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Geodemographic profiles of COVID-19 mortality inside/outside nursing homes. Spatial analysis from microdata in North Spain

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ABSTRACT

After two years of the COVID-19 pandemic, there is extensive research on the spread of the virus and geo-statistical analysis of spatial patterns. However, from the perspective of health geography, COVID-19 mortality is still under-studied. This research aims to provide a geographic profile of COVID-19 mortality, in terms of the space-time evolution and the relationship with individual and contextual variables. To this end, we geocoded the daily COVID-19 microdata of deceased persons provided by the Government of Cantabria (in northern Spain) from March 1, 2020 to March 31, 2022. The study also took cadastral variables, population records, and connections to geo-enrichment services accessed through ArcGIS Pro License (ESRI) into account. Using spatial statistics methods, such as 3D bins and emerging hot spots, local bivariate relationships, and ordinary least squares, we propose an exportable and scalable methodology to help policymakers cope with the current stage of living with the epidemic virus. Our results suggest that the spatial distribution of mortality is less clustered than that of contagion and shed light on differences in COVID-19 mortality profiles inside/outside nursing homes, such as higher age, and the temporal concentration of deaths in nursing homes. Spatial regimes showed hot spots of COVID-19 mortality in urban and metropolitan areas, with a pattern of repetition over time, such as sporadic hot spots that accounted for 36.28% of deaths in only 11.88% of the area with COVID-19 deaths. Despite immunization, periods of high contagion meant a subsequent increase in mortality, such as during the Omicron wave, where consecutive metropolitan hot spots accounted for 37.50% of the area and 51.45% of deaths were concentrated. Finally, there were interesting nuances in the significant local context variables of COVID-19 mortality compared with the explanatory factors of COVID-19 cases.

1. Introduction

Social sciences have contributed extensively to our understanding of the characteristics, evolution, social determinants, and consequences of the pandemic. Particularly from a geographical perspective, the spatial methods implemented by geographic information systems (GIS) were essential for making strategic contributions that helped in managing the pandemic. In fact, during the first year of the pandemic, the research output on COVID-19 spatial factors using GIS and statistical methods was clearly on the rise (Fatima et al., 2021; Franch-Pardo et al., 2021).

Despite the large number of contributions from health geography, according to the review by A.M.R. Pranzo et al. (2023) only about 23% of papers extended their analyses to deaths. Consequently, a spatial analysis of COVID-19 mortality clearly represents a research topic pending analysis compared to the geographic analysis of the spread of cases, which has been the focus of 74% of the papers analyzed.

Focusing on the geographical background of COVID-19 mortality, there is scientific evidence on the relationship of the severity and probability of death from COVID-19 not only with individual characteristics but also contextual factors. Local conditions, such as prevalence by neighborhoods or building conditions and, therefore, the effects of geographic location are important factors on individual and clustered mortality (Decoster et al., 2021).

Not surprisingly, social determinants of health (WHO, 2008) have implications for health conditions and their local circumstances in relation to the likelihood of suffering complications during the pandemic (Sun et al., 2022). In this sense, the heterogeneous impact of COVID-19 incidence and mortality is a magnification of previous health

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and social inequalities, especially in deprived urban neighborhoods and vulnerable communities (Alfaro et al., 2022).

Local context includes not only socio-economic and demographic variables, but also environmental and mobility conditions, among others (Benita & Gasca-Sanchez, 2021). Furthermore, other studies state the importance of considering the interrelationship of explanatory variables of the mortality rate, such as the confluence of density and characteristics of ethnicity (Yue & Hu, 2021).

Individual health conditions have been extensively studied in relation to the severity and mortality of COVID-19. Ageing, comorbidities, especially non-communicable diseases (Alves et al., 2021; Bilal et al., 2020), risky jobs at the beginning of the pandemic, where remote work was not possible during lockdown periods (Albrecht, 2022), and even political tendencies (e.g., pro- or anti-vaccination) had an influence on COVID-19 mortality (Feinhandler et al., 2020). In addition, some studies found leisure time and physical activity to be factors in explaining COVID-19 mortality at a county level in the USA (Akinwumiju et al., 2022).

Moreover, when individual and local approaches are combined, some research has provided interesting contributions on the comparative importance of individual or local characteristics in COVID-19 mortality patterns. In this sense, the research conducted by S. Goutte et al. (2020) showed that, at a French department level, areas with higher indicators of precariousness (poverty rate or unemployment benefit income) and vulnerable living conditions (overcrowding or substandard housing) were more susceptible to the complications of COVID-19, and were more at risk, even when their population was younger.

Other interesting contributions focused on pandemic management demonstrated that control strategies and timely restrictions had positive effects on the spread of the virus and, consequently, on controlling the severity and case fatality rate (Coccia, 2021a).

Nevertheless, Spain was severely affected by the pandemic. During the first wave, it suffered severe periods of bottlenecks in the health care system, and higher mortality rates, similar to other European countries, such as Belgium, France, and Italy (Dzúrová & Keventon, 2021). The strict confinement of the population in Spain and the high Stringency Index based on government restrictions provided by Oxford University (Coccia, 2021b) was not enough to stop deaths.

During the pandemic, disease management shifted from national to regional governments. From the outset, strict national restrictions were implemented through two "states of emergency" until May 9, 2021. Thereafter, the stage of living with the virus, known as the "new normal" was managed by 17 regional governments coordinated by the national inter-territorial committee (De Cos et al., 2022a). Nevertheless, there were no significant differences between regions in terms of restrictions. Spain, like France and Italy, had the least internal variation in terms of location-based COVID-19 policies in Europe (McKenzie & Adams, 2020).

In this context, our research is part of the PRIMVAL20/01 project on vaccination scenarios and the evolution of COVID-19 from the perspective of primary care in the region of Cantabria (Northern Spain), developed at the IDIVAL Biomedical Research Institute.

Following previous research focused on spatial patterns of COVID-19 cases and space-time spread trends (De Cos et al., 2020; De Cos et al, 2021a; De Cos et al., 2023, our aim is to shed light on the geographic profile of COVID-19 mortality, with respect to space-time evolution and to explore the relationship with local variables. To this end, we used daily COVID-19 microdata records on deceased persons provided by the health authorities of the Government of Cantabria, with the permission of the Medicines Ethics Committee of Cantabria (CEIm, June 2020. ID: 2020.238 and CEIm, September 2021. Minutes 14/2021). The study period was from the date data started to be recorded (March 1, 2020) to the date data stopped being recorded in Spain (March 31, 2022), i.e. 761 days. From April 2022, the Government of Spain changed the COVID-19 surveillance and control strategy following the acute phase of the pandemic. The new strategy only records positive cases in vulnerable groups –people aged 60 or over, people who are immunosuppressed due to intrinsic or extrinsic causes, and pregnant women– (Health Ministry of the Government of Spain, 2023).

Geocoding death microdata and implementing geo-statistics analysis using GIS were essential for carrying out this research using a multiscale approach. As a result, our methodological approach was able to avoid the common bias arising from aggregate data for administrative, functional, and statistical units. Furthermore, taking the high impact of COVID-19 severity and mortality in Spanish nursing homes into account, our research distinguishes between deceased persons inside and outside nursing homes, particularly analyzing the space-time profile of mortality outside nursing homes.

2. Data and methods

2.1. Study area

The region of Cantabria is located in northern Spain, has just over 585,000 inhabitants (National Population Register, 2023) and a surface area of 5300 km^2. From a European point of view, Cantabria is classified as a NUTS 3 region, the acronym of the hierarchical classification of "*Nomenclature des Unités territoriales statistiques*" (Nomenclature of territorial units for statistics) (European Parliament, 2003).

The population distribution shows significant disparities between the urbanized coastal areas and rural inland valleys. It also represents the functional urban area (FUA) of Santander in the central area of the region, which includes the region's two main cities (Santander and Torrelavega). This polynuclear (bipolar) urban-metropolitan system organized around Santander and Torrelavega is a dynamic FUA covering a short distance of 25 km between Santander and Torrelavega, connected by highway, with daily commuters in the most densely populated area of Cantabria, which has 381,666 inhabitants (just over 65% of the regional population) in 685.7 km^2 (only 12.9% of the area), i.e., 556.6 inhabitants per km^2 compared to the regional average density of 110.4 inhabitants per km^2. It diverges sharply from non-FUA areas where less than 200,000 inhabitants, i.e. nearly 35% of the regional population, live in 4640.50 km^2, which is just over 87% of the regional area, with an average density of 43.1 inhabitants per km^2.

2.2. Data collection and geocoding

Our research is based on the anonymous daily microdata records of COVID-19 positive cases from the beginning of official record-taking until the end of the homogeneous collection methodology (considering the whole population, not only vulnerable groups). Therefore, the microdata records began on March 1, 2020 and ended on March 31, 2022.

This key source is in the form of a table provided by the health authorities of the Regional Government of Cantabria (Spain), where each anonymous COVID-19 positive case is represented by a row. Microdata include fields about demographic characteristics (such as age and sex), geographic location (address and a binary field on occurrence in nursing homes), COVID-19 severity (hospitalization or intensive care), COVID-19 status (positive if the virus is active, cured or deceased), time fields on dates (onset and cured or deceased, as appropriate).

The status field is useful for filtering out persons with a deceased status. Similarly, the date of death is essential for analyzing evolution, and the nursing home binary field is required to difference mortality profiles inside/outside nursing homes.

The address field is used to geocode the microdata and transform the original table into a point layer that corresponds to the elementary data of our spatial analysis. Geocoding and subsequent spatial analysis are implemented by the research team using geotechnologies provided by ESRI (ArcGIS Pro), licensed by the University of Cantabria. The ESRI world geocoding service is an efficient tool, which, when applied to COVID-19 microdata, reported a success ratio of 98.17% in whole positive cases reported by the health authorities, i.e. 129,182 geocoded records out of 131,585 (Table 1). Furthermore, the geocoding success rate rose to 98.55% for deceased persons.

Missing records correspond to confirmed positive cases without an address in the region of Cantabria, or records without an address match in the ArcGIS world geocoding service.

Although the microdata records were our main source, our research involved other sources on demographic, economic and residential data, such as: official data produced by public institutions (National Institute of Statistics, National Geographic Institute and National Government of Spain) and sources form the private sector, mainly the ESRI Spain COVID-19 GIS Hub and ESRI ArcGIS Geo-Enrichment Service. This service is based on big data and areal interpolation weighted by population and occupied areas, using user-defined polygons as boundaries (De Cos et al., 2022b. More than fifty context variables related to different topics were systematized, such as: origin of the population (Spain vs. other countries, households with immigrant people), income (average per household, unemployed households, average annual income per capita), demographic structure (population by age and gender, and demographic-structural indicators), property values as an indirect social indicator of status (average property and rental prices/m^2), and expenditure, not only total spending, but also differentiating certain products (food, alcoholic beverages and tobacco, or health care, among others).

2.3. Spatial analysis methods

We carried out our research by means of a GIS project using ArcGIS Pro, where two essential geo-databases (GDB) were organized: the health and geographic, GDB with data on the health structure and COVID-19 cases, and the local context GDB, with socio-demographic data and built environment characteristics from cadastral sources.

The research workflow consisted of four stages, framed in spatial statistics and GIS clustering methods (Kulldorff, 2001).

2.3.1. Exploratory spatial statistics methods to determine the likelihood of spatial patterns being non-random

The first stage explored the spatial patterns of COVID-19 deaths, differentiating between deaths recorded inside/outside nursing homes. Here, nearest neighbor analysis (Evans & Evans, 1954) and Global Moran's Index (Moran, 1948) were used to calculate the probability that the distribution pattern of deaths was not random.

These analyses are compared with the spatial reference pattern of homes and nursing homes.

The nearest neighbor analysis (1) is based on individual points of COVID-19 infected people, homes, or nursing homes. Comparability is ensured by employing 5326.85 km^2 as a constant area, corresponding to the area of the Cantabria region.

$$NNA = \frac{\overline{D}_o}{\overline{D}_e} \tag{1}$$

Table 1
Microdata counts and geocoding success ratio.

	Total cases	Geocoded cases	Geocoding success ratio (%)
COVID-19 Positive cases	**131,585**	**129,182**	**98.17**
Inside nursing homes	4721	4719	99.96
Outside nursing homes	126,864	124,463	98.11
COVID-19 Deceased persons	**828**	**816**	**98.55**
Inside nursing homes	364	364	100.00
Outside nursing homes	464	452	97.41

Source: Compiled by the author based on the COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

Where:

$\overline{D}_o$ is the observed mean distance between each point and its nearest neighbor.

$\overline{D}_e$ is the expected mean distance for the points in a random distribution.

In our methodology, we require the nearest neighbor measures of observed and expected distances to establish the 3D bin dimensions based on statistical and non-subjective criteria.

The Global Moran's Index (2) considers individual locations with a numeric field of COVID-19 cases, deceased persons, or residents in case of homes and nursing homes. We established a fixed distance parameter relative to the tool of band from neighbor count, by incorporating the maximum and average distance.

$$GMI = \frac{n}{S_0}\,\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{2}$$

Where:

z_i is the deviation of an attribute for point i from its mean value, being the attribute the number of infected, deceased persons or residents.

$w_{i,j}$ is the spatial matrix weight between points i and j.

n is the total number of points.

S_0 is the normalization factor (aggregated spatial weights).

2.3.2. Preliminary identification of statistically significant spatial clusters

In this stage, hot spot analysis tool based on Getis-Ord Gi* (1992) identifies significant spatial clusters of infections and deceased persons. Hot spots are clusters on high values, whereas cold spots are areas with low values. The spatial context is established using a fixed distance band obtained from neighbor count tool, adding maximum and average distances (Table 2). This tool reports six cluster types depending on the confidence level, with three distinct hot and cold spots specified at 99%, 95%, and 90% confidence levels. An additional type of absence of spatial clustering is reported.

2.3.3. Space-time cluster methods to identify problem areas

The third stage analyzed the space-time clusters of COVID-19 deaths according to spatial and temporal trends based on statistics from A. Getis-Ord Gi* (1992) to identify hot spots as areas of spread and Mann-Kendall statistics to determine trends.

Our methodology included creating 3D bins based on previous points of geocoded deaths, and the emerging hot spot analysis. This method needs two parameters defined by users: internal period slides and bin size. We defined 3D bins using a relative time parameter as internal slides over 2-week periods and a constant tiled area of regular 5 km^2 units. Both parameters are based on relative criteria to avoid arbitrary decisions.

The identification of time intervals follows two guidelines. Firstly,

Table 2
Distance band from neighbor count tool.

A. COVID-19 spatial patterns	Maximum distance	Average distance	Fixed distance band
COVID-19 positive cases	4040.35	4.02	4044.37
Deaths	16,898.98	398.77	17,297.75
Deaths inside nursing homes	9939.48	136.46	10,075.94
Deaths outside nursing homes	16,898.98	797.05	17,696.03
B. Home patterns	Maximum distance	Average distance	Fixed distance band
Residential homes	2589.73	40.45	2630.18
Nursing homes	20,764.86	4108.39	24,873.25

Source: Authors own elaboration based on the COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

the creation tool for 3D bins requires at least ten-time intervals. Secondly, prior studies suggest the importance of defining a relative temporal parameter customized to specific illnesses or viruses in the field of health geography (De Cos et al., 2021b). In this regard, during the COVID-19 pandemic a commonly used period for monitoring incidence was through 2-week intervals.

The 5 km^2 bin size was determined using nearest neighbor distance parameters for COVID-19 deceased individuals/outside nursing homes. We calculated a weighted average distance of 2306.39 m by considering the observed and expected distances of deceased persons outside nursing homes (2513.52 m) and inside nursing homes (2049.19 m). Therefore, the distance of 2306.39 m corresponds to a square area of 5.32 km^2, rounded to 5 km^2 for each bin.

By taking the cumulative number of COVID-19 deaths recorded in each bin over time into account, the resulting analysis provided a maximum of 16 types of significant patterns (8 cold spots, and 8 hot spots) and 1 non-significant type (no pattern detected). Only hot spots were interpreted as significant problem areas, due to significant hot trends in COVID-19 deaths.

2.3.4. Analysis of COVID-19 deaths with context variables

The final stage included different methods to find relationships between COVID-19 deaths and other explanatory variables of the context. Firstly, we analyzed local bivariate relationships, as a useful exploratory approach to identify spatial patterns of mortality in terms of different types of relationships (not necessarily linear) and different spatial behaviors, even in the case of non-stationarity. Then, we used ordinary least square (OLS) analysis to analyze links between COVID-19 deaths and context variables, based on generalized linear regression (Nelder & Wedderburn, 1972). OLS reported key statistics, such as a Koenker index based on the work of T.S. Breusch and A.R. Pagan (1979) to measure non-stationarity (if $p > 0.010$ at a confidence level of 99%), and to identify significant and non-redundant context variables. Furthermore, OLS reported the standard deviation of residuals in a hypothetical prediction model using contextual variables.

3. Results

3.1. Individual characteristics of COVID-19 deceased persons

According to Health authorities, the Region of Cantabria recorded 828 COVID-19 deaths from the beginning of the pandemic to March 31, 2022. We analyzed three main individual characteristics of COVID-19 deceased persons: age, sex, and type of home (inside/outside nursing homes).

As shown in Table 3, there were 364 deaths, i.e., 43.96%, inside nursing homes –a very high proportion– and 464 deaths outside nursing homes, i.e., 56.04%. The main statistics showed some differences in the COVID-19 mortality profiles inside/outside nursing homes, such as a higher age range and a temporal concentration of deaths in nursing homes. In fact, the average age of deceased persons in nursing homes was 6 years higher (86.93 versus 80.91) and the standard deviation for age showed greater disparities outside nursing homes (11.11 versus 8.87 in nursing homes). In terms of temporal concentration, nursing homes had 194 days with deaths reported (25.49% of days), i.e., 1.88 deaths per day, while there were more days with deaths reported (278 days, i.e., 36.53% of days) outside nursing homes, but with a lower number of deaths per day (1.67 on average).

A cross-tabulation of home type with demographic characteristics yielded interesting results. As shown in Table 4, the COVID-19 spread showed more positive cases in women than in men, not only outside nursing homes, with 52.48%, but also in them, with 54.40%, which can be attributed to the more abundant cohort of elderly women due to longer life expectancy. Nevertheless, the COVID-19 mortality profile outside nursing homes was clearly higher for males, representing

Table 4
Cross-tabulation showing positive cases and deaths by age group and sex inside/outside nursing homes in the region of Cantabria between March 1, 2020 and March 31, 2022.

A. Outside nursing homes						
COVID-19 positive cases	Total		<70 years old		≥70 years old	
	Nº	%	Nº	%	Nº	%
Men	60,288	47.52	55,637	92.29	4651	7.71
Women	66,576	52.48	61,109	91.79	5467	8.21
Total	126,864	100.00	116,746	92.02	10,118	7.98
Sex ratio	90.56		91.05		85.07	
Covid19 deaths	**Total**		**<70 years old**		**> = 70 years old**	
	Nº	%	Nº	%	Nº	%
Men	258	56.60	41	15.89	217	84.11
Women	206	44.40	30	14.56	176	85.44
Total	464	100.00	71	15.30	393	84.70
Sex ratio	125.24		136.67		123.30	
COVID-19 mortality rates*	**Total**		**<70 years old**		**> = 70 years old**	
Men	4.28		0.74		46.66	
Women	3.09		0.49		32.19	
Overall	3.66		0.61		38.84	
B. In nursing homes						
COVID-19 positive cases	**Total**		**<70 years old**		**>=70 years old**	
	Nº	**%**	**Nº**	**%**	**Nº**	**%**
Men	1611	34.13	465	28.86	1146	71.14
Women	3109	65.87	348	11.19	2761	88.81
Total	4720	100.00	813	17.22	3907	82.78
Sex ratio	51.82		133.62		41.51	
COVID-19 deaths	**Total**		**<70 years old**		**>=70 years old**	
	Nº	**%**	**Nº**	**%**	**Nº**	**%**
Men	166	45.60	11	6.63	155	93.37
Women	198	54.40	5	2.53	193	97.47
Total	364	100.00	16	4.40	348	95.60
Sex ratio	83.84		220.00		80.31	
COVID-19 mortality rates*	**Total**		**<70 years old**		**>=70 years old**	
Men	103.04		23.66		135.25	
Women	63.69		14.37		69.90	
Overall	77.12		19.68		89.07	

Note: *COVID-19 deaths per 1000 positive cases.
Source: Authors own elaboration based on based on COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

Table 3
Main statistics of COVID-19 deaths by type of home. Region of Cantabria, from March 1, 2020 to March 31, 2022.

	COVID-19 deaths		Days with deaths reported		Average deaths per day**	Age of deceased persons	
	Total	%	Total	%*		Average	Standard deviation
Outside nursing homes	464	56.04	278	36.53	1.67	80.91	11.11
Inside nursing homes	364	43.96	194	25.49	1.88	86.93	8.87
Total	828	100.00	354	46.52	2.34	83.55	10.61

Notes: * Percentage with respect to the overall period (761 days). ** Ratio with respect to the number of days with deaths reported.
Source: Compiled by the author based on the COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

56.60% of deaths.

Age was another key factor in relation to mortality, but here it is necessary to differentiate between types of homes. Fatality rates by age, sex, and type of homes demonstrated the vulnerability of elderly male residents in nursing homes to the severity of COVID-19. Men up to the age of 70 living in nursing homes had a mortality rate of 135.25 per 1000 positive cases, in contrast to the mortality rate for women with same conditions by type of home and age group.

Similarly, outside nursing homes, the COVID-19 mortality rate in men was higher than in women (4.28 deaths per 1000 cases vs. 3.09), although we noted that the values dropped dramatically in comparison with the results for nursing homes, with very high mortality rates (103.04 in men and 63.69 in women).

Although mortality rates were much lower in the under-70 age group, the differentiation by sex demonstrate that fatality rate is always higher in men, in/out nursing homes.

3.2. *Temporal mortality patterns of COVID-19*

The temporalization of COVID-19 mortality was concentrated in three main periods (Fig. 1). Firstly, the most severe period in terms of the number of deaths inside/outside nursing homes was the first wave. Despite the strict lockdown from March to June 2020, and the containment of infections, mortality was high, coinciding with the collapse of hospitals and the difficulties in obtaining protective equipment, such as face masks. The second peak in the number of deaths came in the second wave in summer 2020, after lockdown and during the 'new normal' stage. This continued until Christmas 2020, when new restrictions were implemented by health authorities, such as limiting the number of family members in gatherings. During 2021, mortality was controlled until the rapid spread of the Omicron wave, which was far more transmissible compared to previous waves. The sharp and rapid increase in cases reported led to a new peak in deaths. At this point, immunization was not sufficient to keep the mortality level low in extremely severe cases; however, it did control the number of deaths, bearing in mind the high prevalence of the virus at that time.

The cumulative evolution of COVID-19 deaths was indicative of the high impact of mortality in nursing homes, but, during the evolution of the pandemic, it changed due to vulnerability-prioritized immunization and the protective measures and restrictions implemented in nursing homes. Specifically, we were able to identify a date which marked a turning point at the beginning of March 2021 (Fig. 2), when cumulative mortality outside nursing homes overlapped with mortality in nursing homes.

3.3. *Geographic profile of COVID-19 mortality inside/outside nursing homes*

The nearest neighbor analysis confirmed that the spatial pattern of COVID-19 deaths was statistically significant and showed a clustered distribution (z-score below −2.58), both inside and outside nursing homes (with a z-score of −33.8951 and −21.7860 respectively).

Based on the overall housing pattern, the findings indicate that the COVID-19 cases exhibit a more clustered pattern (z-score of −660.3980) compared to the housing pattern (z-score of −424.0186). The clustering pattern of deceased persons is less pronounced with a z-score of −37.5896. However, when we consider the clustered patterns of deceased persons inside nursing homes, the results demonstrate a more intense clustered pattern compared to deaths outside nursing homes. Additionally, as a reference, the spatial pattern of nursing homes (with a z-score of −1.4242) corresponds to random pattern.

The Global Moran's Index suggests that the spatial distribution of deceased persons shows a random pattern (with z-scores ranging from −1.65 to +1.65 for both inside and outside nursing homes, −0.0029 and −0.0799 respectively – see Table 5), whereas COVID-19 infections exhibit a clustered pattern. As a result, the spatial autocorrelation for COVID-19 infections is more concentrated and significant than that of mortality patterns.

Delving deeper into the geographic distribution of mortality, the hot spot analysis reveals disparities between infections and mortality

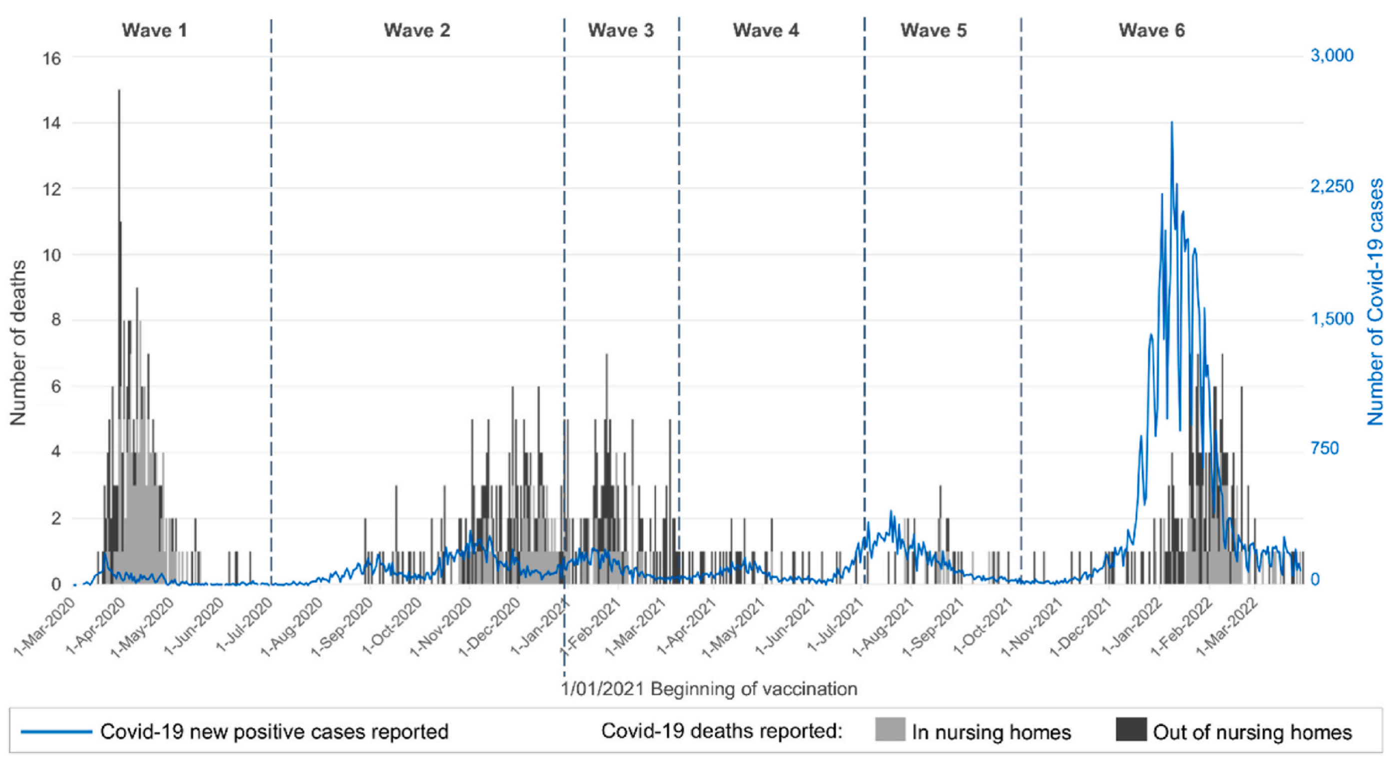

Fig. 1. Evolution of the daily number of COVID-19 cases and deaths by type of home in the region of Cantabria, from March 1, 2020 to March 31, 2022.
Source: Authors own elaboration based on based on COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

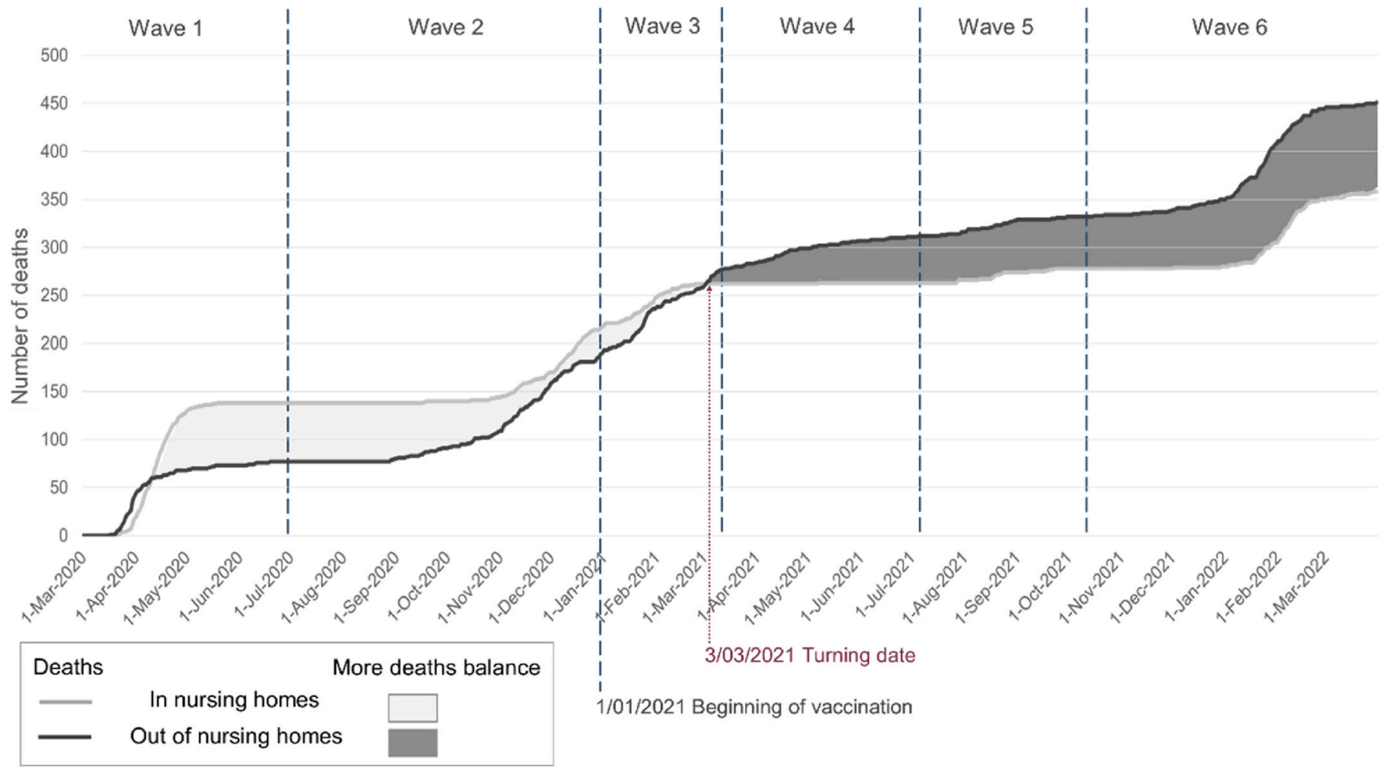

Fig. 2. Cumulative evolution of daily COVID-19 deaths by type of home in the region of Cantabria, from March 1, 2020 to March 31, 2022.
Source: Authors own elaboration based on COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

Table 5
Overall spatial patterns of COVID-19 positive cases and deceased persons in the region of Cantabria, from March 1, 2020 to March 31, 2022.

Nearest neighbor analysis	A. COVID-19 spatial patterns				B. Home patterns	
	Cases	Deceased persons			Homes	Nursing homes
		Total	Outside	Inside		
Observed distance	4.02	398.77	797.05	136.46	40.45	4108.39
Expected distance	101.53	1277.50	1716.47	1912.73	93.11	4526.35
NN Index	0.0396	0.3122	0.4644	0.0713	0.4345	0.9077
z-Score	−660.3980	−37.5896	−21.7860	−33.8951	−424.0186	−1.4242
P value	0.0000	0.0000	0.0000	0.0000	0.0000	0.1544
Pattern	Clustered	Clustered	Clustered	Clustered	Clustered	Random
Random. probability	<1%	<1%	<1%	<1%	<1%	–

Global Moran's Index	A. COVID-19 spatial patterns				B. Home patterns	
		Deceased persons			Homes	Nursing homes
	Cases	Total	Outside	Inside		
GM Index	0.0308	0.0018	−0.0023	−0.0149	0.1168	0.1046
z-Score	38.0684	0.0669	−0.0799	−0.0029	277.8774	0.3039
P value	0.0000	0.9467	0.9363	0.9977	0.0000	0.7612
Pattern	Clustered	Random	Random	Random	Clustered	Random
Random. probability	<1%	–	–	–	<1%	–

Notes: distance values are expressed in meters and outside/inside refers to nursing homes.
Source: Authors own elaboration based on COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

clustering patterns. COVID-19 cases are distributed into both hot and cold spots. Specifically, there are wide hot spots areas in the Santander-Torrelavega FUA and, secondarily, in the eastern coastal area near the metropolitan region of Bilbao in the Basque Country (Fig. 3A).

Nevertheless, there are weaker and less pronounced spatial clusters of mortality than COVID-19 cases. In fact, mortality clusters tend to be limited to highly populated and infected areas, such as the Santander-Torrelavega FUA (Fig. 3B–D). Cold spots of mortality in spatial clusters are infrequent.

Other nuances are important in spatial statistics of clusters. As shown in Table 6A, positive cases of COVID-19 are predominantly located in hotspots, accounting for 71,074 cases with 99% certainty (i.e., 55.02% of 129,180 geocoded cases). Nevertheless, the majority of deceased persons were in areas without statistical significance (Table 6B–D), with 732 deaths occurring outside of clusters, representing 89.71% of the total 816 deceased persons. Of the 364 deaths in nursing homes, 282 occurred in no significant areas, representing 77.47% of cases, with the remaining 82 deaths (i.e., 22.53%) occurring in hot spots.

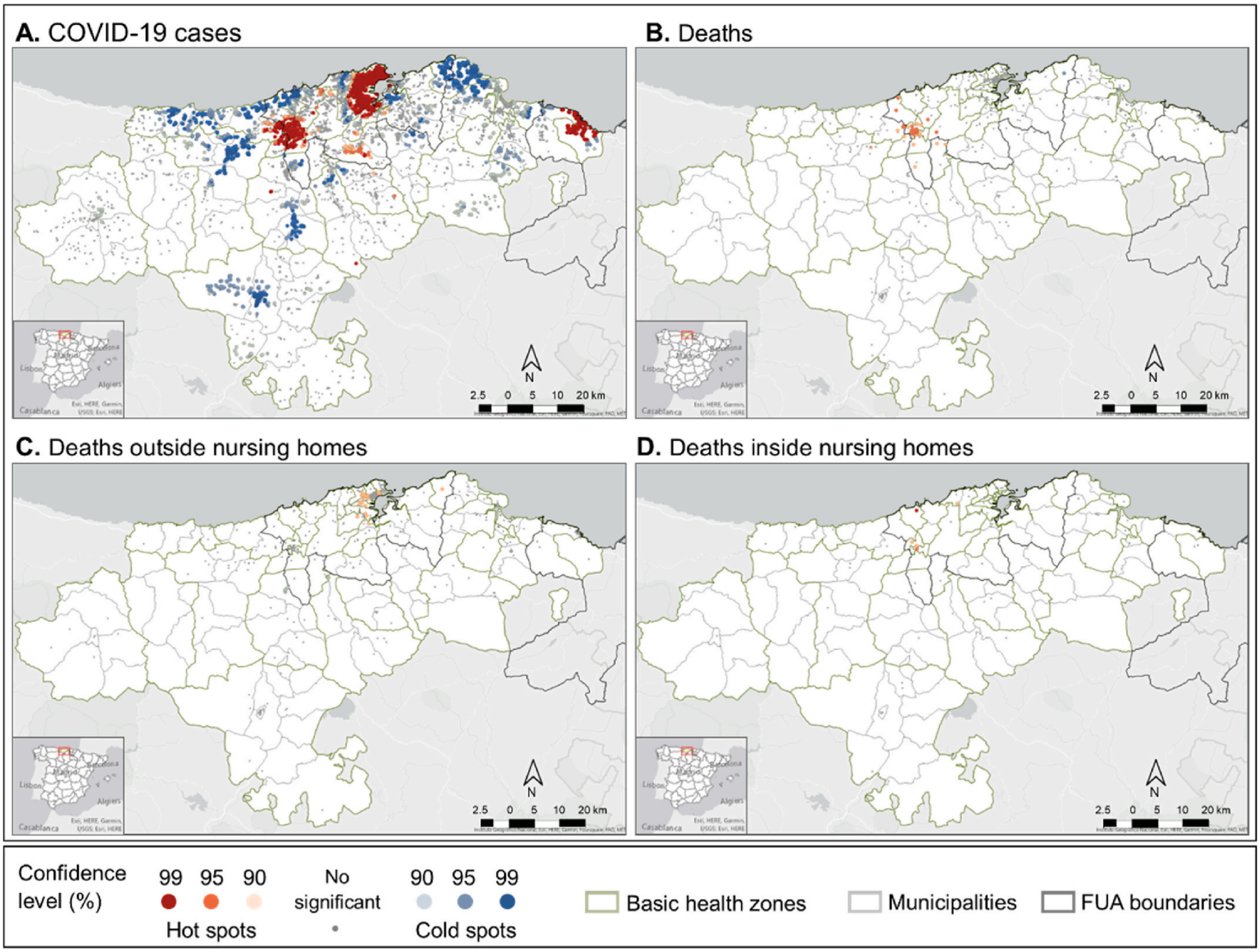

Fig. 3. Distribution of spatial clusters of COVID-19 deaths inside/outside nursing homes in the region of Cantabria, from March 1, 2020 to March 31, 2022.
Source: Authors own elaboration based on data from ESRI (administrative basemap), the Spanish National Geographic Institute (National Cartographic Base 1:200,000 scale), Copernicus FUA boundaries and COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain)

3.4. Space-time approaches for analyzing the behavior of the configuration of problem areas in relation to COVID-19 mortality

From this section, we specifically analyze COVID-19 mortality concerning deaths that occurred outside nursing homes for two main reasons. Firstly, conducting a space-time analysis in nursing homes is not possible based on the spatial statistics of the hot spot (Table 6C-D). There are only 71 locations of nursing homes in the 5326.85 km2 of Cantabria, and only 5 of them were statistically significant. Additionally, the number of nearest neighbors for each significant location ranges only between 6 and 12.

Additionally, mortality data from inside and outside nursing homes should not be combined because the context conditions are not comparable. Nursing homes had stricter management measures during the pandemic than those outside of nursing homes. Moreover, COVID-19 cases and deaths in nursing homes were frequently associated with linked outbreaks, while transmission outside of nursing homes occurred under distinct conditions that are more related to context variables and local spread.

On this basis, 3D bins and emerging hot spots of mortality outside nursing homes showed that most of the locations where deaths occurred were categorized as “No pattern detected” type, i.e., with no statistically increasing or decreasing trend between March 1, 2020 and March 31, 2022 (Fig. 4). By contrast, there were significant trends in the main city, Santander, and nearby area of influence, where the homogeneous “sporadic hot spot” was indicative of an emerging pattern with a significant repetition of deaths over time, i.e., areas that repeatedly appear as hot spots of mortality with no intermediate periods of cold spots.

“No pattern detected” bins represented 88.13% of the area where 63.72% of deaths occurred (2.04 deaths per bin).

Table 7 shows that sporadic hot spots accounted for 36.28% of deaths in only 11.88% of the area with COVID-19 deaths. These areas are understood as “problem areas” as far as COVID-19 mortality is concerned. In fact, sporadic hot spots were significant hot spots during 57.49% of the time considered (i.e., 434 days).

If we organize the study period into two parts based on the date which marked the turning point (March 3, 2021), our results reveal interesting nuances in the geographic profile of COVID-19 mortality. During the first year of the pandemic, including the lockdown period, strict restrictions, and the beginning of vaccination, mortality was only statistically significant in the more densely populated area - Santander and its nearby area of influence (Fig. 5A). Sporadic and oscillating hot spots continued to be hot spots for 58% of the time (Table 8A) and accounted for 34.77% and 5.38% of deaths respectively.

However, after the date which marked the turning point, during the second year of the pandemic there was a spatial expansion of significant

Table 6
Spatial statistics of the hot spot analysis of COVID-19 cases and deaths inside/outside nursing homes in the region of Cantabria, from March 1, 2020 to March 31, 2022.

A. COVID-19 cases

Percentage by certainty	Locations	NN	Cases		Cases per location	Average z-Score
			Total	%		
Cold spot 99%	3846	562.15	12,436	9.63	3.23	−3.4155
Cold spot 95%	1277	406.60	3699	2.86	2.90	−2.2270
Cold spot 90%	1539	486.95	5747	4.45	3.73	−1.7995
No significant	7185	634.57	33,429	25.88	4.65	−0.5388
Hot spot 90%	231	937.57	1258	0.97	5.45	1.8071
Hot spot 95%	322	1285.64	1538	1.19	4.78	2.2568
Hot spot 99%	11,222	3754.41	71,074	55.02	6.33	7.4293

B. Deceased persons

Percentage by certainty	Locations	NN	Deaths		Deaths per location	Average z-Score
			Total	%		
Cold spot 95%	1	167.00	1	0.12	1.00	−2.0101
No significant	444	141.76	732	89.71	1.65	−0.2320
Hot spot 90%	17	121.12	51	6.25	3.00	1.7911
Hot spot 95%	29	119.38	32	3.92	1.10	2.0739

C. Outside nursing homes

Percentage by certainty	Locations	NN	Deaths		Deaths per location	Average z-Score
			Total	%		
Cold spot 90%	8	89.25	8	1.77	1.00	−1.7811
No significant	389	124.88	406	89.82	1.04	0.2074
Hot spot 90%	34	201.62	38	8.41	1.12	1.7942

D. In nursing homes

Percentage by certainty	Locations	NN	Deaths		Deaths per location	Average z-Score
			Total	%		
No significant	66	11.74	282	77.47	4.27	−0.2130
Hot spot 90%	3	12.00	17	4.67	5.67	1.8349
Hot spot 95%	1	10.00	35	9.62	35.00	1.9642
Hot spot 99%	1	6.00	30	8.24	30.00	3.5389

Notes: NN represents the mean number of nearest neighbors. Location denotes the specific point where cases or deaths have been recorded. Each location, assigned by a street number, has an associated attribute of A for cases and B, C, or D for deaths. In cases where nursing homes are involved, the location refers to the address of the facility.
Source: Authors own elaboration based on COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

patterns in the dynamic metropolitan FUA of Santander, including the high mobility Santander-Torrelavega corridor, such as consecutive hot spots (Fig. 5B), i.e., areas where there had been significant hot spots previously (Omicron variant, sixth wave). These consecutive hot spots accounted for 51.45% of COVID-19 deaths in only 37.50% of the area and were hot spots for 20.51% of time considered (Table 8B).

Surprisingly, no cold spots were detected in any analysis. The results were generally 'no pattern detected', except in dynamic urban areas, where there were hot spots.

Therefore, lockdown and strict restrictions revealed the spatial concentration of problem areas in terms of mortality, while during the second year, with the relaxation of restrictions and the spread of the Omicron wave, there was an expansion of problem areas of COVID-19 mortality, as consecutive hot spots occupied 37.50% of the area where 51.45% of deaths were concentrated.

3.5. Context variables as drivers of COVID-19 mortality in urban areas

Contextual variables were considered in addition to the individual characteristics of deceased persons, in areas with the highest concentration of deaths, such as the FUA of Santander. We analyzed data on population origin, income, size of household, property and rental prices, and expenditure, among others.

When we explored local bivariate relationships at bin level, our results revealed positive linear relationships with some context variables, such as number of COVID-19 cases outside nursing homes, and the average age of infected people outside nursing homes, among others. We obtained interesting spatial profiles of mortality in the case of the number of COVID-19 cases as an explanatory variable, with a clear positive relationship with mortality in Santander and its area of influence (Fig. 6A), while the relationship becomes convex in the case of Torrelavega and its periphery and the industrial north-south corridor. The spatial relationship with average age of infected people is clearer. As shown in Fig. 6B, in an overall context of non-significant relationships, there is a clear positively related pattern in the densely populated area of Santander and its outskirts. Some of the reasons are related to the ageing process in the center of Santander and metropolitan processes in the area of influence, where traditional elderly people coexist with the peri-urban adults and young people who live there, but who are normally linked to the center of Santander due to work or studies, among others.

The broader context analysis confirmed the local exploratory results and highlighted new variables in the spatial mortality model, which differed from the contagion model. The Koenker statistic (BP) from ordinary least squares (OLS) reported that the BP was not statistically relevant ($p > 0.010$) in COVID-19 deaths or infections, with p being 0.0819 and 0.9992 respectively (Table 9). Consequently, the COVID-19 spatial distribution of deaths and infections was spatially stationary.

According to our results, the spatial pattern of mortality was related to other variables, but to a lesser extent than the pattern of infections. In fact, the measures of model fit or performance, mainly the R multiple square, showed that the OLS model of deaths explained 87.52% of the deaths, while the OLS for infections explained 92.89% of the infections. In both cases, the adaptation of the model was acceptable.

As shown in Fig. 7A, there were differences in the explanatory

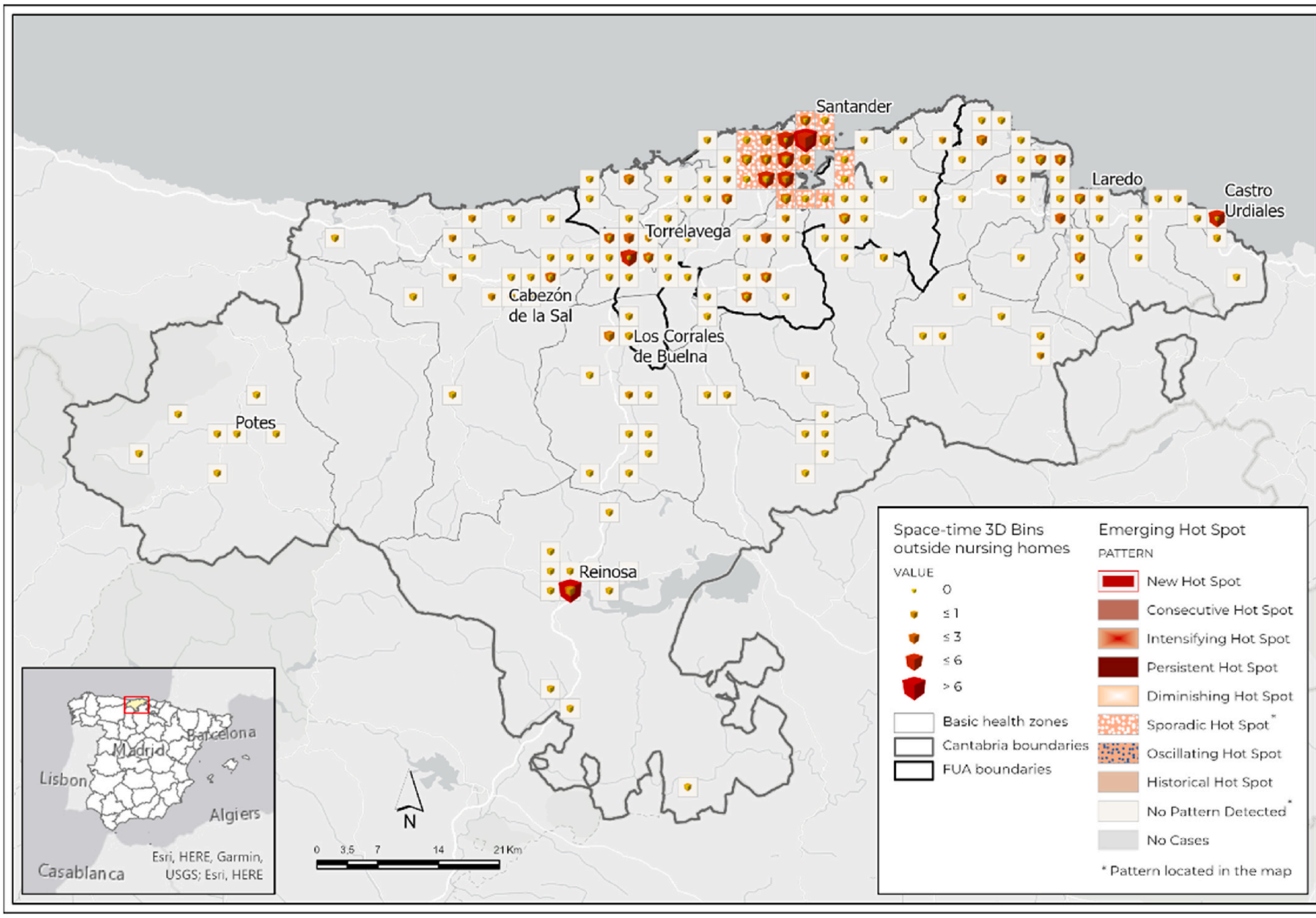

Fig. 4. Distribution of cluster outliers of COVID-19 deaths outside nursing homes in the region of Cantabria, from March 1, 2020 to March 31, 2022.
Source: Authors own elaboration based on data from ESRI (administrative basemap), the Spanish National Geographic Institute (National Cartographic Base 1:200), Copernicus FUA boundaries and COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain)

Table 7
Emerging hot spot types of COVID-19 deaths outside nursing homes in the region of Cantabria, from March 1, 2020 to March 31, 2022.

Type	3D Bins	Deaths			Average % time		Area	
		Total	%	Ratio per bin	Hot spot	Cold spot	km^2	%
No Pattern Detected	141	288	63.72	2.04	2.78	0.00	717.62	88.13
Sporadic Hot Spot	19	164	36.28	8.63	57.49	0.00	96.70	11.88
Total	160	452	100.00	2.83	30.14	0.00	814.33	100.00

Source: Authors own elaboration based on COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

variables for COVID-19 deaths vs. COVID-19 cases. Deaths outside nursing homes were significant and positively related to the number of COVID-19 cases outside nursing homes, the average age of infected people, and some of the expenditure variables, such as spending on alcoholic drinks and tobacco. Meanwhile, the number of cases was closely and positively related to population density, and the percentage of the population born in other countries, and negatively correlated to the average spending per household per year.

Estimating a predictive model of COVID-19 deaths on a detailed scale was beyond our research goals, but the exploratory OLS results were substantial in that regard, in line with the standard deviation residuals. The FUA maps of Santander in Fig. 7B demonstrated that the predictive model of cases was more significant for COVID-19 cases than for COVID-19 deaths. There were many areas on the COVID-19 death map with actual values higher (red) and lower (blue) than predicted, even in nearby pixels and without a clear spatial pattern. Meanwhile, the COVID-19 case map showed a prediction closer to the actual values (yellow) and certain relevant spatial patterns. For example, results similar to those predicted showed clear patterns in the main city, Santander (yellow), and an overcount of cases in the metropolitan area which had a high level of commuting.

4. Discussion

Geodemographic research on COVID-19 deaths had to differentiate individual characteristics related to type of home, i.e., deaths inside/outside nursing homes, similar to other research focused on COVID-19 mortality in institutions (Alves et al., 2021). Age was another key factor in relation to mortality, but differences inside/outside nursing homes were important. The profile with the highest fatality rate was comprised of men over 70 who lived in nursing homes, although overall the mortality rate for men was always higher than for women. Our results are

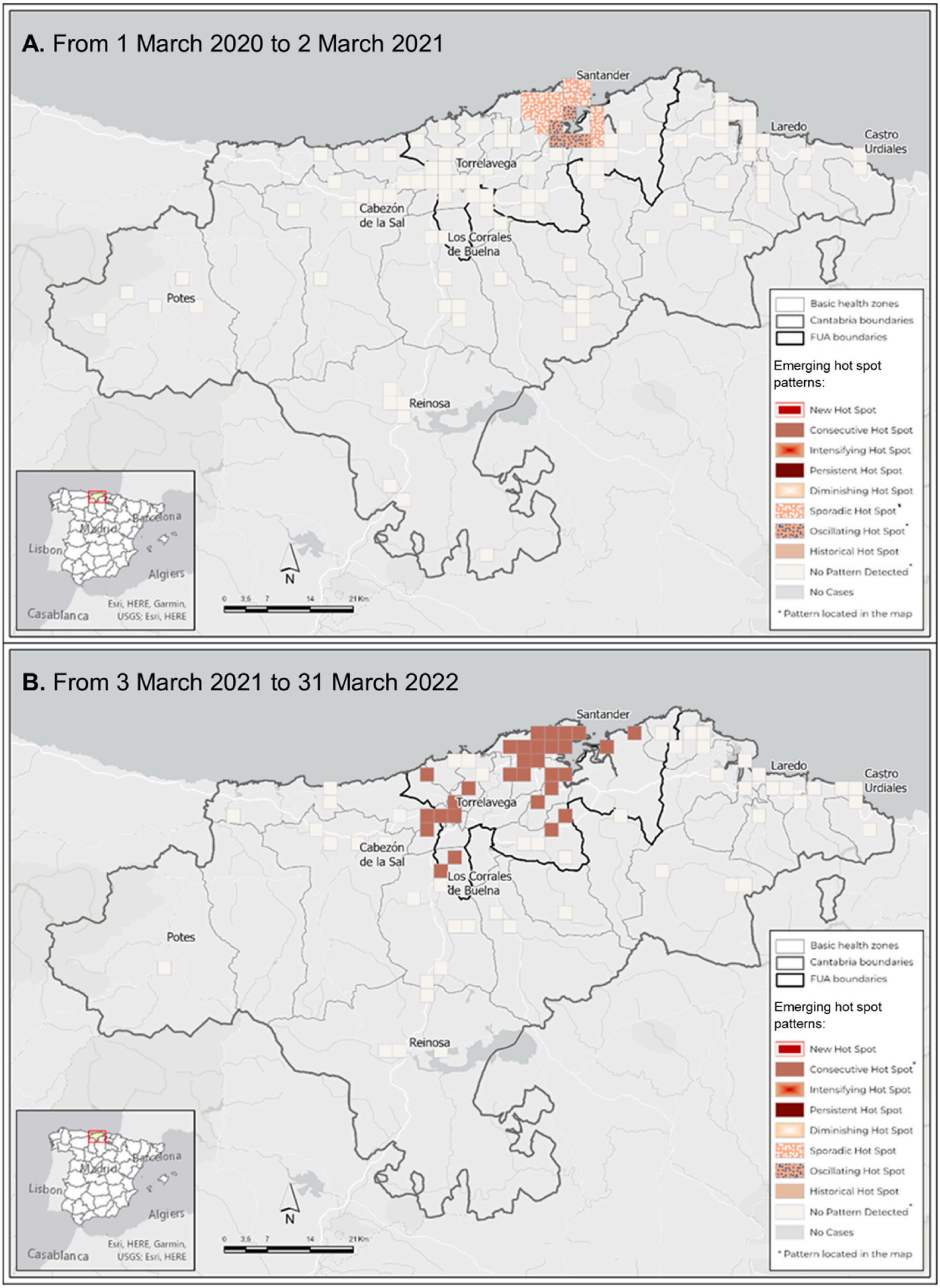

Fig. 5. Distribution of cluster outliers of COVID-19 deaths outside nursing homes by periods in the region of Cantabria, from March 1, 2020 to March 31, 2022. Source: Authors own elaboration based on data from ESRI (administrative basemap), the Spanish National Geographic Institute (National Cartographic Base 1:200), Copernicus FUA boundaries and COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain)

Table 8
Emerging hot spot types of COVID-19 deaths outside nursing homes by periods in the region of Cantabria, from March 1, 2020 to March 31, 2022.

A. From March 1, 2020 to March 2, 2021

Pattern Type	3D Bins	Deaths			Average % time		Area	
		Total	%	Ratio per bin	Hot spot	Cold spot	km^2	%
No Pattern Detected	96	167	59.86	1.74	3.91	0.00	488.60	83.48
Oscillating Hot Spot	5	15	5.38	3.00	58.33	8.33	25.45	4.35
Sporadic Hot Spot	14	97	34.77	6.93	59.52	0.00	71.25	12.17
Total	115	279	100.00	2.43	40.59	2.78	585.30	100.00

B. From March 3, 2020 to March 31, 2022

Pattern Type	3D Bins	Deaths			Average % time		Area	
		Total	%	Ratio per bin	Hot spot	Cold spot	km^2	%
No Pattern Detected	50	84	48.55	1.68	1.85	0.00	254.48	62.50
Consecutive Hot Spot	30	89	51.45	2.97	20.51	0.00	152.69	37.50
Total	80	173	100.00	2.16	1.85	0.00	407.16	100.00

Source: Authors own elaboration based on COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

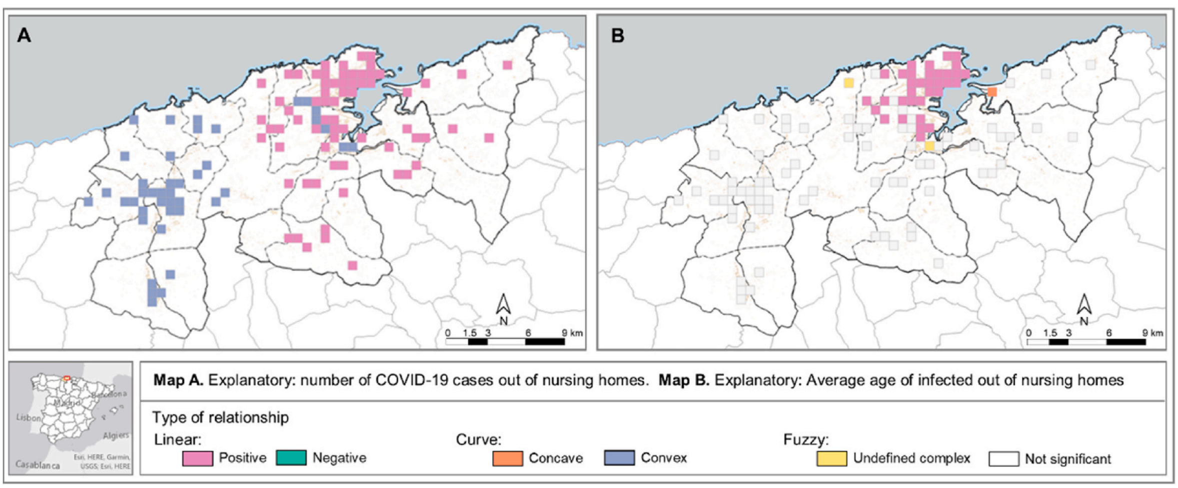

Fig. 6. Local bivariate relationships with the number of COVID-19 deaths outside nursing homes as the dependent variable in the FUA of Santander, from March 1, 2020 to March 31, 2022.
Source: Authors own elaboration based on data from ESRI (administrative basemap), the Spanish National Geographic Institute (National Cartographic Base 1:200), Copernicus FUA boundaries and COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

Table 9
OLS diagnosis of COVID-19 infections and deaths in the FUA of Santander, from March 1, 2020 to March 31, 2022.

Main OLS model results	OLS Deaths	OLS Infections
Number of locations (3D bins)	110	100
Koenker Statistic (BP)	46.0150	13.2263
BP Probability Chi-squared	0.0819	0.9992
R multiple square	0.8752	0.9289
	Explains 87.52%	Explains 92.89%
R adjusted square	0.8186	0.8980

Source: Authors own elaboration based on COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

consistent with the quantitative study conducted by V.P. Alves et al. (2021) on elderly Italians who resided in institutions or were hospitalized, in which the COVID-19 mortality rose with increasing age.

Our findings revealed several differences between the spatial patterns of COVID-19 mortality and COVID-19 positive cases. Furthermore, there were differences in COVID-19 mortality inside and outside nursing homes, such as a greater temporal concentration in nursing homes, but both environments were related. From a local perspective, research showed that mortality in hospitals was influenced by the nearby context and the overall situation of the virus in high spread scenarios (Asch et al., 2020).

In this regard, the geographic context was important. In our research, the rapid spread of positive cases during the Omicron wave (sixth wave) produced a peak in mortality, despite the high level of immunization of the population (De Cos et al., 2023. Moreover, this mortality peak coincided with relaxation of social distancing containment measures and restrictions on gatherings, at a time when a large part of the population had been vaccinated, reinforcing the approach taken by D. Yu et al. (2023), who posited on the effect of non-pharmaceutical measures. We would point out that, according to Health Ministry data, the vaccination rate in Cantabria was of 80.18%, with complete vaccination at the beginning of the sixth wave in October 2021.

The spatial analysis of COVID-19 mortality was complex. Our spatial analysis demonstrated that the spatial distribution of COVID-19 deaths is both less concentrated and less intense than that of infections (the z-score of deaths reported by the nearest neighbor analysis was −37.5896, whereas the z-score of infections was −660.3980). On the other hand, while infections predominantly occur in statistically significant areas (55.02% in hot spots with 99% certainty), the majority of COVID-19 deaths are in non-significant areas (89.71% of deaths outside nursing homes and 77.47% of deaths in nursing homes). Additionally, OLS model results revealed that context variables explain less proportion of deaths than infections (87.52% vs. 92.89%).

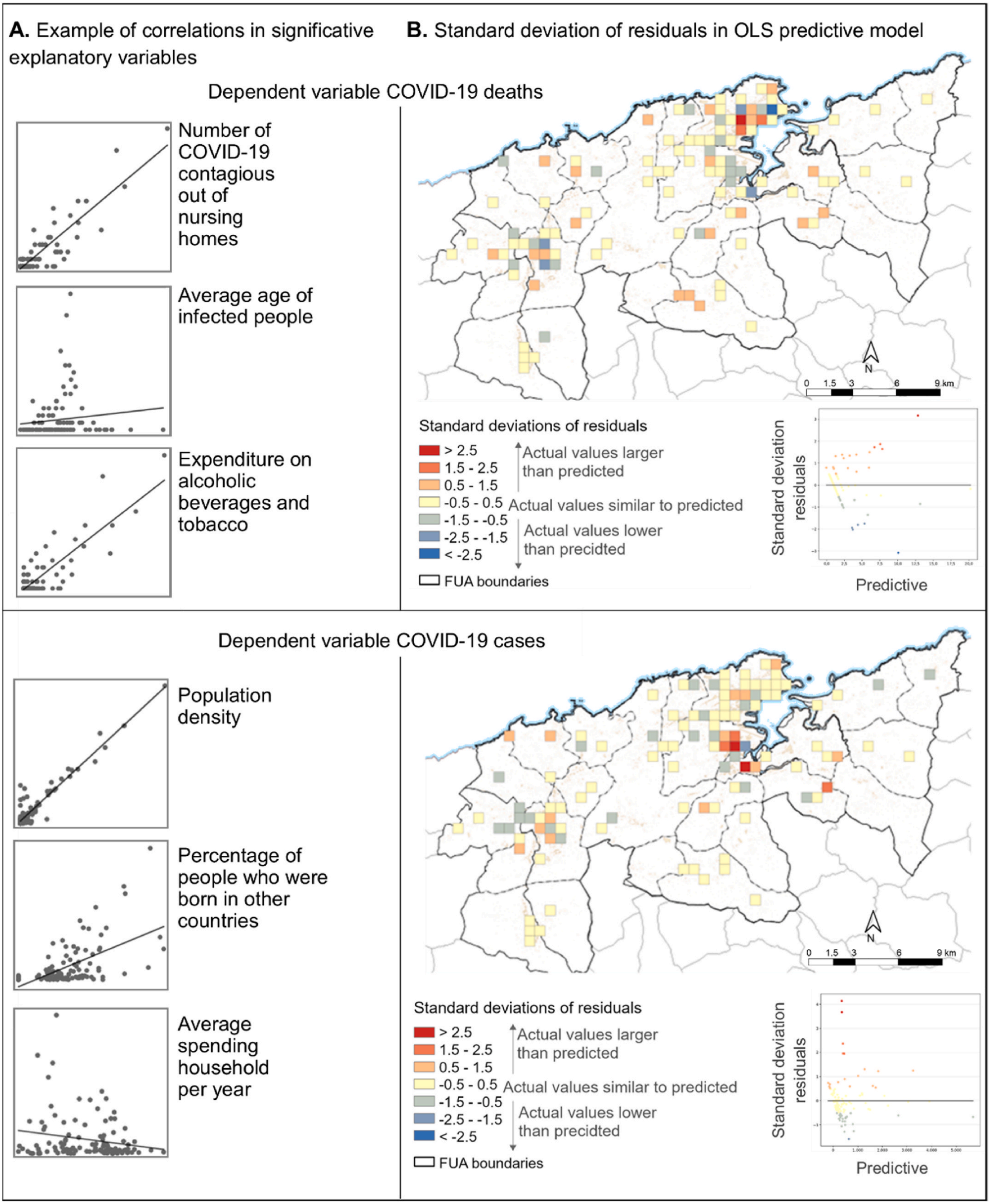

Fig. 7. OLS report on context variables of COVID-19 deaths outside nursing homes and COVID-19 cases in the FUA of Santander, from March 1, 2020 to March 31, 2022.
Source: Authors own elaboration based on COVID-19 Daily Microdata Records from the health authorities (Government of Cantabria, Spain).

Nevertheless, we were able to identify a clear urban-metropolitan character for COVID-19 mortality, similar to other research that highlights the importance of taking spatial regimes into consideration when analyzing mortality, such as metropolitan areas compared to non-metropolitan areas (Grekousis et al., 2022). Indeed, metropolitan areas had a higher mortality rate than micropolitan and rural areas (Karim & Chen, 2021).

Methodologically, our research provides an exportable and scalable proposal and demonstrates the value of using microdata records to define spatial patterns based on the locations where deaths occur, without distortions due to aggregated data. Our research gets around methodological limitations in terms of data aggregation, as Y. Sun et al. (2022) found in their study at a county level, recognizing that many nuances were hidden in counties due to the unavailability of data.

Using this approach, we analyzed specific data on mortality (such as individuals) and designed a methodological approach based on deaths recorded, while other studies have analyzed indirect data, such as excess mortality (Decoster et al., 2021).

We admit that our data may have possible limitations, in the sense that we analyzed officially reported deaths due to the COVID-19 virus. We probably missed out on the perspective of unreported deaths (especially at the start of the pandemic). In the case of Spain, the undercount rate was estimated at 1.5 during the first wave, decreasing to 1.0 during the second wave, due to a more efficient data reporting system (Karlinsky & Kobak, 2021). In addition, we focused on direct deaths, but microdata do not include indirect deaths (Albrecht, 2022).

In accordance with the influence of the social determinants of health (WHO, 2008), our research explores the local context of COVID-19 mortality. Vulnerability to severity and death from COVID-19 was linked to households with lower income households, people not having health insurance, levels of education and ethnicity (Grekousis et al., 2021; Albrecht, 2022; Círio et al., 2022). Furthermore, spatial patterns were not only influenced by a wide range of demographic and socioeconomic characteristics, but also by individual underlying health conditions (Grekousis et al., 2022). Moreover, some research considered the interactive effects between pairs of factors, such as explanatory variables that influenced the spatial distribution of virus cases and deaths (Yue & Hu, 2021).

One of the limitations to our research was that we did not have access to individual health conditions or individual socioeconomic determinants. Therefore, we developed a mixed methodology, based on microdata (individual records) on reported deaths from COVID-19, and analyzed them in the local context (aggregate data by bin).

According to individual health habits, there is scientific evidence that being a smoker and having smoking-related diseases are risk factors for getting severe COVID-19 (Alla et al., 2020), but these data were not available to our research. Further research would be needed in the future, as our OLS analysis showed a significant relationship between COVID-19 mortality and local spending on alcoholic beverages and tobacco. There is scientific evidence that those who take substances and alcohol are more at risk than the general population of suffering complications and worse prognoses with possible morbidity and mortality from the virus (Cattaruzza et al., 2020; Benzano et al., 2021). The situation is aggravated if obesity and alcohol consumption are also combined, reducing immunity, and increasing the propensity for complications and even mortality (Bilal et al., 2020). Nevertheless, our research is limited in the sense that we only found a contextual relationship. Consequently, future research from a health approach would include individual morbidities and consumption habits, so as to get a deeper understanding of individual circumstances and the local context for dealing with the severity of COVID-19.

5. Conclusions

After 2 years of analyzing and learning from the pandemic, spatial patterns of mortality have been thoroughly studied by comparison with deeper and broader geographical research on the spread of positive cases and patterns of contagion. Nevertheless, a spatial analysis of mortality with a multiscale perspective demonstrated the effects of both individually and geographically mixed local factors. Individual characteristics, age and sex were important, but local context was essential according to the contrasting results inside/outside nursing homes and spatial regimes inside/outside urban and metropolitan areas. Research focused on mortality trends demonstrated that, despite the vaccination and immunization process, the increase in infections finally led to peaks in the evolution of deaths.

Therefore, in the new stage of living with COVID-19 as an endemic virus, the spatial approach and geographic methods are the key to helping policymakers take decisions in periods of increased spread. The multiscale perspective and space-time analysis can identify problem areas, such as hot spots, in terms of mortality in real time. Furthermore, our methodological proposal is adaptable and exportable to other areas and periods. Consequently, it represents an opportunity to adapt measures and prioritize surveillance and control strategies based on timely spatial decisions. In this sense, significant hot spots correspond to areas with an increasing trend of COVID-19 deaths in various periods, with a spatially repeating pattern. This fact reinforces the importance of analyzing spatial patterns of deaths not only to understand contextual factors, but also to adapt effective reactive and proactive measures in real time.

Author statement

The authors declare that neither the research nor any parts of its content are currently under consideration. The proposal has never been published in another journal (figures and tables are entirely original and unpublished).

The authors declare that they have approved the reviewed version we submit.

The authors declare that they have no competing interests.

Olga De Cos, on behalf of the authors.

Declaration of competing interest

The authors declare that they have no conflicts of interest.

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