \textit{THEN} \quad Z \text{ is } \mathrm{C}_1 \\ R_2: & \text{IF } (I_1 \text{ is } \mathrm{A}_2) \text{ AND } (I_2 \text{ is } \mathrm{B}_2) \quad \textit{THEN} \quad Z \text{ is } \mathrm{C}_2 \end{cases} \tag{6}$$

where A_1 and A_2 are two fuzzy sets of the linguistic input variable I_1, B_1 and B_2 are two fuzzy sets of the input linguistic variable I_2 and C_1 and C_2 are two Fuzzy sets of the output variable Z.

Now suppose that, after the fuzzification process, we obtain the following membership degree for the input variables: $A_1 = 0.3$, $B_1 = 0.5$, $A_2 = 0.7$, $B_1 = 0.8$.

The strength of the two rules are given by:

$S(R_1) = \min(0.3, 0.5) = 0.3$ $\qquad$ $S(R_2) = \min(0.7, 0.8) = 0.7$.

In the aggregation process we construct the output fuzzy set given by:

$$\mathrm{C}(Z) = \max\left\{\min\left[C_1(Z), S\left(R_1\right)\right], \min\left[C_2(Z), S\left(R_2\right)\right]\right\} \tag{7}$$

In Fig. 4 is shown the output fuzzy set constructed in this example.

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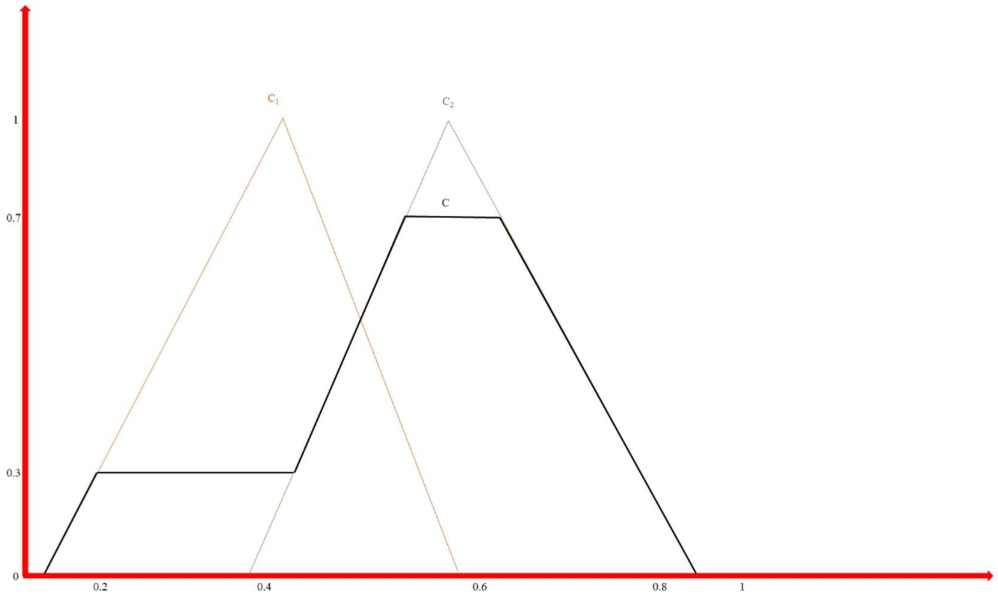

Figure 4. Example of construction of the output fuzzy set in the aggregation process

The defuzzification process of the output fuzzy set is carried out via the discrete Center of Gravity (CoG) method by the formula:

$$\hat{Z} = \frac{\int_0^1 Z \cdot C(Z)dZ}{\int_0^1 C(Z)dZ} \tag{7}$$

where the two integrals are extended in the range [0,1] which is the domain of the output variable Z.

We classify the microzone assigning it to urban class label of the output variable fuzzy set with greater membership degree in the point $\hat{Z}$; the membership degree of the microzone to this class is given by the membership degree of the output variable to C in the point $\hat{Z}$.

In Fig. 5 is show the result of the defuzzification process. As $C_1\left(\hat{Z}\right)$ is greater the $C_2\left(\hat{Z}\right)$, we assign the microzone to the class C_1 with a membership degree given by $C\left(\hat{Z}\right)$.

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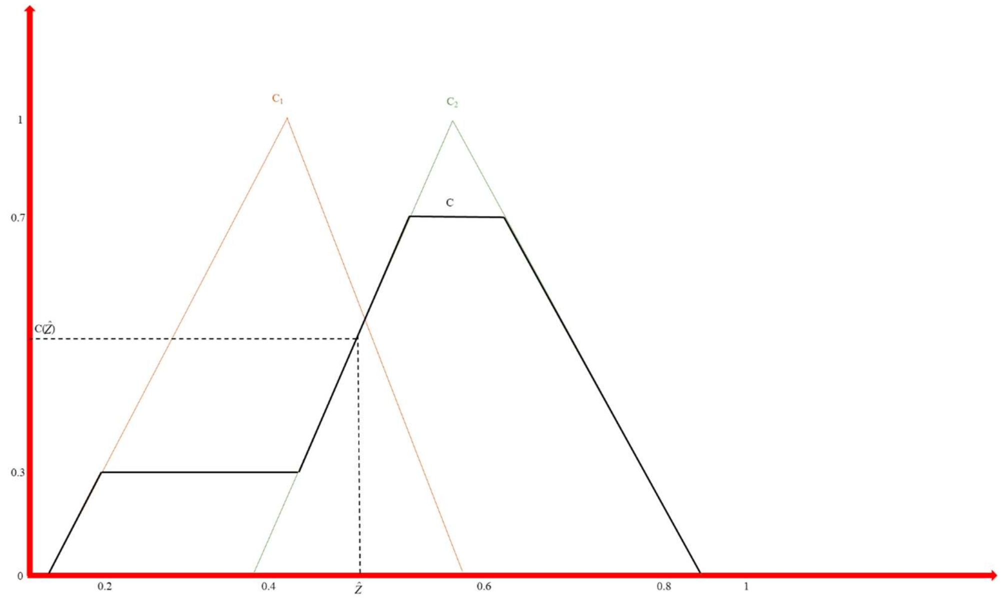

Figure 5. Results of the defuzzification process

2.5. Phase 4. – Homogeneous urban contexts creation

In this phase the area of study is partitioned in urban contexts. Each urban context is obtained dissolving adjoining microzones belonging to the same urban class; then, is realized the thematic map of the urban contexts of the area of study.

A weighted mean of the membership degree of the microzones forming an urban context is calculated, to extract the reliability of the urban context; the weight is given by the area of the microzone as the greater the surface of a micro-zone included in a context greater is its impact on the reliability of the classification of the context.

3. Application on an area of study

We test our model applying it on an urban system in order to partition the area of study in urban contexts by considering the taxonomy of the urban area classes in Tab. 3.

3.1. The area of study

The area of study is given by the Municipality of Pozzuoli (Naples - Italy). The municipality of Pozzuoli shows a multiplicity of urban area classes; it contains industrial areas, modern residential zones, a dense hold town and high uncultivated/wooded green areas. In [7] historical land use, photogrammetric and airborne LiDAR data are used to detect buried landfill sites in the area of Campi Flegrei, that contains the municipality of Pozzuoli; this study shows that in this area are present modifications of the landscape associated with the urban development and quarrying activity. The presence of volcanic hills within the municipal area has allowed an urban development mainly below them and towards the coastal areas. A survey on the seismic activities produced by the Campi Flegrei caldera in densely inhabited areas and the consequent risk for the population was carried out in [11] and recently in [17]. A study of all the different cultural resources presents in the Municipality of Pozzuoli performed by using GIS technologies is presented in [10].

It is interesting to study how are distributed the various contexts in the municipality in relation to its different natural, social and urban characteristics. We apply our model to obtain a partition of the municipality in these different contexts.

In fig. 6 is show the area of study; the microzones are outlined in yellow. The satellite base map is extracted by the ESRI satellite *World Imagery* database.

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Figure 6. The microzones of the municipality of Pozzuoli.

3.2. Spatial data sources

The microzone dataset collected for the study were provided by the ISTAT Italian National Statistical Institute, the Italian public research body that deals with censuses and surveys their social and economic characteristics.

The geo-topographic dataset used to extract the base theme of the municipality is the topographical database provided by the Campania Region in 1: 5000 scale, from which it was possible to extract information on buildings and their intended use, presence of urban green, presence of infrastructure such as hospitals, schools. The area under study is a municipality bordering the sea, it was necessary, to make some indicators of our set, to identify the coastal microzones.

The datasets necessary to calculate the 14 indicators are extracted from four institutional data source: the regional geo-topographic database in scale 1:5000, the census database provided with the last Italian census data per microzone, the aero-photogrammetric spatial database provided by the Municipality of Pozzuoli and the free spatial database provided by the Open StreetMap community.

The datasets are extracted limited to the extension of the municipality of Pozzuoli.

In the following table are described all the data sources used in our tests.

Table 6. Data sources and dataset used in the tests

Geo-topographic Datasets	
Institution	Campania Region
Data Source	Municipality of Pozzuoli – 2012 Geo-topographic Database in scale 1: 5000, coordinate system UTM WGS84 zone 33N, plane coordinates.
Datasets	Industrial and residential buildings Schools Urban streets Urban green areas Woodlands and barred areas Transport facilities Hospitals Sports facilities
Institution	ISTAT – Italian National Institute of Statistics
Data Source	2011 Census database – Socio-demographic Database per census tract in scale 1: 10000, coordinate system UTM WGS84 zone 32N, plane coordinates. WEB site: https://www.istat.it/it/archivio/104317.
Datasets	Census tracts Population dataset Buildings and dwellings dataset
Institution	Municipality of Pozzuoli

Data Source	Municipality spatial database, coordinate system UTM WGS84 zone 33N, scale 1: 4000, coordinate system UTM WGS84 zone 33N, plane coordinates.
Datasets	Municipality Ortho images Road networkRailway network
Institution	Open StreetMap (OSM) community
Data Source	Open StreetMap spatial database, coordinate system UTM WGS84 zone 32N, coordinate system UTM WGS84 zone 33N, plane coordinates. Web site: http://download.geofabrik.de/osm-data
Datasets	Road network Schools Transport facilities Bus and railway stops

The polygonal census tracts dataset provided from the ISTAT institute was used as base dataset to calculate the indicators; the census tracts corresponds to the microzones used in our model. The municipality of Pozzuoli is partitioned in 283 microzones. For each microzone we extract the population dataset, composed of data concerning with various sections of residents as the number of residents in a specific age range, and the building dataset composed of data related to the number of buildings and dwellings with specific characteristics, as the number of buildings built in a period, the mean number of housings in any residential buildings, etc.

The polygonal buildings theme was acquired from the 2011 geo-topographic database in scale 1:5000, distributed by the Campania Region in an Italian National geo-topographic structure following the InSpire GeoUML data model [2, 16].

Other dataset concerning streets, infrastructures and schools, where extracted from the aero-photogrammetric municipality data in scale 1:4000 provided from the municipality of Pozzuoli and from the Open StreetMap community spatial database.

All the datasets were converted in the plane coordinate system UTM WGS84 zone 33N. The same data layers providing from different data source were normalized and integrated.

4. Test results

We test our framework on a Pentium I7 dual core platform by using the tool GIS ESRI ArcGIS 10.5; all the spatial analysis processes are implemented as functions in the tool GIS; the fuzzy inference system is implemented in C++ language and incapsulated in the tool GIS.

In order to calculate the indicators needed to test our model a set of spatial operators as spatial intersects and spatial joins were used to summarize per census tract data assigned to features belonging to the various spatial datasets. Next are synthetized the processes applied to extract the indicators.

To calculate the indicators I_1 and I_2 the polygonal buildings dataset was partitioned in residential and industrial buildings in order to extract, respectively the area covered by residential and industrial building per microzone.

The indicator I_3, given by the mean square meters of green areas for resident, is calculated by selecting the urban green areas and calculating the sum of urban green areas covering any microzone. Finally, this area is divided by the number of residents in the microzone.

The indicator I_4 is calculated by dividing the sum of green areas in the microzone by the area of the microzone.

To calculate the indicators I_5 the district urban roads are selected from the road network layer and the sum of the lengths of the selected arcs falling in every microzone is calculated; finally, this value is divided by the sum of the length of all the road arcs falling in the microzone. The indicator I_6 is calculated by selecting the district urban roads with a width less than 7 m and dividing the sum of the selected arcs fallings in any microzone by the sum of the district urban road arcs falling in the microzone.

The indicator I_7 is calculated by dividing the number of residents in any microzone by the area of the microzone in square kilometers.

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To calculate the indicators I_8, I_9 and I_{10} the Buildings and dwellings census dataset is used, extracting for any microzone, respectively, the number of residential buildings built before 1945, the number of dwellings with at least one resident and the number of residential buildings with at least 16 dwellings, and dividing them, respectively by the number of residential buildings, the number of dwellings and the number of residential buildings in the microzone.

The II level indicators I_{11a}, I_{11b} and I_{11c} are calculated extracting from the point school layer, respectively, the primary, low secondary and secondary schools and constructing circular buffer areas with a radius of 500 meters centered in any school. Then, for any type of school, the area of the microzone covered by the calculated buffer areas is extracted and divided by the area of the microzone.

The II level indicators I_{12a} and I_{12b} are calculated extracting from the point Transport facilitiy layers, respectively, the bus stops and the railway's stops and constructing circular buffer areas with a radius of, respectively, 100 and 300 centered in any stop. Then, for any type of stop, the area of the microzone covered by the calculated buffer areas is extracted and divided by the area of the microzone.

The II level indicators I_{13a} and I_{13b} are calculated selecting, respectively, microzones including coastal areas, and containing a maritime terminal.

The II level indicators I_{14a} and I_{14b} are calculated extracting respectively, the polygon Hospitals and Sports facilities layers and selecting the microzones including the selected elements.

For brevity we show the thematic maps obtained for the indicators I_2 (Fig. 7) and I_4 (Fig. 8) in which an equal interval classification method of the indicator is applied.

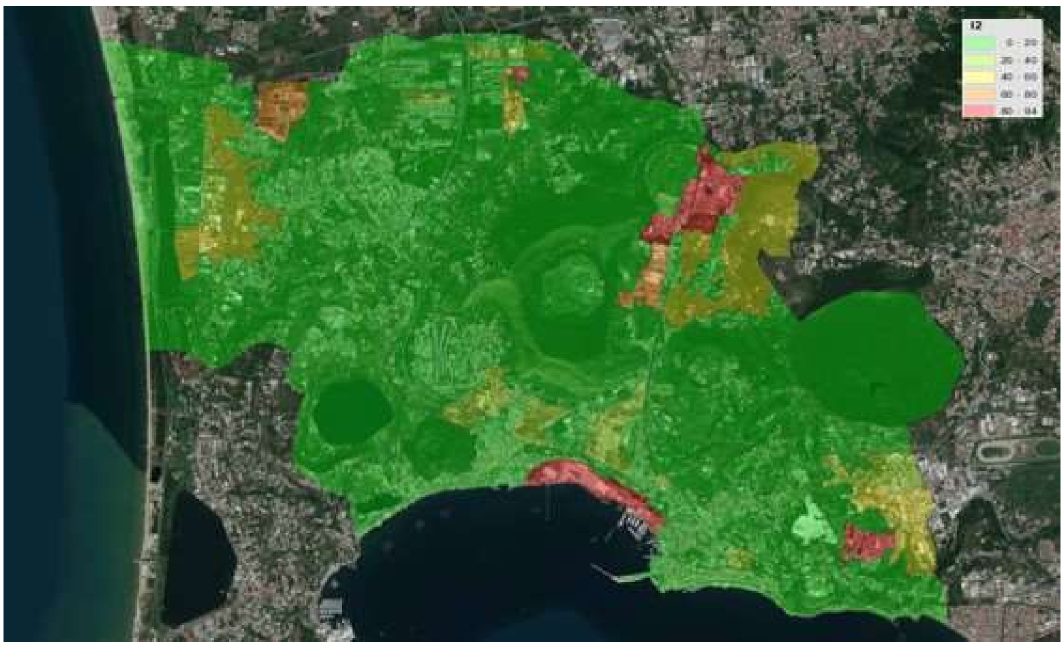

Figure 7. Thematic map of the indicator I2 – Percent of industrial areas with respect to total built areas

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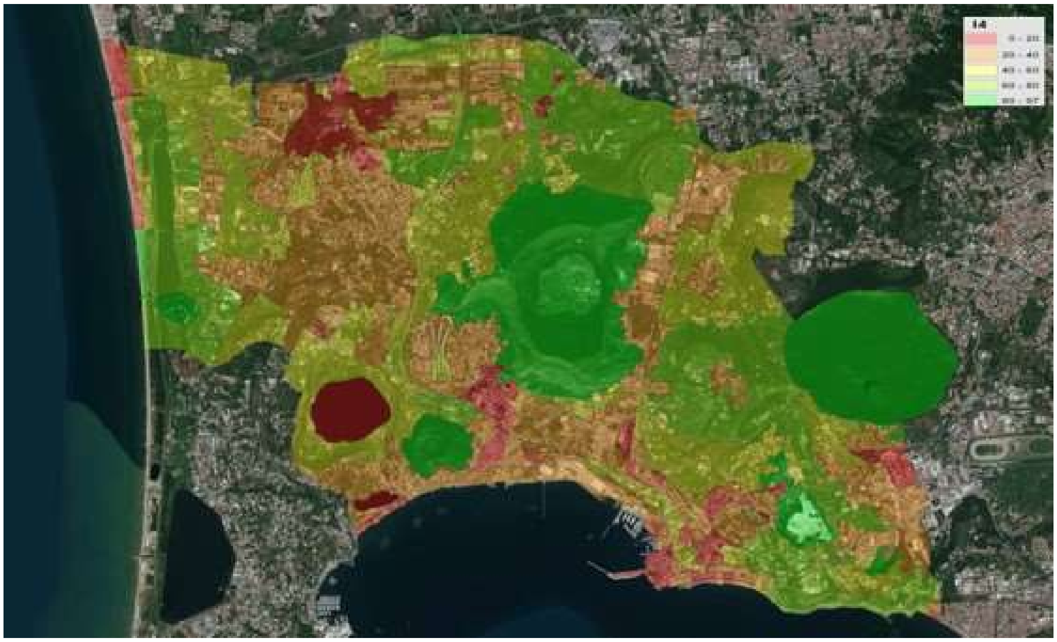

Figure 8. Thematic map of the indicator I_4 – *Percent of green areas with respect to area of the microzone*

After calculating the crisp values of any indicators, we apply the fuzzification process executing the fuzzifier component of the fuzzy rule system.

In Fig. 9 and 10 are shown two thematic maps of, respectively, the indicators I_2 and I_4 in which to any microzone is assigned the label of the fuzzy set to whom the microzone belongs with the highest membership degree.

Figure 9. Thematic map of the indicator I2 in which any microzone is classified assigning it the label of the fuzzy sets to whom it belongs with highest membership degree

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Figure 10. Thematic map of the indicator I4 in which any microzone is classified assigning it the label of the fuzzy sets to whom it belongs with highest membership degree

The two maps in Figs. 9 and 10 are obtained after the fuzzification process and highlight the microzones characterized by the indicator. In fig. 9 the microzone classified as *High* (in red) are characterized by a strong presence of industrial areas. In fig. 10 the microzone classified as *High* (in dark green) are largely covered by urban or overgrown green.

After the fuzzification process the fuzzy inference engine component is started; a set of about 100 fuzzy rules created by the domain experts is used. Finally, the defuzzification process is executed and the appropriated urban area class is assigned to any microzone.

The thematic map in fig. 11 show the classification results. In this map the urban area classification of the microzone is shown.

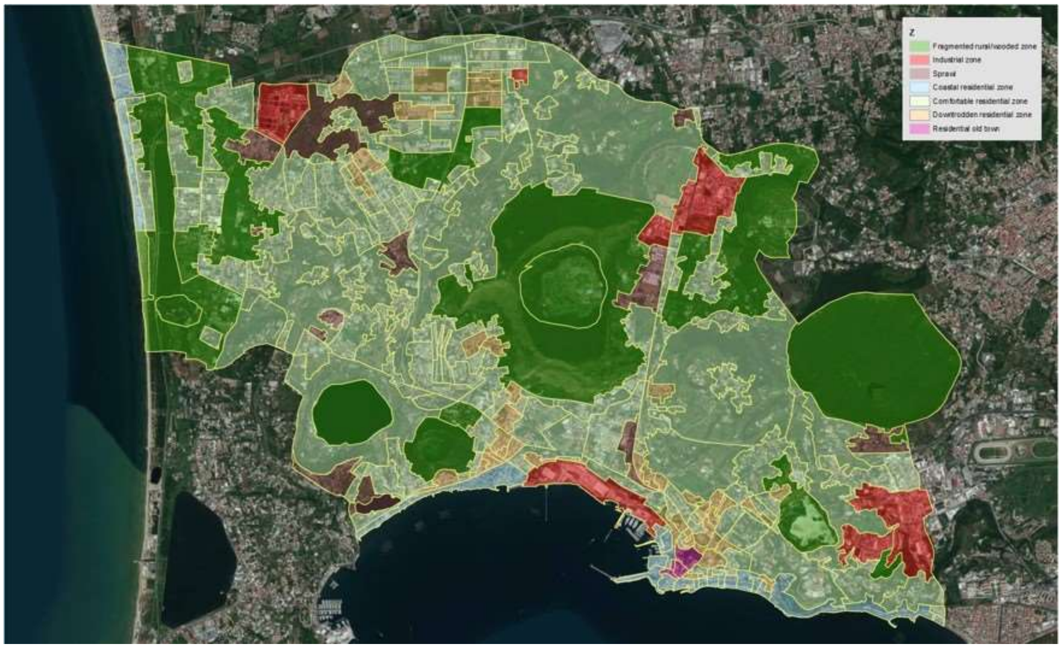

Figure 11. Thematic map of the microzones classified by urban area.

In order to evaluate the performance of the classification we compare the results with the supervised urban area classification of the microzones performed by the experts. For each class we

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calculate the accuracy, precision and recall (or sensitivity) indexes. This calculus is performed by extracting from the confusion matrix the TP, TN, FP and FN parameters, where:

TP (True Positive) is the number of microzones correctly assigned to the class;

TN (True Negative) is the number of microzones correctly not assigned to the class;

FP (False Positive) is the number of microzones wrongly assigned to the class;

FN (False Negative) is the number of microzones wrongly not assigned to the class.

The three indexes are given by:

$$\begin{aligned} &\text{accuracy}=\frac{TP+TN}{TP+TN+FP+FN}\times 100 \\ &\text{precision}=\frac{TP}{TP+FP}\times 100 \\ &\text{recall}=\frac{TP}{TP+FN}\times 100 \end{aligned} \tag{6}$$

Table 7 show the classification results; the three indexes are calculated for any class.

Table 7. Classification results obtained comparing the urban area classifications of the microzone obtained by applying or method with the supervised classification performed by the experts.

Urban area class	Accuracy	Precision	Recall
Fragmented rural/wooded zone	99.29%	100.00%	88.89%
Industrial zone	100.00%	100.00%	100.00%
Sprawl	100.00%	84.62%	100.00%
Coastal residential zone	100.00%	100.00%	100.00%
Comfortable residential zone	100.00%	100.00%	100.00%
Downtrodden residential zone	100.00%	100.00%	100.00%
Residential old town	100.00%	100.00%	100.00%

These results show that the classification of the microzones obtained by applying our model is almost similar to that supervised one attributed by the experts. The only deviations are present in the class *Fragmented rural/wooded zone* and *Sprawl*; two of the 18 microzones classified by the experts as *Fragmented rural/wooded zone* by using our model are classified as *Sprawl*.

Finally adjoining microzones belonging to the same class are dissolved forming urban contexts.

The municipality of Pozzuoli is partitioned in 60 urban contexts, shown in the map in Fig. 12.

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Figure 12. Thematic map of the urban contexts.

The only urban context classified as *Residential old town* (in magenta) is an area including the historical center of Pozzuoli. The urban contexts classified as *Coastal residential zone* (in light blue) area residential coastal areas. The other coastal areas are, respectively, the maritime industrial area, classified as *Industrial zone*, and an area given by a maritime not residential microzone, classified as *Fragmented rural/wooded zone* since it is not a residential zone and a high percentage of this zone is covered by vegetation. All the contexts classified as *Industrial zone* (in red) are areas where most of the buildings are industrial buildings or warehouses. The contexts classified as *Downtrodden residential zone* (in orange) are residential areas with a high density of residential real estates for building and with a high population density. The other on average residential contexts are classified as *Comfortable residential zone* (in light green); in these zones the population density and the number of dwellings per residential building are not high; in addition, these zones are almost covered by transportation services and schools and in them there are public green areas. The contexts classified as *Sprawl* (in brown) are areas where the density of residential buildings is sparse; they are probably urban agglomerations in recent, slow and unplanned expansion. Finally, the contexts classified as *Fragmented rural/wooded zone* (in green) are areas predominantly or completely covered with vegetation.

In fig. 13 is shown a thematic map with the reliability of the results. The reliability is calculated as a weighted average of the membership degree to their urban area class of the microzones included in the context where the weight is given by the area of the microzone.

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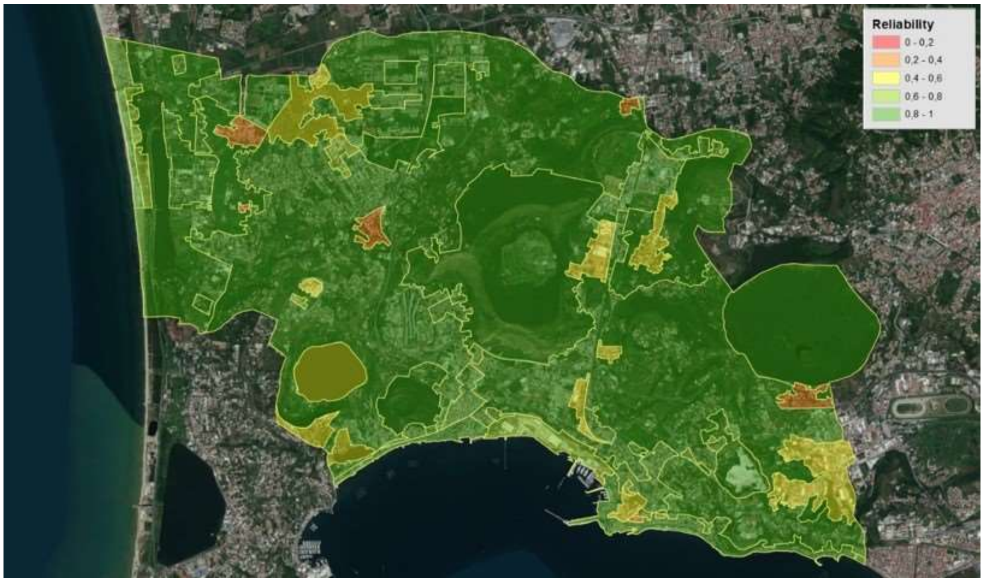

Figure 13. Thematic map of the reliability of the urban contexts.

There are four contexts with a low reliability, in the range 0.2-0.4: three of these contexts are classified as *Sprawl* and the last as *Downtrodden residential zone*. In all these contexts are included microzones with a not high membership degree to their urban area class, meanly under the value 0.4.

These results suggest the need of a finer classification of urban areas that for the urban contexts with a low reliability. In fact, in microzones classified as a specified urban area with a low membership degree probably there are different types of urban areas; a finer classification could also take into account classes of urban area to which microzones belong to a slightly lower degree of membership. For example, the context with low reliability classified as *Downtrodden residential zone* is given by a microzone classified as *Downtrodden residential zone* with a membership degree 0.36 and belonging to the class *Industrial zone* with a membership degree 0.31; this microzone are included a densely populated residential area and a non-residential areas with industrial premises; a finer classification of this microzone could consider both this class in order to characterize in greater detail the type of urban area that it represents.

5. Final considerations

We present a new model based on a Mamdani fuzzy rule system to partition an urban system in homogeneous urban contexts. We implement our model in a GIS platform and construct the urban contexts by considering initially the urban system partitioned in microzones. A set of indicators are defined to characterize urban areas; these indicators are fuzzified and used as variables in a fuzzy rule set used to classify the microzones; the urban contexts are obtained dissolving adjoining microzones belonging to the same urban area class. We assess the reliability of our classification assigning to any urban context the weighted average of the membership degree of the microzones within in it where the weight is given by the area of the microzone.

We test our model applying it to the Municipality of Pozzuoli (Italy) in order to partition the municipality in context classified based to the type of residential or rural area.

A comparison of the results with the results of a supervised classification obtained by expert show that our model has high classification performances in terms of accuracy, precision and recall. The results show that the contexts were the reliability is low include microzones in which are present zones with different characteristics; in the future we intend improve this model in order to obtain a finer partition of the urban system by considering all the more relevant class of urban area characterizing the microzones.

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