Région et Développement

n° 64-2026

www.regionetdeveloppement.org

The spatial analysis of COVID-19 in Greece: Challenges for regional policy

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Abstract - This study examines the geographical variations in COVID-19 mortality across seventy-five Regional Administrative Units in Greece, disaggregated by ten-year age groups and six successive pandemic waves spanning the period 26 October 2020 to 22 March 2022. By estimating Age-Standardized Case-Fatality Ratios (SFR) and applying a Spatial Durbin Error Model (SDEM), the analysis identifies socio-economic, demographic, and geographical determinants of spatiotemporal disparities in COVID-19 mortality. The findings contribute to the literature on regional health inequalities and inform regional policy aimed at building more resilient and shielded communities in the face of future epidemic shocks.

JEL classification
I15, R11, R12, C23

Keywords
Spatial analysis
Health disparities
Socio-economic vulnerability
Regional policy
COVID-19
Age-Standardized Fatality Ratio (SFR)
Spatial Durbin Error Model (SDEM)
Greece

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1. INTRODUCTION

The pandemic ushered modern civilization into a new historical era influencing the ways of thinking and acting of individuals and of collective or institutional actors. The abrupt halt of production activity and the everyday routine of billions of people across the globe, the interruption of travel flows of people and goods, and the changing patterns of interaction and communication have reshaped our thinking and our interpretation of the role of space in scientific investigation and in policy action (Bailey *et al.*, 2020; Dodds *et al.*, 2020; Martin, 2021; Gong *et al.*, 2022; Keil, 2020).

The pandemic has triggered a voluminous body of research on the role of space as an integral and inherent part of our understanding of and reaction to the incidence/occurrence and transmission of the disease and the endurance/resistance, vulnerability and resilience of citizens and places. International institutional bodies (ESPON & European Union, 2022; OECD & European Union, 2022; European Parliament, 2022) and review papers highlight the diversified evidence regarding the impact, spread and responses across the globe (Alizadeh *et al.,* 2023; Bourdin and Levratto, 2023; Bourdin *et al.,* 2024; Psycharis *et al.,* 2021).

However, being distant from the period of the pandemic we need to look back in order to extract useful results for the geographical spread of the pandemic and the vulnerability of cities, regions and localities and their populations as an essential step in order to move forward to prevent and protect people and localities against future pandemic and external shocks. This research attempt could build upon a larger series of data availability for closer inspection of the disease and more robust and statistically tested results.

The Greek case offers a particularly relevant empirical setting because of the country's pronounced geographical diversity, including metropolitan concentrations, mainland transport corridors, border areas, mountainous territories, and island regions.

Against this background, the paper contributes in four main respects. First, it provides fine-grained evidence at the level of Regional Units, allowing a more nuanced understanding of intra-national spatial disparities. Second, it uses age-group information on cases and deaths to estimate Standardized Fatality Ratios (SFR), thus improving the comparability of regional mortality patterns. Third, it adopts a six-wave perspective, making it possible to capture the changing geography of the pandemic over time rather than treating COVID-19 as a single undifferentiated episode. Fourth, by applying a Spatial Durbin Error Model, it highlights the role of spatial dependence and local spillover effects in shaping mortality outcomes. In this way, the paper not only adds new empirical evidence from Greece, but also contributes to wider debates on regional resilience, spatial health inequalities, and crisis-sensitive territorial policy.

Acknowledging the spatial factors that affect vulnerability to external (epidemiological) shocks constitutes a fundamental prerequisite for making regional policy more responsive in order to make the necessary adjustments and take the appropriate measures to make people and localities more shielded and resistant. Feeding policy with sounded statistical evidence allows the perfect bridging between empirical analysis and policy formulation.

The article is organized as follows. Section 2 outlines a brief literature review on the transmission patterns of COVID-19. Section 3 presents the data and analytical methods used. Section 4 examines the results of an exploratory spatial data analysis. Section 5 provides an econometric analysis to explain the spatiotemporal disparities in COVID-19 mortality during the study period. Finally, Section 6 concludes with the regional policy implications to be implemented in the future.

2. SPATIAL ANALYSIS OF COVID-19: A SHORT NAVIGATION TO THE LITERATURE

Spatial models have been widely used in the analysis of COVID-19. Spatial models allow the inclusion of space in the interpretation of incidence and mortality from COVID-19. The voluminous body of scientific research corroborates the statement that space is not at all neutral to the incidence and mortality and thus to policy reactions to COVID-19 pandemic (Díaz Ramírez *et al.*, 2022). Empirical analyses provide an impressive spectrum of applications across the globe (Xie *et al.*, 2021).

Literature provides robust statistical evidence that the level of urbanization is highly correlated with incidence and deaths from the pandemic (Kulu *et al.*, 2021). The application of spatial regression models in the European Union documented that total population, poverty and income level were key factors for the interpretation of fatality from COVID-19 (Sannigrahi *et al.*, 2020). Similarly, socio demographic factors, mobility, and environmental factors asserted an important influence on the geographic variation of COVID-19 incidence rate and mortality in the New York City (Kim *et al.*, 2021). Spatiotemporal analysis of trends in fatality from COVID-19 across the US revealed that urban counties had been more severely affected by the pandemic *vis-à-vis* rural areas (Jackson *et al.*, 2021). The spatial analysis of the transmission of COVID-19 in Wuhan/China, where the virus was first identified, revealed that the spread of the disease and the fatality had been obviously driven by global and local spatial aggregations (Liu *et al.*, 2021b). Spatial econometric analysis in Brazil based on Moran's *I* coefficient indicated a positive spatial autocorrelation between urbanization and mortality and cases from COVID-19 (Castro *et al.*, 2021).

However, while urbanization is a key variable for the incidence and deaths from the pandemic it is not the factor *per se* which stands as an explanatory variable. The socioeconomic and demographic variables are considered as significant determinates of the exposure, vulnerability and resistance to the disease (Sigler *et al.*, 2021). In the case of the US the application of a spatial model unveiled that age, disability, language, race, occupation, and urban status increase vulnerability to COVID-19 (Andersen *et al.*, 2021). Household income was inversely related with COVID-19 across communities in the US while unemployment was positively related (Zhai *et al.*, 2021). Across England, spatial models demonstrated that there exists a high degree of association between socioeconomic and environmental variables and COVID-19 as well as non-COVID-19 mortality (Sun *et al.*, 2020). County level analysis for Germany argues that beyond the clinical risk factors, socioeconomic, demographic, and health-related variables at the regional level related with COVID-19 cases and deaths in Germany (Ehlert, 2021).

Spatial regression models were applied in Iran with a focus on examining the relationship between socio-demographical factors and cases of COVID-19 and highlighted that literacy is a factor associated with a decrease in the number of cases

(Ramirez *et al.*, 2020). Spatial error and spatial lag models were also applied in Bangladesh concluding that there exists a statistically significant relationship between COVID-19 cases and a set of demographic factors such as population density and the number of people aged 60 or higher (Sarkar *et al.*, 2021). Spatial analysis conducted in Oman demonstrated that age, population density, hospital beds, and diabetes rates are statistically significant determinants of COVID-19 incidence rates (Mansour *et al.*, 2021). Similarly, in Bangladesh urban residence, monthly consumption, number of workers in the health sector, and distance from the capital city were significant factors of COVID-19 incidence (Rahman *et al.*, 2021). Spatial regression modeling was also applied in the study area of Brazil which identified that spatial effects are present and that there is a strong relationship between the *Gini* index and the mortality rate in the increase of COVID-19 relative risk (Martines *et al.*, 2021). Finally, GIS and spatial models provide empirical evidence regarding the spread and determinates of COVID-19 in Africa (Hassaan *et al.*, 2021).

3. DATA AND METHODOLOGY

3.1. Data

The empirical analysis is based on official epidemiological data on confirmed COVID-19 cases and diagnosed deaths recorded in Greece during the period from 26 October 2020 to 22 March 2022. For the full study period, the dataset includes 2,741,487 confirmed cases and 25,598 diagnosed deaths. The temporal dimension of the analysis follows the six pandemic waves as defined by the National Organisation for Public Health (EODY).

The geographical unit of analysis is the level of Regional Units. In total, the analysis covers 74 Regional Units together with Agion Oros, resulting in 75 territorial units. These units do not coincide with the statistical NUTS classification. Rather, they constitute sub-regional administrative entities that are broadly comparable to the NUTS 3 scale, although important differences emerge in the island regions, where the correspondence between administrative and statistical territorial organization is less direct.

The dataset provides information on confirmed cases and deaths by ten-year age groups for each territorial unit and for each pandemic wave. This structure allows the implementation of age-weighted analytical procedures and supports more meaningful spatial and temporal comparisons of mortality patterns across the country. The methodological treatment of this age structure is presented in the following section.

3.2. Methods of analysis

3.2.1. Epidemiological Indicator

The case fatality rate is an important parameter in epidemiology that illustrates the seriousness and risk of a disease that leads to death. For the purpose of this study, the Case Fatality Rate (*CFR*) is calculated as the number of diagnosed deaths from COVID-19 observed in a population during a specified period, per 100 confirmed COVID-19 cases of the given population. This measurement is calculated by Regional Unit as well as by wave of the disease.

Additionally, we compute for each region (i) Fatality Location Quotients (FLQ_i) using the simple ratio

$$FLQ_i = \frac{CFR \text{ of region } i}{\text{national } CFR} \times 100 \qquad (1)$$

in order to portray the relative excess or deficit of the severity of the disease at the local level compared to the fatality rate of the whole population.

Particularly when they are available at a regional level, case fatality rates can be useful to assess a range of health-related issues such as public-health policy measures, health care and hospital provisions, vaccination outcomes, medical treatments and health campaigns. On the other hand, however, case fatality rates have some shortcomings including, among others: difficulties in evaluating the actual course of the disease; complications in assessing the time elapsed between the onset of the disease and the occurrence of death; and complexities in the diagnosis and reporting of cases and deaths (Luo *et al.*, 2021; Thomas and Marks, 2021).

From the demographic point of view, a further weakness in *CFR* may be attributable to differences in the age distribution of the cases and deaths. As the numerator and denominator of the conventional *CFR* include total numbers (through all ages) of deaths and cases, differences and variations in the age distributions in the aforementioned events across the populations under research may have an influence on the observed value of the indicator.

As noted above, the material used in this study refers to numbers of COVID-19 deaths and cases cross-classified by 10-year age groups, by Regional Units and by waves of the disease. At such a level of statistical detail, in most instances, the observed numbers of deaths are very small or even zero, and thus data does not allow the calculation of age-specific fatality rates to permit further refined elaboration and appraisal. Hence, in this study we approach the sub-national COVID-19 fatality analysis, statistically, on the basis of the ratio of observed to expected number of COVID-19 deaths making use of the notion of the indirectly age standardization methodology used in the demographic analysis of mortality.

For each administrative unit (i), we calculate a Standardized Fatality Ratio (SFR_i) as follows:

$$SFR_i = \frac{\text{observed number of covid-19 deaths in region } i}{\text{expected number of covid-19 deaths in region } i} \times 100 = \frac{O_i}{E_i} \times 100 \qquad (2)$$

or

$$SFR_i = \frac{\sum_x \left(\frac{O_{x,i}}{C_{x,i}}\right) \cdot C_{x,i}}{\sum_x E_{x,i}} \times 100 = \frac{\sum_x f_{x,i} \cdot C_{x,i}}{\sum_x F_x \cdot C_{x,i}} \times 100 \qquad (3)$$

and finally:

$$SFR_i = \frac{O_i}{\sum_x F_x \cdot C_{x,i}} \times 100 \qquad (4)$$

where:

$O_{x,i}$ is the number of COVID-19 deaths of persons aged *x* in region *I,*

$C_{x,i}$ is the number of COVID-19 cases of persons aged *x* in region *I,*

$f_{x,i}$ is the age-specific case fatality rate (per person) of the population in region *i*,
F_x is the age-specific case fatality rate (per person) of a chosen standard (reference) population:

$$F_x = \frac{D_x}{C_x} = \frac{\text{covid-19 deaths aged } x \text{ in the standard population}}{\text{covid-19 cases aged } x \text{ in the standard population}} \quad (5)$$

We calculate regional Standardized Fatality Ratios (*SFR*s) for all waves combined (for the entire period of observation) as well as separately for each wave of the disease using as standard age-specific fatality schedule (F_x) the age distributions of COVID-19 deaths and cases of the national population (country) of each wave.

As expression (3) shows, the value of the regional estimated standardised fatality ratio depends on the differences in the age-specific fatality rates between the study population ($f_{x,i}$) and the reference population (F_x). A value of *SFR* greater than 100 denotes that the observed deaths are more than the expected ones, indicating a relative excess of COVID-19 fatality in the population under study, compared to the standard (general population); the opposite is revealed when *SFR*<100.

Following the notion and applications of the well-known Standardized Mortality Ratio (*SMR*), the statistical significance of the ratios of the observed to expected numbers of deaths of each regional unit ($O_i \div E_i$) can be assessed on the basis of a chi-2 test or on the estimation and evaluation of appropriate confidence intervals (Armitage *et al.*, 2002; Liddell, 1984).

The interpretation of the Standardised Fatality Ratios is similar to the indices of Fatality Location Quotients. However, the use of the SFR in the analysis has some advantages; firstly, we control for differences in the age distribution of the events across populations; secondly, we can assess the statistical significance of the measure; and thirdly, we can calculate more *SFR* values employing the alternative reference population. For instance, a possible implementation could be to use the national age-specific fatality rates of the first wave as the standard fatality schedule (F_x) throughout the analysis to examine possible differentials by region and time.

3.2.2. Local spatial autocorrelation (Local Moran's I)

To investigate the local spatial structure of COVID-19 mortality, the analysis employs the Local Moran statistic and the corresponding Local Indicators of Spatial Association (LISA), following Anselin (1995). While global measures of spatial autocorrelation provide an overall indication of spatial dependence, the Local Moran statistic makes it possible to identify the specific locations where statistically significant local clusters and spatial outliers emerge. In the present study, this is particularly useful for detecting localized concentrations of high or low Standardized Fatality Ratios (SFRs), both for the total period of observation and for each of the six successive pandemic waves.

Formally, for each territorial unit *i*, the local Moran statistic is defined as:

$$I_i = \frac{(x_i - \bar{x})}{m_2} \sum_j w_{ij} (x_j - \bar{x})$$

where x_i is the observed value of the variable under study in territorial unit i, $\bar{x}$ is the mean of the variable across all territorial units, and w_{ij} are the elements of the spatial weights matrix W. The term m_2 is given by:

$$m_2 = \frac{\sum_i (x_i - \bar{x})^2}{n}$$

and serves as the variance term used for standardisation.

The statistic can also be interpreted through the spatial lag of the standardized variable. Let $z_i = (x_i - \bar{x})$. Then the local Moran statistic may be written in compact form as:

$$I_i = z_i \sum_j w_{ij} z_j$$

where $\sum_j w_{ij} z_j$ is the spatial lag at location i, that is, the spatially weighted average of the standardized values observed in neighbouring territorial units. In this study, the spatial weights matrix is row-standardised and based on the (k=4) nearest neighbouring territorial units for each observation. This choice was considered appropriate for the Greek case, given the fragmented geography of the country and the coexistence of mainland, border, and island territories. Under this specification, the spatial lag reflects the local influence exerted by the six closest neighbours on each territorial unit.

Positive and statistically significant values of $I_i$indicate local clustering of similar values, whereas negative values indicate spatial outliers. The interpretation of the LISA results follows the standard classification of local spatial association: high-high and low-low combinations identify statistically significant clusters of elevated and reduced mortality, respectively, while high-low and low-high combinations indicate spatial outliers. The local Moran analysis complements the descriptive mapping of SFR and provides the basis for the subsequent spatial econometric analysis.

3.2.3. Econometric Model Specification

The empirical modelling strategy proceeds from the identification of local spatial autocorrelation to the estimation of a spatial regression model. Given the evidence of spatial autocorrelation in the Standardized Fatality Ratio, a spatial econometric framework is more appropriate than a conventional non-spatial regression model. COVID-19 mortality is unlikely to be determined solely by the internal characteristics of each territorial unit, since neighbouring areas are connected through commuting flows, transport networks, labour-market interactions, and broader territorial interdependencies. A spatial specification is therefore required in order to account for the fact that mortality outcomes may be shaped both by local conditions and by the characteristics of surrounding areas.

In the present study, the Spatial Durbin Error Model (SDEM) was selected (LeSage and Pace, 2009; Elhorst, 2014; LeSage, 2014). This choice is motivated by both substantive and methodological considerations. From a substantive perspective, the spread and severity of an infectious disease are embedded in regional interaction systems and may therefore generate spillover effects across neighbouring territorial units. From a methodological perspective, the SDEM is particularly suitable because it allows the inclusion of spatially lagged explanatory variables, thereby capturing local spillovers, while at the same time modelling

spatial dependence in the error term. Compared with simpler spatial specifications, this provides a more flexible framework for identifying whether regional mortality patterns are associated only with local characteristics or also with neighbouring conditions. This is especially relevant in the Greek case, where mainland corridors, border areas, metropolitan concentrations, and island territories form a highly differentiated spatial environment.

The Spatial Durbin Error Model is specified as follows:

$$y = X\beta + WX\theta + u$$

$$u = \lambda Wu + \varepsilon$$

where:

y is the dependent variable vector, namely the Standardized Fatality Ratio for each territorial unit; X is the matrix of explanatory variables;
WX denotes the spatial lags of the explanatory variables;
W is the row-standardised spatial weights matrix;
β is the vector of coefficients associated with the explanatory variables;
θ captures the effects of neighbouring explanatory variables;
u is the spatially correlated error term;
λ is the spatial error coefficient; and ε is the independently distributed disturbance term.

In line with the local spatial structure adopted in the preceding subsection, the spatial weights matrix is row-standardised and based on the (k=4) nearest neighbouring territorial units for each observation. Under this specification, the estimated impacts can be interpreted in terms of direct, indirect, and total effects, thus offering a suitable framework for examining how demographic, socio-economic, and geographic characteristics shape regional mortality patterns both locally and through neighbouring interactions.

3.2.4. Selection of variables

In this section, we present the explanatory variables included in the spatial econometric analysis of the Standardized Fatality Ratio. The initial model specification comprises 14 covariates grouped into three broad categories: demographic, socioeconomic, and geographic variables (Table 1). The demographic dimension is represented by the ageing ratio. The socioeconomic variables include tertiary education, hospital-bed availability, location quotients for employment in the primary, secondary, and tertiary sectors, as well as foreign and domestic tourist arrivals. The geographic dimension includes accessibility, island and border status, employees' mobility within the settlement and within the administrative unit of residence, and the share of population living in settlements with fewer than 2,000 inhabitants.

In order to identify the variables most systematically associated with regional mortality patterns across alternative model specifications, a stepwise regression procedure was applied (Draper and Smith, 1981). The variables most consistently retained across the models were ageing, tertiary education, accessibility, island status, border status, employees' mobility within settlements, and bed availability, while the remaining covariates were introduced in alternative specifications presented in Table 1.

Table 1. Explanatory variables used in the econometric analysis

Group	Variable	Definition
Demographic	Ageing ratio	Ratio of elderly population (aged 65 years and over) per 100 individuals younger than 14 years in the resident population (2011).
Socioeconomic	Tertiary education (%)	Share of residents with tertiary education (%) (2011).
	LQ primary sector	Location quotient (LQ) of employed population in the primary sector (2011).
	LQ secondary sector	Location quotient (LQ) of employed population in the secondary sector (2011).
	LQ tertiary sector	Location quotient (LQ) of employed population in the tertiary sector (2011).
	Hospital Beds ratio	Ratio of beds in units of the National Health System per 1,000 inpatients (2021).
	Foreign tourist arrivals	Ratio of foreign tourist arrivals to resident population (2021).
	Domestic tourist arrivals	Ratio of domestic tourist arrivals to resident population (2021).
Geographic	Accessibility	ESPON multimodal accessibility indicator describing how easily people in one region can reach population located in other regions. The indicator integrates road, rail, and air accessibility and is calculated on the basis of population in NUTS 3 regions and the travel time required to reach them.
	Island status	Type of territorial unit according to insularity. Three categories: 1 = island, 2 = island unit with neighbouring regional unit, 3 = mainland.
	Border status	Administrative units including land borders with other countries. Binary variable: 1 = yes, 0 = no.
	Employees' mobility within settlement	Employees whose place of work is located within the settlement of residence (%) (2011).
	Employees' mobility within administrative unit	Employees whose place of work is located within the administrative unit of permanent residence (%) (2011).
	Population in settlements <2,000 (%)	Share of population living in settlements with fewer than 2,000 inhabitants (%) (2011).

4. DESCRIPTIVE AND EXPLORATORY SPATIAL ANALYSIS

4.1. Descriptive overview

Table 2 presents the total number of confirmed COVID-19 cases and diagnosed deaths in Greece by pandemic wave during the study period, while Figure 1 visualises the temporal evolution of cases and deaths across the six waves. Table 3 complements this overview by showing COVID-19 deaths as a percentage of total deaths from all causes in Greece. Taken together, these descriptive materials provide a first summary of the epidemiological burden of the pandemic over time.

Overall, the dataset records 2,741,487 confirmed cases and 25,598 diagnosed deaths during the period under study. COVID-19 deaths account for 12.5% of all

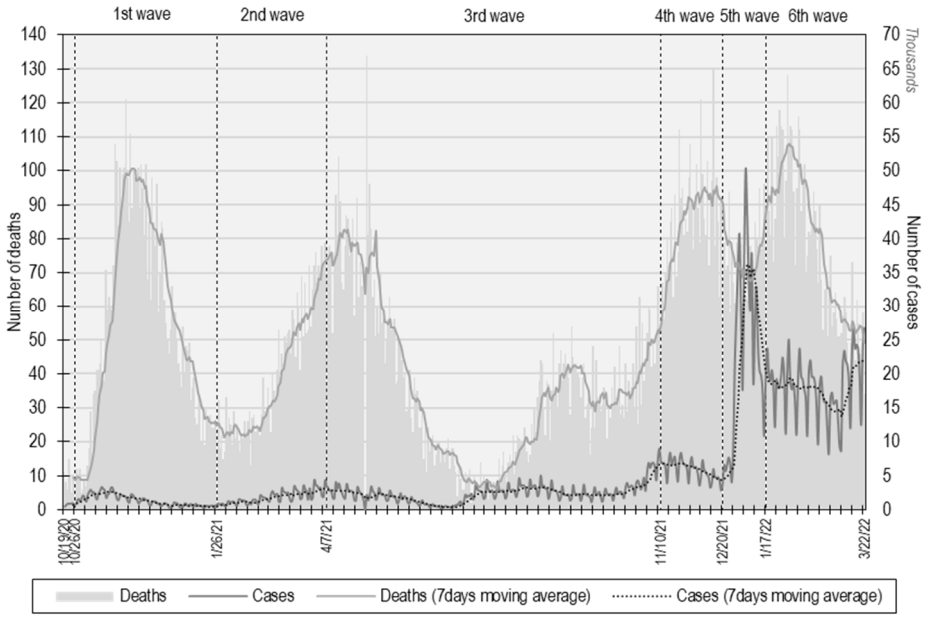
deaths recorded in Greece over the same period (Table 3)[1]. These figures indicate the substantial mortality burden associated with the pandemic at the national level, while also highlighting the importance of examining how this burden evolved across successive waves.

Table 2. Total number of cases and deaths from COVID-19 in Greece by wave

Wave	Period	Cases	Deaths
Wave 1	26/10/2020 - 25/1/2021	115,460	4,946
Wave 2	26/1/2021 - 06/04/2021	132,689	2,844
Wave 3	07/04/2021 - 9/11/2021	500,275	7,528
Wave 4	10/11/2021 - 19/12/2021	224,780	3,414
Wave 5	20/12/2021 - 16/01/2022	621,191	2,095
Wave 6	17/01/2022 - 22/03/2022	1,147,092	4,771
All Waves	26/10/2020 - 22/03/2022	2,741,487	25,598

Source: National Organisation for Public Health (EODY) (authors' own elaboration).

Figure 1. Number of cases and deaths from COVID-19 in Greece by wave of the disease: October 2020 to March 2022



Source: Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University [CSSEGISandData]. https://github.com/CSSEGISandData/COVID-19.

[1] As a matter of comparison, COVID-19 accounted of 400,000 deaths representing the 8% of all deaths in the EU in 2020 and 520,000 deaths representing the 10% of all deaths in 2021 (OECD/European Union, 2022).

Table 3. COVID-19 deaths as a percentage of total deaths (all causes) in Greece by wave

Wave	Number of deaths		Percentage (%) COVID-19
	COVID-19	*All causes*	
Wave 1	4,946	36,256	13.6
Wave 2	2,844	25,312	11.2
Wave 3	7,528	84,111	9.0
Wave 4	3,414	17,725	19.3
Wave 5	2,095	11,595	18.1
Wave 6	4,771	29,863	16.0
All waves	25,598	204,862	12.5

Source: National Organisation for Public Health (EODY) (authors' own elaboration).

A clear contrast emerges between the first three and the last three waves of the pandemic. During the first three waves, the ratio of deaths to confirmed cases was relatively higher, whereas during the later three waves the absolute number of cases increased sharply but the corresponding deaths-to-cases ratio declined. This pattern suggests that, although infections became much more widespread in the later phase of the pandemic, the fatality burden relative to the number of recorded cases was lower than in the earlier phase.

Several factors may have contributed to this shift. A first plausible explanation concerns the temporal contrast between the earlier and later phases of the pandemic. During the first three waves, the population was more exposed and less protected, since vaccination was either unavailable or still limited in coverage. By contrast, during the later waves, the gradual expansion of vaccination is likely to have reduced the severity of outcomes, even though transmission increased substantially[2]. This helps explain why the relative fatality burden was higher in the earlier waves, whereas the later waves combined much larger numbers of infections with a lower deaths-to-cases ratio. At the same time, this pattern cannot be attributed to vaccination alone. Public-health interventions, including lockdowns[3], restrictions on mobility and social contact, the widespread use of masks, and the gradual adoption of stricter hygiene practices, may also have contributed to reducing fatal outcomes over time. In addition, changes in the dominant variants of the virus may have altered the relationship between contagion and lethality, as later waves appear to have been associated with greater transmissibility but a comparatively lower fatality burden. Nevertheless, because the later waves generated a much larger absolute volume of cases, the total number of deaths remained substantial despite the lower relative fatality observed during that phase.

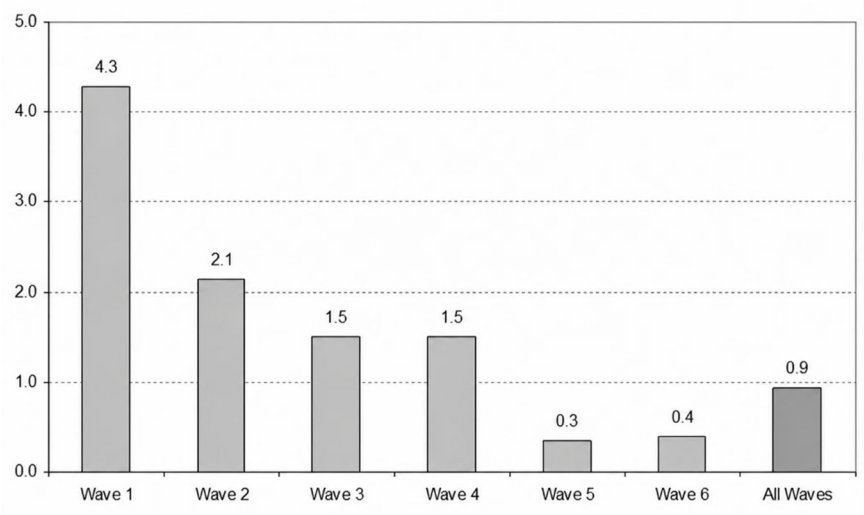
A second notable pattern concerns variation within each of the two three-wave periods. According to Table 3, the share of COVID-19 deaths in total mortality tends to decline from the first to the third wave, and again from the fourth to the sixth

[2] The vaccination in Greece started on Sunday 27 December 2020. President and the Prime Minister of Greece had been among the first who received the vaccine.
[3] As an example, the nationwide lockdown that was imposed on March 13, 2020, had an impact on controlling the spread of the disease. On November 3, 2020, the Greek nationwide lockdown limited transmission around the country.

wave, although the fourth wave stands out with the highest proportion of COVID-19 deaths relative to all-cause mortality (19.3%). This descriptive evidence points to a changing epidemiological profile across waves and underlines the importance of examining mortality not only in absolute terms, but also relative to the broader mortality context.

Figure 2 further highlights the variation in fatality across the six pandemic waves. Although the largest number of cases was recorded in the later waves, the highest case-fatality burden was observed in the earlier phase of the pandemic. A plausible explanation is that the early waves unfolded before widespread vaccination and before the gradual consolidation of treatment protocols, behavioural adaptation, and public-health responses. By contrast, in the later waves, transmission increased sharply but the relative fatality burden declined.

Figure 2. Case fatality rates per 100 by wave of the disease: 26/10/2020 – 22/3/2022



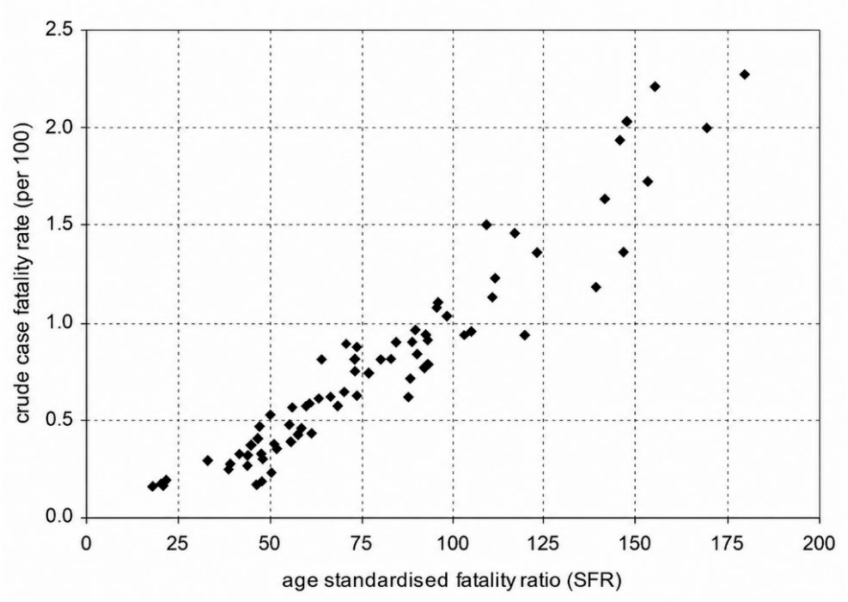
Source: EODY and Hellenic Statistical Authority (authors' calculations).

4.2. Spatial distribution of the Standardized Fatality Ratio (SFR)

The discussion begins with an overview at the level of the 13 administrative regions in order to highlight the broader territorial pattern, and then proceeds in the following subsections to the more fine-grained level of Regional Units. More specifically, although the wider dataset refers to the national geography of Regional Units, the present analytical application is based on 73 Regional Units, as Milos and Agion Oros are excluded from the SFR comparison because of the very small number of recorded cases. The analysis now turns to the spatial distribution of the Standardized Fatality Ratio, which provides an age-adjusted measure of COVID-19 mortality risk across Greek territorial units. In contrast to crude case-fatality measures, the SFR allows more meaningful spatial comparison by taking into account differences in the age composition of cases and deaths across territories.

A comparison between the regional crude fatality rates and the corresponding standardized fatality ratios confirms that the effect of age adjustment is substantial (Figure 3). In general, regions with high crude fatality rates also tend to display high SFR values. However, noticeable deviations emerge between the two measures, reflecting differences in the age structure of recorded cases across territorial units. These deviations are particularly evident in regions with moderate to relatively high mortality risk, indicating that crude fatality measures alone may conceal important territorial differences.

Figure 3. Scatterplot between crude fatality rates and standardized fatality ratios amongst the 73 regions of the study (all waves)



Source: EODY and Hellenic Statistical Authority (authors' calculations).

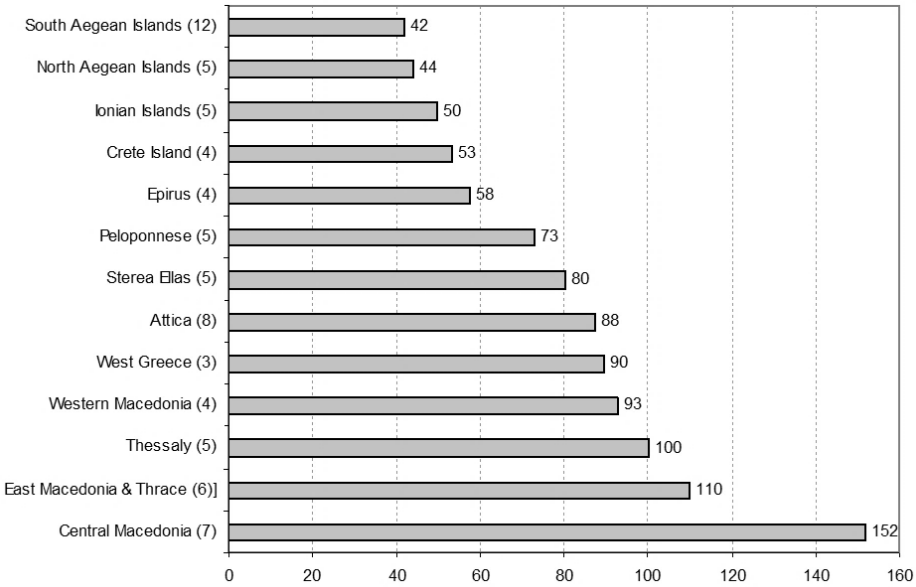
This is in line with (Green *et al.*, 2020) who argue that the crude case-fatality rates (CFR) for COVID-19 "hide more than they reveal", and therefore it is misleading to use crude COVID-19 CFRs comparisons between countries. Rather, age-specific and age-adjusted CFRs should be used for comparisons. Sudharsanan *et al.* (2020) argue that removing age distortions and focusing on differences in age-adjusted case fatality will be essential for accurately comparing countries' performances in caring for patients with COVID-19 and for monitoring the epidemic over time. The literature has underlined the significance of age-adjusted estimations of mortality rates (Bhopal, 2020), there is a scarcity of research based on the *SFR*, not only at the reginal level, due to lack of statistical data, but at the national level as well (Gallo *et al.*, 2021).

Considering the entire period, the standardized fatality ratios range from 18 to 179; the lowest value corresponds to the island of Karpathos (located in South Aegean Sea) denoting an 82% lower COVID-19 risk compared to the national average; the highest SFR value refers to the northern region of Pella (located in Central Macedonia in Northern Greece) indicating an elevated disease risk of 79%

compared to the national average. Of the 73 regions, 43 (59%) are mainland areas and the remaining 30 (41%) are islands; overall, 75% of the Regional Units exhibit fatality ratios lower than national average.

Figure 4 presents the mean SFR values for the 13 administrative regions of the country. Islands exhibit the lowest COVID risk (47% to 52% lower than the national average) while the highest SFRs are observed in the regions of Central Macedonia as well as in Eastern Macedonia and Thrace (52% and 10% higher than national average, respectively).

Figure 4. Mean *SFR* values for the 13 Regions of the country: all waves (in parenthesis the number of Administrative Units)



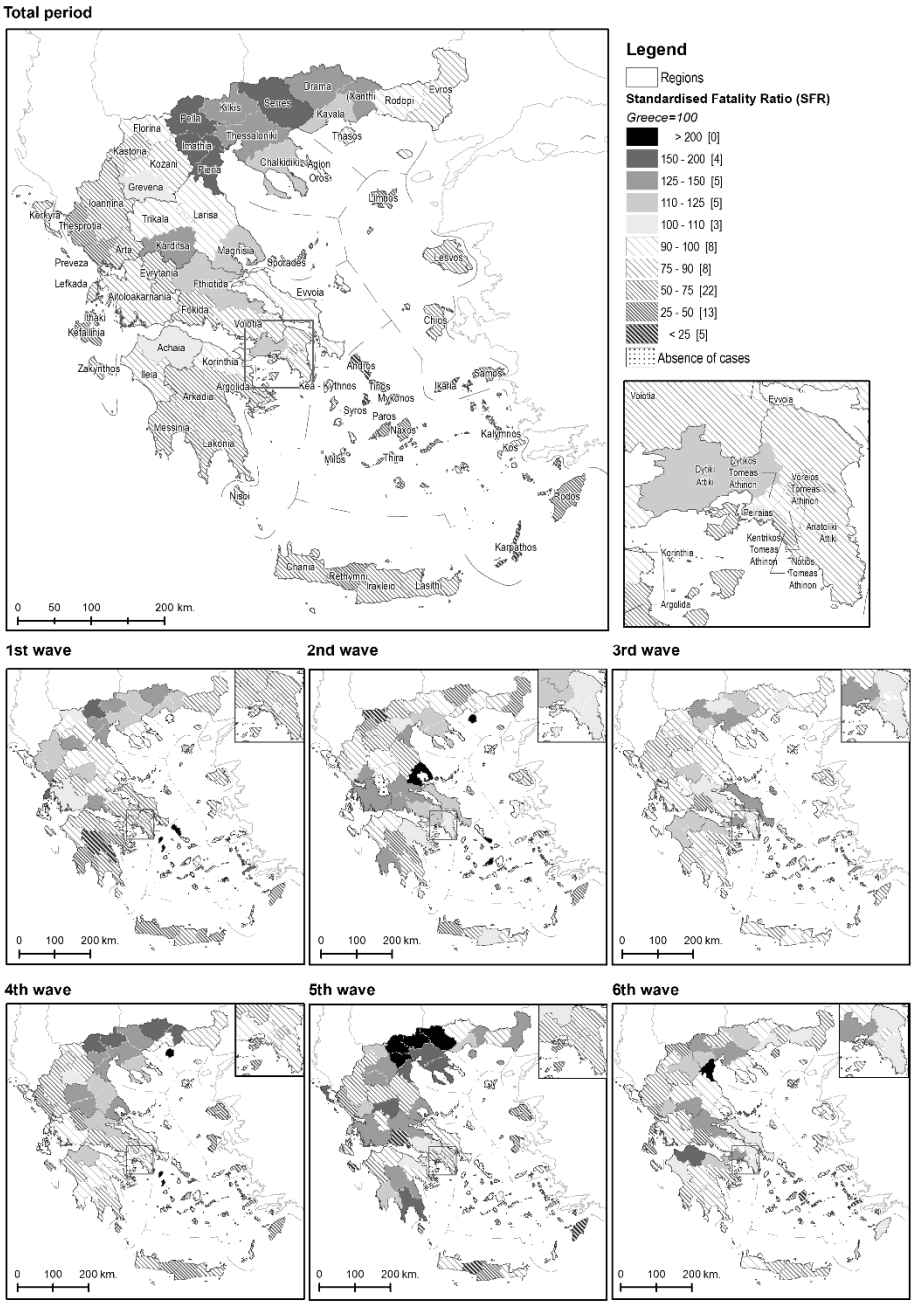
Source: EODY and Hellenic Statistical Authority (authors' calculations).

4.3. SFR across pandemic waves

Figure 5 maps the Standardized Fatality Ratio across the six pandemic waves and highlights the changing geography of COVID-19 mortality over time. A first clear pattern is that, during the initial wave, the areas most severely affected were located in the northern and north-eastern parts of the country. This suggests that the early geography of the pandemic in Greece was far from spatially uniform and that mortality risk was already concentrated in specific territorial zones.

A plausible explanation for this pattern lies in the strong cross-border and interregional interactions characterising northern Greece, particularly in relation to neighbouring countries in the Balkan Peninsula. In the early phase of the pandemic, when vaccination was not yet available and protective measures were still limited in effectiveness, such interaction dynamics may have contributed to greater exposure and higher fatality levels. By contrast, areas such as the Peloponnese, which are less integrated into intense international flows, displayed comparatively lower mortality levels during the same phase.

Figure 5. Mapping SFR by wave and Regional Unit in Greece



Source: EODY and Hellenic Statistical Authority (authors' calculations).

At the same time, the persistence of elevated SFR values in northern and north-eastern parts of the country across several waves suggests that the geography of

mortality cannot be explained solely by cross-border interaction. More structural factors may also have contributed to this pattern, including the relative level of economic development, local demographic composition, and broader socioeconomic conditions. In this respect, the wave-by-wave analysis indicates that the spatial expression of the pandemic was shaped by both circulation dynamics and pre-existing territorial inequalities.

Another noteworthy pattern concerns the metropolitan area of Athens. Although the broader metropolitan region emerges as a zone of elevated mortality, the distribution of SFR within Attica is not spatially uniform. A closer reading of the map suggests that the western part of the metropolitan area experienced a disproportionately higher mortality burden compared with other parts of the capital region. This intra-metropolitan differentiation may be associated with lower levels of economic development, poorer living conditions, lower educational attainment, and a more vulnerable social composition in the western part of the urban agglomeration. The Athens case therefore suggests that the geography of COVID-19 mortality was differentiated not only between regions, but also within major metropolitan areas.

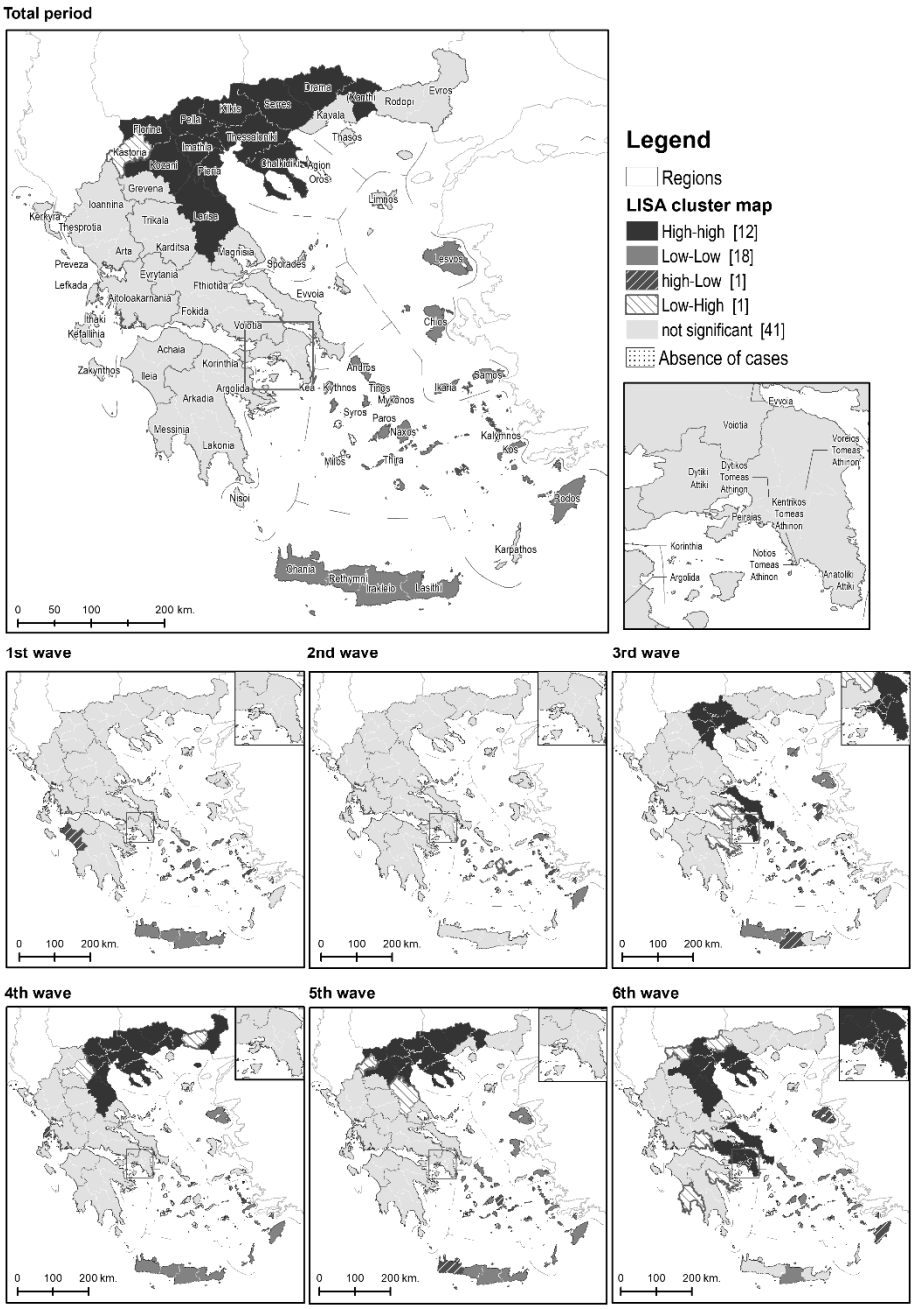
4.4. Local spatial clustering

In order to test spatial clustering, the analysis is making use of the most notable application of spatial autocorrelation with the estimation Local Indicators of Spatial Association (LISA) maps (Anselin, 1995). This method constitutes an established point of reference for a wide variety of applications. This method has been used for the estimation of spatial association in the geographical analysis of incidence and deaths from COVID-19 (Bag *et al.*, 2020; Ghosh and Cartone, 2020; Liu *et al.*, 2021a; Mollalo *et al.*, 2020). Global and local measures of spatial autocorrelation were used at the municipal level in Catalonia to identify spatial clusters of COVID-19 cases weekly (Arauzo-Carod, 2021). Bilal *et al.* (2021) examined spatial clusters of high and low positivity, confirmed cases, and mortality in three U.S. cities and ascertained that were co-located with clusters of low and high social vulnerability. Parvin *et al.* (2021), attempting to detect the hotspot of the novel coronavirus in India examined total population, population density, foreign tourist arrivals in India, reported confirmed cases of the COVID-19 and found statistically significant autocorrelation.

To further explore the local spatial structure of COVID-19 mortality, Local Indicators of Spatial Association (LISA) were estimated for the Standardized Fatality Ratio (SFR) for the full study period as well as for each of the six pandemic waves. In line with the methodological framework presented above, the local spatial analysis was based on a row-standardised (k=6) nearest neighbours spatial weights matrix. Figure 6 presents the resulting LISA maps and highlights the presence of statistically significant local clusters and spatial outliers across Greek territorial units.

The LISA results indicate that the geography of COVID-19 fatality was characterised by persistent local clustering rather than by random spatial dispersion. High-high clusters are concentrated primarily in the northern and north-eastern parts of the country, while additional cluster formations can be identified in the metropolitan area of Athens and, to a lesser extent, in Achaia/Patras and in the Larisa–Volos axis. These findings are consistent with the broader spatial pattern already identified in the descriptive analysis and point to the greater exposure of major mainland urban and transport-connected areas.

Figure 6. LISA maps of the Standardized Fatality Ratio (SFR) by pandemic wave and Regional Unit in Greece



Source: EODY and Hellenic Statistical Authority (authors' calculations).

A substantial part of these high-high clusters appears to be aligned with the main transport corridors of the country. In particular, the PATHE axis, extending from the northern borders through Thessaloniki, Thessaly, and the Athens metropolitan region toward Patras, seems to structure an important geography of transmission and mortality. A second significant axis runs across northern Greece from the eastern border areas toward the north-west and the port of Igoumenitsa, a major gateway connecting Greece to Italy and the rest of Europe. These configurations reinforce the interpretation that accessibility, mobility, and interregional interaction played an important role in shaping the local concentration of fatality.

By contrast, low-low clusters are more commonly identified in southern and western parts of the country and in many island areas. In general, the islands exhibit a more favourable mortality profile over the full period, reflecting their relative insularity and, in several cases, more limited interaction intensity. At the same time, some island territories display occasional deviations from this broader pattern during specific waves. For example, in the sixth wave, Lesvos and Rhodes appear as high-low outliers, while similar localized configurations can be observed sporadically in earlier waves, including Kalymnos in the first and second waves, Chios, Naxos, and Herakleio in the third wave, and Naxos and Chania in the fifth wave. These exceptions indicate that the island geography of the pandemic was not uniform, but varied over time depending on local exposure conditions, connectivity, and wave-specific dynamics.

5. ECONOMETRIC RESULTS AND DISCUSSION

5.1. Overview of model results

The empirical strategy developed in this study proceeds from the identification of local spatial autocorrelation to the estimation of a spatial econometric model. Given the evidence of spatial clustering in the Standardized Fatality Ratio, a spatial regression framework is more appropriate than a conventional non-spatial specification. COVID-19 mortality is unlikely to be determined solely by the internal characteristics of each territorial unit, since neighbouring areas are linked through commuting flows, transport networks, labour-market interactions, tourism activity, and broader territorial interdependencies. A spatial specification is therefore necessary in order to account for the fact that mortality outcomes may be shaped both by local conditions and by the characteristics of surrounding areas.

For this reason, the Spatial Durbin Error Model was selected as the preferred specification (LeSage and Pace, 2009; Elhorst, 2014; LeSage, 2014). The model is especially suitable because it combines two important dimensions of spatial dependence. First, by incorporating spatially lagged explanatory variables, it allows the analysis to capture local spillover effects arising from neighbouring territorial characteristics. Second, by modelling spatial dependence in the error term, it accounts for unobserved influences that remain geographically structured. This provides a more flexible and substantively meaningful framework for examining whether regional mortality inequalities are associated only with the characteristics of each territorial unit or also with neighbouring socio-economic and geographic conditions. The specification is particularly relevant in the Greek case, where metropolitan areas, mainland corridors, border zones, and island territories form a highly differentiated spatial environment.

Against this background, the discussion that follows focuses on the direct, indirect, and total effects of the explanatory variables, with particular attention to Model 3 in Table 4. Overall, the econometric findings suggest that regional mortality patterns during the pandemic were shaped by a combination of demographic, socioeconomic, and geographic characteristics, while also reflecting broader spatial spillovers across neighbouring territories.

5.2. Demographic and socioeconomic effects

A first notable result concerns the ageing ratio. Across the three models, the coefficient of ageing is negative, suggesting an inverse association between age structure and SFR. At first sight, this finding may appear counterintuitive, since older populations are generally more vulnerable to severe COVID-19 outcomes. However, once the full set of explanatory variables is taken into account, ageing no longer operates in isolation. A plausible interpretation is that regions with higher ageing ratios may also have benefited from stronger protective behaviour, earlier vaccination uptake among older age groups, and stricter adherence to preventive measures. In this respect, although biological vulnerability increases with age, the territorial effect of ageing may be mediated by policy interventions, behavioural adaptation, and healthcare provision. This interpretation is consistent with studies emphasizing that policy interventions and healthcare quality can mitigate age-related fatality risks (Onder *et al.*, 2020), as well as with findings pointing to negative statistical dependence between age structure and COVID-19 deaths (Bănică and Muntele, 2023) and the importance of stringent non-pharmaceutical interventions in reducing excess mortality (Gozzi *et al.*, 2021; Zahran *et al.*, 2022; Galmiche, 2024).

Education also emerges as an important factor. In all models, tertiary education is negatively associated with SFR, while in Model 3 the direct effect is statistically significant. This suggests that better-educated populations may have been more likely to adopt preventive health behaviours, comply with public-health guidance, and access healthcare services in a timely manner. The result is consistent with the broader literature linking education, health literacy, and lower mortality risk during pandemics (Angelici *et al.*, 2022; Zhuo and Harrigan, 2023; Bello and Rocco, 2022; Mirza B. *et al.*, 2024; Cutler and Lleras-Muney, 2010). It also resonates with work on the evolution of social inequalities in disease prevalence over time, according to which unequal access to information, prevention, and treatment shapes the changing relationship between socioeconomic status and health outcomes throughout successive phases of an epidemic (Mari-Dell'Olmo *et al.*, 2021; Clouston *et al.*, 2021). Similar temporal shifts in the relationship between education and infection or mortality have been documented in Spain and the United States (Pulido *et al.*, 2024; Matthay *et al.*, 2022).

With regard to economic structure, the location quotient of employment in the primary sector exhibits a negative direct, indirect, and total association with SFR, whereas the secondary sector shows a positive but statistically insignificant relationship. Results for the tertiary sector are more mixed across the three models, although in Model 1 the indirect effect is negative and close to statistical significance. Taken together, these results broadly align with Tsiotas *et al.* (2023). One possible interpretation is that neighbouring service-based economies may indirectly support lower fatality levels through stronger healthcare infrastructure, better service provision, and greater adaptive capacity, a pattern that is also compatible with broader discussions of economic structure and pandemic resilience (Hu *et al.*, 2022).

Table 4. Spatial Durbin and Spatial Error Models

Variables	SDEM								
	Model 1			Model 2			Model 3		
	Direct	*Indirect*	*Total*	*Direct*	*Indirect*	*Total*	*Direct*	*Indirect*	*Total*
Ageing ratio	-2.91 (0.02)**	-4.91 (0.07)*	-7.82 (0.01)***	-1.97 (0.14)	-3.36 (0.29)	-5.33 (0.16)	-1.54 (0.13)	-2.41 (0.34)	-3.96 (0.19)
Tertiary education (%)	-73.81 (0.48)	346.24 (0.19)	272.43 (0.37)	-85.92 (0.39)	205.85 (0.49)	119.93 (0.73)	-166.96 (0.07)*	56.06 (0.81)	-110.90 (0.69)
LQ primary sector	-2.94 (0.65)	-14.28 (0.33)	-17.22 (0.34)						
LQ secondary sector				0.30 (0.98)	5.62 (0.85)	5.92 (0.87)			
LQ tertiary sector	-13.31 (0.80)	-203.64 (0.09)*	-216.95 (0.12)						
Hospital Beds ratio	-0.11 (0.68)	-0.64 (0.31)	-0.76 (0.31)	0.13 (0.64)	-0.16 (0.79)	-0.03 (0.97)	-0.25 (0.33)	-1.29 (0.02)**	-1.54 (0.02)**
Foreign tourist arrivals				-0.17 (0.81)	-2.95 (0.08)*	-3.12 (0.13)			
Domestic tourist arrivals	-17.59 (0.00)**	-26.46 (0.02)**	-44.04 (0.00)***				-13.57 (0.01)***	-33.57 (0.00)***	-47.14 (0.00)***
Accessibility	0.51 (0.10)*	0.55 (0.37)	1.06 (0.05)**	0.49 (0.10)*	0.57 (0.39)	1.06 (0.09)*	0.30 (0.27)	0.42 (0.54)	0.72 (0.29)
Island status (Island with neighbouring unit	13.58 (0.33)	-29.27 (0.26)	-15.68 (0.51)	19.34 (0.18)	2.08 (0.94)	21.42 (0.41)	10.59 (0.43)	-39.68 (0.10)*	-29.09 (0.20)
Island status (Mainland)	32.27 (0.01)***	-7.22 (0.73)	25.04 (0.16)	32.95 (0.00)***	7.34 (0.70)	40.30 (0.02)**	24.79 (0.02)**	3.07 (0.87)	27.86 (0.10)*
Borde status (yes)	-2.22 (0.80)	6.16 (0.77)	3.94 (0.86)	5.08 (0.57)	38.88 (0.15)	43.96 (0.13)	-0.41 (0.96)	16.77 (0.39)	16.36 (0.43)
Employees' mobility within settlement	95.97 (0.02)**	150.07 (0.14)	246.04 (0.04)**	62.75 (0.21)	226.83 (0.12)	289.57 (0.09)*	65.42 (0.08)*	102.54 (0.33)	167.96 (0.17)
Employees' mobility within administrative unit				26.30 (0.69)	-123.28 (0.33)	-96.98 (0.50)			
Population (%) in settlements <2000							38.74 (0.01)***	-24.20 (0.54)	14.54 (0.75)
Lambda	(0.37)***			(0.53)***			(0.45)***		
AIC	705.09			714.42			697.16		
R^2	0.77			0.75			0.78		
Moran's I	0.26 (0.00)***			0.29 (0.00)***			0.30 (0.00)|***		
Breusch - Pagan	21.69 (0.48)			24.07 (0.34)			20.41 (0.43)		

Note. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Island status enters the regression as a three-category factor through the corresponding dummy coding. Border status is coded as a binary variable (see Table 1).

The beds ratio also provides useful insights. Although hospital-bed availability does not show a statistically significant direct effect in the local unit itself, neighbouring values of the hospital beds ratio display a negative and statistically significant indirect effect, while in Model 3 the total effect is also negative and significant. This suggests that healthcare capacity may matter less as an isolated local endowment and more as part of a broader regional support system extending across neighbouring units. In other words, the availability of beds in surrounding territories may reduce pressure on local health systems and contribute to lower

fatality risk more generally. This interpretation is consistent with studies underlining the importance of overall bed availability, ICU capacity, and interregional healthcare coordination in managing fatal outcomes during the pandemic (Parotto *et al.*, 2023; Berkeveld *et al.*, 2025; Zhou *et al.*, 2024).

5.3. Tourism, accessibility and mobility

Tourism-related mobility presents mixed effects. While foreign tourist arrivals do not exert a statistically significant direct effect, domestic tourist arrivals are negatively and significantly associated with SFR in direct, indirect, and total terms. This result requires a nuanced interpretation. It should not be read as evidence that tourism was irrelevant to pandemic dynamics, but rather as a reflection of the specific geography of tourism during the period under study. International tourist flows were strongly constrained by travel restrictions, lockdowns, uncertainty, and shifting health protocols, particularly during the summers of 2020 and 2021 (Linka *et al.*, 2020; Farzanegan *et al.*, 2021; Gozzi *et al.*, 2021; Selvanathan *et al.*, 2022; Koiso *et al.*, 2024). At the same time, hesitation and self-restraint on the part of travellers, especially in the absence of vaccines and pharmaceutical treatments in the earlier phase, also reduced the overall volume and intensity of international mobility (Mertzanis and Papastathopoulos, 2021).

By contrast, domestic tourism appears to have been partly redirected toward less densely populated and island destinations, many of which displayed lower mortality levels overall. The negative association between domestic tourist arrivals and SFR therefore seems to reflect not a protective effect of tourism per se, but the differentiated territorial context in which tourist activity took place. In this sense, the relationship between tourism intensity and mortality is likely to have been mediated by destination type, insularity, settlement density, and proximity to major urban centres. This interpretation is also consistent with studies suggesting that local mobility controls and the geography of mobility flows, rather than tourism intensity alone, influenced long-term COVID-19 mortality trends (Nunkoo *et al.*, 2021; Matsuura and Saito, 2022).

Geographic structure also plays a significant role. Mainland regions display higher SFR values than island areas, a pattern that can plausibly be linked to higher density, stronger mobility flows, and greater exposure to transmission. By contrast, islands may have benefited from relative isolation, more easily controlled entry points, and lower transmission intensity, as documented in other insular contexts during the pandemic (Lemey *et al.*, 2021; Uysal and Ulusinan, 2022).

Accessibility is positively associated with SFR, indicating that regions with better transport links and stronger territorial connectivity experienced higher fatality levels. This finding suggests that accessibility should not be interpreted only as a development advantage, but also as a channel of epidemiological exposure during health crises. Better-connected regions are embedded in denser transport corridors, commuting systems, and interregional interaction networks, all of which may increase repeated contact and facilitate transmission. In this sense, accessibility acts as a territorial amplifier of risk, especially when combined with urban concentration and labour mobility. This result is in line with evidence reported by Tsiotas *et al.* (2023).

Mobility within settlements is another important factor. Higher employee mobility within the settlement of residence is positively associated with SFR, supporting the argument that frequent daily movement and workplace interaction

contributed to greater exposure and, indirectly, to higher fatality levels. Similar patterns have been identified in studies of pandemic transmission in urbanized and industrialized regions (Wahrendorf *et al.*, 2022; Konstantinoudis *et al.*, 2022; Boto-García, 2023). Mobility within the administrative unit of residence also shows a positive, though statistically insignificant, direct effect in Model 2.

Finally, settlement structure appears to matter as well. The positive and statistically significant direct effect associated with the share of population living in settlements with fewer than 2,000 inhabitants suggests that small-settlement structure is also relevant to the geography of COVID-19 mortality. This finding indicates that mortality patterns cannot be explained solely in terms of metropolitan concentration or large urban centres but must also be interpreted in relation to more dispersed and weakly serviced settlement environments. In this sense, the territorial organisation of settlement systems may shape both exposure and access to health-related resources, a pattern that deserves further investigation in light of the broader literature on spatial inequalities and pandemic vulnerability (Bănică and Muntele, 2023; Kawalerowicz *et al.*, 2023; Tsiotas *et al.*, 2023).

5.4. Spatial dependence and broader territorial interpretation

Beyond the effects of individual variables, the econometric results confirm the presence of spatial dependence in regional mortality patterns. The statistically significant lambda coefficient in all three models indicates that the unexplained component of SFR is spatially correlated across neighbouring territorial units. More specifically, higher unexplained values of SFR in surrounding units are associated with higher residual values in a given unit, suggesting that unobserved influences on mortality were not spatially random but tended to propagate across space. In comparative terms, Model 3 provides the best fit according to the Akaike Information Criterion (AIC), and is therefore considered the preferred specification.

More broadly, the spatial effects identified in the econometric analysis indicate that COVID-19 mortality was embedded in wider territorial systems rather than confined to isolated regional units. Neighbouring regions share labour markets, transport infrastructures, service networks, and healthcare interdependencies, and these connections shape both exposure and resilience. For that reason, mortality outcomes in a given region cannot be fully understood without reference to surrounding territories. This is particularly relevant in the Greek context, where metropolitan concentration, border interactions, mainland transport axes, and island-mainland asymmetries create a highly differentiated spatial setting. The findings therefore support a relational understanding of regional vulnerability, according to which pandemic outcomes are produced by the interaction between internal regional characteristics and broader interregional linkages.

6. CONCLUSIONS AND POLICY CHALLENGES

This study examined the geography of COVID-19 fatality in Greece by combining epidemiological indicators, exploratory spatial analysis, and spatial econometric modelling. Given the multidimensional character of the pandemic, the analysis adopted an interdisciplinary approach drawing on concepts and methods from epidemiology, demography, regional analysis, spatial planning, and spatial econometrics. The findings confirm that COVID-19 mortality was not distributed randomly across Greek space, but reflected clear territorial differentiations shaped by spatial dependence, regional structure, and interregional interactions.

The first major finding is that space matters for the unfolding, transmission, and fatality burden of the disease. The spatial analysis identified distinct geographical patterns, with higher fatality burdens in parts of Northern Greece and in several mainland urban and peri-urban areas, while southern and island regions were generally less affected. The analysis by pandemic wave further showed that the temporal evolution of the disease was uneven. Although the later waves generated much larger numbers of cases, the relative fatality burden declined compared with the earlier phase of the pandemic. This pattern is plausibly associated with the gradual expansion of vaccination coverage, the adoption of public health measures, behavioral adaptation, and changes in the dominant variants of the virus.

A second major finding is that the determinants of mortality extend beyond age structure alone. While older populations are biologically more vulnerable to severe outcomes, the econometric results suggest that age structure does not by itself explain higher regional fatality levels once broader demographic, socioeconomic, and geographic conditions are taken into account. Instead, the findings point to the importance of education, healthcare capacity, accessibility, insularity, mobility, tourism-related territorial dynamics, and settlement structure in shaping differentiated mortality outcomes. Education emerges as a relevant protective factor, while healthcare capacity appears to matter primarily through indirect and total spillover effects across neighboring territorial units rather than through a purely local direct effect. The results also suggest that tourism and mobility must be interpreted in relation to the territorial contexts in which they occur, rather than as uniform risk factors across space.

More broadly, the analysis shows that COVID-19 mortality in Greece was embedded in wider territorial systems. Mainland corridors, metropolitan areas, border zones, and several structurally disadvantaged territories were more exposed to transmission and fatality, whereas island areas often displayed lower mortality burdens. At the same time, the significance of the settlement variable indicates that the geography of mortality cannot be reduced to a simple urban–rural divide, but must also take into account the differentiated role of small-settlement structures, mobility patterns, and uneven access to services across space. These findings support a relational understanding of regional vulnerability, according to which mortality outcomes are shaped both by internal regional characteristics and by broader spatial interdependencies. In this respect, the Greek case provides further evidence that pandemics and other exogenous crises interact with pre-existing territorial inequalities, uneven regional resilience, and differentiated access to services and protection.

The policy implications of the analysis extend beyond COVID-19 as a singular historical episode. If pandemic mortality is territorially differentiated and shaped by spatial spillovers, crisis preparedness cannot rely exclusively on uniform national responses. More place-sensitive strategies are needed, combining health system capacity, mobility management, social protection, and interregional coordination. In practical terms, mainland corridors, border regions, metropolitan peripheries, and structurally disadvantaged areas may require differentiated prevention and response mechanisms. Strengthening healthcare provision, improving access to services, reducing educational and socio-economic inequalities, and enhancing coordination across neighboring regions are not only public health priorities but also core dimensions of territorial resilience. More broadly, the findings underline the continuing relevance of state intervention as a practical

necessity in periods of cascading crisis, in a sense not far from the argument advanced by Gunnar Myrdal (1939). In this perspective, preparedness for future pandemics and other exogenous crises should be embedded in a broader regional-development agenda aimed at reducing place-based vulnerability. The broader significance of these findings lies in the fact that the most disadvantaged areas and populations appear to have borne a disproportionate burden during the pandemic, reinforcing existing health inequalities and deepening the condition of populations living at the margins and places that can be understood as "left behind" (Rodríguez-Pose, 2018; Pike *et al.*, 2023).

Despite these contributions, the study also has limitations. The absence of systematic data on vaccination rates limits the possibility of examining more directly the relationship between immunization coverage and regional mortality outcomes. In addition, the lack of finer-grained information by gender and smaller territorial units constrains the analysis of intra-regional inequalities. Finally, the level of geographical aggregation does not allow investigation at the municipality, postcode, or neighborhood scale, where important localized patterns may remain hidden. These limitations point to promising directions for future research, particularly in relation to more detailed territorial data, vaccination dynamics, and the micro-geographies of vulnerability and mortality.

REFERENCES

Alizadeh, H., Sharifi, A., Damanbagh, S. et al. (2023). Impacts of the COVID-19 pandemic on the social sphere and lessons for crisis management: a literature review, *Natural Hazards,* 117, pp. 2139–2164.

Andersen, L.M., Harden, S.R., Sugg, M.M., Runkle, J.D., Lundquist, T.E. (2021). Analyzing the spatial determinants of local Covid-19 transmission in the United States, *Sci. Total Environ.*, 754, 142396.

Angelici, L., Sorge, C., Di Martino, M., Cappai, G., Stafoggia, M., Agabiti, N., Girardi, E., Lanini, S., Nicastri, E., Davoli, M., & Cesaroni, G. (2022). Incidence of SARS-CoV-2 Infection and Related Mortality by Education Level during Three Phases of the 2020 Pandemic: A Population-Based Cohort Study in Rome, *Journal of Clinical Medicine*, 11(3), 877.

Anselin, L. (1995). Local Indicators of Spatial Association - LISA, *Geographical Analysis*, 27: 93–115.

Arauzo-Carod, J.-M. (2021). A first insight about spatial dimension of COVID-19: Analysis at municipality level, *Public Health*, 43, pp. 98–106.

Armitage, P., Berry, G., Matthews J.N.S. (2002) *Statistical methods in medical research*, 4th ed, Oxford: Blackwell.

Bag, R., Ghosh, M., Biswas, B., Chatterjee, M. (2020). Understanding the spatio-temporal pattern of COVID-19 outbreak in India using GIS and India's response in managing the pandemic, *Regional Science Policy & Practice*, 12, 1063–1103.

Bănică, A., Muntele, I. (2023). Local and regional factors of spatial differentiation of the excess mortality related to the COVID-19 pandemic in Romania, *Letters in Spatial and Resource Sciences,* 16, 23.

Bello, P., Rocco, L., (2022). Education and COVID-19 excess mortality, *Economics & Human Biology*, 47, 101194.

Berkeveld, E., Rhebergen, M.D.F., Bloemers, F.W. et al. (2025). Patient coordination during the COVID-19 pandemic in the Amsterdam region: effects on capacity utilization and patient flow, *BMC Health Serv Res,* 25, 266.

Bhopal, R. (2020). Covid-19 worldwide: we need precise data by age group and sex urgently, *BMJ* 2020, 369:m1366.

Bilal, U., Tabb, L.P., Barber, S., Diez Roux, A.V. (2021). Spatial Inequities in COVID-19 Testing, Positivity, Confirmed Cases, and Mortality in 3 U.S. Cities: An Ecological Study, *Annals of Internal Medicine*, 174, pp. 936–944.

Boto-García, D. (2023). Investigating the two-way relationship between mobility flows and COVID-19 cases, *Economic Modelling*, 118: 106083.

Bourdin, S., & Levratto, N. (2023). Regional Implications of COVID-19. *International Regional Science Review*, 46(5-6), 515-522.

Bourdin, S., Moodie, J., Gassen, N. S., Evers, D., Adobati, F., Amdaoud, M., ... Remete, Z. (2024). COVID-19 as a systemic shock: curb or catalyst for proactive policies towards territorial cohesion?, *Regional Studies*, 58(8), pp. 1543–1556.

Castro, R.R., Santos, R.S.C., Sousa, G.J.B., Pinheiro, Y.T., Martins, R.R.I.M., Pereira, M.L.D., Silva, R.A.R. (2021). Spatial dynamics of the COVID-19 pandemic in Brazil, *Epidemiol. Infect*, 149, e60.

Clouston, S.A.P., Natale, G., Link, B.G. (2021). Socioeconomic inequalities in the spread of coronavirus-19 in the United States: A examination of the emergence of social inequalities, *Social Science & Medicine* 268, 113554.

Cutler, D. M., & Lleras-Muney, A. (2010). Understanding differences in health behaviors by education, *Journal of Health Economics, 29*(1), pp. 1–28.

Díaz Ramírez, M., Veneri, P., and Lembcke, A.C. (2022). Where did it hit harder? Understanding the geography of excess mortality during the COVID-19 pandemic, *Journal of Regional Science*, 62, pp. 889–908.

Dodds, K., Castan Broto, V., Detterbeck, K., Jones, M., Mamadouh, V., Ramutsindela, M., Varsanyi, M., Wachsmuth D. and Woon C.H. (2020). The COVID-19 pandemic: territorial, political and governance dimensions of the crisis, *Territory, Politics, Governance*, 8(3): 289-298.

Ehlert, A. (2021). The socio-economic determinants of COVID-19: a spatial analysis of German County level data, *Socio-Economic Planning Sciences, 78:* 101083.

Elhorst, J.P. (2014). *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*, Springer.

ESPON & European Union (2022) *Territorial impacts of COVID-19 and policy answers in European regions and cities*, Final report, June.

European Parliament (2022). The impacts of the COVID-19 pandemic on EU cohesion and EU cohesion policy - Part I: Overview and first analysis, European Parliament, Policy Department for Structural and Cohesion Policies, Brussels.

Farzanegan, M. R., Gholipour, H. F., Feizi, M., Nunkoo, R., & Andargoli, A. E. (2021). International Tourism and Outbreak of Coronavirus (COVID-19): A Cross-Country Analysis, *Journal of Travel Research*, 60(3), pp. 687-692.

Gallo, V., Chiodini, P., Bruzzese, D., Kondilis, E., Howdon, D., Mierau, J., Bhopal, R. (2021). Comparing the COVID-19 pandemic in space and over time in Europe, using numbers of deaths, crude rates and adjusted mortality trend ratios, *Scientific Reports,* 11: 16443.

Galmiche, S., Coustaury, C., Charniga, K. Grant, R., Cauchemez, S., Fontanet A. (2024). Patterns and drivers of excess mortality during the COVID-19 pandemic in 13 Western European countries, *BMC Global Public Health,* 2, 78.

Ghosh, P. and Cartone, A. (2020). A Spatio-temporal analysis of COVID-19 outbreak in Italy, *Regional Science Policy & Practice*,12, pp. 1047–1062.

Gong, H., Hassink, R., Foster, C., Hess, M., Garretsen, H. (2022). Globalisation in reverse? Reconfiguring the geographies of value chains and production networks, Cambridge, *Journal of Regions, Economy and Society*, 15(2): 165–181.

Gozzi, N., Bajardi, P., & Perra, N. (2021). The importance of non-pharmaceutical interventions during the COVID-19 vaccine rollout, *PLoS Comput Biol* 17(9), e1009346.

Green, M.S., Peer, V., Schwartz, N., Nitzan, D. (2020). The confounded crude case-fatality rates (CFR) for COVID-19 hide more than they reveal - a comparison of age-specific and age-adjusted CFRs between seven countries, *PLoS ONE,* 15(10), e0241031.

Hassaan, M.A., Abdelwahab, R.G., Elbarky, T.A., Ghazy, R.M. (2021). GIS-Based Analysis Framework to Identify the Determinants of COVID-19 Incidence and Fatality in Africa'. *Journal of Primary Care & Community Health*, 12.

Hu, X, Li, L, Dong, K. (2022). What matters for regional economic resilience amid COVID-19? Evidence from cities in Northeast China, *Cities*, 120, 103440.

Jackson, S.L., Derakhshan, S., Blackwood, L., Lee, L., Huang, Q., Habets, M., Cutter, S.L. (2021). Spatial Disparities of COVID-19 Cases and Fatalities in United States Counties, *International Journal of Environmental Research* and *Public Health*, 18: 8259.

Kawalerowicz, J., Cederström, A., Andersson, E., & Malmberg, B. (2023). COVID-19 in the neighbourhood: the socio-spatial selectivity of severe COVID-19 cases in Sweden, March 2020–June 2021, *GeoJournal,* 88, pp. 5757–5773.

Keil, R., (2020). The Space and Time a Pandemic Makes, disP- *The Planning Review*, 56(3), pp. 4-9.

Kim, B., Rundle, A.G., Goodwin, A.T.S., Morrison, C.N., Branas, C.C., El-Sadr, W., Duncan, D.T. (2021). COVID-19 testing, case, and death rates and spatial socio-demographics in New York City: An ecological analysis as of June 2020, *Health Place*, 68, 102539.

Koiso, S., Gulbas, E., Dike, L., Mulroy, N.M., Ciaranello, A.L., Freedberg, K.A., Jalali, M.S., Walker A.T., Ryan, E.T., LaRocque R.C., Hyle, E.P. (2024). Modeling approaches to inform travel-related policies for COVID-19 containment: A scoping review and future directions, *Travel Medicine and Infectious Disease* 62, 102730.

Konstantinoudis, G., Cameletti, M., Gómez-Rubio, V. *et al.* (2022). Regional excess mortality during the 2020 COVID-19 pandemic in five European countries, *Nat Commun* 13, 482.

Kulu, H., Dorey, P. (2021). Infection rates from COVID-19 in Great Britain by geographical units: A model-based estimation from mortality data, *Health Place*, 67, 102460.

Lemey, P., Ruktanonchai, N. W., Hong, S. L., Colizza, V., Poletto, C., Van Boven, M., & Pybus, O. G. (2021). Untangling introductions and persistence in COVID-19 resurgence in Europe, *Nature, 595*(7869), pp. 713–717.

LeSage, J., & Pace, R.K. (2009). *Introduction to Spatial Econometrics*, CRC Press/Taylor & Francis Group.

LeSage, J., (2014). What Regional Scientists Need to Know about Spatial Econometrics, *The Review of Regional Studies*, 44(1), pp. 13-32.

Liddell, F.D.K. (1984). Simple exact analysis of the standardised mortality ratio, *Journal of Epidemiology and Community Health*, 38, pp. 85–8.

Linka, K., Peirlinck, M., Sahli Costabal, F., & Kuhl, E. (2020). Outbreak dynamics of COVID-19 in Europe and the effect of travel restrictions, *Computer Methods in Biomechanics and Biomedical Engineering*, *23*(11), pp. 710–717.

Liu, M., Liu, M., Li, Z., Zhu, Y., Liu, Y., Wang, X., Tao, L., Guo, X. (2021a). The spatial clustering analysis of COVID-19 and its associated factors in mainland China at the prefecture level, *Science of the Total Environment*, 777, 145992.

Liu, W., Wang, D., Hua, S., Xie, C., Wang, B., Qiu, W., Xu, T., Ye, Z., Yu, L., Yang, M., Xiao, Y., Feng, X., Shi, T., Li, M., Chen, W. (2021b). Spatiotemporal analysis of COVID-19 outbreaks in Wuhan, China, *Scientific Reports,* 11, 13648.

Luo, G., Zhang, X., Zheng, H., He D. (2021). Infection fatality ratio and case fatality ratio of COVID-19, *International Journal of Infectious Diseases,* 113, pp. 43–46.

Mansour, S., Al-Kindi, A., Al-Said, A., Al-Said, A., Atkinson, P. (2021). Sociodemographic determinants of COVID-19 incidence rates in Oman: Geospatial modelling using multiscale geographically weighted regression (MGWR), *Sustainable Cities* and *Society,* 65, 102627.

Mari-Dell'Olmo, M., Gotsens, M., Pasar, M.I., Rodr, M., De Olalla, P.G., Rius, C., Borrell, C. (2021). Socioeconomic Inequalities in COVID-19 in a European Urban Area: Two Waves, Two Patterns, *International Journal of Environmental Research* and *Public Health*, 18, 1256.

Martin, R. (2021). Rebuilding the economy from the Covid crisis: time to rethink regional studies? Regional Studies, *Regional Science*, 8(1), pp. 43-161.

Martines, M.R., Ferreira, R.V., Toppa, R.H., Assunção, L.M., Desjardins, M.R., Delmelle, E.M. (2021). Detecting space–time clusters of COVID-19 in Brazil: Mortality, inequality, socioeconomic vulnerability, and the relative risk of the disease in Brazilian municipalities, *Journal of Geographical Systems*, 23, pp. 7–36.

Matsuura, Y., Saito, H. (2022). The COVID-19 pandemic and domestic travel subsidies, *Annals of Tourism Research*, 92: 103326.

Matthay, E.C., Duchowny, K.A., Riley, A.R., Thomas, M.D., Chen, Y.-H., Bibbins-Domingo, K., & Glymour, M.M. (2022). Occupation and educational attainment characteristics associated with COVID-19 mortality by race and ethnicity in California, *JAMA Network Open,* 5(4), e228406.

Mertzanis, C., & Papastathopoulos, A. (2021). Epidemiological susceptibility and tourist flows around the world, *Annals of Tourism Research,* 86, 103095.

Mirza, B. *et al.* (2024). Effects of education on adult mortality: a global systematic review and meta-analysis, *The Lancet Public Health*, 9(3), e155 - e165.

Mollalo, A., Vahedi, B., Rivera, K.M. (2020). GIS-based spatial modeling of COVID-19 incidence rate in the continental United States, *Science of the Total Environment*, 728, 138884.

Myrdal G. (1939). Fiscal Policy in the Business Cycle, The American Economic Review, Vol. 29, No. 1, Supplement, Papers and Proceedings of the Fifty-first Annual Meeting of the American Economic Association, pp. 183-193.

Nunkoo, R., Daronkola, H. K., & Gholipour, H. F. (2021). Does domestic tourism influence COVID-19 cases and deaths? *Current Issues in Tourism, 25*(3), pp. 338–351.

OECD/European Union (2022) *Health at a Glance: Europe 2022: State of Health in the EU Cycle*, OECD Publishing, Paris.

Onder, G., Rezza G, Brusaferro, S. (2020). Case-Fatality Rate and Characteristics of Patients Dying in Relation to COVID-19 in Italy". JAMA. 2020 May 12;323(18):1775-1776. Erratum in: JAMA. 2020 Apr 28; 323(16), 1619.

Parotto, E., Lamberti-Castronuovo, A., Censi, V., Valente, M., Atzori, A., Ragazzoni, L. (2023). Exploring Italian healthcare facilities response to COVID-19 pandemic: Lessons learned from the Italian Response to COVID-19 initiative, *Front Public Health* 10, 1016649.

Parvin, F., Ali, S.A., Hashmi, S.N.I., Ahmad, A. (2021). Spatial prediction and mapping of the COVID-19 hotspot in India using geostatistical technique, *Spatial Information Research*, 29, pp. 479–494.

Pike A., Béal V., Cauchi-Duval N., Franklin R., Kinossian N., Lang T., Leibert T., MacKinnon D., Rousseau M., Royer J., Servillo L., Tomaney J., & Velthuis, S. (2023) 'Left behind places': a geographical etymology, *Regional Studies,* 58, pp. 1167-1179.

Pulido, J., Donat, M., Moreno, A., Politi, J., Cea-Soriano, L., Sordo, L., Mateo-Urdiales, A., Ronda, E., Belza, M.J., Barrio, G., & Regidor, E. (2024). Assessing educational disparities in COVID-19 related excess mortality in Spain: a population register-linked mortality study, *Frontiers in Public Health,* 12.

Psycharis, Y., Tsimbos C., Verropoulou, G., & Doukissas, L. (2021). The determinants of Covid-19 mortality rates across Europe: Assessing the role of demographic and socioeconomic factors during the first wave of the pandemic, *Region,* 8(1), pp. 199–219.

Rahman, M.d.H., Zafri, N.M., Ashik, F.R., Waliullah, M., Khan, A. (2021). Identification of risk factors contributing to COVID-19 incidence rates in Bangladesh: A GIS-based spatial modeling approach, *Heliyon*, 7, e06260.

Rodríguez-Pose, A. (2018), "The revenge of the places that don't matter (and what to do about it), *Cambridge Journal of Regions, Economy and Society*, 11(1), pp. 189–209.

Sannigrahi, S., Pilla, F., Basu, B., Basu, A.S., Molter, A. (2020). Examining the association between socio-demographic composition and COVID-19 fatalities in the European region using spatial regression approach, *Sustain. Cities Soc*., 62, 102418.

Sarkar, S.K., Ekram, K.M.M., Das, P.C. (2021). Spatial modeling of COVID-19 transmission in Bangladesh, *Spatial Information Research,* 29, pp. 715–726.

Selvanathan, E. A., Jayasinghe, M., & Selvanathan, S. (2022). International Tourism and Infectious Disease Transmission Nexus: A Cross-Country and Regional Study, *Journal of Travel Research*, *61*(8), pp. 1910-1927.

Sigler, T., Mahmuda, S., Kimpton, A., Loginova, J., Wohland P., Charles-Edwards, E. and Corcoran, J. (2021). The socio-spatial determinants of COVID-19 diffusion: the impact of globalisation, settlement characteristics and population, *Global Health* 17, 56.

Sudharsanan, N, Didzun, O., Bärnighausen, T., Geldsetzer, P. (2020). The Contribution of the Age Distribution of Cases to COVID-19 Case Fatality Across Countries: A Nine-Country Demographic Study, *Annals of Internal Medicine,* 173(9), pp. 714-720.

Sun, F., Matthews, S.A., Yang, T.C., Hu, M.H. (2020). A spatial analysis of the COVID-19 period prevalence in U.S. counties through June 28, 2020: Where geography matters?, *Ann. Epidemiol*., 52, pp. 54–59.

Thomas, B.S., Marks, N.A. (2021). Estimating the case fatality ratio for COVID-19 using a time-shifted distribution analysis, *Epidemiology and Infection* 149, e197, pp. 1–12.

Tsiotas, D., Dialesiotis, S., & Christopoulou, O. (2023). Examining the relationship between regional economic resilience and epidemiologic spread of COVID-19: evidence from Greece, *Environment, Development and Sustainability,* 27, pp. 8433-8469.

Uysal, B., Ulusinan, E. (2022). Investigation the Effect of Geographical Isolation On COVID-19 Pandemic In Terms Of Island Countries, *Selçuk Sağlık Dergisi*, 3(1), pp. 34–49.

Wahrendorf, M., Reuter, M., Hoebe,l J., Wachtler B., Höhmann, A., Dragano N. (2022). Regional disparities in SARS-CoV-2 infections by labour market indicators: a spatial panel analysis using nationwide German data on notified infections, *BMC Infect Dis.* 22(1), 661.

Xie, Z., Zhao, R., Ding, M., Zhang, Z. (2021). A Review of Influencing Factors on Spatial Spread of COVID-19 Based on Geographical Perspective*, International Journal of Environmental Research and Public Health*, 18(22), 12182.

Zahran, S., Altringer, L., & Prasad, A. (2022). The Longevity-Frailty Hypothesis: Evidence from COVID-19 Death Rates in Europe, *International Journal of Environmental Research and Public Health*, *19*(4), pp. 2434.

Zhai, W., Liu, M., Fu, X., Peng, Z.-R. (2021). American Inequality Meets COVID-19: Uneven Spread of the Disease across Communities, *Annals of the Association of American Geographers*, 111, pp. 2023–2043.

Zhou, C., Wheelock, Å.M., Zhang, C. Ma J., Li, Z., Liang, W., Gao, J., & Xu, L. (2024). Country-specific determinants for COVID-19 case fatality rate and response strategies from a global perspective: an interpretable machine learning framework, *Popul Health Metrics,* (22)10.

Zhuo, J., Harrigan, N. (2023). Low education predicts large increase in COVID-19 mortality: the role of collective culture and individual literacy, *Public Health,* 221, pp. 201-207.

Analyse spatiale de la Covid-19 en Grèce : les enjeux pour la politique régionale

Résumé **-** Cette étude examine la mortalité liée à la Covid-19 au sein de soixante-quinze unités administratives régionales en Grèce, ventilées par tranches d'âge de dix ans et selon les six vagues pandémiques successives couvrant la période du 26 octobre 2020 au 22 mars 2022. En estimant les taux de létalité standardisés selon l'âge (SFR) et en appliquant un modèle d'erreur spatiale de Durbin (SDEM), l'analyse identifie les déterminants socio-économiques, démographiques et géographiques des disparités spatiotemporelles de la mortalité due à la Covid-19. Les résultats obtenus contribuent à la littérature sur les inégalités régionales en matière de santé et peuvent éclairer les politiques régionales visant à construire des communautés plus résilientes et mieux protégées face aux futurs chocs épidémiques.

Mots-clés

Analyse spatiale
Inégalités de santé
Vulnérabilité socio-économique
Politique régionale
Covid-19
Taux de létalité standardisé selon l'âge
Modèle de Durbin spatial (SDEM)
Grèce