



# Article Construction of a Composite Vulnerability Index to Map Peripheralization Risk in Urban and Metropolitan Areas

# Roberto Gerundo \*, Alessandra Marra \*D and Viviana De Salvatore

Department of Civil Engineering, University of Salerno, Via Giovanni Paolo II, 132-84084 Fisciano (SA), Italy; desalvatoreviviana@gmail.com

\* Correspondence: r.gerundo@unisa.it (R.G.); almarra@unisa.it (A.M.); Tel.: +39-089964123 (R.G.)

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**Abstract:** As cities and poverty continue to grow worldwide, both spatial and a-spatial peripheralization processes expose entire urban and metropolitan areas at risk of degradation, not just traditional peripheries. The main aim of this paper is to propose a methodology for peripheralization risk assessment, according to the general theory of territorial risk, in order to identify priority areas where mitigation actions should be envisaged through urban and territorial planning. Such an approach constitutes the novelty of the work. So, peripheralization risk is defined for the first time, depending on aggregated vulnerability and exposure. Based on a literature review, a set of vulnerability indicators structured in three dimensions is defined in order to construct the composite vulnerability index in the Italian geographical context. Due to the absence of well-established threshold values, an aggregation method based on fuzzy logic is used. The methodology was applied to a conurbation of 16 municipalities in Campania Region (Italy). Obtained results showed that areas most at risk can be both peripheral and central neighborhoods, but also entire municipalities, demonstrating how mitigation actions are needed at different planning levels. Since the necessary input data are ordinarily available in planning processes, the proposed methodology can be transferred to other geographical contexts.

**Keywords:** risk analysis; urban vulnerability; sustainable development; urban planning; fuzzy logic; geographic information systems

# 1. Introduction

In urban literature, the term periphery traditionally has a spatial meaning referring to the neighborhood micro-scale, with reference to expansion areas born at the margins of historic cities starting from the post-war period [1]. In some geographical contexts, such as in Europe and in Italy, this term has often been associated with negative meanings, which have become indicative of a peripheral condition: Economic and social marginality, building degradation, and lack of services [2–4]. The urbanization trends taking place at a global scale—the metropolization on the one hand and the depopulation of the inner areas on the other—have changed the traditional meaning attributed to the term periphery, which concerns the geographical-spatial distance from a center on which it is functionally dependent [5].

Some recent studies, also within other disciplines such as economic geography, sociology, and political sciences, have shown that today it is appropriate to talk about peripheralization rather than peripheries. Peripheralization is intended as a dynamic process that produces a-spatial peripheries, which are defined as spaces that have a peripheral condition regardless of their proximity to urban centers and which are recognizable at different observation scales: From the national macro-scale to

the micro-scale of urban neighborhoods [6–8]. However, although peripheralization at meso-scale has already been studied, there is a lack of literature about peripheralization at intra-city level [9].

Consequently, a univocal meaning given to the term urban periphery is not recognizable in the planning literature [10]. Nevertheless, two different approaches are adopted by researchers depending on whether the reference to spatial aspects is present or not. In the first case, one refers to the peri-urban areas, i.e., to the urban-rural interface areas characterized by sprawl and territorial resources consumption. In the second one, the peripheral condition is not necessarily associated with the spatial dimension but with a situation of urban decay or social disadvantage [11]. In the latter case, the terms most used to express this concept are 'degraded urban areas' [12] or 'urban poverty areas' [13]. First in the United Kingdom, then in the whole of Europe, the term 'deprived areas' has been used as a synonym [14].

The new Urban Agenda, enacted during the United Nations Habitat III Conference, states that the persistence of multiple forms of poverty, growing inequalities, and environmental degradation remain among the major obstacles to sustainable urban development worldwide. Moreover, the document clearly states the importance of urban and territorial planning to reverse this trend [15]. According to the European Commission, the persistence of deprived areas represents a threat to the sustainability of the urban development model and a social risk [16]. Furthermore, the fight against degradation in existing urban areas can discourage the increasing land consumption [17].

In Italy, where national legislation on urban regeneration and limitation of land consumption is still lacking, urban renewal programs, known as complex urban programs, have been widespread since the 1990s to fight degradation [18]. Then, the theme was overlooked in government actions. Only recently, from 2015 to 2016, two programs have been defined aimed at providing public funding to local authorities for measures addressed at peripheries, intended as degraded urban areas [12,19].

Unlike other European countries, in Italy, scientific criteria are not used for the identification of degraded areas of intervention, usually delegated to the municipal authorities on the occasion of sporadic calls for funding, as the one above-mentioned. As a consequence of this and of the scarcity of resources that characterizes local authorities, in practice, urban and environmental regeneration are not primarily addressed at areas that have a significant presence of degradation factors, but result in disconnected building operations, at a small scale and guided by the prevailing real estate convenience. This is attributable to the fact that these activities are often independent of urban planning and, even more, from the strategic planning at a large scale, to which less and less importance is attributed. However, by considering the inter-municipal nature of these processes, it is necessary that spatial planning responds to the different levels in which it operates, starting from the vast area.

Nevertheless, in the new urban geography, to draw a map that clearly distinguishes peripheries from centers and the different levels and degrees of peripheralization results really challenging [20], hence, it is necessary to develop methodologies capable of managing this complexity, in order to identify priority areas of intervention.

The methods, available in the technical literature, that adopt scientific criteria to spatially identify priority intervention areas are based on a set of indicators structured into multiple domains for measuring both urban poverty [21] and the above-mentioned urban deprivation. The most recent English index of multiple deprivation (IMD) allows the mapping of the deprivation degree on the territory, at a neighborhood scale, given by a composite index which is based on 37 indicators organized in different domains: Income, employment, education, skills and training, health and disability, crime, barriers to housing and services, living environment [22,23]. For each domain, representative index is obtained. Therefore, the obtained indices are combined through appropriate weights, derived from both literature and robustness analysis of the indicators [24,25].

Outside the United Kingdom, a research activity has been developed aimed at calculating neighborhood deprivation/urban poverty indices in several European countries, some of which have founded Urban Deprivation and Poverty Observatories [26]. From the data collected by observatories it emerges that the considered domains, among those already examined in the IMD, vary with the

different interpretations of the concept of deprivation given by each country, as well as available data concerning the specific geographical context.

In particular, it arises that the indicators chosen to calculate the deprivation indices mostly refer to the demographic, employment, and economic characteristics of the population. Consequently, the most investigated domains relate to income, employment, and education. In some cases, this type of analysis is supplemented by the calculation of descriptive indicators of housing conditions and buildings, which can be considered proxy variables to measure the potential building degradation, as also suggested by a recent Italian call for funding [12]. In the case of English IMD, the analysis also concerns the life context of the population, according to a broader vision of deprivation, which is inspired by a holistic type of interpretative approach to urban poverty. Other aspects of greater interest for urban planning, such as the degradation of public space or the lack of infrastructure and services, are investigated when the phenomenon to be measured is not urban deprivation or poverty but, more generally, quality of life—as in the Dutch case—where the priority intervention areas are identified through an index that is used inversely to individuate vulnerable areas [27].

In general, different statistical methods like factorial analysis, regression, and shrinkage are used to calculate these indices [26]. Some Italian scholars, who propose approaches to identify priority intervention areas, used traditional indicators of urban poverty, with reference to the social and housing disadvantages, and applied several methods: Spatial autocorrelation techniques, used in Bari and Taranto municipalities [28]; fuzzy analysis and integrated fuzzy multicriteria analysis, applied in the city of Bari [29], on the basis of fuzzy set approach to poverty measurement [30].

In almost all the studies mentioned, starting information refers to census data, while minimum spatial reference unit for mapping is the neighborhood.

In all cases, geographic information systems (GIS) are an indispensable support for managing the large amount of data relating to the set of indicators. Furthermore, they allow associating the data with the chosen spatial units and, therefore, to view the starting information and the subsequent processing on maps.

From the brief examination carried out on the current the state of affairs, some open issues arise:

- An agreement lacks the most suitable set of indicators to identify degraded areas requiring priority interventions;
- The most frequently investigated dimensions concern social and housing problems, neglecting the aspects related to the configuration and composition of the urban fabric subject to planning studies;
- There is a heterogeneity of methods useful to establish threshold values within which to classify the indicators, while a univocal criterion lacks.

In relation to the first and second points, this is closely associated with the absence of a shared definition of the concept of urban periphery or deprived area. With reference to the third point, it has already been observed, for what the assessment of urban sustainability concerns, that the main problem of indicator-based methods, in addition to the little data available, consists in the subjectivity of the classification of the obtained values for the indices, when well-established threshold values are missing [31].

Some researchers have proposed an innovative use of fuzzy logic for taking into account the uncertainty in the classification and combination of urban sustainability indicators [32,33]. Such an approach has been adopted in recent studies among the analysis of other complex issues that are characterized by uncertainty, like vulnerability to climate change [34–36]. This new use of fuzzy logic allows the evaluation of a different degree of membership of each indicator to several classes, unlike the classical theory, based on the logic of crisp sets according to which each indicator belongs to a well-defined class.

The main objective of this work is to propose an innovative method for the identification of priority areas, corresponding to urban areas at greater risk of peripheralization, according to the

general theory of territorial risk, in order to identify mitigation actions in urban and territorial planning. This risk-based approach constitutes the novelty of the present work.

Within this framework, a further objective is to provide a set of indicators, structured on multiple domains, to assess urban vulnerability to peripheralization risk in the Italian national context.

The methodology was applied to the vast area of the Caserta conurbation, in Campania Region (Italy), as described in Section 2. The details of the proposed method are explained in Section 3, where the risk of urban peripheralization is defined, for the first time, with reference to the components of hazard, vulnerability, and exposure. In the same section, the study defines a set of vulnerability indicators and a method of combining them based on the fuzzy logic, so as to overcome the criticality due to the absence of reference values for their classification. The results of the application of this method to the study area are presented in Section 4. Contributions of the proposed methodology and potential implications for planning are also discussed in Section 5. Finally, the main conclusions and future research developments are pointed out (Section 6).

#### 2. Study Area

The area selected for applying the methodology includes the municipalities belonging to one of the complex territorial fields (CTC) identified by the Regional Territorial Plan (PTR) of Campania Region and, in particular, that relating to the Caserta area, most of it coinciding with its conurbation. Since the post-war period, Caserta City, today the capital of the province, has been merging with the neighboring municipalities in a large urban area. It is a conurbation constituted by 16 municipalities included in the area under study: Capodrise, Capua, Casagiove, Casapulla, Caserta, Curti, Macerata Campania, Marcianise, Maddaloni, Portico di Caserta, Recale, San Marco Evangelista, San Nicola La Strada, San Prisco, San Tammaro, Santa Maria Capua Vetere.

The territory under analysis, inhabited today by about 320,000 people, is divided into 1014 census sections and is influenced by a high housing density, with an average of 2128 inhabitants/km<sup>2</sup> and high urbanization. It contains productive centers important for the whole of Southern Italy, such as the industrial agglomeration of Marcianise. Furthermore, it has a cultural heritage of great interest, which includes two UNESCO sites—the famous Royal Palace of Caserta, with its monumental park, and the Royal Site of San Leucio (Figure 1). The level of environmental pollution is significant due to existing production activities and the disposal, often illegal, of solid urban waste.



**Figure 1.** Study area. Source: Own elaboration on data from the Territorial Coordination Plan of Caserta Province [37].

The urban disorder, the degradation of the cultural heritage, and the occupational stagnation, together with environmental pollution, make the Caserta conurbation one of the most complex territories in Italy [38]. The CTCs, in fact, are identified as areas of noteworthy criticality, i.e., areas of intense concentration of risk factors, where it is believed that the Campania Region institutions should promote a priority action of particularly integrated interventions [39].

#### 3. Materials and Methods

The application of the methodology requires the prior explanation of peripheralization risk components, with reference to the fundamental equation, which expresses the latter as a product of hazard, vulnerability, and exposure [40]. The definition of the equation is to be carried out with reference to the purpose of risk assessment, which is to identify priority areas of intervention, where a coexistence of degradation conditions or multiple deprivation might occur. By integrating the different approaches investigated in the present work, so considering both spatial and a-spatial aspects, it is assumed that the peripheral condition concerns the areas that, regardless of their location with respect to the urban center, are affected by: Socio-economic and demographic inequalities, poor quality of buildings, lack of services; underused or abandoned spaces; configuration and composition of the urban fabric so as to encourage soil consumption.

Peripheralization risk is therefore understood as the risk that an urban or metropolitan area may be affected by this condition, in part or entirely, with reference to three dimensions: Social, building, and urban. With regard to these domains, the exposed goods are represented, in order: By the population; from buildings; by the urban fabric, in which the first two are inserted. Vulnerability is intended as an expression of the greater or lesser propensity of exposed goods to degradation, deriving from some

endogenous characteristics of the latter, and belongs to the three aforementioned domains. Thus, it can be decomposed into social, building, and urban vulnerability.

In addition, a hazard analysis was performed, from which it emerged that peripheralization risk is not associated with a specific hazard or with the occurrence of a certain event, as in the case of natural and technological risks [41,42], but to a multiplicity of causes, which are considered by literature to induce consequences in terms of social, building, and urban degradation. The quantification of such causes belongs to different disciplines. Furthermore, for some types of hazard, further studies are needed to validate actual causality relationships [43]. However, it is reasonable to assume that a high value reached by the intensity of the aggregated vulnerability ( $V_a$ ), given by the combination of social ( $V_s$ ), building ( $V_b$ ), and urban vulnerability ( $V_u$ ), corresponds to a greater occurrence probability of the peripheral condition, due to the coexistence of potential degradation factors. Hazard, therefore, can be expressed as a function of aggregated vulnerability.

The peripheralization risk equation is thus defined as follows:

$$R = V_a \times E \text{ where: } V_a = V_s \times V_b \times V_u \tag{1}$$

That being said, the methodology proposed for the construction of the aggregated vulnerability index is divided into the following macro-phases:

- Choice of indicators for measuring the propensity to degradation in each of the domains under analysis;
- Collection of data necessary for the values estimation of the chosen indicators;
- Normalization of the indicators;
- Construction of the composite vulnerability index by fuzzy analysis (Figure 2).



**Figure 2.** Schematic workflow of the proposed methodology to construct the aggregated vulnerability index.

As a first step, the basic indicators selected for each domain are divided into subdomains representative of the vulnerability factors, according to a hierarchical framework. The quantitative values of the basic indicators, referring to the census sections, which are chosen as the minimum spatial mapping unit are organized within a geodatabase. These values, subsequently normalized, constitute the input data for the fuzzy analysis. The latter consists of some main phases which, starting from input data, lead to the required output, in particular the following: Fuzzification, through the definition of membership functions; inference; aggregation; defuzzification. As a model calibration, in order to reduce the subjectivity of the choices made in each of the four phases, a sensitivity analysis

was performed by testing different fuzzy schemes obtained by varying the membership functions, the inference method, the aggregation method, and the method of defuzzification. As a discriminant for the choice of the better scheme, the standard deviations of the outputs of all the performed fuzzy analyses are compared with the ones of the input data: The scheme to be selected is the one that guarantees input and output distributions characterized by similar dispersion. In this way, the secondary composite indices, representative of the subdomains, are obtained first, then the primary composite indices, relating to the domains, and finally, the composite index of aggregated vulnerability.

Therefore, output data of the analyses are incorporated in the original geodatabase, and associated to the census sections, in order to spatially map vulnerability levels. Finally, by over-laying the so-obtained vulnerability map and the exposure map, it is possible to derive the risk map, to support the identification of priority areas of intervention. To this end, it is necessary to quantify the exposed good. By considering that built-up areas also include the buildings and the population exposed, the highest level of exposure is associated with these areas: In numerical terms, this is equivalent to the claim that the exposed value, in correspondence with the urban fabric, is equal to the unit. Hence, by overlaying the aggregated vulnerability map and the exposure map, it is possible to obtain the final risk map.

#### 3.1. Indicators Selection for Measuring Vulnerability

The measure of vulnerability in the social, building, and urban domains is carried out starting from the definition of a set of indicators, descriptive of the potential propensity for degradation of the exposed goods. With regard to non-spatial aspects, the indicators were selected, taking into account those proposed to identify degraded urban areas among the technical-scientific literature examined. On the other hand, with regard to spatial aspects, they derive from international reports and guidelines for measuring urban sustainability. In both cases, with the aim of defining indicators suitable for the Italian geographical context, many of them have been traced in documents of the Italian National Institute of Statistics [44–47].

Specifically, the indicators proposed to quantify social vulnerability measure the population's propensity to a situation of socio-economic disadvantage, which are: The unemployment or inactivity rate; failure to reach minimum education levels; the incidence of large families, and the elderly population. These indicators refer to different subdomains, defined as social vulnerability factors: Employment; education and culture; demographic structure. The indicators of potential degradation for the building domain refer to different subdomains or building vulnerability factors: Building construction quality and dwellings use. With reference to the first subdomain, they measure the state of conservation and technological obsolescence of buildings, while in relation to the second, they refer to the property deed and the time spent in them. The indicators for urban domain give a measure of the fragmentation of the urban fabric and its composition, with reference to the incidence of non-permeable areas. Other indicators, selected for this domain, are the lack of services and accessibility, as well as the presence of urban criticalities such as abandoned, disused, and illegally transformed areas. Then, for what concerns the social and building domains, all the chosen peripheral factors are non-spatial, i.e., they can be as high in typically peripheral neighborhoods—intended in a geographical spatial sense—as in historical centers. On the other hand, for the urban domain, more properly spatial vulnerability factors have also been individuated, such as the composition of permeable areas, which typically increase as housing density decreases, moving from the center to the urban-rural interface. Similar arguments hold for unauthorized built-up areas, which are in contrast to existing urban planning tools. This phenomenon is present in Italy and it is particularly considerable in Southern Italy [48].

In general, the criterion that guided the choice of indicators set was to identify those critical factors which can be faced and managed through planning, starting from the vast area in order to ensure sustainable development, intended also as equity and shared economic prosperity [49]. In fact, the selected indicators are associated with the related sustainable development goals according to the 2030 Agenda, to which mitigation actions should be targeted (Table 1).

**Table 1.** Indicators selected for mapping vulnerability and the corresponding sustainable developmentgoals (SDGs) to be achieved in compliance with the 2030 Agenda.

Sub-Domain	Indicator	Definition and Unit of Measurement	SDGs				
Social Domain							
Employment	I <sub>1</sub> —Unemployment rate	Ratio between the unemployed in a given age group and the set of employed and unemployed people of the same age group (%).	Decent work and economic growth (SDG 8)				
	I <sub>2</sub> —Inactivity rate	Ratio between people not belonging to the labor force, i.e., those not classified as employed or looking for employment, and the corresponding reference population (%).	Decent work and economic growth (SDG 8)				
Education and culture	I <sub>3</sub> —Index of non-completion of the secondary school cycle (middle school)	Percentage of population in the 15–52 age group who did not obtain a middle school diploma out of the total population of the same age class (%).	Quality education (SDG 4)				
	I <sub>4</sub> —Incidence of illiterate	Number of illiterates aged six and over and the total resident population aged six and over (%).	Quality education (SDG 4)				
Demographic structure	I5—Old age index	Ratio between the population aged 65 and over and the population aged 0–14 (%).	Good health and well-being (SDG 3)				
	I <sub>6</sub> —Incidence of large families	Ratio between the number of families of six or more people and the total number of families (%),	No poverty (SDG 1)				
		Building Domain					
Building construction quality	I7—Disused buildings with historical, architectural, or artistic value	Number of abandoned buildings with historical, architectural, or artistic value out of total buildings with historical, architectural, or artistic value (%).	Sustainable cities and communities (SDG 11)				
	I <sub>8</sub> —Buildings in bad and mediocre conservation state	Ratio between residential buildings in bad and mediocre conservation state and the total of residential buildings (%).	Sustainable cities and communities (SDG 11)				
	I9—Index of improper housing	Ratio between the number of accommodations of other type $^1$ and the total of the housing units (%).	No poverty (SDG 1) Sustainable cities and communities (SDG 11)				
Dwellings use	I <sub>10</sub> —Empty dwellings	Number of empty dwellings out of the total of the housing units (%).	Reduced inequalities (SDG 10)				
	I <sub>11</sub> —Property deed	Number of rental dwellings out of the total of occupied housing units (%).	Reduced inequalities (SDG 10)				
	Urban Domain						
Configuration and composition	I <sub>12</sub> —Edge Density	Ratio between the total sum of the perimeters of the polygons of the built areas and their surface (m/ha).	Sustainable cities and communities (SDG 11) Life on land (SDG 15)				
	I <sub>13</sub> —Housing density	Ratio between the number of resident inhabitants and the surface of the urban fabric (ab/ha).	Sustainable cities and communities (SDG 11)				
	I <sub>14</sub> —Incidence of impermeable areas	Ratio between the surface of the urban fabric minus the urban green areas and the surface of the urban fabric (%).	Sustainable cities and communities (SDG 11) Life on land (SDG 15)				

Sub-Domain	Indicator	Definition and Unit of Measurement	SDGs
Services and accessibility	I <sub>15</sub> —Lack of public interest facilities and services	Ratio between the number of facilities of supra-municipal interest and the total of resident inhabitants (N °/Ab).	Sustainable cities and communities (SDG 11)
	I <sub>16</sub> —Distance from the main railway station	Time needed to reach the nearest railway station measured on basis of the travel isochrones (class).	Industry, innovation, and infrastructure (SDG 9)
	I <sub>17</sub> —Index of centrality	Ratio between the number of commuter flows leaving the area (net of commuters residing and working in the area itself) and the number of commuter flows entering the area (net of the same amount) (%).	Decent work and economic growth (SDG 8)
Urban criticalities	I <sub>18</sub> —Incidence of abandoned or underused areas	Ratio between the surface of urban wasteland $^2$ in the urban fabric and the total surface of the urban fabric (%).	Sustainable cities and communities (SDG 11) Life on land (SDG 15)
	I <sub>19</sub> —Index of unauthorized buildings	Ratio between the areas built-up in a given period not foreseen by the urban planning tool and the total area of the built-up areas (%).	Sustainable cities and communities (SDG 11)

Table 1. Cont.

<sup>1</sup> Accommodation of other types are defined as the ones other than housing occupied by resident persons, such as campers, caravans, garages, attics, and cellars. <sup>2</sup> Urban wasteland is constituted by: Abandoned productive areas; unused areas with newly built artifacts; undeveloped areas devoid of specific use, or abandoned.

## 3.2. Data Collection and Preparation

The selection of indicators for the Italian context was carried out also taking into account the quality and availability of the necessary data by census section, which represents the reference unit chosen for the spatialization of the indices obtained in the present study, with the aim of mapping vulnerability. In fact, for the purpose of measuring the indicators selected for the social and building domain, census data, which are made available by the Italian National Institute of Statistics and periodically updated, are mainly required. Moreover, it is necessary to acquire a series of additional data, both in raster and vector format, for the numerical formalization of the indicators selected for the urban domain (Table 2).

Indicators	Data Source	Data Format	Level of Spatial Detail	Solar Year
$\begin{matrix} I_1, I_2, I_3, I_4, I_5, I_6, I_8, \\ I_9, I_{10}, I_{11}, I_{13} \end{matrix}$	Istat—Census of population and housing	Shapefile	Census section	2011
I <sub>12</sub> , I <sub>14</sub>	Elaboration on Imperviousness Cartography	Raster	20 × 20 m	2015
I <sub>16</sub>	Regional topographic database <sup>1</sup>	Shapefile	1:5000	Various <sup>1</sup>
I <sub>17</sub>	Istat—Commuting	Shapefile	Census section	2011
I <sub>7</sub> , I <sub>15</sub> , I <sub>18</sub> , I <sub>19</sub>	Territorial plans of provincial coordination <sup>2</sup>	Shapefile, raster	1:25,000	Various <sup>2</sup>

Table 2. Sources, typology, and level of spatial detail of data necessary to measure indicators.

<sup>1</sup> The database used for the study area is that of Campania Region, dated 2011. <sup>2</sup> The specific source plan for the study area is that of Caserta Province, dating back to 2012.

The construction of the indicators obtained from the census data requires simple algebraic operations, while more complex elaborations are necessary to measure the other indicators. In particular, some indicators of the urban domain are measured in relation to the extent of the urban fabric, which

represents the exposed good, falling within the perimeter of the census section. Hence, it is necessary to map the built-up areas, which are here assimilated to the urban fabric. To this aim, Copernicus Imperviousness cartography is available, in raster format, in which each pixel is associated with a degree of imperviousness, expressed as a percentage. Therefore, in a GIS environment, the surface occupied by built-up areas can be obtained by wrapping all the pixels with imperviousness degree greater than 30%, according to the approach suggested by the European Environment Agency—EEA [50]. A more complex processing is also necessary for the calculation of the indicator relating to the distance from the railway stations. In this case, on the basis of the road map and information relating to the average travel speed, as well as the precise location of the railway stations, it is possible to construct an isochronous map using the Network Analyst tool of ArcGis software. To deal with the lack of data relating to travel speed, a value can be attributed to this on the basis of the legislative standards in relation to the type of road. Each census section is assigned a value proportional to the time needed to reach the nearest station based on the isochronous in which it falls. The value of the indicator, by census section, varies from 1 to 4, where 1 corresponds to the longest travel time and 4 the shortest.

Additional data need to be acquired to calculate the incidence of unauthorized built-up areas and abandoned areas on the total surface of the urban fabric. The sources for these data are constituted by the territorial plans of provincial coordination, in which they must be identified on the basis of current legislation on urban and territorial planning, so such information is public and easy to obtain.

#### 3.3. Normalization

Normalization is useful in making indicators comparable since these are frequently expressed in different units of measurement and polarities. Therefore, the numerical values reached by the indicators are rendered dimensionless and, where necessary, the polarity is reversed. In the case under analysis, the selected indicators all have the same polarity. Furthermore, most indicators are characterized by dimensionless values, being defined as the ratio between quantities having the same unit of measurement.

However, according to the proposed methodology, it is necessary to normalize the origin indicators in order to standardize the membership functions in the subsequent fuzzy analysis, which otherwise would require the definition of specific functions for each indicator. In this model, a linear interpolation formula is used which requires standard values for each indicator, i.e., the maximum and minimum value assumed among all the census sections into which the territory time to time in question is divided, and reads:

$$y_{i} = \left\{ \begin{array}{c} 0\\ \frac{x_{i} - x_{i,min}}{x_{i,max} - x_{i,min}}\\ 1 \end{array} \right\}$$
(2)

where:

y<sub>i</sub> = normalized value of the i-th basic indicator by census section;

 $x_i$  = value of the i-th basic indicator by census section;

 $x_{i,min}$  = minimum value of the i-th basic indicator assumed among all the census sections;

 $x_{i,max}$  = maximum value of the i-th basic indicator assumed among all the census sections.

This formula takes into account the fact that all the indicators have positive polarity, i.e., an increment in their value corresponds to a growth in the potential degradation in the different dimensions, therefore an increase of the vulnerability in the latter. The domain of each normalized indicator consists of the interval (0, 1), where 1 corresponds to the maximum degree of criticality or potential degradation, while 0 represents the minimum one (Figure 3).



Figure 3. Plot of the normalization function.

#### 3.4. Fuzzy Analysis

Theory based on fuzzy logic, introduced by the mathematician Lotfi A. Zadeh [51], is less used for risk analyses than probabilistic models, however it is preferable when the evaluation is characterized by a strong uncertainty [52,53].

For the purpose of calculating the composite index of aggregated vulnerability, the fuzzy analysis is repeated several times in the method here proposed. With reference to the hierarchical scheme in Figure 4, at the first step the input data for the analysis are characterized by normalized indicators, while the output data, at the upper level, are the secondary composite indices, representative of the subdomains.



Figure 4. Hierarchical analysis scheme.

The latter constitute input data for the subsequent fuzzy analysis, which returns as output, at an even higher level, the primary composite indices, representative of the vulnerability in the three social, building, and urban domains. The last analysis is performed by assuming the primary composite indices as input data, so as to define the final output, constituted by the aggregated vulnerability index, at the highest level of the hierarchical scheme.

The first phase of the analysis is fuzzification, with the definition of membership functions, which allow assigning the degree of membership of every input and output data to each fuzzy class by converting its numerical value into a linguistic one. For the case at hand, when the input data are represented by the normalized values of the indicators (y) and the output ones consist of the secondary composite indices ( $y_{sd, out}$ ), the functions  $\mu(y)$  and  $\mu(y_{sd, out})$  define, respectively, the degree of membership to three classes: Low, medium, or high. In the same way, this is done when the secondary composite indices become input data of the subsequent analysis ( $y_{sd, inp}$ ). On the other hand, for the output data corresponding to the primary composite indices ( $y_{d, out}$ ), the functions establish the degree of membership to four classes: Low, medium, high, and very high. By analogy, the same functions are adopted when the primary composite indices constitute the inputs in the subsequent analysis ( $y_{d, inp}$ ), in which, instead, for the output data, corresponding to the aggregated vulnerability index ( $y_f$ ), the functions establish a degree of membership to five classes: Very low, low, medium, high, and very high.

In order to obtain the output data through the combination of the input variables, it must be taken into account that the latter have a degree of membership to several classes at the same time, as is typical of fuzzy logic. So, it is necessary to establish rules of inference for all the possible combinations. In general, these rules are equal to the number of classes, raised to the number of input variables. For example, in the case of the subdomain 'dwellings use' of the building domain,  $3^2$  rules need to be defined for obtaining the V<sub>b2</sub> index, starting from i<sub>10</sub> and i<sub>11</sub> indicators. The inference rules here adopted are of the *if-then* type with operator *and*. For the sake of example, a rule referring to the case just mentioned reads: If (i<sub>10</sub> is low) and (i<sub>11</sub> is medium) then (V<sub>b2</sub> is medium).

The aggregation in a single inferred area of the output areas, which result from each rule, constitutes the output of the fuzzy inference.

The latter is subsequently converted back to a numerical value, i.e., it is defuzzified, which therefore represents the inverse process to fuzzification.

The fuzzy analysis described has been repeated for each of the 1014 census sections composing the study area. So, the aid of a computational software was indispensable to manage the large number of data to be processed due to the high number of census sections [54]. Hence, all the phases of the fuzzy analysis have been implemented in the Matlab software, through the Fuzzy Logic Toolbox graphical interface. The membership functions, the rules and the inference method, as well as the modalities for aggregation and defuzzification, have been preset in a file of format fis (fuzzy inference system). The values reached by the input variables for each census section were formalized into Matlab software as data vectors, while the preset fuzzy scheme was read through the readfis function and performed with the evalfis function.

#### 3.5. Sensitivity Analysis

The first analyzed fuzzy scheme is characterized by the triangular membership functions of the type of Figure 5; the second from the trapezoidal functions shown in Figure 6. In both scenarios the min–max inference method, the union aggregation method, and the centroid defuzzification method were adopted.

For the sake of example, the level of building vulnerability is assessed on basis of five standardized input indicators, whose values have an average standard deviation approximately equal to 0.21. The standard deviation of the outputs obtained using triangular functions turns out to be equal to 0.07, which is certainly too low, so this type of function has been discarded. The standard deviation found by using the trapezoidal functions of Figure 6a,b is equal to 0.14, while, using the functions with reduced transition area (Figure 6c,d), a standard deviation of 0.18 is obtained. In both cases specific membership functions (Figure 6e) were adopted for the output, i.e., the primary composite index, representative of the building vulnerability. Since 0.18 is very close to 0.21 of the input indicators, the trapezoidal functions of Figure 6c–e have been chosen. By following the same rationale, the trapezoidal functions of Figure 6f for the input data were represented by the primary composite indices, while those of Figure 6f for the final output, i.e., the aggregated vulnerability index.



**Figure 5.** Triangular membership functions: (a) Normalized indicators y; (b) secondary composite indices  $y_{sd,inp}$  and  $y_{sd,out}$ ; (c) primary composite indices  $y_{d,out}$  and  $y_{d,inp}$ ; (d) final output  $y_{f}$ .



**Figure 6.** Trapezoidal membership functions: (a) Normalized indicators y; (b) secondary composite indices  $y_{sd,out}$  and  $y_{sd,inp}$ ; (c) with reduced transition area, for normalized indicators y; (d) with reduced transition area, for secondary composite indices  $y_{sd,out}$  and  $y_{sd,inp}$ ; (e) primary composite indices  $y_{d,out}$  and  $y_{d,inp}$ ; (f) final output  $y_f$ .

Once the membership functions were defined, three fuzzy schemes were constructed, varying the inference, aggregation, and defuzzification methods, which are:

- Fuzzy scheme 1 (min–max; union; centroid);
- Fuzzy scheme 2 (min–max; sum; centroid);
- Fuzzy scheme 3 (max–dot; sum; bisector).

The results of the different simulations were then observed by comparing the standard deviation of the output values and of the input values. In this way, the scheme that guarantees similar dispersion values was found to be the second one, characterized by the min–max as the inference method, the sum as the aggregation method, and the centroid as the defuzzification method. For the sake of clarity, the box plot relative to the composite building vulnerability index is shown in Figure 7, which allows a quick observation of the results of the analysis



Figure 7. Box plot relative to the results obtained through the various considered fuzzy schemes.

Hence, it is confirmed that the output data obtained through triangular functions have an excessively low dispersion. The same is true, albeit to a lesser extent, for those obtained using the trapezoidal membership functions of Figure 6a,b for the input variables (y) and for the intermediate outputs ( $y_{sd, out}$ ). Furthermore, it is evident that by adopting the Fuzzy Scheme 1 the distribution of the values reached by the output presents an anomalous concentration around the value 0.5. In fact, this scheme, although presenting a standard deviation of 0.18, similar to that of input variables, is to be discarded. This does not happen for the results obtained through Fuzzy Schemes 2 and 3, which are characterized by a standard deviation of 0.20 and 0.16, respectively, very close to 0.21 of the input variables. Finally, the Fuzzy Scheme 2 has been chosen, by also considering that the min–max inference method and the centroid defuzzification method are those most used for the analyses recorded in the technical literature.

# 4. Results

#### 4.1. Indices Spazialization and Vulnerability Mapping

Once the choices consequent to the sensitivity analysis have been made, the defuzzified values for the primary composite indices and the composite aggregated vulnerability index must be converted back into linguistic values, corresponding to crisp vulnerability classes, so as to be able to carry out mapping. In particular, the linguistic values for the primary composite indices, associated with the four classes (low, medium, high, and very high) have been obtained by posing the defuzzified output values in the ranges on the scale from 0 to 1 shown in Figure 8. On the other hand, the defuzzified value of the composite index of aggregated vulnerability has been converted back into a linguistic value corresponding to the five classes (very low, low, medium, high, and very high), by individuating its position in the ranges shown in Figure 9.



Figure 8. Scale for the classification of the primary composite indices.

0	0,125	0,375	0,625	0,875	1
L	1		1		
	,	······		~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	
Very I	Low Lo	ow M	ledium	High Very	High

Figure 9. Scale for the classification of the composite index of aggregated vulnerability.

In both cases, the threshold values for each class are derived from the fuzzy membership functions adopted for the outputs: The trapezoidal functions shown in Figure 6e for the primary composite indices, and the trapezoidal functions of Figure 6f for the aggregated vulnerability index. In particular, they coincide with abscissas of the intersections between the various fuzzy membership functions, so as to annihilate the transitions area and to define crisp classes.

The just specified reclassification of the defuzzified outputs was carried out in the GIS environment. For this purpose, the data resulting from the fuzzy analysis, which refer to the values of the aforementioned indices for each census section, have been associated with the polygonal spatial entities representative of the census sections themselves, through the commercial software ArcGis 10.3.1. By carrying out the reclassification as explained above, the vulnerability maps were obtained for the social, building, and urban domain, respectively, according to the four levels of intensity above-mentioned (Figures 10–12). The same procedure was carried out to map the aggregated vulnerability, by starting from the defuzzified output values of the composite vulnerability index, but, in this case, according to five classes (Figure 13).



Figure 11. Building vulnerability map.



Figure 13. Aggregated vulnerability map.

#### 4.2. Mapping Peripheralization Risk

The last step of the proposed methodology provides the construction of the final risk map, through overlay mapping of the aggregated vulnerability map, previously obtained, and that of the exposure. The latter one was derived from the built-up areas map, made by enveloping all areas with a degree of imperviousness higher than 30%, based on the imperviousness cartography, as mentioned in Section 3.2. The territorial extent of the urban fabric, which is representative of the exposed goods as a whole, was then obtained by incorporating in this map also spaces with a lower imperviousness degree falling within the perimeter of the built-up areas, with the aid of the land use map. The urban fabric, in fact, is intended to be comprehensive of all residential and production settlements, of which public spaces and those reserved for collective activities, even outdoors, including, in addition, peri-urban areas with widespread construction (Figure 14).



Figure 14. Peripheralization risk map.

The risk map, thus obtained, shows how severe peripheralization processes, identifiable spatially where the risk level is high and very high, can affect both neighborhoods traditionally considered peripheral, such as the case of the economic and popular building area falling in the Municipality of Marcianise, both typically central neighborhoods, within historic agglomerations, as in the cases of the municipalities of Capua, Caserta, Casagiove, Maddaloni, Recale, San Marco Evangelista, Santa Maria Capua Vetere, and San Prisco (Figure 15). The case of Maddaloni, which lays in the south-east part of the study area, may be considered emblematic, since such a municipality is characterized by the largest number of areas affected by high risk, and it turns out to be at risk of peripheralization as a whole. In the Municipality of Marcianise, the aforementioned area, which is the largest among the high-risk ones in the municipal territory, results from the implementation of an economic and social housing plan (PEEP), established by the general urban plan (PRG), pursuant to law April 18th 1962, n. 167. In fact, it is characterized by a high percentage of social housing, and presents the characteristics of a typical urban periphery, as conceived in the Italian urbanistic tradition, i.e., a more

or less extensive neighborhood, located on the edge of the consolidated city and inhabited by the weaker sections of the population. In particular, in this area, social and urban vulnerabilities contribute at the determination of a high risk, as is evident by observing the maps related to these domains. The fact that, in several municipalities, neighborhoods or sets of contiguous neighborhoods present a high risk even in ancient buildings agglomerations, manifesting the phenomenon of the peripheralization of historic centers [7,20], which is ongoing in numerous Italian cities. A relevant role in the development of this process has been played by the evolution of the real estate market and of the land rent, which have led the population and, in particular, the middle classes, to move from the historical centers to the traditional peripheries, built-up on their edges in place of agricultural land, or, in more recent years, towards peri-urban areas characterized by a low housing density [3,5]. On the other hand, within the conurbation, the municipality of Maddaloni is configured as a city-periphery, widely affected by potential degradation in all the considered domains, a circumstance that determines a significant vulnerability and, consequently, an extended risk of peripheralization.



Figure 15. Details of peripheralization risk map.

#### 5. Discussion

The obtained vulnerability maps aim at integrating the knowledge relative to the traditional territorial risk factors in the vast area planning. In addition, the aggregated vulnerability map, together with the exposure one, constitutes an input datum for the construction of the final risk map, which is intended to be a tool to support decision-making in the identification of priority areas of intervention within complex urban and metropolitan systems. This is done with the more general aim of the optimization of public spending for mitigation actions, since local institutions responsible for urban planning often have scarce economic resources.

Compared to previous methods to identify priority areas of intervention addressed in Section 1, this approach, based on the general theory of territorial risk, constitutes the main novelty of the work and determines a series of advantages.

A first fundamental difference from vulnerability-based approaches to conducting urban poverty assessments [13], is that in this paper vulnerability is defined as deriving from endogenous characteristics of potential degradation of the exposed goods, while the exogenous factors have been excluded, because they are associated with the hazard component, as is typical of territorial risk theory. We have considered environmental hazards as exogenous factors, i.e., while these methods include the latter in the dimensions of poverty, due to definition of vulnerability as the probability of being exposed to a number of risks such as natural disasters [21], a feature evaluated by specific indicators. This means that comparing the final map obtained from the aggregation of all the indicators with that of landslide risk or flood one as usually happens in spatial planning processes, this information will have been computed twice and with different methodologies. Given that cities are increasingly faced with both natural and man-made hazards, it is important in urban and land-use planning to compare maps of the different risks involved, so as to have a synthesis of information that can guide the choices about spatial transformation. This is possible if the risk analyses refer to the same theoretical framework, such as that of the general theory of territorial risk.

Moreover, in all the studies mentioned in Section 1, the starting information refers to census data, so in almost all cases maps were done by census section [22,26,29], the limits of which do not correspond to the perimeters of urban areas falling into them, but also incorporate non-urban areas, which are not considered exposed. In fact, as already noted, sometimes only a part of a census section is interested in urban degradation [28]. In this study, defining the exposed goods with reference to each domain investigated, it was possible to separate the related data and localize them spatially on the territory. Therefore, by building the exposure map and intersecting it with that of aggregate vulnerability, we identified urban areas actually at risk, overcoming the administrative limits of the census sections. Of course, the level of detail in identifying the exposure is consistent with the investigation scale, which here is that of a vast area, but it is possible to further refine the perimeter when working in greater detail.

Another novelty of the study is the indicator set design. In most of the mentioned methods, although varying the indicators chosen, the dimensions investigated concern social and residential deprivation [26,28,29], neglecting the factors of potential degradation of the urban fabric that have been computed here. In the present paper, considering the lack of agreement between the studies available in the technical literature, the choice of dimensions and vulnerability factors was carried out by taking into account both the spatial and the non-spatial aspects, which characterize the peripheralization processes. Furthermore, the choice of the indicators for the quantification of such factors, which describe a potential degradation of urban areas, has been affected by the possibility of response, in terms of mitigation, through urban and territorial planning.

This allows to take into account the multiple peripheral conditions affecting urban and metropolitan systems today. Conversely, in light of recent urbanization trends and the economic crisis that has accentuated existing territorial inequalities and created new ones, the latter risk not being read if we continue to consider only traditional indicators of urban poverty. This approach, in addition to

producing repercussions on the choice of priority areas, limits the possibility of response in terms of mitigation.

Another different element compared to previous studies to locate degraded areas of intervention is that in the aggregation of the indicators weights were not defined, widely used in the mentioned methods [22,26]. The attribution of weights is a critical moment, regardless of the aggregation method chosen, because of a certain subjectivity in their assignment [31]. To overcome this problem, in the proposed aggregation method, based on the fuzzy logic, when the inference rules are defined, the heaviest condition is preferred in favor of safety. Finally, a sensitivity analysis was performed to reduce the subjectivity of the choices made, on the basis of a statistical criterion valid in all cases. This makes the methodology transferable to many geographical contexts, while the use of weights often takes into account the incidence of a certain factor in a specific study area.

Furthermore, this work is innovative in relation to the implications it has on urban and territorial planning. The aforementioned studies that explicitly refer to planning tools as a remedy, identify urban renewal or regeneration programs to be implemented in the areas identified as priorities for intervention [28,29]. That is, reference is made to the local dimension of the urban project, neglecting the role that strategic planning can have, at various scales, in light of the most recent urbanization and socio-economic trends. The results, outcoming from the application of the proposed methodology to the case study, have shown how relevant peripheralization processes, identifiable spatially in areas where the risk is high and very high, can affect neighborhoods traditionally considered peripheral, but also central neighborhoods, which fall in historic agglomerations, or entire municipal territories. This, as well as confirming the multiscalarity of peripheralization processes [7,9], allows claiming that enforcement actions are needed at different planning levels, from the neighborhood scale, in the context of operative municipal planning, to the vast area scale, generally subject to inter-municipal or provincial strategic planning. From these considerations, it follows that the first step of the decision-making process consists in establishing the institutional level of work and the related planning tool, where mitigation interventions need to be framed. On the other hand, the level of detail of the performed analysis, on a neighborhood scale, allows to support, in a more robust way, any provision dictated by the provincial planning tools to the municipal urban plans.

## 6. Conclusions

The continuous growth of cities and multiple forms of poverty, on a global level, determines both spatial and non-spatial peripheralization processes, which expose entire urban and metropolitan areas at risk of degradation, not only traditional peripheries. The scarcity of resources to combat this phenomenon requires the identification of selected areas where interventions are prioritized. However, given the occurrence of peripheralization processes at various scales of analysis and the multiple factors to consider, it is necessary to identify methodologies able to manage this complexity.

The current work, by starting from the definition of the peripheralization risk, proposes a methodology for selecting the most vulnerable urban areas, identifying the factors of potential degradation that can contribute to the formation of a peripheral condition, regardless of the spatial proximity to the urban center. For what concerns the measurement of these factors, based on the reviewed literature, a set of quantitative indicators has been proposed, structured in three dimensions, and a combination method based on fuzzy logic, useful to overcome the problem of the lack of threshold values, universally accepted by the scientific community, for the classification of such indicators. In this way, the composite indices of social, building, and urban vulnerability were obtained, classified according to four levels, and, finally, the aggregated vulnerability index was constructed, subdivided in five classes. The proposed method, by spatializing the obtained indices, at census section detail, allows the individuation of sections with a significant vulnerability, or a specific vulnerability in the different examined domains. Then, intersecting the aggregate vulnerability map with the exposure one, it is possible to build the risk map, according to five intensity classes, so as to support decision-making process in the identification of priority areas to mitigate risk through urban and territorial planning

tools. The methodology was applied to a conurbation of 16 municipalities in Campania Region (Italy), showing the ability of the proposed method to identify priority areas in a particularly complex urban system.

Results of this application showed that areas most at risk can be both peripheral and central neighborhoods, but also entire municipalities, demonstrating how mitigation actions are needed at different scales, corresponding to the various urban and territorial planning levels. Moreover, the obtained results, confirm the importance of analyzing and contrasting peripheralization processes starting from vast area planning. Such an approach is followed in the current work, according to which it is not useful to design interventions on small-scale areas, whose borders are often defined just on the basis of real estate convenience, as frequently happens in the Italian context.

It should be noted that the analysis is conducted with reference to quantitative data, therefore it does not take into account, for example, the qualitative data represented by subjective perception of overall risk by the population [55]. So it is desirable to encourage participation of the population in the decision-making process, to verify and discuss the correspondence of technical contents of the obtained maps with the subjective risk perception, as well as to collect observations and proposals from people who live in urban areas subject to intervention [56–58]. Once the priority areas have been individuated, the various vulnerability maps in the different considered domains can guide the decision-making process by pointing out the factors on which to focus to reduce the potential degradation, both for more effective risk mitigation and for greater optimization of the resources necessary to carry out the planned interventions.

Further limit of the work is that the application of the proposed methodology to the case study was affected from not always updated data, referring to the intra-urban scale. In particular, the last Istat population and housing census, which provides data at this level of detail, dates back to 2011, while more updated data, if available, are generally at a less detailed level, at the municipal scale. However, the census data are widely used for the localization of degraded areas in the methods analyzed in the current work, since they are made public by the statistical research institutions of the main countries free of charge and periodically updated. In such a way, the proposed method can be applied to many geographical contexts. To overcome this limitation, a further analysis using the same indicators should be carried out in the future with updated data. Furthermore, this might allow for tracing the diachronic evolution over time of the peripheralization process.

For what concerns the other data necessary for the application of the proposed methodology, they are generally obtainable from ordinary urban and territorial planning tools. The present methodology, therefore, can be easily applied in another complex urban or metropolitan system, by using the so-called poor data.

In this regard, we recognize that the proposed indicators set can be expanded with reference to other vulnerability factors. In that direction, further research may concern the integration of the vulnerability factors here investigated, by considering aspects of potential degradation relating to the issues of energy poverty and environmental justice. Energy dissipation, polluting emissions, ineffective waste management, for example, can affect living conditions of the population [59–64], the potential building degradation and, in general, the environment, contributing to determine inequalities and peripheral conditions in urban and metropolitan areas.

Similarly, the study does not consider peripheralization risk affecting non-urban areas. Potential degradation factors of the open territory, such as agricultural and mountain zones, can indirectly affect the nearest urban and metropolitan areas, as well as the territories directly involved. Hence, it will certainly be of interest to analyze how the results obtained from the analysis vary if one considers also these aspects, so as to better guide the decision-making process regarding risk mitigation and the possible allocation of resources.

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