

# Are spatial patterns of Covid-19 changing? Spatiotemporal analysis over four waves in the region of Cantabria, Spain

Olga De Cos Guerra<sup>1,2</sup>  | Valentín Castillo Salcines<sup>1,2</sup>  |  
David Cantarero Prieto<sup>2,3</sup> 

<sup>1</sup>Department of Geography, Urban and Regional Planning, Universidad de Cantabria, Santander, Spain

<sup>2</sup>Research Group on Health Economics and Health Services Management—Marqués de Valdecilla Research Institute (IDIVAL), Santander, Spain

<sup>3</sup>Department of Economics, Universidad de Cantabria, Santander, Spain

## Correspondence

Olga De Cos Guerra, Department of Geography, Urban and Regional Planning, Universidad de Cantabria, Santander 39005, Spain.

Email: [olga.decos@unican.es](mailto:olga.decos@unican.es)

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## Abstract

This research approaches the empirical study of the pandemic from a social science perspective. The main goal is to reveal spatiotemporal changes in Covid-19, at regional scale, using GIS technologies and the emerging three-dimensional bins method. We analyze a case study of the region of Cantabria (northern Spain) based on 29,288 geocoded positive Covid-19 cases in the four waves from the outset in March 2020 to June 2021. Our results suggest three main spatial processes: a reversal in the spatial trend, spreading first followed by contraction in the third and fourth waves; then the reduction of hot spots that represent problematic areas because of high presence of cases and growing trends; and finally, an increase in cold spots. All this generates relevant knowledge to help policy-makers from regional governments to design efficient containment and mitigation strategies. Our research is conducted from a geoprevention perspective, based on the application of targeted measures depending on spatial patterns of Covid-19 in real time. It represents an opportunity to reduce the socioeconomic impact of global containment measures in pandemic management.

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## 1 | INTRODUCTION

GIS and GIScience studies are essential in enabling social sciences in general and health geography in particular (Patel & Patel, 2021) to contribute to analyzing and managing the pandemic, using spatial models and choropleth maps (Juergens, 2020).

A year after the beginning of the Covid-19 pandemic, studies based on location intelligence methods (Gerber, Ping, Armstrong-Brown, McNutt, & Cole, 2009) can, as in other diseases, reveal interesting space-temporal patterns in the behavior of the virus (Cromley, 2019; Gerber et al., 2009). After reviewing more than 200 spatial science papers in 2020, Franch-Pardo, Desjardins, Barea-Navarro, and Cerdà (2021) demonstrate that the use of GIS statistical tools and the analysis of Covid-19 spatial factors are clearly increasing.

This article was authored at a time when Spain, with a population close to 47.5 million, had suffered 3.8 million Covid-19 cases and close to 80,000 deaths in June 2021. This is despite the imposition of a strict lockdown period, of about 2 months, similar to France and Italy, which had a direct effect on the control of incidence rates (Coccia, 2021a). Additionally, according to the Stringency Index from Oxford University, Spain achieved a very high level of stringency based on government measures in schools, social distancing, and mobility restrictions, among others, but a low level of resilience and preparedness indexes, like Italy, Portugal, and France (Coccia, 2021b).

Regarding the management of the pandemic in Spain, it is essential to point out the difficulties due to institutional structure and changes in administrative levels with competences in public health. From the beginning, at national level, two “states of alarm” were declared in Spain. The first, which ran from March 14, 2020 to June 21, 2020, established a strict lockdown of the population and included a transitional period with four levels, from worse to better incidence, called “de-escalation.” The second state of alarm ran from October 25, 2020 to May 9, 2021 and was intended to control the spread of the pandemic during the “new normal” stage (the phase of coexistence with the virus). It included significant rules such as not meeting with non-cohabitants, forbidding the use of the interiors of bars and restaurants, and a curfew from 9 or 10 p.m. During this time, the management of the pandemic changed from the national to the regional level. Spain's 17 regional governments are coordinated via the Inter-territorial Committee at the national level. Another significant milestone in the evolution of the pandemic is the beginning of the vaccination campaign, which was phased in at the national level from December 2020.

In this context, we analyze a case study of the region of Cantabria (northern Spain). Our research is based on daily records of microdata on positive Covid-19 cases 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). The research is framed within the collaboration between the University of Cantabria, the Valdecilla Hospital Research Institute (IDIVAL), and the Department of Health of the Regional Government of Cantabria.

Our goal is to reveal, at the regional scale, the spatiotemporal changes in Covid-19 over the four waves recognized by health authorities, using GIS technologies to model three-dimensional (3D) bins and emerging hot spots. In this regard, we hypothesize that space-time patterns are influenced by frameworks of measures. In fact, regulations affect mobility, as an important factor to control the virus spread. To this end, we address two crucial research questions: (1) identifying the duration of waves; and (2) characterizing the evolution of emerging patterns over waves.

In the diachronic analysis of Covid-19 it is necessary to divide the continuous series of daily microdata into separate periods equivalent to waves. The “wave” concept is commonly used by policy-makers, researchers, and reporters around the world, but in the realm of science there is no official definition. Many indicators are used in the identification and duration of Covid-19 waves: cumulative incidence, deaths, hospitalizations (Vasconcelos et al., 2021), trend changes in infection rates (Lai & Cheong, 2020), the  $R$  number (Zhang, Arroyo-Marioli, & Gao, 2021), and complex methods such as agent-based simulations with sub-epidemic waves (Chowell, Tariq, &

Hyman, 2019) or the multiple-wave forced susceptible–infectious–removed (SIR) model implemented by Kaxiras and Neofotistos (2020) that reveals Covid-19 waves as something other than single waves (with only one peak).

The accumulated knowledge of Covid-19 demonstrates that the pandemic is a complex issue, regardless of the research approach. In the social sciences, from spatial and multiscale perspectives, multiple factors influence the virus spread. The pandemic is closely related to urban and dense population areas (Meer & Mishra, 2021). Factors of connectivity (Hamidi, Sabouri, & Ewing, 2020), mobility, and transportation or even urban design can be identified as factors that facilitate the virus spread, especially in areas with high concentration of jobs, activities, and services (Brizuela, García-Chan, Gutiérrez, & Chowell, 2021; Pérez et al., 2020). Other studies also highlight the role of income, socioeconomic conditions, demographic variables, and vulnerability indexes in relation to the incidence of cases, which is very important at local scale (Baena-Díez, Barroso, Cordeiro-Coelho, Díaz, & Grau, 2020; Jackson et al., 2021).

Furthermore, some variables change their relationship with Covid-19 incidence, depending on scale. One of the most interesting cases in point is the density. This variable is highly correlated with Covid-19 incidence at a national or regional level but, by contrast, density is not the trigger or the main explanatory factor at local and intra-urban scales. The beginning of new outbreaks is related to density at detailed scales, but density is not the driver to explain the virus spread, severity or mortality rates (Carozzi, Provenzano, & Roth, 2020).

Additionally, geo-environmental factors, such as atmospheric conditions, wind speed (Coccia, 2020) and pollution, play a key role in acceleration of Covid-19 spread (Coccia, 2021c). Some studies suggest that chronic exposure to certain air pollutants, such as from urban traffic, might be related to Covid-19 severity and respiratory infections in general (Domingo, Marquès, & Rovira, 2020). Moreover, some research suggests that geo-environmental factors combined with urbanization and density can promote the spread of the virus, as happens in hinterland areas (Coccia, 2021d).

The pandemic has dominated political agendas from the beginning. Taking measures is vital; even more, the strictness and duration of measures is an important factor in stopping the spread of the virus and managing the impact on health systems. Furthermore, it has a serious socioeconomic impact, such as the contraction of gross domestic product (GDP) growth (Coccia, 2021a). Social distancing, restrictions on restaurants and bars, and limitations on tourism have negative effects on the global economy, especially in countries such as Spain where tourism accounts for more than 12% of GDP. Some 500,000 workers in different economic sectors have been subject to temporary measures under the Record of Temporary Employment Regulation (ERTE), a consequence of containment and mitigation strategies to combat the pandemic (Coccia, 2021e).

Given that measures are vital to control the pandemic but have direct socioeconomic consequences on society, this article seeks to help policy-makers to design efficient containment and mitigation strategies from a geoprevention perspective, with targeted measures depending on the spatial hot spot patterns of Covid-19 daily. From a similar perspective, Campagna (2020) defends local custom approaches, similarly to geoprevention leading, as a sensible way of making efficient decisions that improve the balance between the health of the economy and the health of the people.

## 2 | MATERIALS AND METHODS

Our research falls within the framework of GIS cluster methodologies (Al-Ahmadi, Alahmadi, & Al-Zahrani, 2019; Mala & Jat, 2019) and has two main pillars: (1) the anonymous daily microdata records of Covid-19 positive cases from the beginning of the official register to the present; and (2) the geotechnologies included in the Fast Action Territorial Information System (SITAR) implemented by the research team specifically to study the spatial patterns of Covid-19 in the region of Cantabria. The geotechnologies used are ArcGIS Pro and ArcGIS Online (Esri).

## 2.1 | Research setting, sample, and data

The microdata produced by the health authorities of the Regional Government of Cantabria (Spain) are the key data due to their high spatial and temporal resolution (pair coordinates and daily, respectively). The data series began on 1 March 2020 and continues to be updated daily. The anonymized microdata structure is widely explained in previous publications (e.g., De Cos, Castillo, & Cantarero, 2020). For each case the microdata include fields for address, age, sex, and dates of onset and recovery or death. The initial table is geocoded and transformed into a point layer of 29,288 geocoded cases of Covid-19 (excluding homes for the elderly), that correspond to the elementary data of our spatial analysis.

## 2.2 | Measures of variables and accurate definition

We organize the geocoded microdata into waves to distinguish spatiotemporal changes. In Spain and Cantabria health authorities recognize four waves from the beginning of the pandemic until June 2021 (the end of our study). Nevertheless, authorities do not identify precise dates of each wave. Here, we have to point out that we identify continuous waves (without dates of waves). The evolution and trends in Covid-19 waves are studied in many works that consider the seasonality inconclusive and the future evolution of waves as an unpredictable issue in relation to height and duration (Engelbrecht & Scholes, 2021; Zoran et al., 2021).

We therefore measure the duration of waves bearing in mind two variables: (1) 14-day cumulative incidence; and (2)  $R_0$ . Both help us to identify waves without constraints of direct correspondence between the number of waves and number of peaks (Vasconcelos et al., 2021).

In the 14-day cumulative incidence model (cases per 100,000 people) we consider the epidemiologic SIR approach (Kaxiras & Neofotistos, 2020). The incidence SIR is defined with reference to the susceptible population day by day. It is given by:

$$\frac{C(t-14)}{S(t)} \times 100,000 \quad (1)$$

where  $C(t-14)$  is the 14-day cumulative incidence, and, in the denominator, rather than the total population  $N$ , we consider the susceptible population:

$$S(t) = N - [I(t) + D(t) + V(t)] + I_6(t) \quad (2)$$

in which  $I(t)$  is the number infected,  $D(t)$  the number of deaths,  $V(t)$  the number vaccinated, and  $I_6(t)$  the number infected after 6 months. An incidence SIR of 250 is taken as the threshold of extreme risk (wave peaks) by the Inter-territorial Council of the Government of Spain (2020), taking into account relevant studies on Covid-19 immunization (Hansen, Michlmayr, Gubbels, Mølbak, & Ethelberg, 2021).

In the trend in reproduction number  $R_0$  it is important to note whether  $R_0$  above or below 1.0 (Zhang et al., 2021):  $R_0 < 1$  indicates that the spread of the virus is waning, while  $R_0 > 1$  indicates exponential growth (i.e., each positive Covid-19 case is infecting more than one person).

## 2.3 | Data analysis procedure

As Figure 1 shows, the methodology from an overall perspective (from March 2020 to June 2021) is replicated by waves to model the spatial patterns of Covid-19 of each wave.

The methodology consists of four phases as follows:

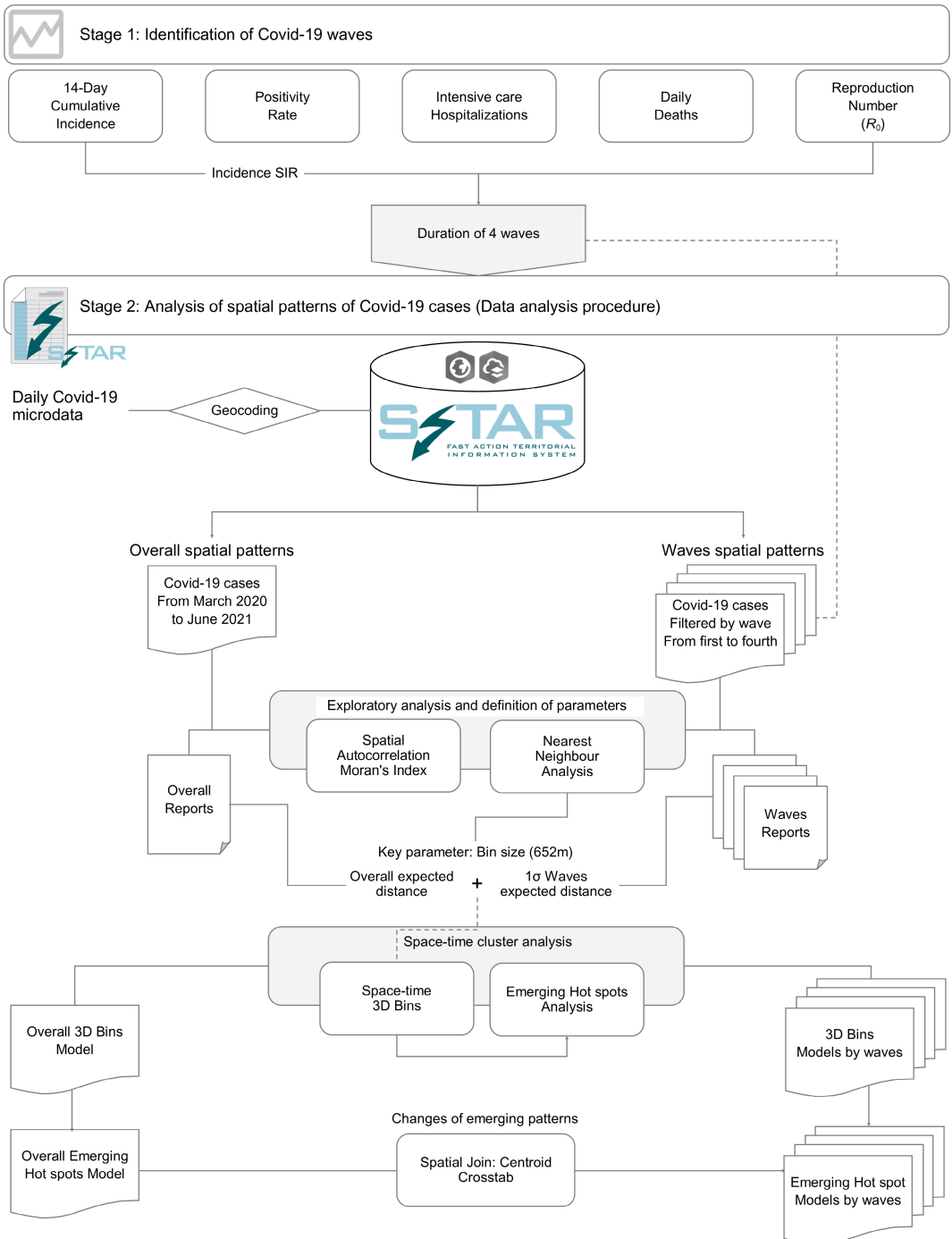


FIGURE 1 Methodological workflow of the research and GIS spatial analysis tools.

### 2.3.1 | Phase 1: Non-randomness check

We check the non-randomness of the distribution to ensure valid results in subsequent GIS analysis. Two widely used methods are applied for this purpose: the global Moran's index and nearest-neighbor analysis. Both these

spatial statistics confirm that the spatial pattern of the geocoded microdata is statistically significant and shows a clustered distribution. The GIS analyses outlined below are thus suitable for their intended purpose.

### 2.3.2 | Phase 2: Creation of 3D bins

This phase marks the beginning of the core of the method to identify Covid-19 trends in space and time. The focus is on creating 3D bins of Covid-19, covering not only overall trends but also changes from one wave to another. These bins include both dimensions of the pandemic: space and time. This method has been applied before in epidemiological studies (Abdrakhmanov et al., 2017; Youlin et al., 2019). Indeed, in the case of Covid-19 there is an interesting reference for the case of cities in China (Chunbao et al., 2020). In light of previous research showing the relevance of 3D bins to the study of Covid-19 spatial patterns (De Cos, Castillo, & Cantarero, 2021), we focus on specific details to ensure that our method can be applied to other case studies. One of the main methodological risks in 3D bin analysis is the definition of space and time parameters, especially in data series covering a long period of time (Kulldorff, 2001). Thus, we use non-subjective criteria and standardized approaches to ensure the “exportability” of our method.

The bin size is determined by the spatial exploratory analysis of the cases themselves in phase 1. Furthermore, the necessary comparability of wave patterns means that the dimension of bins must be constant over time. We thus consider the overall expected distance from nearest-neighbor analysis and its standard deviation of specific waves. The size of bins is the overall expected distance plus 1 standard deviation of the expected distance of waves (i.e., 652 m, so each bin accumulates Covid-19 cases in an area of 0.425104 km<sup>2</sup>).

A minimum of 10 internal time intervals must be ensured because of the requirement of the GIS tool for 3D bin creation. On that basis and considering the difference in duration between the overall period and the period for each wave, we draw up a hypothetical base period using cumulative incidence figures (for 14 and 7 days, respectively), as shown in Table 1.

### 2.3.3 | Phase 3: Emerging hot spots analysis

Using 3D bins, the emerging hot spot analysis (overall and detailed by waves) determines the statistical significance of accumulated cases of Covid-19 from the point of view of space (neighbor distance) and time (in

TABLE 1 Definition of method parameters

Period	Nearest neighbor analysis			Moran's index Z-score <sup>b</sup>	Time (days)	
	Expected distance (m)	Observed distance (m)	Z-score <sup>a</sup>		Duration	Internal 3D bins periods
Wave 1	1,057.26	276.09	-59.13	2.18	135	13 days (11 intervals)
Wave 2	585.37	125.22	-122.26	7.08	160	14 days (12 intervals)
Wave 3	772.92	180.85	-88.41	2.39	75	7 days (11 intervals)
Wave 4	891.60	204.52	-78.25	2.88	97	7 days (14 intervals)
Overall	453.34	84.89	-163.27	9.06	467	28 days (17 intervals)

<sup>a</sup>A nearest-neighbor Z-score less than -2.58 implies a probability of less than 1% that the clustered pattern could be random.

<sup>b</sup>A Moran's index Z-score greater than 2.58 implies a probability of less than 1% that the clustered pattern could be random and a Z-score between 1.96 and 2.58 implies a probability of less than 5%.

Source: Own work based on Covid-19 microdata daily records from the health authorities (Regional Government of Cantabria, Spain).

comparison with previous periods). The emerging analysis gives a maximum of 17 pattern types (1 no pattern, 8 cold spots, and 8 hot spot types) (Esri, 2021). In interpreting the risk in these patterns, we consider that no-pattern areas and cold spots are not problematic, but hot spots are related to the spread and a significant presence of the virus. Five main characteristics are considered in relation to the risk position of each hot spot pattern (Figure A1 in the Appendix):

- “Final time” refers to statistically significant areas in the latest periods (recently).
- “Trend” informs of a progressive presence of the virus.
- “Proportion of time” (>90%) means that some patterns are significant hot spots for at least 90% of the time considered.
- “Temporary cold” is a favorable (less problematic) characteristic that appears in some patterns where there are internal periods of cold spots while the general pattern shows a hot spot.
- “Repetition” refers to areas that show up as significant hot spots many times in the period considered.

### 2.3.4 | Phase 4: Cross-tabulation of emerging patterns

The method concludes with the cross-tabulation of emerging patterns for waves from the overall model to changes in wave types.

Our methodological workflow ensures the absence of conditioning of results by administrative base units, using geocoded microdata. This methodology is scalable from intra-urban to regional level, because the 3D bin size is based on relative spatial statistics (phase 1). It clearly synthesizes spatiotemporal trends, revealing problem areas (as hot spots) that are studied and compared over waves with the final cross-tabulation (phase 4).

## 3 | RESULTS

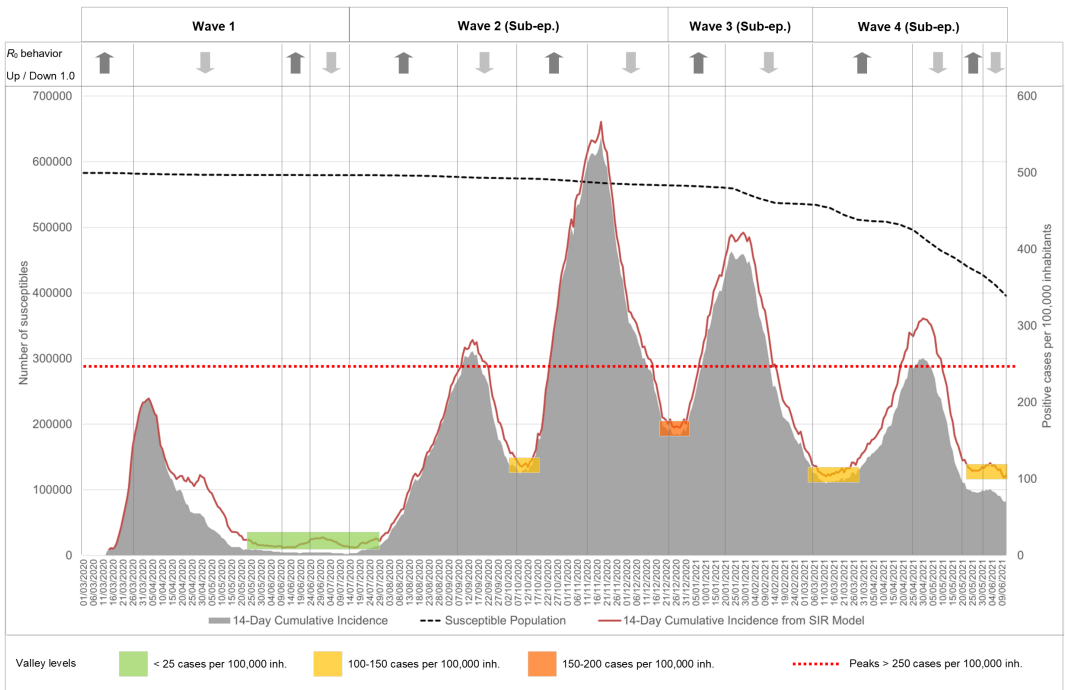
The region of Cantabria is located on the Cantabrian coast in northern Spain. It has a population of 584,308 and a surface area of 5,321 km<sup>2</sup>. Cantabria recorded 31,738 Covid-19 cases and 574 direct deaths in the 467 days of our study from the beginning of the pandemic, from March 2020 to June 2021. During that time many rules and measures were implemented by the national and regional governments that helped to profile the curve.

### 3.1 | Duration of waves and evolution of main variables

Considering the 14-day cumulative incidence (Figure 2) and the positivity rate (Figure A2 in the Appendix), we obtain five peaks and only one clear trough because of the strict lockdown (with 70 days and less than 25 cases per 100,000 people). After that, no more clear troughs are identified. The lag between the official 14-day cumulative incidence (based on total population) and the 14-day cumulative incidence under the SIR approach is interesting. Differences in incidence are smaller in the upward periods than in the downward ones and show progressive differences over time.

Other pandemic data show different shapes:

- The daily admissions to intensive care show a strongly contrasting profile over the lockdown and the long period of the “new normal” stage (more compact and highlighted), coinciding with the second state of alarm to prevent hospitals becoming saturated.



**FIGURE 2** Graphic identification of wave dates in the region of Cantabria, March 2020 to June 2021. *Source:* Own work based on past data on Covid-19 in Cantabria (open data from the Government of Cantabria) and the Epidemiological Situation of Covid-19 in Cantabria dashboard (from ICANE, the Statistical Office of Cantabria)

- The number of deaths per day showed a highly critical trend at the beginning, a second worrying period coinciding with the increase in intensive care hospitalizations, and a final constant trough period from January 2021.
- $R_0$  fluctuates around 1.0.

As Figure 2 shows, we obtain precise dates for the four waves recognized by health authorities of the Government of Cantabria:

- The clearest wave 1 from the beginning to a turning point in  $R_0$  parameter on July 14, 2020. After a wide and deep trough period, a new long period characterized by  $R_0 > 1.0$  begins.
- Wave 2 from the end of wave 1 to December 21, 2020, when the  $R_0$  trend changes after one month in which it is less than 1.0. This wave includes two peaks, but the first one sees more than 250 cases per 100,000 inhabitants for only 14 days and  $R_0$  is under control at that time. Therefore, we agree with the health authorities' understanding of a broad second wave with two peaks.
- After December 21, 2020, coinciding with the Christmas period and severe mobility restrictions, the third wave comprises more than one month of more than 250 cases per 100,000 inhabitants and  $R_0$  constantly below 1.0 in the decreasing period of the wave (with a steep slope) until March 6, 2021, which marks the beginning of the fourth wave, with  $R_0$  above 1.0 and a new peak.

We observe that the wave slopes during increase periods are steeper than in decreasing periods (Table A1 in the Appendix). However, in the last wave they tend to look more alike, with more gradual increasing period (slope 3.96) compared to the first and second waves (slopes 12.28 and 13.70, respectively).



### 3.2 | Spatiotemporal patterns of Covid-19 problem areas

The spatial autocorrelation suggests that waves with more and stricter control measures show a more highly significant cluster pattern than waves with less control. The second wave, when less stringent measures were in force following the strict lockdown, shows a global Moran's index probability of less than 5% that the pattern could be random, compared to a probability of less than 1% in the first wave (lockdown), as in the third (with strict restrictions for Christmas 2020).

The 3D bins model shows 1,559 bins with interesting disparities between urbanized coastal/rural inland and east/west areas (Figure 3a). There is a higher concentration in the central coastal area, where the main cities are located (Santander, the regional capital, and the second largest city of Torrelavega). Both cities are included in the functional urban area (FUA) identified at European level as a dynamic and polynuclear metropolitan area where about 350,000 people live. Our model also shows differences between the western and eastern coastal areas. It must be clarified that the eastern coastal area is more urbanized (near Bilbao, with a metropolitan area over 1 million inhabitants). In the inland areas the biggest bins are located exceptionally in service hubs that concentrate economic activities and essential services for rural areas (Table 2).

The emerging hot spots reveal four main problem areas (Figure 3b): two in the Santander FUA, one in the eastern coastal area close to Bilbao, and the last inland, around a rural service hub in the south.

For about 80% of the 1,559 bins the result is "no pattern detected." There are cases during the period, but their spatiotemporal trend is not statistically significant (Table 3). Average ratios of cases per bins reveal that "no pattern" bins have only 9.9 cases, while significant areas reach 54.5 cases per bin.

Although there are 16 possible significant patterns (eight cold spots and eight hot spots, as shown in Figure A1) our results show only four of them. They are mostly hot spots, though 1.92% of the bins considered show cold spots.

We highlight the repetition behavior in some areas that show up as hot spots several times over the period considered:

- Sporadic hot spots (6.35% of bins and 31.81% of cases). This pattern is concentrated in Santander (city center and consolidated periphery).
- Oscillating hot spots (8.21% of bins and 17.79% of cases). These hot spots are mainly in periurban and influence areas.

On the other hand, in the eastern area consecutive hot spots stand out (representative hot spots at final time of period considered).

### 3.3 | Spatiotemporal changes of Covid-19 problem areas over waves

The most intense wave is the second, with 27.18 cases per square kilometer. It comprised 14,166 cases, 48.37% of the total, coinciding with the "new normal" stage. By contrast, the first wave, with its very restrictive measures, was the smallest, with a density of 9.59 cases per square kilometer, as shown in Table 4. Additionally, we detect a gradual decrease in the third and fourth waves.

Focusing on changes in spatial patterns over waves, we obtain the following results:

- An increase in bin sizes (i.e., number of cases in each bin). The first wave has many small bins (83.54% have under five cases), while in the subsequent waves small bins dropped to about 65–70% and larger bins became more significant.

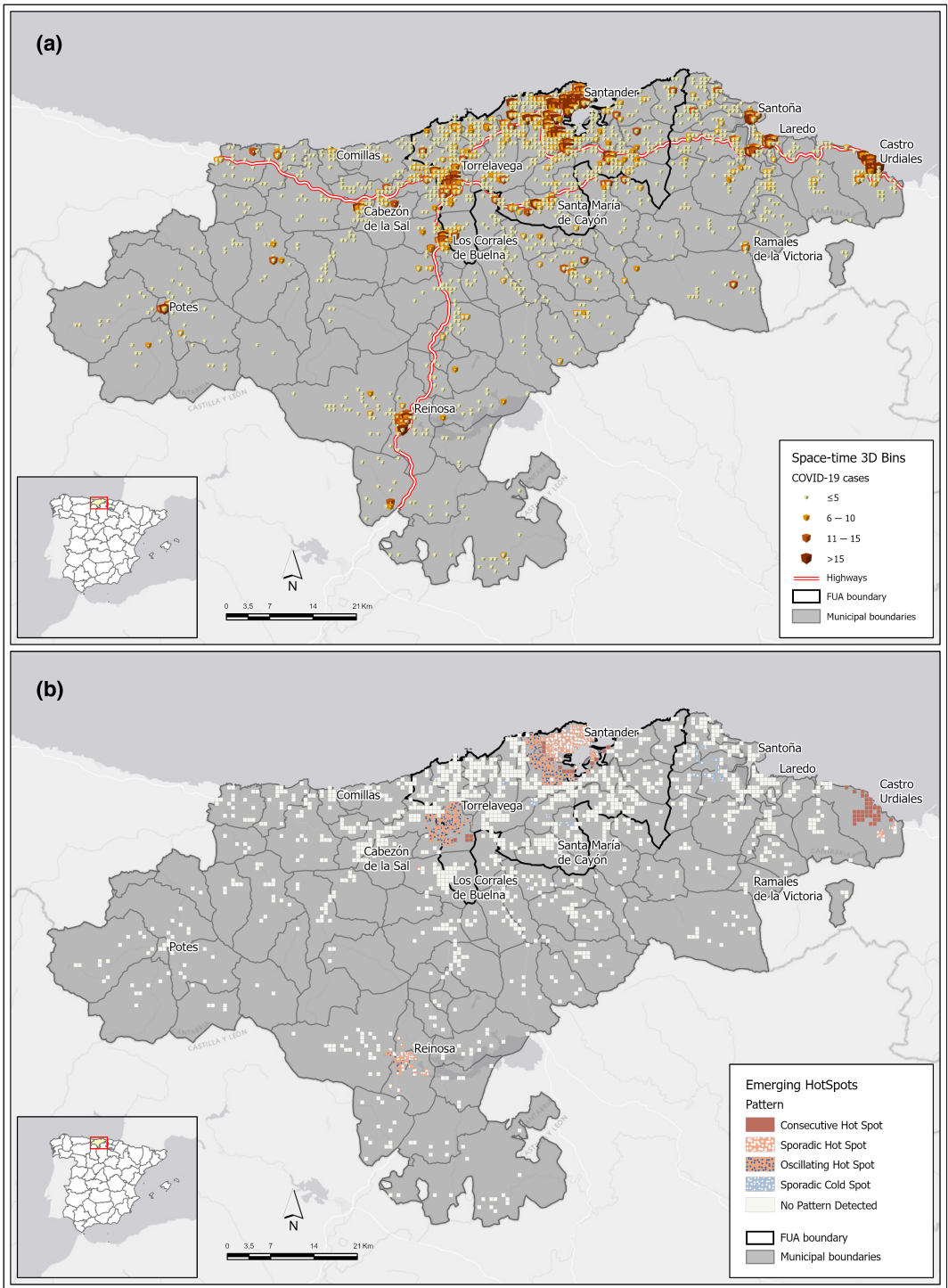


FIGURE 3 (a) Overall model 3D bins; and (b) emerging hot spots, region of Cantabria, March 1, 2020 to June 10, 2021. Source: Own work based on administrative base map (Esri), National Geographic Institute (National Cartographic Base 200), Copernicus FUA layer and Covid-19 microdata daily records from health authorities (Government of Cantabria, Spain)

TABLE 2 Dimension of waves in main pandemic variables in the region of Cantabria from March 2020 to June 2021

	Wave 1	Wave 2	Wave 3	Wave 4
Beginning	1/03/2020 <sup>a</sup>	14/07/2020	21/12/2020	6/03/2021
End	13/07/2020	20/12/2020	5/03/2021	10/06/2021 <sup>a</sup>
Days	135	160	75	97
Total cases	3,116	15,180	7,816	5,626
Average cases per day	23	95	104	58
Geocoded cases <sup>b</sup>	3,073	14,850	7,681	5,519
Geocoded cases out of homes for the elderly <sup>c</sup>	2,303	14,166	7,344	5,475

<sup>a</sup>Date conditioned by beginning/end of data series. The first wave may have started before the data are recorded and the fourth wave may continue after the end date of this study.

<sup>b</sup>Some registered cases have no address in the region of Cantabria. These cases are omitted from the geocoded layer. Out of a total of 31,738 cases, there are 31,123 geocoded cases in the Cantabria area.

<sup>c</sup>One peculiarity of the pandemic is the high incidence in homes for the elderly in Spain. However, previous research demonstrates that spatial patterns are disturbed (with less statistical significance) if cases in these residential centers are considered (De Cos et al., 2021). Our spatial analysis is thus based on cases not found in homes for the elderly, and we analyze the distribution of 29,288 such geocoded Covid-19 cases.

Source: Own work based on past data on Covid-19 in Cantabria (open data from the Government of Cantabria) and the Epidemiological Situation of Covid-19 in Cantabria dashboard (from ICANE, the Statistical Office of Cantabria).

TABLE 3 Results of analysis of emerging hot spots, region of Cantabria, March 1, 2020 to June 10, 2021

Pattern type	Bins		Cases	
	No.	%	No.	%
No pattern detected	1,250	80.18	12,457	42.53
Oscillating hot spot	128	8.21	5,210	17.79
Sporadic hot spot	99	6.35	9,316	31.81
Consecutive hot spot	52	3.34	2,099	7.17
Sporadic cold spot	30	1.92	206	0.70
Total	1,559	100.00	29,288	100.00

Source: Own work based on Covid-19 microdata daily records from health authorities (Government of Cantabria, Spain).

- A reversal of the spatial trend, from spread to contraction. The high spread observed in the second wave is followed by a spatial contraction in the third and fourth waves. This can be seen in the number of bins (1226, 888, and 739 in the fourth) and in the ratio of cases per bin (Table A2 in the Appendix).
- A decrease in problematic areas from the third wave on, due to the increase of “no pattern” and cold spots.
  - The hot spots of the first wave were radically disrupted, coinciding with the rules of lockdown and the first state of alarm (87.26% of bins and 92.88% of cases are classed as “no pattern”), in contrast to the remainder of the waves (Figure 4a). The second wave stands out (coinciding with the relaxing of measures), as only 29.36% of cases correspond to “no pattern” bins. This proportion increases in the third and fourth waves, coinciding with strict social distancing measures to stop the spread before New Year and Easter, respectively.
  - An increase in cold spots from the third wave on. The second wave shows no cold spots, but 70.64% of the cases are in hot spots with a repetition pattern over time and spatially focused on the Santander FUA, the eastern coastal area, and the inland service hub in the south of the region (Figure 4b). The third and fourth

TABLE 4 Results for 3D bins by waves and bin size, region of Cantabria, March 1, 2020 to June 10, 2021

Bin sizes by cases	Wave 1		Wave 2		Wave 3		Wave 4		Overall	
	Bins	Cases	Bins	Cases	Bins	Cases	Bins	Cases	Bins	Cases
≤5 cases	472	821	798	1,736	619	1,319	537	1,154	880	2,022
6-15 cases	62	565	244	2,175	166	1,549	119	1,086	353	3,291
16-35 cases	24	557	103	2,354	59	1,377	48	1,082	166	3,864
> 35 cases	7	360	81	7,901	44	3,099	35	2,153	160	20,111
Total	565	2,303	1,226	14,166	888	7,344	739	5,475	1,559	29,288
Area (km <sup>2</sup> )	240.18		521.18		377.49		314.15		662.74	
Density	9.59		27.18		19.45		17.43		44.19	

Note: Intervals defined by geometric criteria.

Source: Own work based Covid-19 microdata daily records from health authorities (Government of Cantabria, Spain).

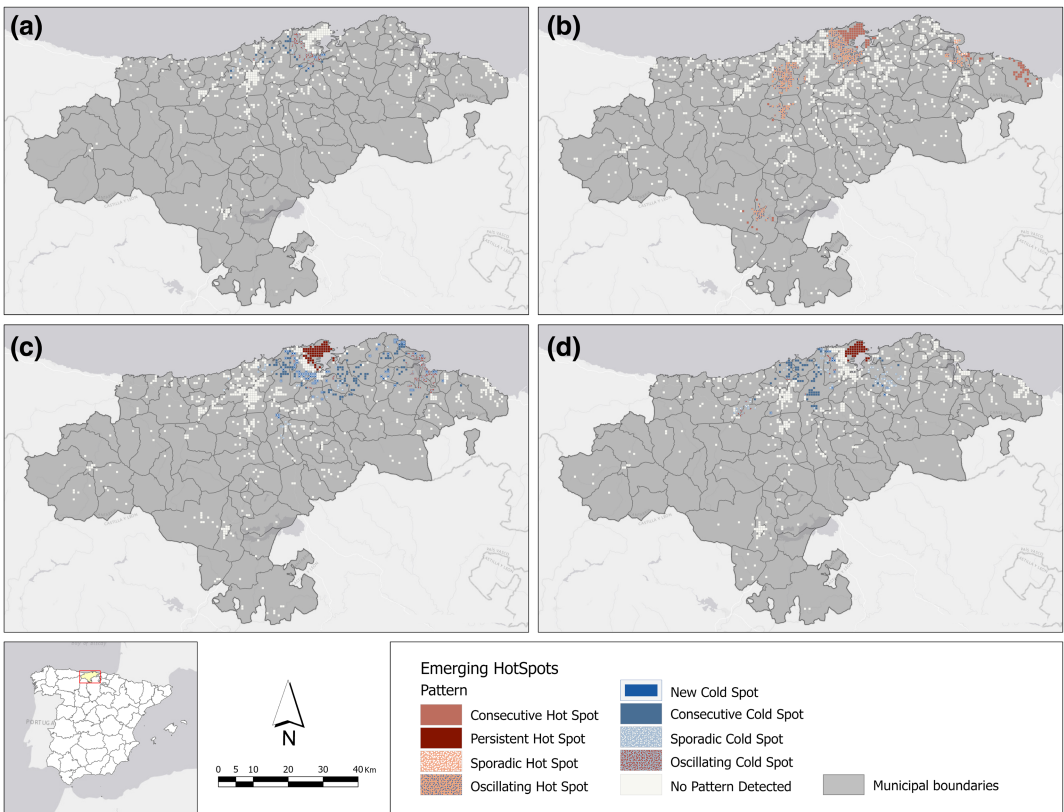


FIGURE 4 The spatial behavior of Covid-19 emerging hot spots by wave, region of Cantabria: (a) wave 1, March 1, 2020 to July 13, 2020; (b) wave 2, July 14, 2020 to December 12, 2020; (c) wave 3, December 21, 2020 to March 5, 2021; and (d) wave 4, March 6, 2021 to June 10, 2021. Source: Own work based on administrative base map (Esri), National Geographic Institute (National Cartographic Base 200) and Covid-19 microdata daily records from health authorities (Government of Cantabria, Spain)

waves show a return to spatial containment of the virus, with four categories of cold spots in both waves (Figures 4c,d).

The cross-tabulation of emerging patterns across waves results in 232 combinations. Our results confirm the spatial spread from the first wave to the second with new bins in this wave and the contraction process after wave 2 (Figure 5). Furthermore, the evolution of cases by pattern shows interesting results (Table A3 in the Appendix):

- There are 7,321 Covid-19 cases in the overall period in sporadic hot spots as a result of: “no pattern” in wave 1 that changes into significant patterns in wave 2. Specifically, these areas present a consecutive pattern in the final period of the second wave and then are reaffirmed as persistent hot spots in the third and fourth waves.
- There are 3,110 Covid-19 cases in the overall period in oscillating hot spots as a result of: “no pattern” in wave 1 that changes into oscillating pattern in the second wave and shows again “no pattern” from the third wave on. This result is aligned with a decrease in cases in the latest waves compared to the second.

### 4 | DISCUSSION

In this section we provide logical explanations for the results of our study from different approaches and at different scales. We focus first on the Spanish context and then on the international perspective. Finally, we focus on the limitations of our study regarding to the variety of factors related to the evolution of the pandemic.

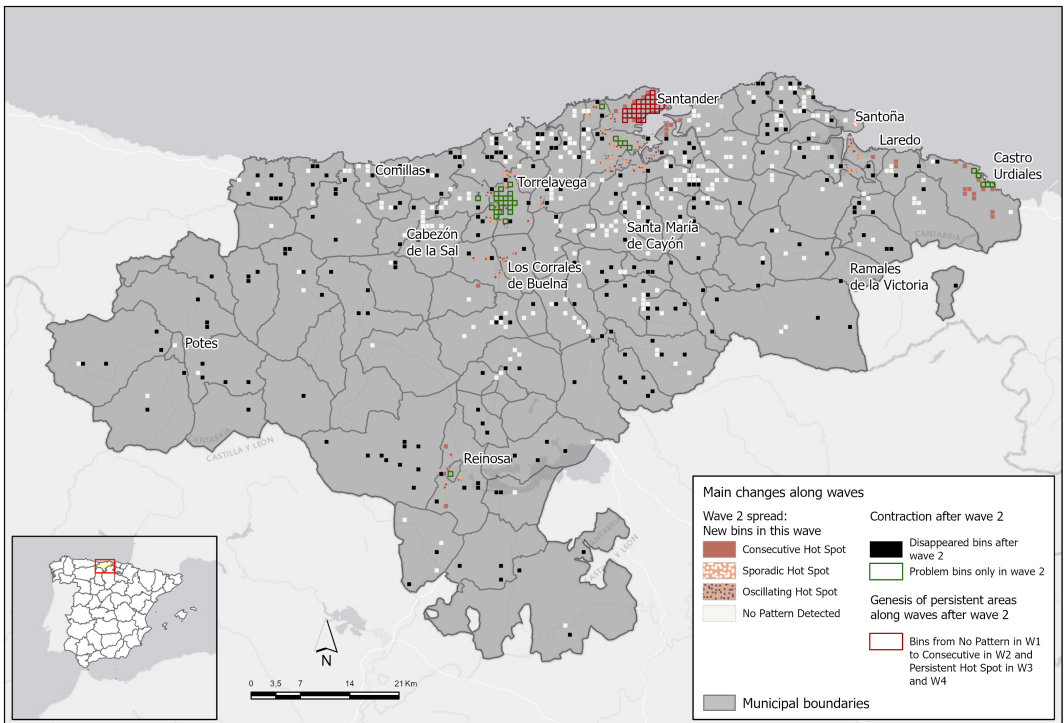


FIGURE 5 The main emerging cross-tabulation spatial patterns. Source: Own work based on administrative base map (Esri), National Geographic Institute (National Cartographic Base 200) and Covid-19 microdata daily records from health authorities (Government of Cantabria, Spain)

Our research demonstrates differences in spatiotemporal patterns of the pandemic over waves. These are related to national and regional measures framework (which indirectly affects mobility). The spread of the second wave, in summer and fall 2020, coincided with attempts to return to the pre-crisis level of economic activity in the main sectors in Spain (and Cantabria), such as tourism. In fact, part of the second wave coincided with a period from June 21, 2020 to October 25, 2020 when there was no state of alarm in Spain (the legal instrument required for strict mobility and control measures to be taken, as we mentioned before). This framework is also supported by City Analytics mobility reports, which show movements of +30% to +90% in summer 2020 with respect to the reference period prior to the pandemic, because of the relaxing of pandemic restrictions.

In contrast, the third wave (in winter 2020 including the Christmas period) shows a contracted emerging model and presents a more controlled distribution until the end of our analysis period. It must be noted that the third wave and a part of the fourth wave were regulated under the second state of alarm. So, health authorities implemented special rules in special risk periods regarding mobility and gatherings (such as Christmas in the third wave and Easter in the fourth). In an attempt to reduce these two factors (gatherings and mobility) health authorities introduced two key strategies: (1) controlling movement by stay-at-home and social distancing measures; and (2) regulating movements among Spanish regions and with other countries (Lai & Cheong, 2020).

In fact, movements were down on average by 20% in the region over Christmas and by 15% over Easter compared to the pre-pandemic reference period, according to data from the City Analytics Dashboard developed by Endesa X.

At the national level, in Spain, only other two case studies have been conducted using microdata: Galicia (Miramontes Carballada & Balsa-Barreiro, 2021) and Málaga (part of the region of Andalusia), where Perles, Sortino, and Mérida (2021) demonstrate the existence of neighbor contagion, as we did in our 3D bins analysis. Therefore, we find more links and relevant lessons abroad, in the international field of health geographic research context.

Our results on the greater spatial significance when the virus coincides with stricter control and mitigation measures are in line with non-spatialized theories put forward by Zhang et al. (2021), who state that there is a close relationship between containment strategies established by policy-makers and the evolution of waves.

The latest studies on pandemic monitoring using cellular tracking show that low mobility rates guarantee low spread because they keep infection rates low (Khatib, Perles-Roselló, Miranda-Páez, Giralt, & Barco, 2021). In this sense, timely decisions and early rules before incidence increases are needed to effectively control each wave (Seong et al., 2021).

Regarding the similarities and differences between our results and other case studies abroad, it is difficult to establish a comparative approach. Other studies of the space-time evolution of Covid-19 use different methods, considering aggregate data for administrative units (polygons as opposed to our points), for example prefectures in the analysis of Wuhan (Liu et al., 2021). Our study presents a higher spatial and temporal resolution and reveals the spatial patterns of Covid-19 without artificial aggregations in polygons (as ZIP code units or districts, among others). Fatima, O'Keefe, Wei, Arshad, and Gruebner (2021), after reviewing many spatial studies of Covid-19, state as the most common methods the use of clustering, hotspot analysis, spatiotemporal scan statistics, and regression models. Additionally, different methods sometimes refer to goals that differ from our research. Many GIS and Covid-19 contributions are focused on predicting high-risk areas (Scarpone et al., 2020; Yahya, Yahya, & Thannoun, 2021). So, the focus of these studies differs from our approach to closely monitor spatiotemporal patterns of the virus.

Finally, regarding the limitations of our study, it lacks quantitative analysis of social, demographic or mobility factors that could additionally explain the results of our problem areas. Those factors have been widely studied using other GIS methods, as multiscale geographically weighted regression to contrast the strong spatial relation between Covid-19 spread and other variables, such as social media activity (Forati & Ghose, 2021), density and urbanization degree (Dutta, Basu, & Das, 2021), or even built environment using analytical hierarchy methods (Rahman, Islam, & Islam, 2021).

In future studies it would be interesting to relate our emerging patterns of problem areas to risk factors or vulnerability variables as in some previous studies. Many references focus on the link between Covid-19 and economic activity, suggesting a higher incidence in hubs of activity (Ascani, Faggian, & Montresor, 2021), and invoking socioeconomic characteristics and contextual and environmental factors (Paez, Lopez, Meneces, Cavalcanti, & Da Rocha Pitta, 2020), rather than on the spatial changes from one wave to another, as here.

Regarding the risk factors, another weakness of our study method is the absence of environmental data, mainly pollution (Coccia, 2021c; Lipsitt et al., 2021) and meteorological variables. Nevertheless, a recent study based on a cross-sectional analysis of 409 cities demonstrates the scant influence of meteorological conditions in the virus spread in comparison to the greater influence of population behavior and government measures, as main drivers of the virus spread (Sera et al., 2021). It is aligned with our approach to the influence of measures (and indirectly mobility conditions, gathering, etc.) in the spatiotemporal patterns over waves.

As a final limitation, we admit that we did not consider the influence of the vaccination process on spatial patterns. We would need data on vaccination spatialized at least at the level of basic health management areas because the vaccination index could differ widely from one area to another. Nevertheless, vaccination seems to be insufficient to contain outbreaks and spread (Moore, Hill, Tildesley, Dyson, & Keeling, 2021) and, therefore, we can consider that the vaccination process is not essential in spatial patterns, at least in our research period (with 27.56% of the population fully immunized by the end of the fourth wave).

## 5 | CONCLUSIONS

The spatial analysis of the pandemic is not easy. Many contextual factors are related to the incidence ratios, not only socio-demographic aspects (density, mobility, urbanization degree, economic activities, and socioeconomic profiles) but also environmental variables (such as pollution and wind speed). Additionally, other factors pertaining to individuals could influence in the spread of Covid-19, such as the state of health (comorbidities, chronic diseases) or habits (walking, practicing sports). Additionally, from a geographic approach, there are two characteristics of the pandemic that complicate spatial analysis: (1) non-stationarity; and (2) multiscale behavior.

Despite all the limitations and difficulties, we model the changes in spatial trends over waves, considering both space and time of the case study of the region of Cantabria. We find and demonstrate the essential role of GIS and 3D bins and emerging hot spots in obtaining revealing spatial diagnosis of problem areas, distinguishing between hot and cold spots. In hot spots we highlight specific areas, distinguishing categories of patterns at regional level which are essential in helping regional health authorities to design spatial strategies.

The research demonstrates that the spatial behavior of the pandemic changes over waves and we relate it to the framework of control measures. The stricter framework during lockdown resulted in an anomalous spatial pattern where Covid-19 is undermined and there were large cold spot areas. By contrast, the “new normal” conditions and the relaxing of rules in the second wave coincided with the worst spatial pattern of the pandemic, in terms of spread and statistical significance of hot spots. The third and fourth waves show a contraction pattern coinciding with new control measures.

A knowledge of problem areas with empirical models help policy-makers to design adapted measures for each area, depending on danger levels and dynamism of spread (new, growing or persistent hotspots, among others).

Hence, in the latest, fifth wave that the regional health authorities are starting to tackle at the conclusion of the period covered by this research, emerging hot spots may play an interesting role in implementing new measures from a spatial perspective. Moreover, this study is essential to answer in real time the key questions in the pandemic management from a geoprevention perspective: where to increase vigilance and face-mask controls, where to implement mass testing to detect asymptomatic cases, where improve the vaccination rate, where to control mobility, where to intensify the control of airborne contaminants, and so on. Timely decisions and specific restrictions in problem areas can reduce the effects of pandemic not only in relation to economic

activities and social conditions, but also in terms of the overall state of health, for instance in psychological health.

Finally, new lines of research are also being opened up in the contribution of social sciences to knowledge of pandemics. Our methodological workflow can be applied after the fifth wave to increase the spatiotemporal perspective of Covid-19 by waves. Moreover, other research teams can replicate our method in other regions or with other scales using our relative parameters (size of the side of bins and number of internal time slides).

The main drawback is the common access restrictions to use of microdata records. Often, the data remain in the hands of the administration in spite of its great potential for reporting strategic information to supplement the toolkit of policy analysts and help policy-makers to design a long-term strategy to control the pandemic at a regional scale (Ienca & Vayena, 2020; Rosenkrantz, Schuurman, Bell, & Amram, 2020). Our work, like other work cited in this article, highlights the importance of social sciences, and the spatial point of view, to design targeted measures depending on the spatial patterns of Covid-19 in real time. It represents an opportunity to reduce the socioeconomic impact of global containment measures in pandemic management.

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## CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

## DATA AVAILABILITY STATEMENT

The permission to use COVID-19 microdata given by the CEIm in June 2020 (ID: 2020.238) prevents us from sharing or publishing the original data.

## ORCID

Olga De Cos Guerra  <https://orcid.org/0000-0002-2245-5378>

Valentín Castillo Salcines  <https://orcid.org/0000-0001-8025-4892>

David Cantarero Prieto  <https://orcid.org/0000-0001-8082-0639>

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## APPENDIX

TABLE A1 Shape of pandemic waves in the region of Cantabria from March 2020 to June 2021

	Wave 1	Wave 2	Wave 3	Wave 4
Number of peaks	1	2	1	1
Maximum incidence	205.02	566.58	421.70	309.78
Minimum incidence	8.24	10.35	118.58	101.78
Days >250	0	66	37	21
% Time	0.0%	41.3%	49.3%	21.6%
Days >150 to ≤250	13	35	33	22
% Time	9.8%	21.9%	44.0%	22.7%
Days >50 to ≤150	35	35	5	54
% Time	26.5%	21.9%	6.7%	55.7%
Days >25 to ≤50	12	7	0	0
% Time	9.1%	4.4%	0.0%	0.0%
Days ≤25	72	17	0	0
% Time	54.6%	10.5%	0.0%	0.0%
Increasing slope	12.28	Peak 1: 4.74 Peak 2: 13.70	8.21	3.96
Decreasing slope	-1.45	Peak 1: -6.91 Peak 2: -11.17	-8.56	-5.43

Note: Incidence intervals correspond to 14-day cumulative incidence using the SIR approach (cases per 100,000 people). Intervals defined by the Inter-territorial Council of the National Health System of the Government of Spain (2020): no risk, up to 25; low risk, 25–50; medium risk, 50–150; high risk, 150–250 and extreme risk, over 250.

Source: Own work based on past data on Covid-19 in Cantabria (open data from the Government of Cantabria) and the Epidemiological Situation of Covid-19 in Cantabria dashboard (from ICANE, the Statistical Office of Cantabria).

TABLE A2 Emerging hot spot results per wave, region of Cantabria, March 1, 2020 to June 10, 2021

Wave	Pattern category	No. bins	% Bins	No. cases	% Cases	Average cases per bin
1	No pattern detected	493	87.26	2139	92.88	4.34
	Oscillating cold spot	36	6.37	94	4.08	2.61
	Consecutive cold spot	22	3.89	49	2.13	2.23
	Sporadic cold spot	9	1.59	16	0.69	1.78
	New cold spot	5	0.88	5	0.22	1.00
	Total first wave	565	100.00	2303	100.00	4.08
2	No pattern detected	852	69.49	4159	29.36	4.88
	Oscillating hot spot	257	20.96	4433	31.29	17.25
	Consecutive hot spot	108	8.81	5236	36.96	48.48
	Sporadic hot spot	9	0.73	338	2.39	37.56
	Total second wave	1226	100.00	14,166	100.00	11.55
3	No pattern detected	561	63.18	3543	48.24	6.32
	Consecutive cold spot	106	11.94	491	6.69	4.63
	New cold spot	68	7.66	408	5.56	6.00
	Persistent hot spot	67	7.55	2194	29.87	32.75
	Oscillating cold spot	55	6.19	605	8.24	11.00
	Sporadic cold spot	31	3.49	103	1.40	3.32
	Total third wave	888	100.00	7344	100.00	8.27
4	No pattern detected	530	71.72	3468	63.34	6.54
	Consecutive cold spot	75	10.15	308	5.63	4.11
	Sporadic cold spot	63	8.53	266	4.86	4.22
	Persistent hot spot	45	6.09	1332	24.33	29.60
	Oscillating cold spot	14	1.89	69	1.26	4.93
	New cold spot	12	1.62	32	0.58	2.67
	Total fourth wave	739	100.00	5475	100.00	7.41

Note: Pattern types per wave are presented in decreasing order by number of bins.

Source: Own work based Covid-19 microdata daily records from the Health Authorities (Government of Cantabria, Spain).

TABLE A3 Crosstab emerging patterns across waves with more than 1000 accumulated cases

Pattern type crosstab waves	No. bins	Total cases	Cases Wave 1	Cases Wave 2	Cases Wave 3	Cases Wave 4
Overall: Sporadic hot spot	31	7,321	606	3,654	1,645	1,278
Wave 1 No pattern detected						
Wave 2 Consecutive hot spot						
Wave 3 Persistent hot spot						
Wave 4 Persistent hot spot						
Overall: Oscillating hot spot	27	3,110	292	1,421	569	592
Wave 1 No pattern detected						
Wave 2 Oscillating hot spot						
Wave 3 No pattern detected						
Wave 4 No pattern detected						
Overall: Consecutive hot spot	5	1,069	35	375	224	288
Wave 1 No pattern detected						
Wave 2 Consecutive hot spot						
Wave 3 No pattern detected						
Wave 4 No pattern detected						

Source: Own work based on Covid-19 microdata daily records from the Health Authorities (Government of Cantabria, Spain).

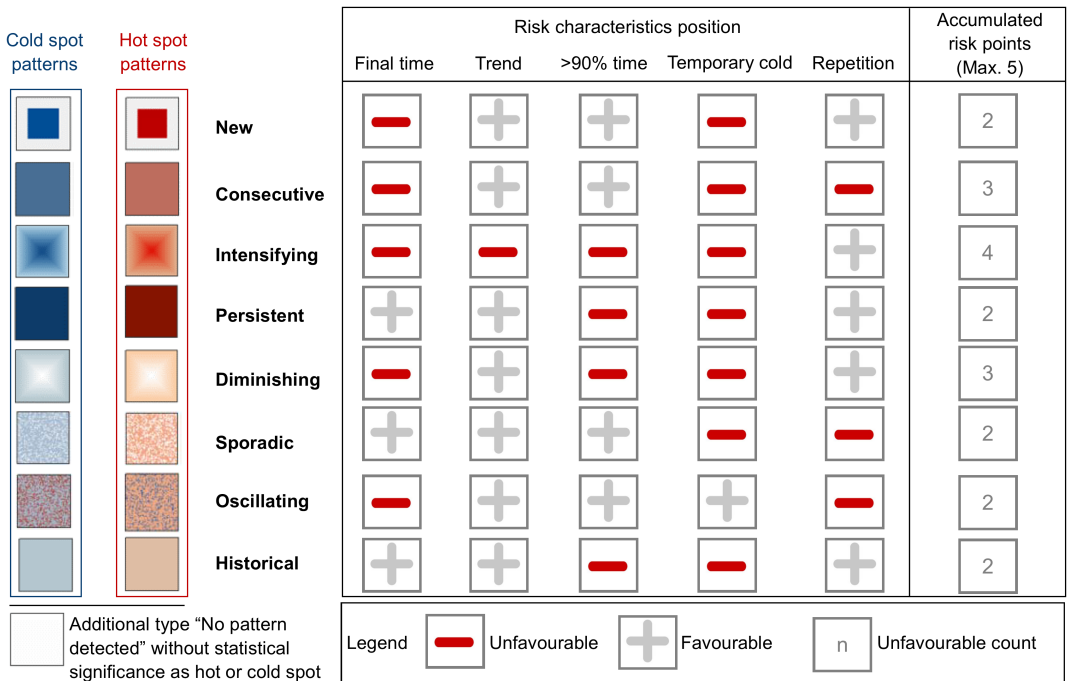
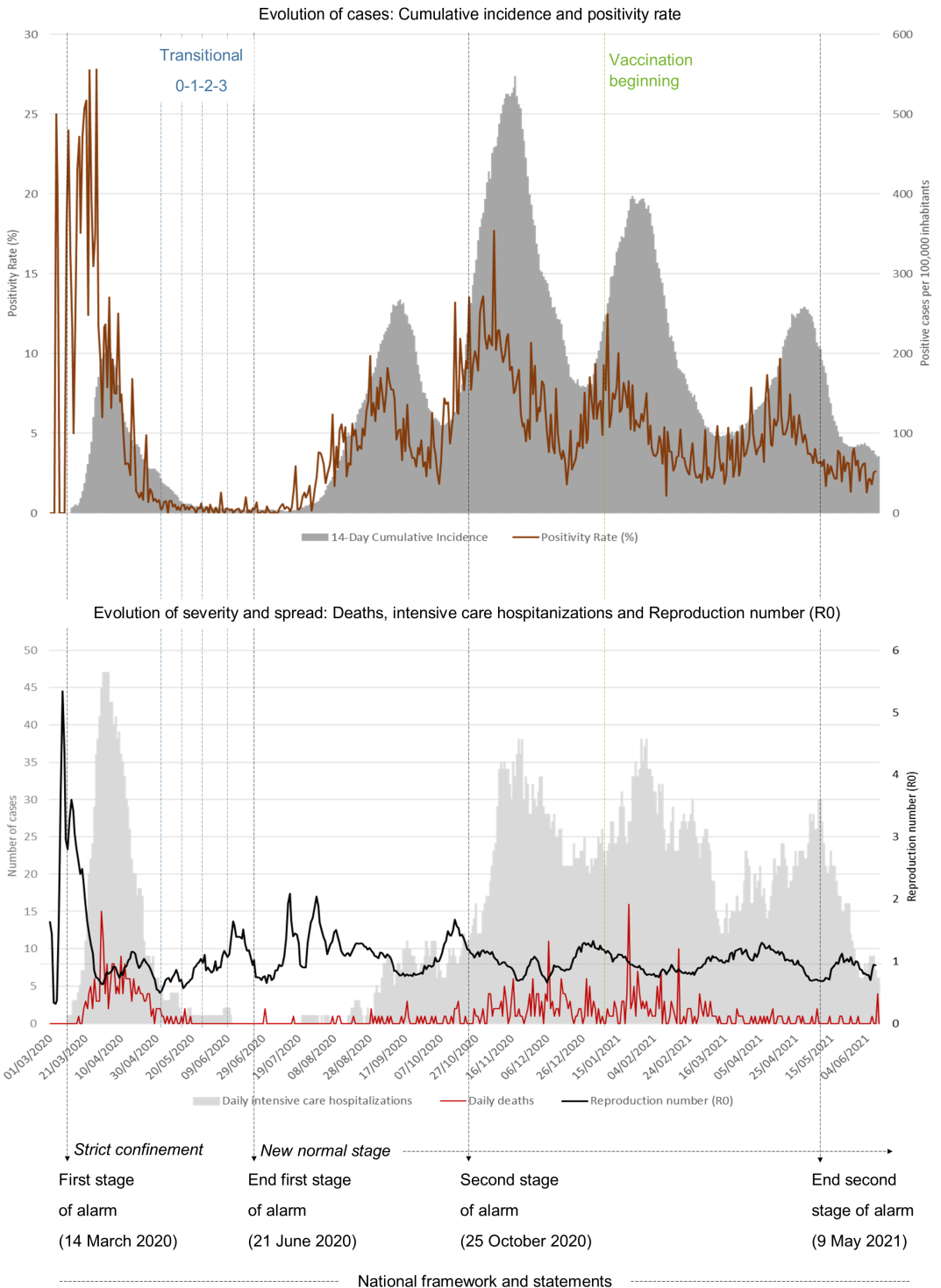


FIGURE A1 Hot and cold spot patterns: An interpretation based on risk characteristics. Source: Own work based on Esri, Reference for the emerging hot spots analysis tool  
 Note. Negative red symbols correspond to characteristics that contribute to create more problematic Covid-19 patterns (by trend, proportion of time or repetition factor). By contrast, positive grey symbols correspond to characteristics that reduce the problem level of Covid-19 patterns. According to this, the value "accumulated risk points" represents the number of negative red symbols in each hot spot pattern.



**FIGURE A2** Trend in the main pandemic variables in the region of Cantabria from March 2020 to June 2021. Source: Own work based on past data on Covid-19 in Cantabria (open data from the Government of Cantabria) and the Epidemiological Situation of Covid-19 in Cantabria dashboard (from ICANE, the Statistical Office of Cantabria)