

Article

# An Emotion Detection GIS-Based Framework for Evaluating Exposure to Heatwave Scenarios in Urban Settlements During a Pandemic

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**Abstract:** The study of impacts on and risks to citizens generated by climatic or environmental phenomena in urban settlements is made complex by the coexistence of events that can affect the risk assessment. In this work, a model for the assessment of impacts on and risks to the population generated by heatwaves in urban settlements in the presence of pandemic periods is proposed. The presence of epidemics is treated as a stressor that contributes to altering exposure. To assess the prevalence of this stressor, a fuzzy-based emotion detection method is utilized, which uses the FREDoC framework to categorize the subzones that comprise the urban study area according to the relevance of the pleasant and unpleasant emotions of the citizens, identified based on the examination of posts that have been published on social networks. The proposed model was tested on the urban area of study of the city of Naples in Italy, taking into consideration a heatwave scenario that occurred in the summer of 2021 during the COVID-19 pandemic and analyzing the variation in exposure in the thirty districts into which the city is partitioned. The findings demonstrate that the model can accurately represent the range of impacts and hazards associated with the heatwave brought on by the COVID-19 pandemic.

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**Keywords:** heatwave; pandemic; risk; stressor; exposure; emotion detection; FREDoC

## 1. Introduction

Urban settlement residents' stress conditions generated by fears and health restrictions during pandemic periods are an aggravating factor in estimates of the impacts/risks of urban heatwaves.

A recent study conducted in [1] on 28 countries to analyze how citizens' level of concern about climate change risks varied during the COVID-19 pandemic showed that this level increased during the pandemic. This is a positive sign, because it can increase citizens' support for climate risk reduction policies; on the other hand, it is worrying, as it leads to an increase in population discomfort during climate hazard scenarios due to the presence of the pandemic.

The presence of stressors, such as an environmental/climate emergency or a pandemic, can change exposure and vulnerability, impacting people or entities at risk. For example, the presence of a pandemic can further increase exposure to heatwave hazard

scenarios of population fuel poverty due to increased unemployment resulting from office and business closures.

The United Nations Office for Disaster Risk Recovery (UNDRR) defines exposure as “The situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas” [2]. Measures of exposure can include, for example, the number of population groups particularly exposed to the hazard or the values of specific assets more exposed to the phenomenon.

Exposure is combined with the vulnerability of the area of study and the hazard scenario to assess the quantitative impact/risks. The presence of stressors during the phenomenon can potentially intensify the impacts/risks, increasing the number of people or assets exposed to the risk.

The evaluation of the variation in exposure caused by the presence of stressors in some cases cannot be determined directly due to the unavailability of information that allows us to measure how much it has varied. For example, a phenomenon of urban expansion in an area at risk of flooding increases the exposure to risk; this growth over time can be estimated by measuring the growth rate of the population or the assets exposed. On the contrary, it is difficult to evaluate the growth in exposure due to the appearance of pandemic diseases in urban areas subject to heatwave scenarios, as information on the subjects most exposed to contagion in healthy states is hardly available.

In addition, hazard, exposure, and vulnerability can influence each other, as they are not independent of each other [3,4], and it is challenging to determine how their interrelationships change in the presence of stressors.

Some authors have proposed synthetic indices to assess the effects of these influences on the vulnerability and exposure of risk drivers. The Urban Disaster Risk Index (UDRI) [5] is used in [6] to capture the aggravating factors of natural hazards in urban settlements related to physical harm to infrastructure and structures, as well as social vulnerability.

In order to consider the aggravating factor generated by the inability to cope with humanitarian crises and disasters, in [7], a composite indicator was used, called the INFORM Risk Index, given by the formula  $(\text{Hazard} \& \text{Exposure})^{\frac{1}{3}} \cdot (\text{Vulnerability})^{\frac{1}{3}} \cdot (\text{Lack of coping capacity})^{\frac{1}{3}}$ , where the lack of resources available to mitigate the impact or risk is expressed by the Lack of Coping Capacity Index, which worsens the risk.

A simulation model is proposed in [8] to assess the user behavioral response to environmental conditions in urban built environments and derive the dynamic users' risk in public open spaces due to heat stress and air pollution stress.

The main critical point of these models is the difficulty of finding the information necessary to determine the impact of stressors in the risk assessment.

An approach to solving this problem in assessing the effects of multiple stressors that contribute to exacerbating natural risks has been proposed in [9]. This method aims to reduce the combinations between stressors and represents a trade-off between the accuracy of the assessment, which requires the use of specific data, which are often unavailable, and the bias introduced by incorrect assumptions regarding the contribution of stressors. The authors applied the method to assess aggravation of the exposure of wild animals and their habitat generated by stressors caused by human activities and climate change. The major difficulty of this approach, however, is the determination of the priority set of stressors and stressor combinations.

In this study, a new approach to assess stressors generated by the presence of epidemics/pandemics in urban settlements during heatwaves is tested. These stressors are assessed in terms of increased exposure by evaluating the level of discomfort of the population, which is measured in terms of the relevance of unpleasant emotional states expressed in posts on a social network.

This model has the advantage of improving the imprecision of the assessment of the aggravating contribution of the stressor. In fact, in order to assess this contribution, it would be necessary to determine the variation of exposure due to the increase in citizens' discomfort in the presence of stressors, such as, for example, in periods of pandemic crisis. However, this information is difficult to estimate, as it could be generated by numerous factors, such as, for example, an increase in energy poverty due to job losses, increases in costs caused by the pandemic, or the proliferation of respiratory or cardiovascular diseases generated by the disease, which increase the discomfort of the population during heatwaves.

The model evaluates the contribution of stressors generated by a pandemic/epidemic on the impact of heatwave scenarios in urban settlements in terms of variations in the population exposed to risk. The fuzzy-based emotion detection model FREDoC [10] is applied to extract, for each subzone in which the urban settlement is partitioned, the relevance of pleasant and unpleasant emotions, as established by examining posts published by users on social media that dealt with pandemic and heatwave scenarios.

The relevance of unpleasant emotional categories is used to assess the contribution of pandemic stressors during the heatwave in terms of increased/decreased heatwave exposure. Exposure may have increased or decreased depending on whether unpleasant or pleasant emotions of the citizens prevailed.

We propose an index of discomfort calculated by considering the relevance of unpleasant and pleasant emotions. It represents an aggravating or mitigating factor of exposure, which contributes to amplifying or reducing the impacts of heatwave scenarios compared to those assessed if the urban heatwave occurred in normal periods.

Section 2 describes the adopted method. A brief discussion is included regarding the climate risk assessment models and the FREDoC framework for document classification by prevalent emotional categories. Subsequently, the proposed model for assessing exposure in the presence of stressors is synthesized and described in detail, and the case study used to test the model is discussed. The results of the comparative tests are presented and discussed in Section 3. Section 4 includes concluding remarks and future research perspectives.

## 2. Materials and Methods

This section defines in detail the methodology proposed for the assessment of exposure in the evaluation of heatwave impact/risks.

The next two sections introduce, respectively, a description of heatwave models used to assess the impact/risks in urban settlements and the FREDoC framework applied to classify documents based on the relevance of emotion categories. Finally, Section 2.3 describes the proposed model.

### 2.1. Urban Climate Change Impact/Risk Models

The general model applied for the generation of climatic impact/risk scenarios is defined in the AR5 and AR6 reports of the IPCC, the Intergovernmental Panel on Climate Change [11,12]. In the two reports, a climatic impact scenario of an area of study generated by a hazard scenario occurring in the area of study is defined as *“the effects on lives, livelihoods, health, ecosystems, economies, societies, cultures, services, and infrastructure due to the interaction of climate changes or hazardous climate events occurring within a specific time period and the vulnerability of an exposed society or system”*.

The impact scenario in an urban settlement is assessed by considering a combination of the vulnerabilities of the urban subsystems with which the exposure interacts, the exposure, and the hazard triggered by a climate change scenario.

In general, it is difficult to determine functionally how the impact depends on the vulnerability, exposure, and hazard parameters. Recently, various models have been proposed to assess heatwave impact scenarios as combinations of these three parameters.

In [13], the Universal Thermal Climate Index (UTCI) is used to evaluate impact by measuring human thermal comfort perception based on a combination of heat stress–social vulnerability and human exposure. A variety of social factors, including the percentage of the population under 14, the percentage of the population over 65, the percentage of women, the percentage of the population with less than a high school education, and the GDP per capital, are used to determine social vulnerability to heat stress. Exposure is given by the population density.

In the model developed by [14], the urban settlement is divided into subsystems, and the impact scenario is given by a combination of the vulnerabilities of the two subsystems' residential buildings and the open spaces with which it interacts, called Intrinsic Vulnerabilities, of the exposure and of the hazard scenario. The vulnerability of residential buildings is assessed considering four characteristics of the buildings: thermal lag, the thermal decrement factor, building volume, and solar exposure of the building envelope. The vulnerability of open spaces is assessed considering four characteristics of open spaces: the Albedo, the sky view factor, the Normalized Difference Vegetation Index (NDVI), and the soil's solar exposure. The model is tested in [15] on the city of Naples, Italy, considering three types of exposure: population density, density of people under 5 and over 65 and elderly people, and density of residents in fuel poverty. The most critical impact scenarios are obtained by considering exposure to the density of residents in fuel poverty.

In [16], the vulnerability is combined with a hazard heatwave scenario measuring the indoor building temperatures and blackout conditions during the heatwave; the exposure is given by the population of residents. The model is applied to the United States cities of Atlanta, Detroit, and Phoenix.

The impact is assessed as a weighted average of vulnerability, exposure, and hazard in [17], where the Weighted Comprehensive Evaluation Method [18] is used to assign the weights of the three parameters.

The vulnerability is evaluated based on social sensitivity characteristics (the number of people under 5 and over 65, the number of employees in the construction industry, and the number of illiterate people) and adaptability characteristics (the number of doctors, the number of hospital and sanitary beds, the NDVI, etc.). Exposure is assessed considering the total population and the GDP.

In all of these models, exposure is determined based on a set of characteristics of the resident population, which are acquired from census datasets. These estimates do not take into account the discomforts experienced and perceived following the presence of stressors that may affect impacts/risks.

## 2.2. The FREDoC Framework

FREDoC [10] is a fuzzy-based emotion multi-classification model used to classify documents considering the prevalence of pleasant and unpleasant emotions detected in the text. It was used in [19–21] to classify urban areas and urban facilities based on the relevance of pleasant and unpleasant emotions detected in posts published on a social network.

Formally, let  $D = \{d_1, d_2, \dots, d_N\}$  be a corpus of  $N$  documents where each document contains the set of texts coming from a data flow that refers to common keywords (for example, the same entity, the same geographical area, or the same period). A text-parsing algorithm is used to remove irrelevant words in the texts and to stem the other words.

A dictionary of emotional terms, called a Dictionary of Emotional Category words, is built to detect in the document all of the terms, identified in their inflectional form, that

are connected to emotions. In [10], the Plutchick wheel of emotions is used; it divides emotions into sixteen categories: eight primary emotions and eight secondary emotions (Table 1). Each term related to an emotional category is inserted into the catalog in its inflectional form.

**Table 1.** Emotional category in the Plutchick wheel.

Type of Emotion	Pleasant/Unpleasant	Emotional Category
Primary	Pleasant	Joy
		Trust
	Unpleasant	Surprise
		Expectation
Secondary	Pleasant	Fear
		Sadness
		Disgust
		Anger
	Unpleasant	Optimism
		Love
		Aggression
		Submission
Unpleasant	Disapproval	
	Contempt	
	Remorse	
	Awe	

To measure the relevance of a term appearing in a document, we calculated its Term Frequency Inverse Document Frequency information retrieval index (tf-idf). The tf-idf index evaluates the frequency with which the term appears in the document in relation to the frequencies with which it appears in other documents in the corpus.

Let  $\{d_1, d_2, \dots, d_N\}$  be the corpus given by  $N$  documents. If  $t_{jk}$  is the  $k$ th term assigned to an emotional category, the tf-idf of this term in the document  $d_i$  is given by  $\text{tf-idf}(t_{jk}, d_i)$ .

In [10], the relevance of the  $j$ th emotional category in the  $i$ th document is given by

$$r(c_j, d_i) = \frac{\sum_{k=1}^{T_j} \text{tf-idf}(t_{jk}, d_i)}{\sum_{s=1}^N \sum_{h=1}^{T_h} \text{tf-idf}(t_{hs}, d_i)} \tag{1}$$

where  $T_j$  is the number of terms assigned to the  $j$ th emotional category in the dictionary.

The relevance  $r(c_j, d_i)$  is given by the sum of the tf-idf of all terms belonging to the  $j$ th emotional category divided by the sum of the tf-idf of all terms in the dictionary. It is normalized in  $[0, 1]$  using the formula

$$r'(c_j, d_i) = \frac{r(c_j, d_i)}{\sum_{h=1}^C r(c_h, d_i)} \tag{2}$$

in which it is divided by the sum of the relevance of all emotional categories in the  $i$ th document.

Subsequently, the relevance values are fuzzified by building a fuzzy partition in the discourse universe  $[0, 1]$ , where the fuzzy partition is composed of fuzzy sets that respect the Ruspini constraint [22] that the sum of the membership degrees of an emotional category to all of the fuzzy sets is equal to 1. FREDoC performs the multi-classification of each document of the corpus by assigning to it for each emotional category the linguistic label of the fuzzy set with the highest membership degree. This linguistic label is called the *fuzzy relevance* of the emotional category in the document.

As an example, Figure 1 shows a fuzzy partition of the domain of relevance of emotional categories composed of five triangular fuzzy numbers: low, medium low, medium, medium high, and high. Each triangular fuzzy number is a fuzzy set represented by three points. For example, the fuzzy set medium high is a triangular number given by the triplet (0.07, 0.15, 0.18). The central number, 0.15, is the relevance value at which the membership degree to the fuzzy set is at its maximum and equal to 1. The first triangular fuzzy set, low, is a right function triangular fuzzy number; its central value is 0.01. For relevance values less than or equal to 0.01, the degree of membership in the low fuzzy set is always equal to 1.

Similarly, the last fuzzy set, very high, is a triangular left function fuzzy number. Its central value is 0.18. For relevance values greater than or equal to 0.18, the degree of membership in the very high fuzzy set is always equal to 1.

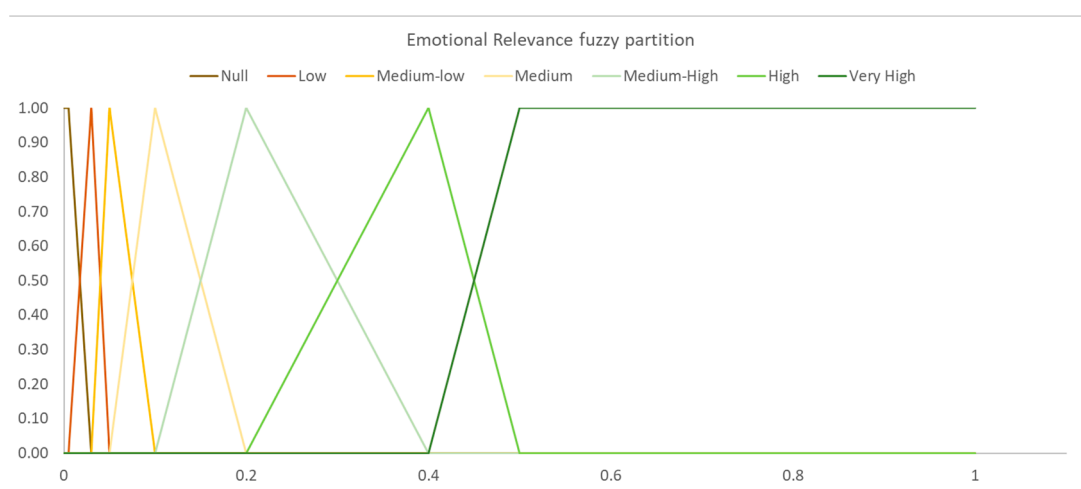


Figure 1. Example of fuzzy partition of the relevance universe of discourse [0, 1].

The fuzzy partition in Figure 1 respects the Ruspini constraint; in fact, the sum of the membership degrees of a value of relevance to all five fuzzy sets is always equal to 1.

In Table 2 are shown the values of relevance of each emotional category to a document ( $r$ ), the normalized relevance ( $r'$ ), and the final fuzzy relevance assigned to the emotional category.

Table 2. Example of classification of a document in FREDoC.

Emotional Category	$r$	$r'$	Fuzzy Relevance
Joy	0.05	0.05	Medium low (Ml)
Trust	0.10	0.09	Medium (M)
Surprise	0.13	0.13	Medium high (Mh)
Expectation	0.21	0.20	High (H)
Fear	0.05	0.05	Medium low (Ml)
Sadness	0.05	0.05	Medium low (Ml)
Disgust	0.02	0.02	Low (L)
Anger	0.05	0.04	Medium low (Ml)
Optimism	0.09	0.09	Medium (M)
Love	0.01	0.01	Low (L)
Aggression	0.18	0.17	High (H)
Submission	0.01	0.01	Low (L)
Disapproval	0.05	0.05	Medium low (Ml)

Contempt	0.01	0.01	Low (L)
Remorse	0.01	0.01	Low (L)
Awe	0.02	0.02	Low (L)

By setting a threshold for fuzzy relevance, below which the incidence of the emotional category in the document is considered not significant, FREDoC will classify the document by assigning to it only the emotional categories with fuzzy relevance greater than or equal to the threshold, together with their respective fuzzy relevance.

In the example in Table 2, setting as the threshold the fuzzy relevance medium high, the document will be classified as Surprise, with fuzzy relevance medium high, Expectation, with fuzzy relevance high, and Aggression, with fuzzy relevance high.

### 2.3. The Proposed Model

The model determines the variation of risks/impacts of heatwave phenomena in urban settlements generated by the presence of periods of pandemic or epidemic crisis. The pandemic/epidemic crisis is modeled as a stressor that produces an increase in exposure to the phenomenon. The impact of this stressor on exposure is assessed by measuring the relevance of unpleasant emotions detected in posts by citizens to a social network.

The urban settlement area of study is partitioned into subzones, such as, for example, districts or wards of a city. Queries are then performed on the social network that refer to the investigated heatwave period, the subzone, and hashtags connected to keywords related to the heatwave and the pandemic/endemic crisis phenomena.

The FREDoC framework is used to build, starting from the acquired flows, the corpus of documents, where each document is made up of the set of posts published in the investigation period and referring to a specific subzone. Using a dictionary of emotional categories, FREDoC classifies the documents by measuring the relevance of pleasant and unpleasant emotions in each document.

We measure an index of discomfort of the citizens by aggregating the relevance of unpleasant emotions.

Formally, let  $\{c_{p1}, c_{p2}, \dots, c_{pN_p}\}$  be the set of  $N_p$  pleasant emotional categories with fuzzy relevance greater than or equal to a fixed threshold, and let  $\{c_{u1}, c_{u2}, \dots, c_{uN_u}\}$  be the set of  $N_u$  unpleasant emotional categories with fuzzy relevance greater than or equal to this threshold. If  $r(c_{pj}, d_i)$  ( $r(c_{uj}, d_i)$ ) is the relevance of the  $j$ th pleasant (unpleasant) emotional category detected in the  $i$ th subzone, we define an index of discomfort of the citizens in the  $i$ th subzone given using the following equation:

$$ds_i = \sum_{j=1}^{N_u} r(c_{uj}, d_i) - \sum_{j=1}^{N_p} r(c_{pj}, d_i) \quad (3)$$

This value is between  $-1$  and  $1$ , and it is positive if there is a prevalence of relevant unpleasant emotions. It is negative if, instead, pleasant emotions are more relevant.

Let  $e_i$  be the exposure value determined for the  $k$ th subzone, normalized in the range of  $[0, 1]$ . The new exposure value will be given by

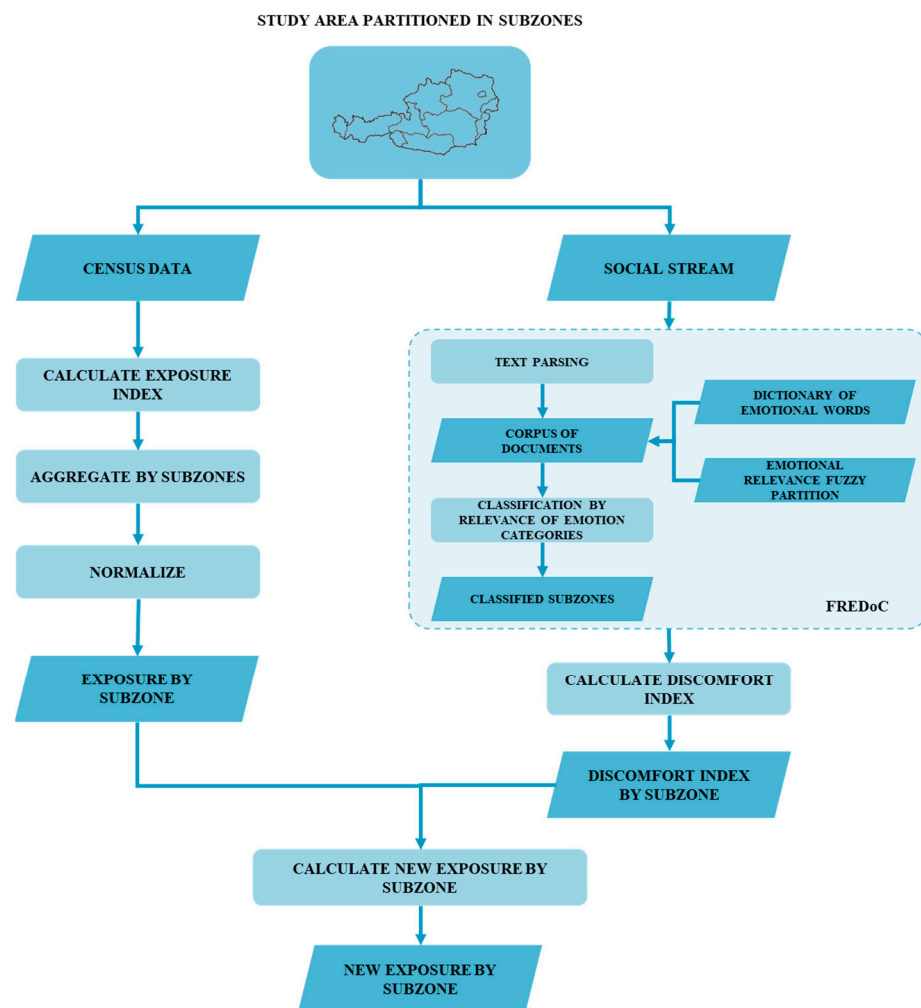
$$e'_i = \max(0, \min(e_i + ds_i, 1)) \quad (4)$$

where the new exposure  $e'_i$  adds to the exposure the discomfort perceived by citizens if unpleasant emotions prevail, while it subtracts the discomfort index from the exposure if pleasant emotions prevail. The max and min operators are used to obtain an exposure value between 0 and 1.

The stressor can represent an aggravating factor for the exposure if unpleasant emotions prevail in the subzone; on the contrary, it can contribute to reducing the exposure if pleasant emotions prevail in the subzone. In the first case, the discomfort index will be a

positive value between 0 and 1, in the second case it will be a negative value between -1 and 0.

In Figure 2, the proposed method is schematized.



**Figure 2.** Schema of the proposed model.

After having partitioned the urban area of study into subzones, the two processes of exposure evaluation are started, starting from the available institutional data and the discomfort index obtained by determining the relevance of unpleasant emotions detected in posts published on the social network.

The *Calculate exposure* index function calculates the exposure using census data on the resident population and aggregates the measure by subzone. The *Normalize* function is then executed to normalize the exposure value in the interval [0, 1], obtaining the normalized exposure for each subzone.

In parallel, the data extracted from the social network containing posts related to the heatwave and the pandemic/endemic period are processed using the FREDoC framework. After the text-parsing phase in which the posts related to the two phenomena are filtered, the corpus of documents is created, in which each document includes posts by residents in a specific subzone. FREDoC classifies the documents, detecting and annotating terms connected to emotional categories; this operation is performed using a dictionary of emotional categories in which each emotional category is associated with the corresponding terms assigned in their inflectional form.

The classification of each subzone is performed using a fuzzy partition of the emotional categories. The label of the fuzzy sets with the highest relevance value and the corresponding membership degree are assigned to an emotional category for a subzone.

The *Calculate discomfort index* function calculates the discomfort index in the subzone through (3). Finally, the *Calculate new exposure by subzone* function calculates for each subzone the new exposure value obtained through (4), providing the new exposure thematic map. The new exposure map can be combined with vulnerability and hazard to generate the new impact/risk map.

#### 2.4. The Case Study

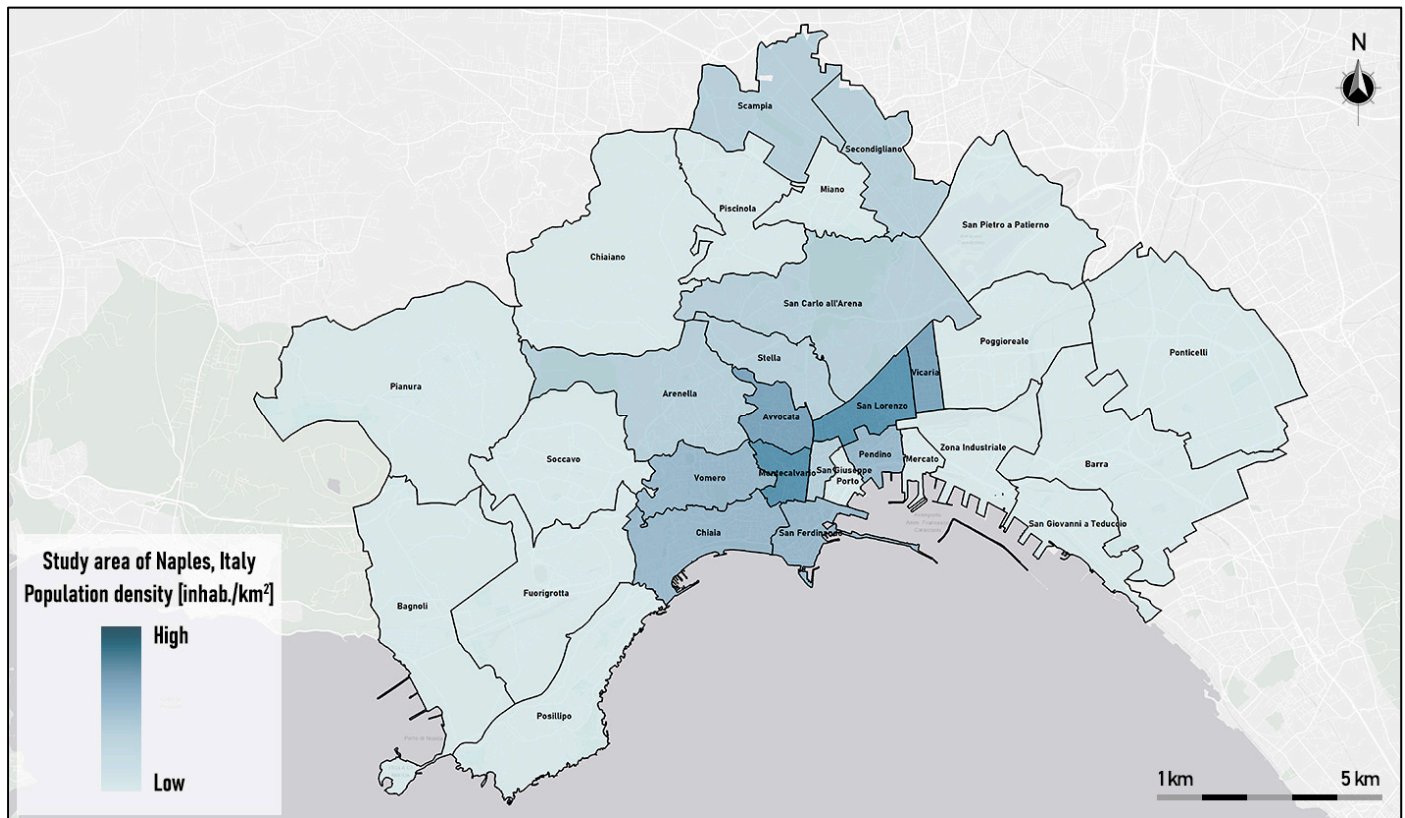
The model has been tested on an urban area in the city of Naples (Italy); it is a complex urban settlement with a diversity of urban forms that include historic centers with high building and population density, predominantly wooded areas, and mainly industrial areas.

In a study carried out in [15], the model proposed in [14] was applied to the city of Naples for the assessment of the impacts generated by heatwaves, taking into account three types of exposure: population density, density of weak groups, and density of residents in fuel poverty. The results of the study highlighted that the major critical issues are obtained by taking into consideration as exposure the density of inhabitants in conditions of fuel poverty.

To test our model, we used this exposure, defined as the density of inhabitants who are in families with more than five members or who are unemployed or non-income earners.

Following [15], in the test, the area of study was partitioned into census zones in order to have the official population census data, which are released by census section. Subsequently, these data were aggregated by district in order to determine exposure for each of the thirty districts into which the city is divided, where the districts constitute the subzones in which exposure is calculated.

In Figure 3, a map representing the districts of Naples is shown.



**Figure 3.** Thematic map of the districts of Naples classified by population density.

The study area of the city of Naples (Italy) is divided into 30 subzones, represented by districts. As it can be seen from Figure 3, the most densely populated districts are close to the city center, including, in particular, San Lorenzo and Montecalvario, which record the highest population density. In the northern area, the districts of Scampia and Secondigliano record a fair population density, while the peripheral districts located both to the east and to the west record low levels of density compared to all of the others.

The tests were performed by selecting a heatwave period in July 2021. To calculate the fuel poverty index, we used the 2021 population census dataset provided by ISTAT, the Italian Institute of Statistics.

Subsequently, the data were aggregated by district, and, for each district, the population density in a state of fuel poverty was calculated. It is given by the population in the district of large families with more than 5 members or unemployed or non-income earners, subsequently divided by the extension of the district in km<sup>2</sup> [14].

The social data flow was collected by making queries on the social network  $X$ , considering the heatwave period analyzed as the time interval for posting and inserting the name of the district as a hashtag and as keywords terms connected to the heatwave phenomenon and the COVID-19 pandemic. Approximately 17,900 posts were selected, with an average of 600 posts for each district. One-twentieth of these posts were subsequently discarded following the text-parsing process because they were not relevant or pertinent as they did not contain emotional terms or terms associated with the heatwave and/or the COVID-19 pandemic.

In order to evaluate the effect of the COVID-19 pandemic as a stressor on impacts/risks, the framework in [15] was used to determine the impact values for each district, considering both fuel poverty, calculated from the census data as exposure, and new fuel poverty, corrected by evaluating the discomfort index of the inhabitants in the district as exposure.

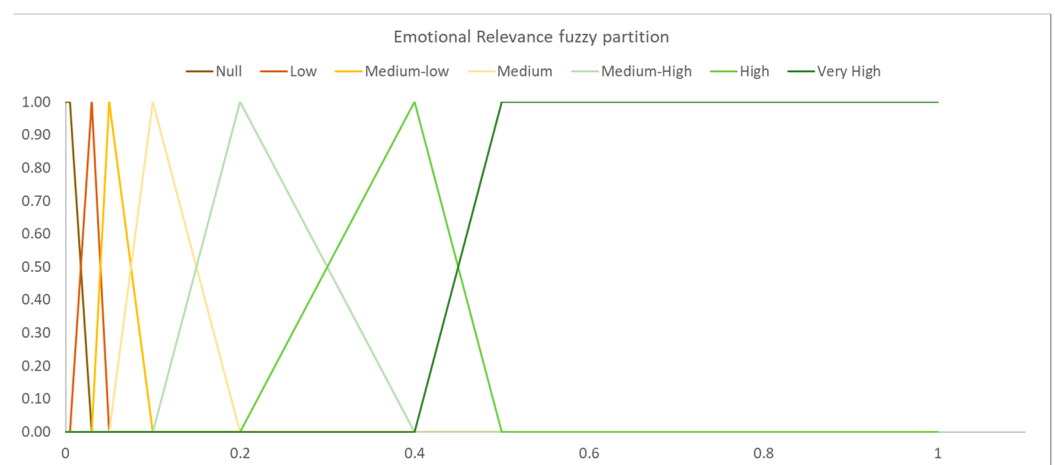
The difference between the impact values in the two scenarios measures the influence of the presence of the COVID-19 pandemic on the assessment of the impact/risk scenarios.

The model was implemented on a GIS platform built using the ESRI ArcGIS Pro Suite 3.4 and the ESRI ArcPy Python 3.4 libraries.

The pleasant and unpleasant emotional categories were identified using the Plutchik wheel of emotions' sixteen primary and secondary emotional categories [23]. In the Italian language, the terminology associated with each emotional category was assigned to create the dictionary of emotional words. To search for all terms connected to an emotional category, in this phase, for each term, we searched for related terms by analyzing synonyms and antonyms of the term. Finally, each term was assigned its inflectional form. Upon completion of this process, each emotional category was assigned an average of 40 terms in their inflectional form.

To determine the relevance of the emotional categories in each document, FREDoC measured the frequency of each term in all documents and, subsequently, the TF-IDF index value of the term in the document.

In addition, to calculate the emotional category fuzzy relevance, we used the triangular emotional relevance fuzzy partition used in [10], shown in Figure 4. It is given by seven triangular fuzzy numbers, labeled *null*, *low*, *medium low*, *medium*, *medium high*, *high*, and *very high*. This fuzzy partition respects the Ruspini constraint. In the triangular fuzzy set, *low* is a right function triangular fuzzy number; the fuzzy set *very high* is a triangular left function fuzzy number; and the other fuzzy sets are normal triangular fuzzy sets.



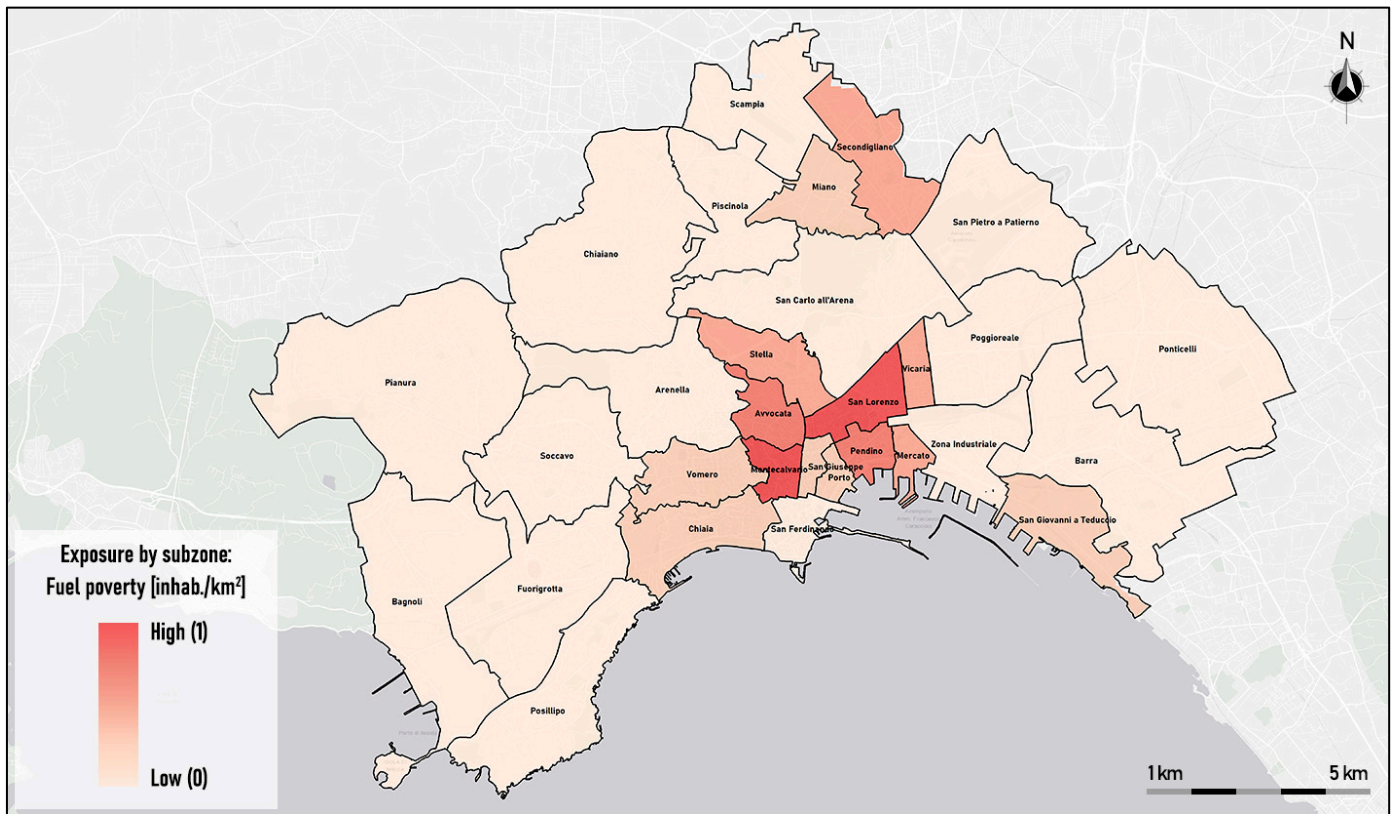
**Figure 4.** Emotion relevance fuzzy partition used to execute the tests.

The results are displayed and explained in Section 3.

### 3. Results and Discussion

Initially, we calculated exposure based on the residents experiencing fuel poverty in each district. The exposure in number of inhabitants per km<sup>2</sup> was normalized in the interval [0, 1], where the minimum value is 826 inhabitants per square kilometer and the maximum value is 11,801 inhabitants per square kilometer.

The thematic map in Figure 5 shows the exposure values calculated for the thirty districts.



**Figure 5.** Fuel poverty exposure distribution across the thirty districts.

The results show the presence of a high correlation between population density and weak population density; the correlation index is equal to 0.91.

In fact, upon comparing the thematic map in Figure 5 to the one showing the population density in Figure 4, the highest values of fuel poverty and population density are recorded in the districts near the city center, specifically in Montecalvario and San Lorenzo. Remarkably high exposure values are also recorded in the northern peripheral districts Secondigliano and Miano; the district San Giovanni a Teduccio also shows rather significant exposure.

Subsequently, after extracting the social data flow from the social network X, FRE-DoC was run to classify the documents in the corpus, where each document refers to posts published by residents in a district during the investigation period with hashtags related to heatwaves and the COVID-19 pandemic.

The threshold was fixed to the label *medium high*, as the contribution of emotional categories in a document with relevance less than 0.2 can be considered insignificant. Based on the emotional relevance fuzzy partition shown in Figure 4, emotional categories with relevance in a document greater than 0.2 are always classified as at least medium high. Each district is classified by assigning to it the emotion categories with fuzzy relevance greater than or equal to the threshold. In Table 3, for each pleasant emotional category and for each district, the labels of the emotion categories that record fuzzy relevance greater than or equal to the threshold are shown.

**Table 3.** Classification of the districts by significant pleasant emotion categories.

District	Pleasant Emotional Category					
	Joy	Trust	Surprise	Expectation	Optimism	Love
Arenella		H			H	
Avvocata						
Bagnoli						

Barra		
Chiaia		Mh
Chiaiano	Mh	
Fuorigrotta		
Mercato		
Miano		
Montecalvario		
Pendino		
Pianura		
Piscinola		
Poggioreale		Mh
Ponticelli		
Porto	H	
Posillipo	Mh	H
San Carlo all' Arena		
San Ferdinando		
San Giovanni a Teduccio	Mh	Mh
San Giuseppe		
San Lorenzo		
San Pietro a Patierno		
Scampia		
Secondigliano		
Soccavo	Mh	
Stella		
Vicaria		
Vomero	Mh	H
Zona Industriale		

In Table 4, for each unpleasant emotional category and for each district, the labels of the emotion categories that record fuzzy reliabilities greater than or equal to the threshold are shown.

**Table 4.** Classification of the districts by significant unpleasant emotion categories.

District	Unpleasant Emotional Category									
	Fear	Sadness	Disgust	Anger	Aggression	Submis- sion	Disap- proval	Remorse	Contempt	Awe
Arenella				Mh		Mh				
Avvocata	Vh			Mh						
Bagnoli					Mh	H				
Barra	H	Mh								
Chiaia										
Chiaiano				Mh						
Fuorigrotta	H			H	Mh					
Mercato					H	Mh				
Miano	H							Mh		
Montecalvario										
Pendino					H				Mh	
Pianura		H		Mh	Mh					
Piscinola										
Poggioreale	Mh				H	H				
Ponticelli						Mh				

Porto				
Posillipo		H		
San Carlo all’Arena	Mh		H	
San Ferdinando	H		Mh	
San Giovanni a Teduccio				
San Giuseppe	H		H	
San Lorenzo			Mh	H
San Pietro a Patierno				Mh H
Scampia	Mh		V h	
Secondigliano				
Soccavo	H		Mh	
Stella	H		H	Mh
Vicaria		Mh		H
Vomero			Mh	
Zona Industriale		H		

After classifying each district by pleasant and unpleasant relevant emotion categories, the discomfort index in each district was calculated using Formula (3). Figure 6 shows the distribution of the discomfort index for each district.

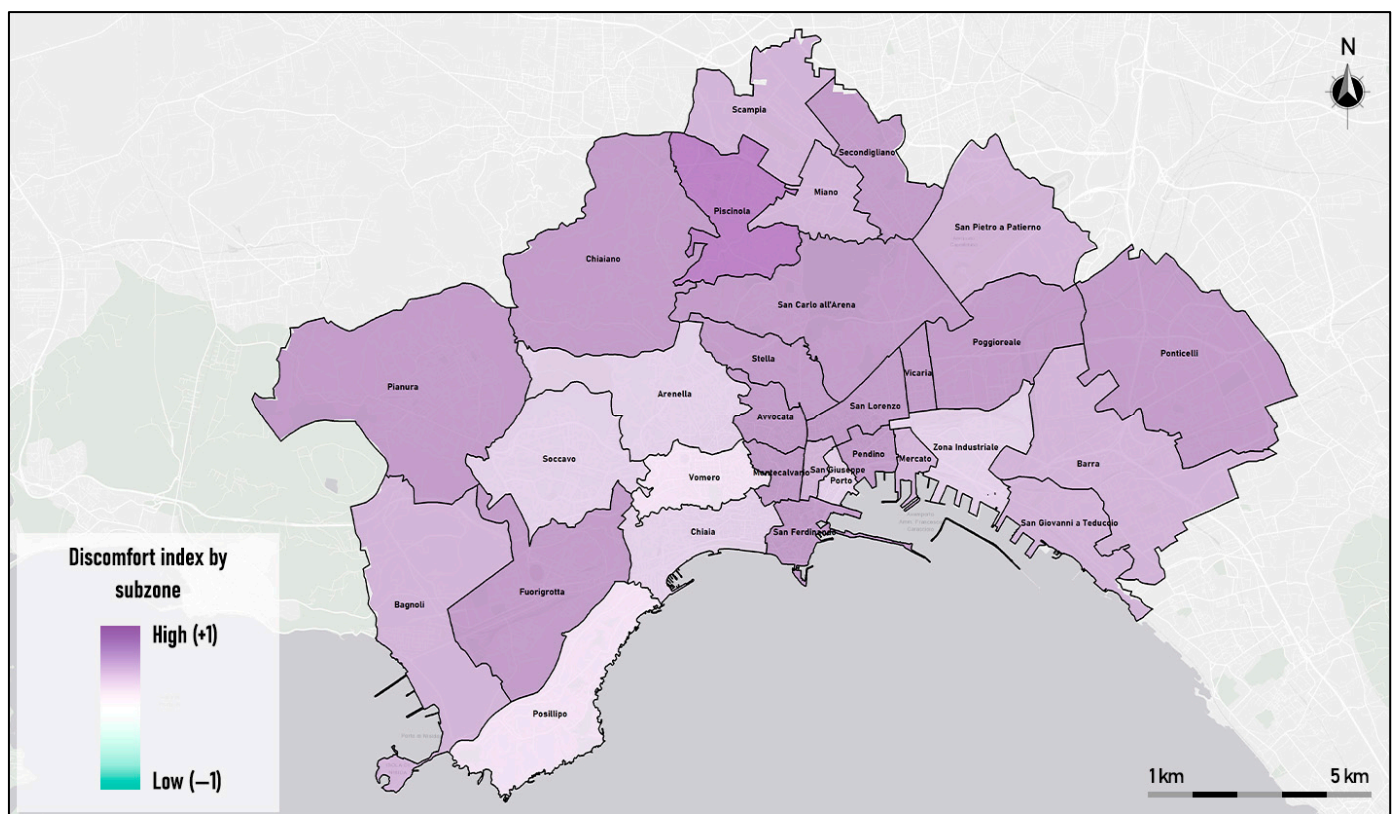
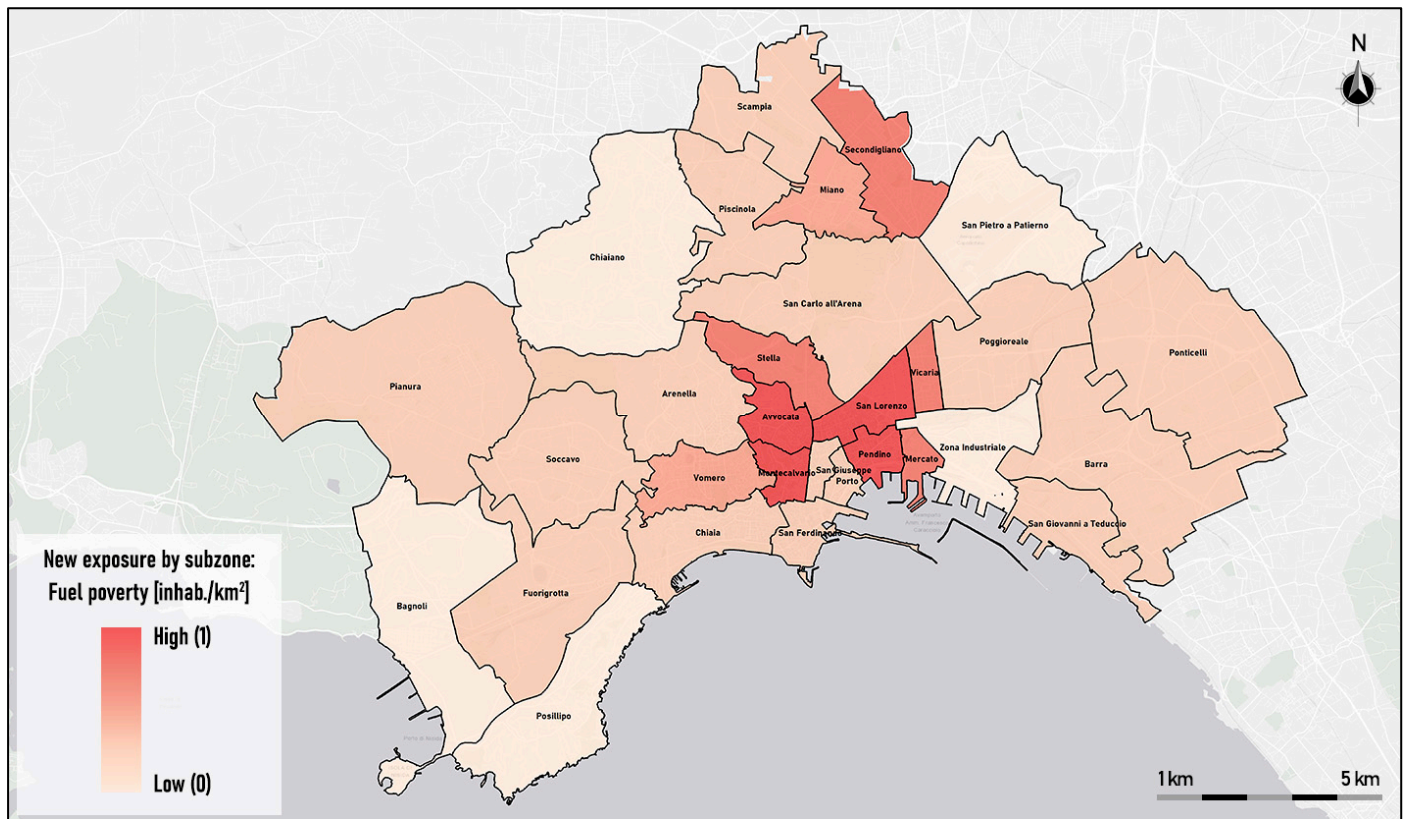


Figure 6. Thematic map of the discomfort index by subzone.

The thematic map in Figure 6 highlights that the prevalence of the entire study area is of the unpleasant type; in fact, in all districts, the discomfort index is greater than zero. In no district is the discomfort index negative; that is, in no district do pleasant emotional categories prevail. This result shows that the presence of the COVID-19 pandemic causes greater discomfort for citizens, worsening the exposure condition in all districts.

Piscinola records the highest discomfort index (0.22), which is a symptom of a more critical condition, while the districts Vomero and Posillipo record the lowest values (0.04), which means they enjoy less critical conditions.

Finally, new exposure via Formula (4) was calculated. The thematic map in Figure 7 shows the new exposure values for the thirty districts.



**Figure 7.** Thematic map of new exposure to fuel poverty.

Upon comparing the thematic map of new fuel poverty exposure in Figure 7 with that of fuel poverty exposure in Figure 5, a general worsening of exposure can also be seen in the districts of the western, eastern, and northern areas of the city. Only in five districts (Bagnoli, Posillipo, Chiaiano, Zona industriale, and San Pietro a Patierno) did the exposure remain negligible.

The thematic map of new exposure in Figure 7 highlights that the districts that record a higher degree of exposure to fuel poverty are located in the city center, specifically the districts of Montecalvario, Arenella, San Lorenzo, and Pendino. In the northern area, the districts of Secondigliano and Miano record a non-negligible increase in exposure compared to the rest of the districts, which record a more restrained increase.

#### 4. Conclusions and Future Works

We propose a model for evaluating the contribution of the presence of pandemics/epidemics during heatwave periods to aggravating heatwave exposure in urban settlements. The model evaluates this contribution by analyzing the relevance of pleasant and unpleasant emotional categories detected in texts posted by citizens to a social network during the analyzed period. The fuzzy-based emotion detection classification method FREDoC is used to classify the subzones of the urban area of study; an index of discomfort is calculated to measure the contribution of the stressor to altering exposure. Finally, a new exposure value is calculated.

The model was tested on the city of Naples in Italy by analyzing posts to X during a heatwave period that occurred in the summer of 2021 during the COVID-19 pandemic.

#### 4.1. Main Advantages of the Model

This model's main advantage is that it assesses citizens' discomfort brought on by the two phenomena by taking into account the hidden knowledge that is taken from the social network. In fact, while institutional datasets allow for evaluating in dimensional terms exposure, determined in the experimental tests by the density of residents in a state of fuel poverty per district, only the evaluation of citizens' emotions expressed in posts to a social network allows for evaluating the level of perceived discomfort. A limitation of the model is the fact that the posts are anonymous; they can be geolocalized by neighborhood and selected by insertion period, but they cannot be further filtered based on additional characteristics of the users, such as age group, gender, income level, etc. Furthermore, the use of FREDoC introduces noise that can affect the accuracy of the measured discomfort index values, which is generated by the fact that in favor of greater computational speed, FREDoC does not perform complete semantic analysis of the posts.

#### 4.2. Future Work

Possible future research perspectives could be focused on the refinement of the model for assessing the impact of the stressor on exposure, taking into account additional parameters that may affect the perceived discomfort of citizens. Furthermore, the model is intended to be tested on further case studies in order to evaluate its adaptability to further urban settlements with different morphological, climatic, and social conditions.

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