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Environmental justice: geostatistical analysis of environmental hazards and socioeconomic factors—the case of Italy

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Abstract The analysis of environmental issues and the pursuit of environmental justice have gained significant attention in modern times. While progress has been made in understanding environmental impacts and establishing the right to access environmental information, the need to examine environmental inequalities persists. This study aimed to propose a methodology to identify and analyse potential 'sacrifice zones' within a region of interest using: (i) Exploratory Spatial Data Analysis (ESDA), (ii) Municipal Risk Indicators, and (iii) Spatial Autoregressive (SAR) models. The relationship between environmental hazards and social disadvantage in the Campania region of Italy was estimated and the findings of this preliminary study in this area are presented. Our preliminary results: (i) reveal a non-random distribution of contaminated sites and waste management plants (ii) localize the 'sacrifice zones' that are predominantly located in municipalities between the provinces of Naples and Caserta, (iii) show a disproportionately burdened with higher environmental risk and greater social vulnerability in some specific areas. Further investigations are required to replicate the results of this study under different environmental conditions. Additionally, enabling more precise identification of affected populations and areas subjected to heightened environmental pressures that would enhance the potential of the proposed approach. The proposed methodology can be adapted to different spatial contexts and data sources.

Keywords Environmental justice · Geo-statistical analysis · Environmental inequalities · Social disadvantage · Waste · Italy

Introduction

In recent years, environmental issues have become increasingly central to the analysis of the well-being of individuals and communities, and much progress has been made in measuring environmental conditions, understanding their impacts, and establishing the right of access to information about the environment. At the same time, there is a growing need to examine *environmental inequalities,* recognized by governmental and international bodies, understood as differences in the accessibility and quality of environmental goods and/or services, and in the impacts of environmental degradation on territories and society. This becomes particularly important when the burden of environmental 'bads' (Chakraborty et al., 2011; Damery et al., 2008) is borne disproportionately by

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disadvantaged or minority individuals, groups, and populations, whose greater vulnerability to negative effects generates further inequalities. It is in this sense that the so-called *environmental justice* paradigm highlights certain dynamics and denounces their unsustainability, along with the danger of compromising the well-being of socially disadvantaged communities and groups who, according to empirical studies, not only tend to be more exposed to *environmental hazards* and their negative consequences (especially about health) but are less able to protect themselves and remain less resilient (WHO, 2010, 2019; Kaÿmierczak, 2018).

With this in mind, politicians, activists, and researchers have begun to investigate the distribution of environmental hazards and its link with socioeconomic deprivation. While most studies have focused on the United States, leaving the European case partially under-investigated, it is essential to recognize that environmental justice concerns are not confined to a single geographical region. Despite the growing awareness of the issue in Italy, published studies are still few and in their early stages (Althor & Witt, 2019; Di Fonzo et al., 2022; Laurent, 2011). Yet the history of the country is studded with environmental emergencies and disasters that have often seen minorities, working-class and farming families pay for the choices, decisions, and actions of industries, corrupt administrators, and organized crime: the Seveso disaster, Ilva in Taranto, the Eternit affair in Casale Monferrato and the *environmental struggles* in Campania are just a few examples. In particular, in the Campania region (Southern Italy) an enormous environmental disaster has been unfolding for more than twenty years, often summed up by the phrase ‘Land of Fires’. Toxic fires, waste abandoned in the streets, in the water, and in the subsoil, fumes from malfunctioning plants and open-air dumps, contaminated sites that have never been cleaned up: these are images that have become part of normality that one becomes accustomed to, just as one becomes accustomed to the din of bombs in war-torn countries.

With an aim to investigate the environmental justice phenomenon, the objectives of this paper were two-fold. A methodology that incorporates statistical spatial based tools was proposed to identify and analyse potential ‘sacrifice zones’ (Armiero & D’Alisa, 2012; Bullard, 1990; Lerner, 2010) within a region of interest using: (i) Exploratory Spatial Data Analysis (ESDA), (ii) Municipal Risk Indicator, and (iii) Spatial Autoregressive (SAR) models. Second, based on the notion that in the environmental justice paradigm these areas often coincide with places of marginality and social disadvantage, the relationship between environmental hazards and social disadvantage was estimated and the findings of this preliminary study in this area are presented.

The case study seeks to contribute to deepen the understanding of environmental justice through an analysis of the phenomenon in the Campania region of Italy, by proposing and testing a methodology of spatial analysis that with the necessary adjustments could be extended to different areas and territorial contexts. It also attempts to provide an important perspective for public administrations to adopt targeted policies aimed at eliminating existing inequalities and improving community well-being.

The paper is structured as follows. In Sect. “Background”, we report a brief overview of the main theoretical framework that is fundamental for interpreting environmental justice issues, with attention to statistical and spatial analysis methods and tools that should be the starting point for any empirical study on the topic. After discussing the construction of the database and the methodology used (Sect. “Materials and methods”), we present and discuss the main results of the geostatistical analysis (Sects. “Results”, “Discussion”). The conclusion highlights the strengths of the methodology proposed as well as future lines of research.

Background

Theoretical framework and state of art

Various terms have been used to conceptualize the inequality, real or perceived, resulting from the unequal distribution of environmental ‘bads’ (Chakraborty et al., 2011; Damery et al., 2008), the burden of which is borne disproportionately by disadvantaged or minority individuals, groups and populations (Alier, 2004). This has been referred to as environmental racism, environmental inequity, environmental discrimination, eco-justice, and especially environmental justice, the most popular term (Chakraborty et al., 2011; Most et al., 2004). The United States Environmental Protection Agency (US EPA) defined it as: ‘the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies' in which the concept of *fairness* refers to 'the same degree of protection from environmental and health risks, and equal access to the decision-making process to have a healthy environment in which to live, learn, and work' (US EPA, 2014). The definition relies on the traditional distinction between *distributional* and *procedural* aspects of justice. The first is concerned with how environmental 'goods' (e.g. access to green space) and environmental 'bads' (e.g. pollution, environmental hazards) are distributed among different groups and the fairness or equity of this distribution; the second is concerned with the fairness or equity of access to environmental decision-making processes that affect the distribution of environmental hazards and benefits (Damery et al., 2008; Schlosberg, 2007).

The origin of the concept goes back to the late 1970s and early 1980s in the US context, from civil rights movements against the disproportionate location of polluting landfills and industrial complexes in the proximity of deprived communities, especially those with a higher proportion of African Americans and Hispanics (Bullard, 2000; GAO, 1983; Schlosberg, 2007). From people's claims a real field of research, Environmental Justice Research (EJR), was created, followed by a variety of studies exposing and offering empirical evidence of environmental inequalities. Most of them have been conducted in the United States, with waste disposal as the main 'battleground' of environmental justice and the racial element as the primary object of investigation (Bullard, 1983, 1990; Bryant, 1995; Krieg, 1995; GAO, 1983; United Church of Christ, 1987). Instead, in Europe EJR is at its early stages (Di Fonzo et al., 2022) and environmental justice issues are predominantly perceived, examined, and framed in terms of social categories (Laurent, 2011).

In Italy, the concept of environmental justice arrived late (around the 2000s), long ignored by academics, politicians and environmental movements which have been more oriented towards traditional issues such as nature or landscape protection (Rosignoli, 2020). Research and scholarly contributions have often been reticent in using the term 'environmental justice' and have approached the issue mainly within the category of *environmental conflicts*,[1] concepts which, anyway, seem to overlap. A narrow but meaningful range of works in the frame of environmental justice published over the years has suggested that rather than along racial or ethnic terms, environmental justice issues in Italy are more likely to manifest in terms of social categories, as in the rest of Europe. A number of Italian case studies have analysed *environmental injustices* through the lens of socioenvironmental inequalities, notably in the areas of waste management, industrial pollution, and contaminated sites. Most quantitative studies have examined the relationship between environmental hazards, social variables, and health in selected municipalities (Di Fonzo et al., 2022; Martuzzi et al., 2010; Pasetto et al., 2019, 2022) or individual cities (Cesaroni et al., 2013; Forastiere et al., 2007), with some exceptions, like Germani et al. (2014) examining the relationship between income, demographic characteristics, and concentrations of industrial air pollutants, and Mazzanti et al. (2009) exploring the link between income and landfilling, both within the Italian provinces. The SENTIERI study, which has been photographing health status in Sites of National Interest[2] for years, has recently brought the concept of environmental justice and distributive injustice into the sphere of Health Impact Assessment. The study documented the existence of a North–South gradient of distributive injustice, with worse conditions in the South and Islands, associated with greater socioeconomic deprivation and higher mortality risk (Pasetto & Marsili, 2023; Pasetto et al., 2021; Zona et al., 2023). Meanwhile, a wider range of environmental justice issues has been addressed by qualitative studies; they have taken into account the social, economic and political dimension of the problem often adopting a political ecology perspective. Several works have explored the role of

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[1] Environmental conflicts are defined as mobilisations of local communities against economic activities with strong environmental impacts (Centro Documentazione Conflitti Ambientali 2019).

[2] The contaminated Sites of National Interest (SIN) are defined by specific statutory provisions on the basis of their characteristics, quantity and hazardousness of pollutants, extent of the environmental impact in terms of health and ecological risk, and the detriment to cultural and environmental heritage. The administrative competence in remediation procedures is a responsibility of the Italian Ministry for the Ecological Transition (MiTE) (cf. Law No. 426 of 09.12.1998 and Law no. 179 of 31.07.2002).

social movements, emphasizing the importance of community involvement and solidarity networks (Armiero & D'Alisa, 2012; Bonatti, 2015; Falcone & De Rosa, 2020; Falcone et al., 2020; Palestino, 2015). Some have suggested policy strategies and governance approaches to address environmental injustices (Falcone et al., 2020), often emphasizing the need for more inclusive and participatory decision-making processes, as well as the need to combine technically relevant arguments and knowledge with local testimonies, experiences and know-how (Armiero & Fava, 2016; Palestino, 2015). D'Alisa et al. (2017), integrating qualitative and quantitative methods, have investigated how the perception of being a victim of waste-related environmental crimes in Campania is influenced by personal story, experiences and events; in particular, they point out that external factors such as contracting a serious illness, living in a *sick* environment, perhaps in the vicinity of legal or illegal waste treatment/disposal facilities, explain the self-perception of being a victim, and not behavioural factors such as lifestyle. Barca and Leonardi (2016) have examined the environmental injustice around the ILVA steel plant in Taranto, Puglia, focusing on the little-explored relationship between work, environmental concerns and social justice; they highlight how work is relevant to the EJ struggles because 'subaltern people' are typically also working-class people, those who occupy the lowest ranks of the labour hierarchy, who do the most dangerous and unhealthy jobs and who live in the most polluted places. Armiero (2021) has theorized the Wasteocene, 'the era of waste', employing it as an interpretive framework for the current socio-ecological crisis; within this framework, the continuous production of 'discarded' people, communities, and places emerges due to the imposition of *toxic ecologies* made of contaminating substances and narratives. Moreover, he has examined how the body is the most powerful weapon that can be mobilized to resist environmental injustice, emphasizing the importance of personal narratives and collective knowledge in the struggle for environmental justice (). Finally, in the same vein, Iengo and Armiero (2017) as well as Iengo (2022) have examined how the bodies and the experience of illness, including her own, become a political act against environmental injustice; by transforming private issues into collective resistance is possible to create counter-hegemonic narratives that challenge mainstream knowledge production and gendered, classed, racialized, and sexualized power dynamics in medicine. Therefore, while progress has been made, in Italy the empirical literature on environmental justice is a relatively novel topic compared to US context. As already mentioned, the Italian context is one of the least investigated, even though environmental injustice exists and is relevant, and further studies and exploration on the topic are needed (Althor & Witt, 2019; Di Fonzo et al., 2022; Laurent, 2011).

Spatial analysis in environmental justice research

Geographic Information Systems (GIS) have been increasingly used to examine environmental justice, proving particularly well suited because of their broad potential: the integration of multiple data sources, the representation of geographic data, and the application of various spatial analysis techniques (Sheppard et al., 1999). Most GIS-based studies have followed a consistent pattern. In general, they have identified the geographic boundaries of areas potentially 'exposed'[3] to the environmental hazards of interest; then they have examined the characteristics (racial, ethnic, economic, social) of potentially 'exposed' populations and compared them with the characteristics of a reference population, i.e., located in other areas not (or not as likely to be) 'exposed' to the environmental hazards under consideration (Burke, 1993; Chakraborty et al., 2011; Maantay, 2002; United Church of Christ, 1987; Zandbergen & Chakraborty, 2006). Although such maps, especially when supported by sound theoretical arguments, can be very effective in visually demonstrating the disproportionate *spatial distribution* of factors with high levels of dangerousness, they have often been criticized for being misleading and inaccurate (Chakraborty et al., 2011). In particular, results can be strongly influenced by the often-arbitrary choice of: the geographic scale; the 'exposed' subpopulation and the comparison population; environmental hazards and characteristics of

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[3] The term should be taken with caution, as it is not always possible to determine actual exposure to pollutants in air, soil, water, or food. Most environmental equity studies rely on proximity to the site as a proxy for exposure. However, this can only be a surrogate for hazard and risk exposure: living closer to a source of pollution does not necessarily imply a higher level of exposure; in fact, the distribution of emissions is often complex, with weather conditions leading to spatially irregular patterns of pollution exposure (Chakraborty & Maantay, 2011; Zandbergen & Chakraborty, 2006).

the population to be examined; and the time period (Bowen, 2002; Chakraborty et al., 2011; Most et al., 2004).

The choice of geographic scale is the subject of much debate in EJ research: studies suggest in their findings that different spatial units of analysis lead to different conclusions about environmental justice (Di Fonzo et al., 2022; Walker, 2009). This choice is certainly dependent on the specific research question and the data available. However, it is generally recognized that using the smallest feasible spatial unit of analysis (e.g., census tracts) produces the most accurate results, whereas using larger areal units (e.g., a county or metropolitan area) increases the strength and significance of the statistical relationships between environmental hazards and key sociodemographic variables (Chakraborty et al., 2011). This is because significant differences between neighbouring communities can be missed or underestimated if the territorial unit of analysis is so large to include potentially 'exposed' and 'unexposed' areas. On the other hand, units that are too small may underestimate the area potentially 'exposed' to environmental hazards (Di Fonzo et al., 2022).

As regards the election of environmental hazards (dependent variables), it has in most cases involved: air pollution (Cesaroni et al., 2010; Germani et al., 2014), polluting industrial facilities (Johnston & Cushing, 2020; Pasetto et al., 2021; Pulido et al., 1996; Taylor, 2014), hazardous waste transfer, storage, and disposal facilities (Anderton et al., 1994; Been & Gupta, 1997; Bullard, 1990; GAO, 1983; United Church of Christ, 1987), renewable energy technologies (Levenda et al., 2021); with a net prevalence for studies about aerial emissions both from the USA and Europe (Di Fonzo et al., 2022). Environmental hazards have been measured in a variety of ways, consistent with the research design, the available data, and the nature of the context being examined: presence, number or density of hazards, distance from them, or a measure of their magnitude (quantity of pollutants, toxicity, risk, health risk). Most studies have used the number of sites as a dependent variable and did not take into account the nature of the latter (size, type, quantity and kind of materials or pollutants, geology, hydrology, regulatory regime) due to databases that are still deficient in this respect (Rosignoli, 2020). While for what concerns the characteristics of the populations under study and reference (independent variables), they typically have included socioeconomic status and/or race/ethnicity (Bullard, 1990; GAO, 1983; Mohai & Bryant, 1992; United Church of Christ, 1987); some also have included age (Szász & Meuser, 1997) and gender (Germani et al., 2014).

The statistical methods used are very heterogeneous and reflect differences in study design and data availability. Nearly all research has taken a snapshot over time (cross-sectional analysis) of the distribution of environmental hazards and the populations on which they might impact while ignoring, often due to the absence of detailed longitudinal data, the process questions necessary for a causal analysis (Been & Gupta, 1997; Damery et al., 2008; Szász & Meuser, 1997). Most have relied on linear correlation or multivariate regression analysis to measure the statistical relationship between environmental hazards and relevant sociodemographic characteristics of the potentially 'exposed' population (Chakraborty & Maantay, 2011). The use of Spatial Autoregressive models (or SAR models) has increased in recent years thanks to the spread of GIS and easy-to-use spatial analysis programs (ibidem). It has been used in some studies to account for autocorrelation and other *spatial effects* (Grineski & Collins, 2008; Mennis & Heckert, 2017), and generally resulted, at least for air pollution-related studies, in weaker coefficients, but also revealed localized variations in associations (Goodman et al., 2011); while very few papers have provided a comparison between different statistical methods (Schoolman & Ma, 2012).

The complex effects of environmental hazards on populations

Exposure to environmental hazards, such as residing near contaminated sites or waste landfills, has significant negative effects on the resident population (Pasetto et al., 2019), and can result in a wide range of health issues, both in the short term and over the long term (Mattiello et al., 2013; Porta et al., 2009). Studies have identified, among the short-term *health effects*, congenital anomalies, respiratory infections, stress, anxiety, and other symptoms like headache, dizziness, and nausea. Whereas long-term effects can include chronic respiratory and cardiovascular diseases, various types of cancers, and diseases affecting the brain, nerves, liver, lymphohematopoietic, and kidneys (Triassi et al., 2015). The impact is especially pronounced in vulnerable communities and individuals who face various social and economic factors such as age, gender, poor health, lifestyle, nutrition, and low income (Kaÿmierczak, 2018). Indeed, the adverse effects of social disadvantage, including limited access to quality healthcare, compound the health risks posed by environmental hazards. This effect has often been described as 'triple jeopardy' (Jerrett et al., 2001). Not surprisingly, numerous epidemiological studies consider socioeconomic factors as confounding variables and standardize their analysis to account for the association between environmental exposure and social disadvantage (Martuzzi et al., 2010).

Examining health effects can drive equitable environmental hazards distribution policies and improved monitoring of high-risk populations (Jerrett et al., 2001). Indeed, a considerable portion of environmental justice studies has concentrated on evaluating health effects caused by environmental hazards by using quantitative methodologies derived from epidemiology, toxicology, disease ecology, and risk assessment (Wakefield & Baxter, 2010). The debate has been centred especially on identifying a correlation between the presence of legal and illegal waste facilities and landfills and increased mortality and morbidity rates for various disease (Comba et al., 2003; Parodi et al., 2004; Martuzzi et al., 2009). The evidence for a *causal* role is limited and not clean of bias and confounding factors (Fazzo et al., 2017; Vrijheid, 2000). However, as Wakefield and Baxter pointed out (2010), focusing exclusively on the direct causal link between exposure to environmental hazards and health runs the risk of considering distributive environmental inequalities a problem only when this is demonstrated. Instead, they can significantly reduce *quality of life* and cause psychosocial impacts (e.g. uncertainty, anxiety and distress) that should in their own right be considered unfair (Wakefield & Baxter, 2010).

With explicit reference to environmental pressure from waste, the UK Environment Agency (EA) has identified various social, economic, community, political, and demographic impacts. These include disturbance and stress effects due, for example, to bad odours, noise, and visual intrusion, devaluation of properties near waste sites, stigmatization of communities, political disempowerment, and demographic changes due to migration patterns (Damery et al., 2008). Beyond the actual effects, even the perception and representation of environmental hazards can decrease the quality of life for those living under the suspicion of an objective risk, even when it is not proven to have significant negative consequences (D'Alisa et al., 2017; Lima, 2004). This means that even when physical health may not be directly linked to disproportionate environmental degradation, it is crucial to address the broader consequences and undertake corrective and preventive actions (Wakefield & Baxter, 2010).

Materials and methods

Study area

Campania is a region in the South of Italy, divided into 5 provinces: Naples (Regional capital), Avellino, Benevento, Caserta and Salerno. With 5679 million residents as of 2021 according to ISTAT data, it is the third most populous region in Italy. Half of the population resides in the Province of Naples, the least extensive, while in the other provinces it's distributed in this way: Salerno 18%, Caserta 16%, Avellino 7%, Benevento 5%. With over 430 inhabitants per km^2, it records the highest regional population density in Italy (national average: 190 inhabitants per km^2). This is mainly due to the provinces of Naples (2,636 inhabitants per km^2) and Caserta (366 inhabitants per km^2), while Avellino and Benevento show values below the national average. With an average age of 43.3, it is the youngest region in Italy thanks to its high birth rate (8.2 compared to a national average of 7). However, it is last in life expectancy at birth (78.4 for men and 82.8 for women as of 2019), first in premature deaths (Potential Years of Life Lost—PYLL Index) and standardized mortality rates for major causes (81.4 deaths per 10 thousand inhabitants) and second in standardized mortality rates for cancer (29.5 per 10 thousand inhabitants) (ISTAT, 2019) (Fig. 1).

The region is a significant case study to be read through the lens of environmental justice. The illegal dumping of hazardous waste from northern Italy and other European countries as well as the prolonged and problematic management of the *waste emergency* made the region the first in Italy for environmental conflicts (Temper & Shmelev, 2015). In its 15-year

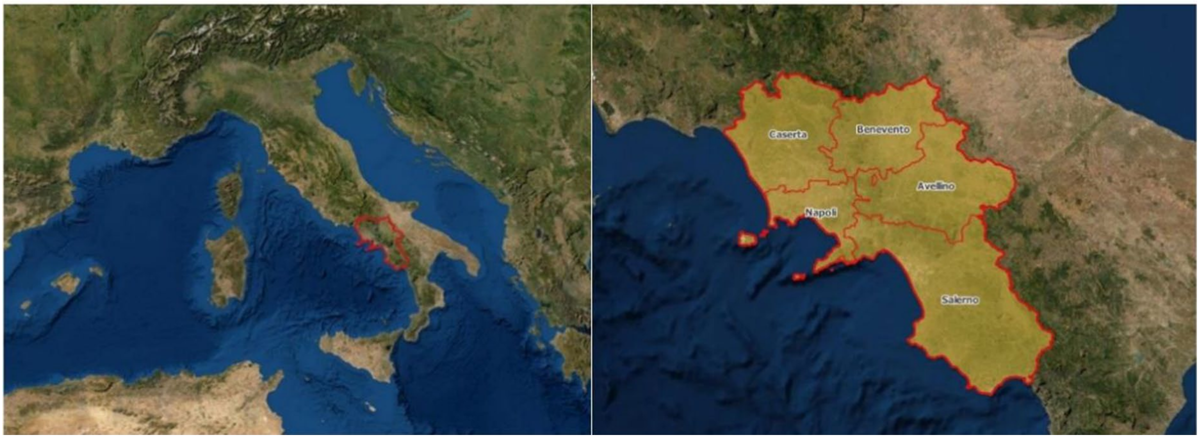

Fig. 1 Campania Region, geographical position in the Italian context, subdivision of the regional territory into its provinces. *Source* graphic elaboration in GIS environment

span (1994–2009), the emergency regime suppressed democratic dialectics, repressed opposition, and depoliticized the issue of unequal burdens and risks (Armiero & D'Alisa, 2012; D'Alisa & Armiero, 2013). This contributed to an unprecedented environmental and health disaster, with numerous waste treatment plants (often malfunctioning), landfills, toxic fires, and contaminated sites that have compromised air, water, and land quality and impacts a heavily anthropized and population-intensive territory, drawing a 'geography of catastrophe' (Petrillo, 2009). Moreover, the region can be considered geographically, economically, socially and culturally *marginal*, and one of the sacrifice zones of Italy (Armiero & D'Alisa, 2012). It is one of the poorest regions of Italy and, according to the Eurostat Regional Yearbook (European Commission, 2020), the poorest in Europe, with 41.4% of the population at risk of poverty. Its economic backwardness has gone hand in hand with its social problems, such as the strong influence of criminal organizations (Petrillo, 2009). On the inside, the outskirts of Naples and partly that of Caserta, represent marginal territories, not only for urban and social disintegration and unemployment rates among the highest in Europe (Armiero & D'Alisa, 2012). Hotspots of illegal disposal and burning of waste, their territories have been baptized as the 'Land of Fires' and local communities forced to suffer disproportionately the full weight of contamination and environmental crime. The region has been the focus of several studies on the relationship between waste exposure and health outcomes, especially since the outbreak of the media scandal on the 'Land of Fires' in 2013–2014. Some oncologists, pathologists and toxicologists have used the word 'biocide' to describe the genetic weakening of the Campania population due to continuous exposure to toxic contaminants (D'Alisa et al., 2017). Studies have shown a significant increase in cancer incidence (Fazzo et al., 2008; 2011), and cancer mortality rate (Altavista et al., 2004; Martuzzi et al., 2008; Agovino et al., 2018) in the provinces of Naples and Caserta. In particular, Senior and Mazza (2004) identified the 'Triangle of Death', an area characterized by illegal waste disposal, poorly managed urban waste facilities, and a high incidence of cancer mortality. Despite the alarming health trends, establishing a direct causal relationship between waste exposure and specific health outcomes has been really challenging for researchers (Triassi et al., 2015), and for years some authorities have attributed the increased cancer rates to poor lifestyle habits. However, local perceptions of the link between environmental hazards and health effects in Campania do not align with the cautious scientific approach. A study by D'Alisa et al. (2017) found that local residents strongly believe the quality of their environment impacts their health, with many reporting severe diseases linked to environmental contamination. The recent report of the Italian Superior Institute of Health (Beccaloni et al., 2020) certified a 'causal or concausal relationship' between the presence of uncontrolled waste sites and the onset of cancer pathologies in the 38 municipalities analysed

Table 1 Characteristics and sources of data for environmental hazards

Data type	Variable extracted	Spatial scale	Date	Provider/Source
Basic data	Boundaries of administrative units	Region and Municipality	2021	ISTAT boundaries of administrative units for statistical purposes
Contaminated sites	Sites to be reclaimed[a] (no. 282 sites)	Municipality	2019	ARPAC register of sites to be reclaimed
	Potentially contaminated sites in sites of national interest[b]–CSPC SINs (n.403 sites)	Municipality	2019	ARPAC census of potentially contaminated sites in sites of national interest
	Potentially contaminated sites in former sites of national interest[c]–CSPC former SINs (n.2984 sites)	Municipality	2019	ARPAC census of potentially contaminated sites in former sites of national interest
	Local Potentially contaminated sites[d]–Local CSPCs (no. 152 sites)	Municipality	2019	ARPAC census of potentially contaminated sites in former sites of national interest
Waste management plants	Authorized waste facilities (n. 900 facilities)	Municipality	2020	ARPAC regional section of the waste cadastre
	Large wastewater treatment plants	Municipality	2018	ISTAT processing on ARPAC data

[a] Sites to be subjected to remediation and environmental restoration

[b] Sites defined by specific statutory provisions based on their characteristics, quantity and hazardousness of pollutants, extent of the environmental impact in terms of health and ecological risk, and the detriment to cultural and environmental heritage

[c] Sites whose competence has been transferred to the Region by Ministerial Decree January 11, 2013

[d] Sites for which the Contamination Threshold Concentrations (CSCs) have been determined to be exceeded, not falling within the perimeter of SINs or former-SINs

in the provinces of Naples and Caserta. Further research is needed for the empirical assessment of environmental justice which is still in its infancy as also highlighted in sub-Sect. "Theoretical framework and state of art".

Data collection

Environmental hazards

To quantify environmental hazards, information on the waste management plants and Italian contaminated sites was used. This choice took into account the theoretical framework, the context being examined and the available data.

The data on contaminated sites were collected from the Campania Regional Environmental Protection Agency (ARPAC). These data come from the 2020 Regional Reclamation Plan of the Campania Region which censuses 4692 sites grouped into 8 typologies[4] and 7 lists. The lists examined are presented in Table 1.

The waste management plants data were also collected from the ARPAC database, which aggregates data from the institutional websites of territorially competent provincial administrations, the Unique Environmental Declaration Model and the web-based software O.R.So. (Sovraregional Waste Observatory). The 2019 list includes about 900 plants but, although quite reliable, it is not to be considered exhaustive, as there is no standardized information flow in Italy. Furthermore, ISTAT data on large wastewater treatment plants, i.e., those that treat (project) pollutant loads greater than 50,000 population-equivalents, were added to the waste management plants database. Due to the variety of formats, the data were pre-processed and harmonized to prepare the analysis; downloaded in

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[4] Productive Activity, Decommissioned Activity, Fuel Selling Point, Waste Management Activity, Site with Waste, Landfills, Decommissioned Quarries, Other.

Table 2 Characteristics and sources of data: demographic and socioeconomic data

Data type	Variable extracted	Spatial scale	Date	Provider/Source
Demographic/socioeconomic data	Employed out the total resident population over 15 (‘employed’)	Municipality	2019	ISTAT permanent census of population and housing
	Homemaker[a] out of the total resident population over 15 (‘homemaker’)	Municipality	2019	ISTAT permanent census of population and housing
	Illiterate and literate without a qualification out of the total resident population over 9 (‘notitle’)	Municipality	2019	ISTAT permanent census of population and housing
	Masculinity ratio (‘masc_ratio’)	Municipality	2019	ISTAT permanent census of population and housing
	Foreign households as a percentage of total households (‘foreign_households’)	Municipality	2019	ISTAT permanent census of population and housing
	Average number of household members (‘household_membs’)	Municipality	2019	ISTAT permanent census of population and housing
	Population density (‘pop_dens’)	Municipality	2019	ISTAT statistical data for the territory
	Average incomes (‘income’)	Municipality	2019	Italian ministry of economy and finance

[a] They are not in the labour force; they mainly do household chores, and do not work or look for work

Excel or PDF format, they were transformed into Shape-files.

Demographic and socioeconomic data

The primary source for the demographic and socioeconomic data used in this analysis is the Italian Permanent Census of Population and Housing (Italian Statistical Agency—ISTAT). In particular: demographic characteristics of the resident population, level of education and professional status. Unlike the data released by the decennial censuses in Italy, these are made available only at the municipal (not sub-municipal) level, which reduces the possibilities for detailed analysis. However, we chose to prioritize data updating, rather than spatial detail, as the last decennial census (of 2011) was too far back in time for the case at hand. The continuity and reliability of the source ensure that detailed and up-to-date information will be available in the future through the continuous census. Additional variables such as the ‘population density’ and ‘average incomes of municipalities’ have been included to enrich the analysis. More details on the data collected are presented in Table 2.

Study design and geostatistical analysis

The analysis is cross-sectional and conducted at a municipal scale; and uses GIS technology, in particular ArcGIS and GeoDa software. In selecting the specific methods employed in this study, careful consideration was given to their alignment with the research goals and the characteristics of the data. The process involved three steps: the first two steps, aimed at understanding the spatial distribution of environmental hazards and at identifying potential clusters, consist of exploratory spatial analysis and the construction of a Municipal Risk Indicator; the last step consists of correlation and regression analyses to assess links between the Municipal Risk Indicator and a set of demographic and socioeconomic factors, by enlarging the regression analysis to consider spatial effects. The steps are presented in Fig. 2 and explained in detail in the following sub-sections where limits and potential are also highlighted.

CSR Model and spatial autocorrelation techniques

As a first step in our geostatistical analysis, we examined the spatial distribution of environmental hazards to empirically verify the existence of an unequal

Fig. 2 Flow chart of the applied geostatistical analysis methodology

spatial distribution of them in the region and among municipalities. To this end, we used a Complete Spatial Randomness (CSR) model (Gimond, 2019) and *spatial autocorrelation* techniques both of which are useful for assessing whether environmental hazards are randomly distributed (or not) in the area, whether they are *clustered*, and where. In fact, the maps allow rapid identification of the geographical location of *hotspots* where the distribution of environmental hazards is more extensive, although they can only partially help to identify the reasons why they are concentrated in certain locations. Even if supported by sound theoretical arguments, maps are not sufficient for the construction of effective spatial models for which it is appropriate to resort to additional tools and statistical methods (Atzeni et al., 2004; Chakraborty & Maantay, 2011). An important aspect of pattern recognition techniques and hotspot representations lies in the possibility of tracing 'true' *clusters*, any *outliers* or spurious values (Gahegan & O'Brien, 1997; MacEachren & Kraak, 1997; Rheingans & Landreth, 1995). The set of statistical methods for analysing and visualizing spatial data is referred to as Exploratory Spatial Data Analysis (ESDA). It is a subset of Exploratory Data Analysis (Tukey, 1977) with an explicit focus on distinguishing characteristics of geographic data (Anselin, 1989). It allows for describing and visualizing spatial distributions; identifying atypical positions or spatial outliers; detecting patterns of spatial association, clusters, or hot spots; and suggesting spatial regimes/clusters or other forms of spatial heterogeneity (1999a; Anselin, 1994, 1998). Such techniques are extremely useful in assessing the existence and non-random location of units in space; recently developed approaches that focus on 'local' indicators of spatial association (LISA) can be used to detect hot spots and spatial outliers; and they and are also useful in 'suggesting' potential associations between variables by eliciting working hypotheses whose formal verification must, however, be confirmed.

Both the CSR and autocorrelation techniques were run in ArcGIS software. We tested for CSR with the Average Nearest Neighbour (ANN) tool. It compares the *expected* mean distance, assuming the point pattern is obtained from a random process, with the *observed* mean distance. The instrument was run separately for waste management plants and contaminated sites; for convenience, the various shapefile layers concerning contaminated sites and the ones concerning the waste management plants were merged with the Merge tool; the study area set is the entire regional territory, covering 13,590 km^2. Then, we used Moran's I-index tool that, given a set of features and an associated attribute, assesses whether the expressed pattern is *clustered, dispersed*, or *random*. The application of Moran's I-index is more complex and requires some preliminary steps. In examining the distribution of environmental hazards in space, the reference spatial unit is no longer the entire regional territory but the municipalities of the Campania region. Therefore, the Spatial join[5] technique was used to associate the representative points of the sites under examination (waste management plants and contaminated sites) with the polygons of the municipalities. A new field, Join_Count, is added to the output feature class; it identifies the number of points contained in each polygon, thus the number of environmental hazards located within each municipality. After that, before proceeding to the calculation of Moran's I, a Spatial Weights Matrix in SWM format was constructed as a matrix of weights, adopting as a criterion that of inverse distance.[6] Lastly, Anselin Local Moran's I statistic was used for the *cluster-outlier analysis*, to locate in the regional territory the groups of adjacent environmental hazards that contribute most to positive spatial autocorrelation.

Construction of the Municipal Risk Indicator

Once the existence of spatial concentration was verified, the construction of a Municipal Risk Indicator (*IPC*) allowed us to establish a ranking among municipalities based on the number and hazard level of environmental hazards and the area occupied by them within their boundaries. Particular attention has been paid to trying to overcome, albeit partially, the limitations of the technique of *spatial coincidence*[7] (Been & Gupta, 1997; Burke, 1993; UCC, 1987; Walker, 2009). In fact, in addition to the site-specific analysis, the creation of *buffers* (Bullard, 1990; GAO, 1983; Maantay & Maroko, 2009; Mohai & Saha, 2006; Sheppard et al., 1999) around each environmental hazard of interest allows to take into account the 'border effects'; the index is assigned not only on the basis of environmental hazards hosted by each municipality but also on the basis of sites that are outside the administrative boundary but still close enough to potentially produce negative impacts.

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[5] The Spatial Join tool joins attributes from one feature class to another based on their mutual spatial relationship.

[6] All features impact or influence all other features, but the further away something is, the smaller its impact is.

[7] Spatial coincidence technique assumes that exposure to environmental hazards is limited within the boundaries of predefined geographic entities that host them, not considering 'boundary effects.' It does not consider the exact location of the environmental hazard within the spatial unit, and all host units are treated equally, not distinguished by the number and magnitude of environmental hazards.

The approach for the construction of the indicator has been used in other geographical-epidemiological studies relative to the health effects from waste presence (Fazzo et al., 2020; Musumeci et al., 2010). Since the primary objective is not to measure the actual human health risk of populations residing in the study area but to highlight the differences in the distribution of environmental hazards from an environmental justice perspective, the scoring of each site followed a simpler and more intuitive scheme, relying on numbers instead of alphanumeric codes. Since it is impossible to have precise information on what has been disposed of, treated and/or abandoned, and since waste by its nature consists of mixtures of complex chemicals not always known, it is impossible to consider the pollutants actually released into the environment. The criteria used for the assessment were, therefore:

- The presumed impact and risk of release and spread of pollutants (depending on the type of site);
- The presence of municipal or special waste;
- The presence of hazardous and non-hazardous waste;
- The presence of waste in controlled/authorized or uncontrolled/illegal situations;
- The contamination by toxic/carcinogenic substances.

Based on the presumed impact and the risk of release and spread of pollutants and taking into account Directive 2008/98/EC on the waste hierarchy, the facilities were ranked with a score from 1 to 5. The highest score was assigned to landfills due to: excessive land consumption; significant and irreversible environmental impact; diffuse pollution and risk of spreading pollutants and leachates into the air, water, soil and food chain. Score 4 was assigned to all recovery plants with a risk of hazardous substance release (chemical-physical-biological treatment, vehicle shredding/demolition, WEEE treatment, incineration, biomass cogeneration, and inadequately functioning scrubbers). Score 3 was assigned to wastewater treatment plants and temporary storage and warehousing sites. Lower scores were assigned to transfer stations (2) and low-impact recovery facilities (anaerobic digestion, TMB and composting). Material recycling/recovery plants (see codes R3, R4, and R5) have been excluded from the analysis.[8] Plants that carry out more than one treatment are evaluated as belonging to the type with the highest score. In addition to the distinction by type, facilities are classified based on the presence or absence of hazardous waste (1,0) and the presence of municipal waste (0) or special waste (1). Where not specified, the score assigned is 0.5.

Not having enough information to distinguish contaminated sites based on type, as done for the plants, the same starting score, equal to 1, was assigned to all, to which are added the scores related to contamination (1 if the presence of toxic/carcinogenic substances is ascertained, 0 otherwise) and the presence of the same in authorized (0) or illegal (1) situations. Although identified and mapped, sites such as ‘production activities’ and ‘disused activities’ were excluded from the construction of the indicator: although they may use hazardous raw materials, their environmental impacts are not related to the waste cycle and the information available is insufficient for an effective characterization. The assignment of scores, although the result of objective and accurately described criteria, does not take into account all the possible variables that can explain and influence the degree of risk identified by the Municipal Risk Indicator. Therefore, when examining the results, it is important to always keep in mind the criteria used.

Once the scores were assigned to each site, they were standardized to make them comparable. To move from a site-specific analysis to a municipal-scale analysis that considers ‘boundary effects’, a 1 km buffer was calculated around each site to which was associated the same score (or site-specific index, IP_i) as the site that generated it. The choice of the 1 km radius is due to the large number of sites diversified in nature and dimensions, sometimes very close to each other, in an area characterized by a high population density (Musmeci et al., 2010). However, the technique is not without limitations: the radius of the buffer is arbitrarily chosen and applied equally to all sites (Liu, 2001); the hazard (representing the

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[8] These are mainly production activities for which recovery is an excellent source of supply of secondary raw materials (steel, aluminum, paper, glass, wood, plastics and textiles).

centroid of the buffer) is assumed to be small enough to be treated as a point; and adverse impacts are assumed to be limited only to the specified distance.

The next step was to associate the impact areas of each site with the municipalities of the Campania region, through a Spatial join (intersect tool), in order to describe the overall risk to which they are subjected.[9] Using the plug-in Group Stat, the site-specific indices have been summed according to the municipality of belonging, to obtain, for each municipality, a single value corresponding to the sum of the site-specific indices related to environmental hazards to which it is subject, which we called Total Risk Index (IPt_i).[10]

For a classification of municipalities according to environmental risk, it is necessary to calculate an indicator that considers not only the site-specific indices, but the area occupied by the impact areas within each municipality. To do this, it is necessary to calculate the area in m^2 of the impact areas contained in or intersecting each municipality and relate it to the total corresponding municipal area. Once the value of the municipal area occupied by impact areas S_i (where i is the number of impact areas present in the municipality) was obtained, it was multiplied by the IPt total risk index (given by the sum, per municipality, of the site-specific risk indices), to obtain a synthetic Municipal Risk Indicator (IPC). Formally:

$$IPC = \sum_{i=1}^{n} IPt_i * S_i$$

Spatial correlation and regression analysis

The last step was the regression analysis to test for the relationship between the potential 'exposure' to environmental hazards represented by the IPC and a set of demographic and socioeconomic variables: employed out the total resident population over 15 ('employed'), homemakers out of the total resident population over 15 ('homemaker'), illiterate and literate without a qualification out of the total resident population over 9 ('notitle'), masculinity ratio ('masc_ratio'), foreign households as a percentage of total households ('foreign_households'), average number of household members ('household_membs'), population density ('pop_dens'), average incomes ('income').

Although much of environmental justice studies is based on classical regression analysis, evidence from spatial correlation analysis necessitated a regression analysis that includes spatial effects. In fact, the presence of spatial effects, induced by *spatial dependence* and/or *spatial heterogeneity*, leads to violating the basic assumptions of classical regression analysis and the specification of spatial models is necessary to avoid the distortions produced in the results of the estimates due to the presence of spatial variables constituted to take into account spatial dependence and spatial heterogeneity (Anselin, 1999b). There are basically two different procedures for introducing spatial effects into regression: the first involves treating spatial dependence as a nuisance (data-driven approach); the second admits and models spatial dependence (theory-driven approach) (Anselin, 1989). This results in techniques to model spatial dependence in the error term of the regression model, respectively, or to transform variables in the model and eliminate spatial correlation (spatial filtering), as opposed to methods that explicitly add a spatial interaction variable between regressors in the model. Common to all methodological approaches is the need to rigorously express the notion of 'neighbour effects', which is based on the concept of a matrix of spatial weights. A spatial variable takes the form of a 'spatial lag' or spatially lagged dependent variable, which consists of a weighted average of the neighbouring values. More precisely, the spatial lag of a dependent variable at location i, yi, would be Σj wijyj, where the weighted sum is over those 'neighbours' j that have a nonzero value for element w ij in the weights matrix (or, in general, the weight is w ij) (Anselin, 1988; Anselin & Bera, 1998). A typical specification of a linear regression equation that expresses substantive spatial interaction (or spatial autocorrelation) is the mixed regressive, spatial autoregressive model, or *spatial lag model*. This includes, in addition to the usual set of regressors (say, xi, the regressive part), a spatially lagged dependent variable Σj wijyj, (the spatial autoregressive part), with a spatial autoregressive coefficient ρ. The inclusion of a

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[9] Fully included and intersected impact areas were treated the same way.

[10] In the output, municipalities that neither contain nor are intersected by impact areas will have the value NULL in the *'IPt'* field. In order to consider these municipalities within the calculations and therefore in the comparison with municipalities at risk, the value NULL has been replaced with the value 0 and hazard indices converted from negative to positive.

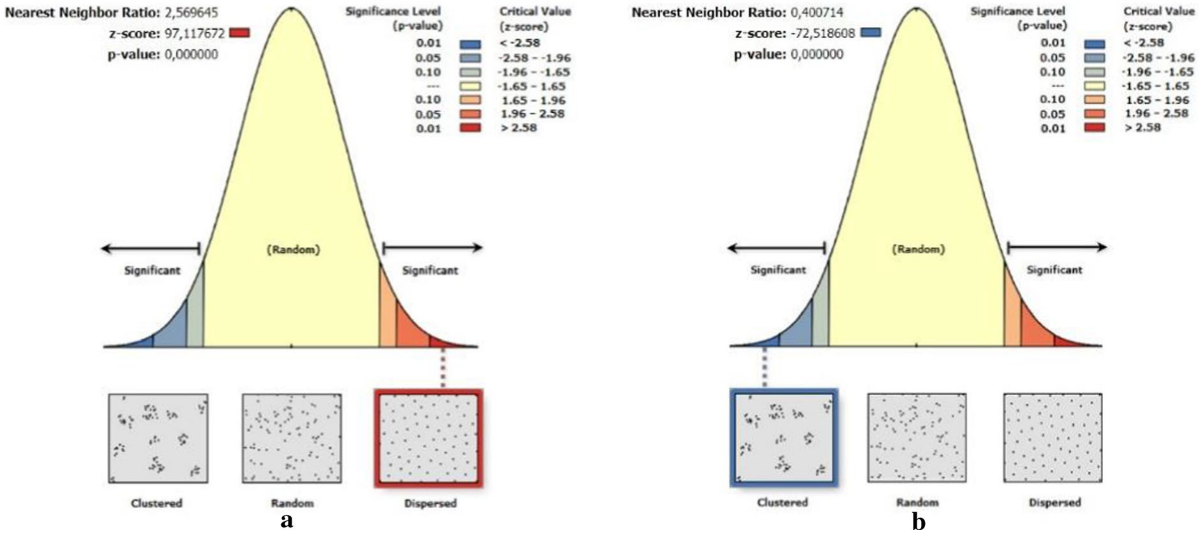

Fig. 3 Average nearest neighbour summary: waste management plants (**a**), contaminated sites (**b**). *Source* ArcGIS processing

spatial lag term is similar to a progressive term in time series analysis, although there are several important differences in references that require a specialized methodology for estimation and testing.

GeoDa software was used for the regression analysis (Anselin, 2005). Before applying it, we employed Pearson's correlation analysis and Moran's spatial correlation analysis between the Municipal Risk Indicator and our covariates. Then, three different methods were applied and compared: we started with the baseline model Eq. (1) and subsequently, the spatial error model Eq. (2) and spatial lag model Eq. (3) have been considered to control for spatial autocorrelation. The econometric models are specified as follows:

$$\begin{aligned} IPC_i = {} & b_o + b_1 employed_i + b_2 homemaker_i + b_3 notitle_i \\ & + b_4 masc\_ratio_i + b_5 foreign\_households_i \\ & + b_6 household\_membs_i + b_7 pop\_dens_i + b_8 income_i + e_i \end{aligned} \tag{1}$$

$$\begin{aligned} IPC_i = {} & b_o + b_1 employed_i + b_2 homemaker_i + b_3 notitle_i \\ & + b_4 masc\_ratio_i + b_5 foreign\_households_i \\ & + b_6 household\_membs_i + b_7 pop\_dens_i + b_8 income_i + u \end{aligned} \tag{2}$$

where u is the spatial error term.

$$\begin{aligned} IPC_i = {} & b_o + \rho WIPC + b_1 employed_i + b_2 homemaker_i \\ & + b_3 notitle_i + b_4 masc\_ratio_i + b_5 foreign\_households_i \\ & + b_6 household\_membs_i + b_7 pop\_dens_i + b_8 income_i + e_i \end{aligned} \tag{3}$$

where $\rho WIPC$ is the spatially lagged IPC value

Results

Spatial patterns of environmental hazards in Campania

The Average Nearest Neighbour (ANN) tool returns five values: Observed Mean Distance, Expected Mean Distance, Nearest Neighbour Index, z-score and p-value. These values are accessible from the results window and, optionally, from an HTML file with a graphical summary of the results. The results of our analysis showed that both the distributions of contaminated sites and waste management plants are not the result of a random process: the first one ($ANN > 1$) tends to dispersion (see Fig. 3a), the second one ($ANN < 1$) tends to clustering (see Fig. 3b). Both z-scores imply the probability of less than 1% that the pattern of points resulted from a random process.

The spatial autocorrelation tool returns five values: Moran's I-index, Expected Index, Variance, z-score and *p*-value. These values are again accessible from

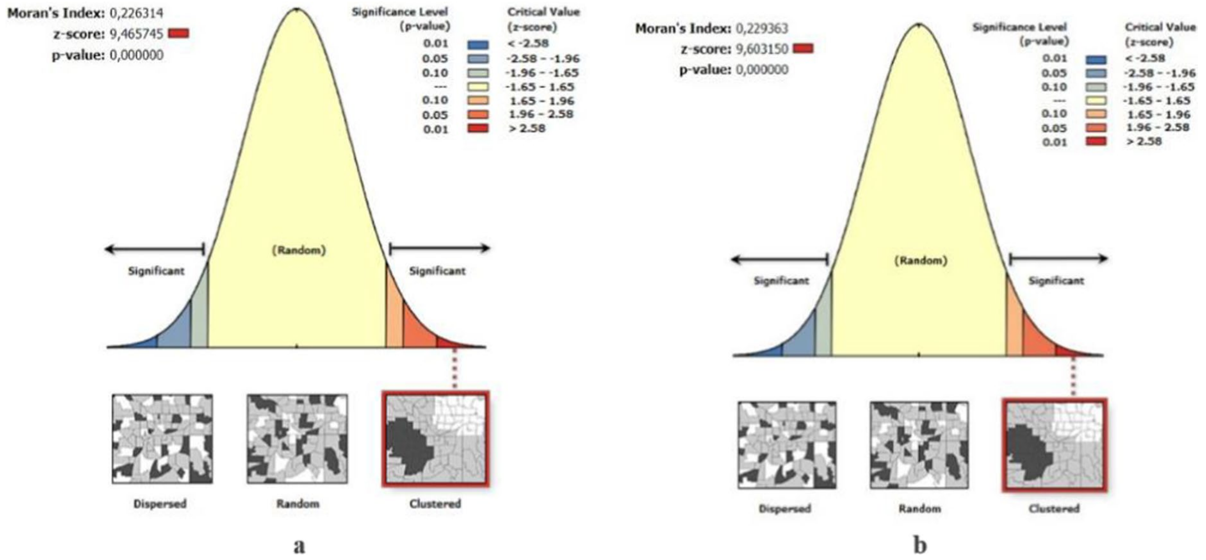

Fig. 4 Spatial Autocorrelation Summary: waste management facilities (**a**) contaminated sites (**b**). *Source* ArcGIS processing

the results window and, optionally, from an HTML file with graphical summary of the results. For both waste management plants (Fig. 4a) and contaminated sites (Fig. 4b), Moran's I-index was positive and greater than the expected value, indicating the presence of positive autocorrelation of the data. In addition, both the statistically significant *p*-value and the positive z-score lead to the rejection of the null hypothesis (no spatial correlation); thus, we can conclude that the spatial distribution is more spatially clustered than would be expected if the underlying spatial processes were random.

The output of the Cluster-Outlier Analysis returns the map representation, a histogram representing the value of the input field (number of environmental hazards in each municipality) and a Moran Scatterplot. The COType (Cluster/Outlier Type) indicates the type of correlation observed, however, it only has values for clusters and outliers that are statistically significant for a 95% confidence level. A high positive z-score indicates the presence of similar values: the COType is HH (High-High) for a statistically significant cluster of high values and LL (Low-Low) for a statistically significant cluster of low values. A low negative z-score, on the other hand, indicates a statistically significant spatial data outlier: the COType indicates whether the feature has a high value and is surrounded by features with low values (HL, High-Low) or whether the feature has a low value and is surrounded by features with high values (LH, Low–High). For both waste management facilities and contaminated sites, the COType contains more significant clusters than outliers (Fig. 5). As a result, one waste management facility or contaminated site is more likely to be located in close proximity to another, thus within the same or adjacent municipalities. The HH clusters are predominantly located between the provinces of Naples and Caserta, with some exceptions in the province of Salerno; while the LL clusters are almost all between the provinces of Benevento, Avellino and Salerno.

Spatial variation of the Municipal Risk Indicator

The *IPC* assumes values between 0 and 360. A cartographic representation of municipalities by value taken by the index is shown in Fig. 6. Municipalities were divided into 5 classes as default using the method of *natural breaks* and a scale of colours from white to red (*graduated colours*). Consistent with expectations, the Municipal Risk Indicator assumes the highest values in the territories between the province of Naples and Caserta, with 16 municipalities falling in the last two classes (108–219). The main changes that emerge when taking into account the number, the hazard level, and the area occupied by

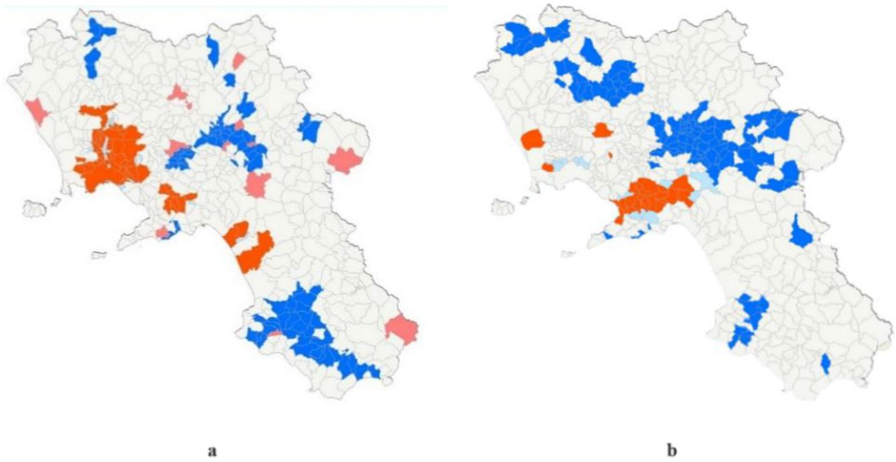

Fig. 5 Cluster analysis: waste management facilities (**a**), contaminated sites (**b**). Red (HH), Pink (HL), Light blue (LH), and Blue (LL). *Source* ArcGIS processing. (Color figure online)

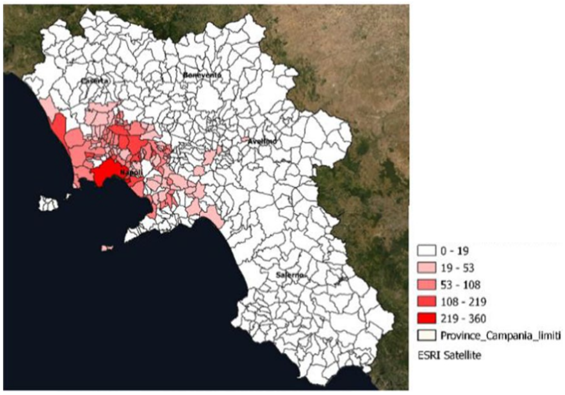

Fig. 6 Municipalities classified according to municipal risk indicator. *Source* ArcGIS processing

environmental hazards within the municipality relate especially to the province of Salerno: some municipalities that emerged in the cluster analysis (Fig. 5) for the concentration of waste facilities take relatively low scores. In fact, with a few exceptions, in the provinces of Salerno, Benevento and Avellino, the municipalities all fall into the first class (0–19).

The relationship between environmental hazards and socioeconomic factors

Pearson's correlation analysis and Moran's spatial correlation analysis provide a first insight into the relationships between the variables in terms of *linear correlation* and *spatial autocorrelation*. This can help identify any spatial patterns or trends and provide additional information for interpreting the results. Pearson's correlation coefficients are shown in Table 3; most coefficients are significant and have positive signs: a higher *IPC* value is significantly correlated with a higher percentage of homemakers, a lower percentage of illiterate and literate without qualification, a lower masculinity ratio (thus a greater presence of female individuals than male individuals), a higher percentage of foreign households, a higher average number of household members, a higher population density and average income.

Table 3 Correlations of covariates and IPC (N = 550)

Covariates	IPC
employed	– 0.0699
homemaker	0.5425*
notitle	– 0.2774*
masc_ratio	– 0.0929*
foreign_households	0.1632*
household_membs	0.4219*
pop_dens	0.6619*
income	0.3291*

Source Processing in Gretl environment

*correlation significant at the 0.05 level

The *bivariate spatial correlation analysis* results are shown in Fig. 7. The *IPC* shows positive spatial correlation with the variables 'homemaker' (0.534), 'foreign_households' (0.110), 'household_membs' (0.447), 'pop_dens' (0.568) and 'income' (0.217), and negative spatial correlation with the

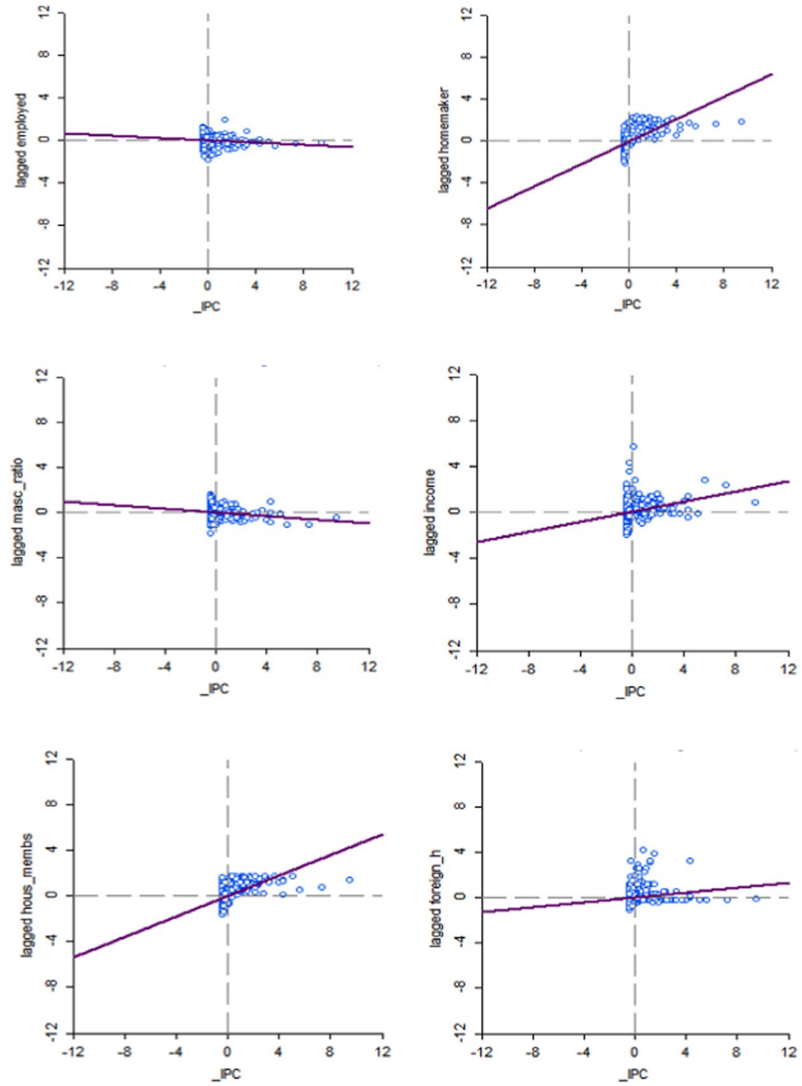

Fig. 7 Bivariate Moran scatter plot for each covariate and IPC, p-value of 0.001 (for 999 permutations). From left to right: employed, homemaker, notitle, masc_ratio, foreign_families, pop_dens, income. *Source* processing in GeoDa environment

variables ‘masc_ratio’ (− 0.082), ‘notitle’ (− 0.265), ‘employed’ (− 0.054) in a manner consistent with linear correlation analysis.

Additionally, Local Moran Cluster maps (Fig. 8) can be useful in visualizing, with appropriate caution, the relationship between the IPC at location *i* and the average of the neighbouring values of the demographic and socioeconomic variables. The variables ‘homemaker’, ‘notitle’, ‘pop_dens’, and ‘household_membs’ have the highest number of significant clusters: ‘homemaker’, ‘pop_dens’ and ‘household_membs’ have a consistent number of statistically significant clusters of high values (HH), while ‘notitle’ of Low–High (LH) clusters. Remarkably, statistically significant HH clusters are concentrated between the provinces of Naples and Caserta, while statistically significant LL clusters are between the provinces of Benevento, Avellino and Salerno.

Finally, we applied multiple regression techniques (baseline model, spatial lag model, spatial error model) with the relationship between *IPC* and social disadvantage identified by all 8 demographic and

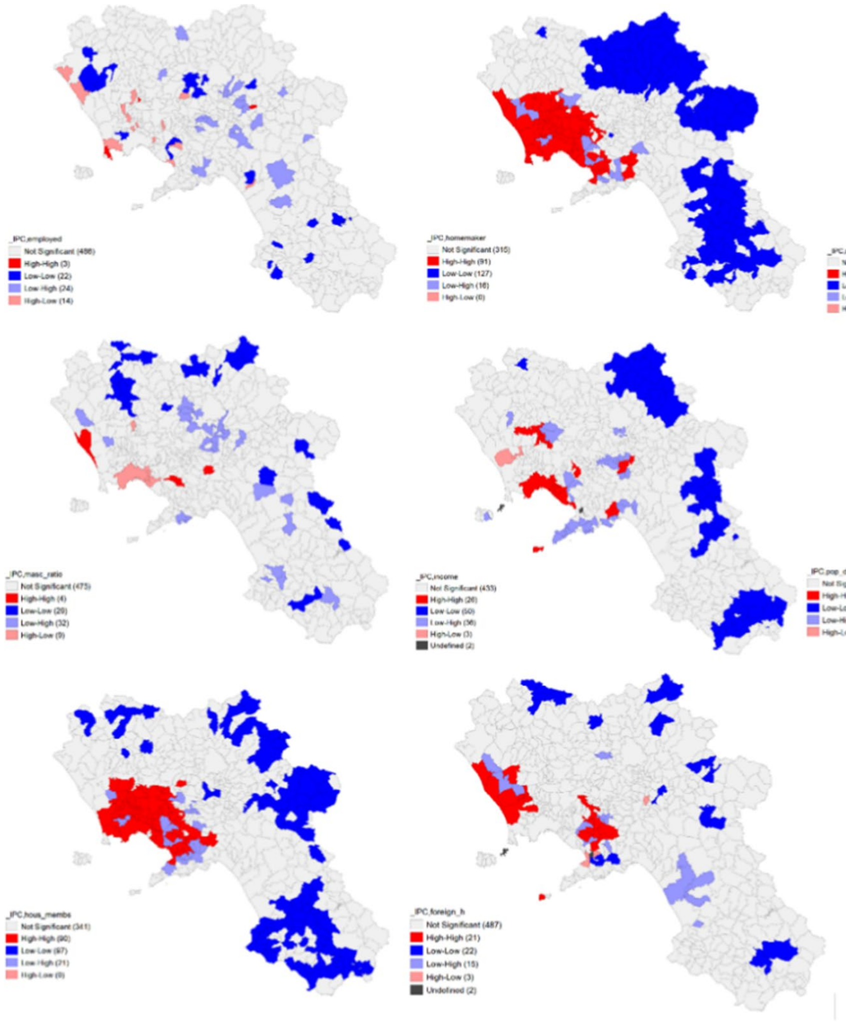

Fig. 8 Bivariate cluster maps for each covariate and IPC (p-value < 0.05). From left to right: employed, homemaker, notitle, masc_ratio, foreign_households, pop_dens, income. Red (HH), Pink (HL), Liliac blue (LH), and Blue (LL). *Source* processing in GeoDa environment. (Color figure online)

socioeconomic variables as our starting hypothesis. The spatial dependency tests for the baseline regression model showed not surprisingly significant spatial autocorrelation of the residuals in terms of Moran's I value. We used the values of the Lagrange Multiplier (lag), Lagrange Multiplier (error) and Lagrange Multiplier (SARMA) tests to evaluate the need for either a spatial lag or spatial error model; they suggested the model with the spatially lagged dependent variable as the best one. R2, Akaike, Schwarz and Log-Likelihood information criteria showed a clear improvement in estimation following the introduction of the spatial lag and error term dependence particularly in the spatial lag model. The best model specification, conditional on the set of variables tested, was found to be a spatial lag model with four independent variables: 'homemaker', 'pop_dens', 'foreign_households' and 'income' (Table 4). The coefficients are all significant and positive: a positive relationship between the *IPC* and the variables 'homemaker', 'pop_dens', 'foreign_households' and 'income' emerge.

Table 4 Spatial lag regression model: fit and results

Model fit				
R-squared				0.600077
Log likelihood				−542.897
Akaike info criterion				1097.79
Schwarz criterion				1123.64
Model estimates				
Variable	Coefficient	Std.error	z-value	*p*-value
W_IPC	0.514542	0.045464	11.3176	0.00001
CONSTANT	−0.0369371	0.027654	−1.33569	0.18165
homemaker	0.0662398	0.0361871	1.83048	0.06718
pop_dens	0.232683	0.0369503	6.29719	0.00001
foreign_households	0.112268	0.0375069	2.99326	0.00276
income	0.096656	0.0407329	2.37292	0.01765
Regression diagnostics				
Test		Value		*p*-value
Breusch–Pagan test		1246.8613		0.00001
Likelihood ratio test		108.6342		0.00001

Source processing in GeoDa environment

Discussion

The outcomes of this analysis have provided valuable insights into the spatial distribution of environmental hazards and their relationship with demographic and socioeconomic variables. They shed light on the presence of spatial patterns, clustering tendencies, and correlations between various factors, providing valuable context for understanding the interplay between environmental hazards and social disadvantage.

The application of the spatial analysis tools, such as the Average Nearest Neighbour (ANN) tool and Moran's I-index discerned patterns in the distribution of environmental hazards. The findings revealed that both the distributions of contaminated sites and waste management plants are not the result of a random process but tend to be grouped and spread out over the region, respectively. The differences are due to the intrinsic characteristics of the sites: most of the contaminated sites are not dispersed on the regional territory as are the waste management plants (usually located in urban areas), but many of them are grouped within larger areas (cf. SIN or SIR). Moreover, the positive spatial autocorrelation for both types of environmental hazards suggested that areas with a similar number (high or low) of contaminated sites and waste management plants tend to be close in space, reinforcing the concept of spatial clustering. If this were not the case, their distribution would not follow any particular structure or logic, making it unnecessary to talk about environmental justice. The Cluster-Outlier Analysis added another layer to the narrative, highlighting the prevalence of areas where waste management plants and contaminated sites are grouped closely together, especially in the provinces of Naples and Caserta, with some clusters overlapping with the municipalities of the 'Land of Fires'.

Even when we looked at the Municipal Risk Indicator (*IPC*), it showed that municipalities between the provinces of Naples and Caserta have the highest values, while with a few exceptions, those in the provinces of Salerno, Benevento and Avellino have the lowest values. This spatial pattern aligns with the context of the study area (Sect. "Study area") where illegal waste dumping and problematic waste management have led to the concentration of environmental hazards in certain areas, disproportionately affecting local communities to 'solve' the waste emergency (Armiero, 2014a, 2014b). It also aligns with the insights from the literature that emphasize the alarming health trends in the provinces of Naples and Caserta (Altavista et al., 2004; Senior & Mazza, 2004; Martuzzi et al., 2008; Fazzo et al., 2008; 2011; Beccaloni et al., 2020) and further validate existing narratives of environmental inequalities (De Biase 2015; Armiero & Fava, 2016; Iengo & Armiero, 2017; Armiero et al., 2019).

When we checked the correlation between the *IPC* and social factors, we found that areas with higher environmental risk tend to have certain social characteristics, like more homemakers, more women, a higher percentage of foreign households or higher population density. Though negative sign like expectations, no significant correlation was found between the percentage of employed and *IPC*. Finally, the multiple regression analysis offered a comprehensive perspective, considering the influence of multiple variables on the *IPC*.

The positive relationship between *IPC* and the percentage of homemakers, the percentage of foreign households, and the population density aligns with the expectations, further corroborating the link between environmental hazards and social disadvantage. The positive relationship between *IPC* and population density can be affected by the fact that the municipalities of Naples and Caserta are the most densely populated and at the same time subject to the greatest environmental pressure. The higher percentage of foreign households in municipalities with a high *IPC* can be influenced by the structure of the territory (urbanization) and job availability but can also suggest the existence of socioeconomic disparities. This result is worth noting for two reasons. First, because it draws attention to the relationship between foreign presence and environmental justice issues widely addressed in U.S. studies and to the close link in Italy, and particularly in the South, between foreign status and poverty conditions (ISTAT, 2022). Moreover, when we look at the Bivariate Cluster Map (Fig. 8), we can see that the clusters of high-high values for the variable in question and *IPC* assume a different spatial behaviour from the clusters of the other covariates, concentrating in the municipalities of the Caserta coast, in some municipalities of the Vesuvian area and in the Sarno River basin. However, this variable excludes illegally present foreigners, an even more disadvantaged segment of the population that although difficult to detect would be worth addressing. Similarly, the positive relationship between *IPC* and the presence of homemakers (according to ISTAT data, mostly women) could suggest a high rate of female inactivity, which often corresponds to poor economic conditions, limited mobility, and low education rate.

The unexpected positive relationship between *IPC* and income raises an interesting point. In fact, results suggest that areas with higher environmental risk tend to have higher average income: this finding may seem at odds with the environmental justice paradigm, while is consistent with other spatial analyses that have related income to environmental variables (Di Fonzo et al., 2022); this could be due to the fact that generally the higher-income areas are also the most urbanized and therefore likely to host industrial activities and other pollution sources. This variable should be interpreted very carefully since it doesn't consider inequalities within municipalities.

In sum, the findings provide empirical support for many concepts discussed in the literature on environmental justice. They highlight the spatial clustering of environmental hazards around certain 'sacrifice zones' (Armiero & D'Alisa, 2012), the presence of significant spatial patterns, and the correlation between environmental hazards and certain socioeconomic characteristics, strengthening the overall understanding of the issue.

Conclusions

1. This paper aimed to address the issue of environmental justice by employing statistical analysis tools from a spatial perspective with geo-referenced data. Exploratory tools of spatial analysis and the use of models that include spatial effects are suggested. The use of a Municipal Risk Indicator is proposed to establish a ranking among municipalities based on the number, the hazard level, and the area occupied by environmental hazards within their boundaries. The spatial regression analysis has enabled the exploration of the interplay between the Municipal Risk Indicator and a set of demographic and socioeconomic variables.
2. The proposed methodology was applied to the case of the Italian region Campania to identify the existence of 'sacrifice zones' (Bullard, 1990; Lerner, 2010) and investigate the relationship

between environmental hazards and social disadvantage. The investigation was conducted using data from the year 2019.

3. The results showed that the distribution of contaminated sites and waste management plants on the regional territory does not come from a completely random process, but follows a particular structure and logic that, although unknown, makes it reasonable to talk about environmental injustice. The spatial pattern assumed by the environmental hazards and the Municipal Risk Indicator confirmed the initial hypothesis on the existence of some 'sacrifice zones' located particularly in municipalities between the provinces of Naples and Caserta. Moreover, the analysis by means of spatial models showed, albeit in a partial way, how environmental hazards in Campania are disproportionately borne by territories characterized by greater social vulnerability, consistently with the paradigm of environmental justice. This evidence substantiates claims made in the literature and public discourse about the unequal burden of environmental 'bads' borne by disadvantaged communities and sheds light on specific areas that require targeted attention for public health initiatives and policy intervention toward more equitable and just distribution of environmental benefits and burdens.
4. The study does not pretend to be exhaustive, in fact, the use of data on a municipal basis, although suitable to give an idea of the phenomenon of environmental justice than a large-scale analysis, leaves out aspects that could have emerged with the use of sub-municipal data. This appears to be particularly true in a differentiated context such as the provinces of Naples and Caserta, especially in terms of population characteristics.
5. There are still some limitations in this study which highlight future scope for research. Further future research could carry out a similar study with greater spatial detail, so as to distinguish, within municipalities, areas more or less subject to disproportionate environmental pressure and to identify with greater precision the population potentially affected and exposed. Since the analysis refers to a limited number of variables, it is to be considered exploratory and its results cannot in any way be generalized and remain strictly linked to the choice of variables included in the spatial model. Some findings, such as the relationship between *IPC* and income, *IPC* and foreign households, might require more nuanced interpretation and could potentially be explored further in future research. Additionally, future research should couple quantitative assessments with qualitative analysis to fully capture the complex and multidimensional aspects of environmental justice, including residents' perceptions, possible structural causes and mechanisms of injustice, procedural aspects, and tangible effects on affected territories and communities. Such an approach can enrich the understanding of the phenomenon with a more inclusive and in-depth perspective that takes into account both objective data and the subjective experiences of those involved.
6. Based on these results, it can be concluded that the methodology applied to the case study has the potential to be adopted, with appropriate adjustments, to different data and spatial contexts, thereby further advancing the discourse surrounding environmental justice. The examination of environmental justice issues and the identification of 'sacrifice zones', in addition to enriching the existing scientific literature, can provide an important perspective for public administrations to better involve potentially affected/exposed populations in decision-making processes and adopt targeted policies aimed at eliminating existing inequalities and improving community well-being.

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Declarations

Conflict of interest The authors declare that there are no conflicts of interest regarding the publication of this research article.

Ethical approval We confirm that this manuscript has not been published or presented elsewhere, in part or in its entirety, and it is not under consideration by any other journal. We have carefully reviewed and understood the ethical standards and policies of GeoJournal, and we confirm that neither the manuscript nor the study violates any of these guidelines.

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