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ORIGINAL PAPER

Local and regional factors of spatial differentiation of the excess mortality related to the COVID-19 pandemic in Romania

Alexandru Bănică[1,2] · Ionel Muntele[1,2]

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Abstract
COVID-19 revealed some major weaknesses and threats that are related to the level of territorial development. In Romania, the manifestation and the impact of the pandemic were not homogenous, which was influenced, to a large extent, by a diversity of sociodemographic, economic, and environmental/geographic factors. The paper is an exploratory analysis focused on selecting and integrating multiple indicators that could explain the spatial differentiation of COVID-19-related excess mortality (EXCMORT) in 2020 and 2021. These indicators include, among others, health infrastructure, population density and mobility, health services, education, the ageing population and distance to the closest urban center. We analyzed the data from local (LAU2) and county level (NUTS3) by applying multiple linear regression and geographically weighted regression models. The results show that mobility and lower social distancing were far more critical factors for higher mortality than the intrinsic vulnerability of the population, at least in the first two years of COVID-19. However, the highly differentiated patterns and specificities of different areas of Romania resulting from the modelling of EXCMORT factors drive to the conclusion that the decision-making approaches should be place-specific in order to have more efficiency in case of pandemics.

Keywords Coronavirus · Excess mortality · Drivers · MLR · GWR

JEL Classification C21 · I12 · I31 · J10 · Q54

✉ Alexandru Bănică
alexandru.banica@uaic.ro

Ionel Muntele
imuntele@yahoo.fr

1 Alexandru Ioan Cuza" University of Iași, Iași, Romania

2 Geographic Research Center, Romanian Academy, Iași Branch, Iași, Romania

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1 Introduction

The outbreak of coronavirus disease in 2019 caused by the novel SARS-CoV-2 was first reported in late December 2019 in Wuhan, located in the Hubei province of central China, and has since diffused in most of the world's countries and regions, radically changing human lives and society in general. The COVID-19 pandemic increased public awareness regarding the limits of the progress generated by globalization and the difficulties of monitoring and controlling certain unpredictable phenomena with effects on the entire socio-economic system. Regardless of the level of technological development, the pandemic determined hesitant reactions from governments which did not succeed to reduce the risk of incidence and casualties in many countries.

However, some critical differences emerged: scientific research in many countries analyzed the territorial variability and showed that clustered concentration of COVID-19 incidence and mortality have a strong spatial interdependency (Krisztin et al. 2020; Desmet and Wacziarg 2020; Zhang and Schwartz 2020). They demonstrated the influence of different factors driving these spatial disparities, factors specific to every territory, manifesting themselves in distinct forms at different geographic scales. These are, among others, global interconnection, the capacity of the health system, the quality of institutions and governance, economic vulnerability, polarization and social fragmentation (Collins et al. 2020; Rose et al. 2021).

Romania, a state located in South-Eastern Europe, at the intersection of several transcontinental human and economic flows, could not avoid the pandemic circuit, being heavily affected, similar to most European states. Romania's close ties with other states which were heavily influenced by the first wave of the pandemic, such as Italy and Spain (towards which there is a permanent flow of Romanian workers' circular migration), determined a rapid spread of the virus, forcing the authorities to institute a state of emergency on 16.03.2020. The adopted measures, considered excessive from particular perspectives (especially in the countries that have the least trust in public institutions such as the post-communist European states) were justified and reduced the impact of the first wave, resulting in a slower spread of the pandemic compared to states that had a more relaxed attitude (e.g. Sweden) (Georgieva et al 2021; Durnescu and Morar 2020). The subsequent relaxations, especially during the summers of 2020 and 2021, amplified the pandemic's effects, despite the immunization campaign that started in the winter of 2020. Initially alert, the pace of vaccination was negatively affected by population reluctance and by a lack of firmness in applying measures aimed at vulnerable groups. Seasonally, there was an explosion of cases, with massive lethal effects, especially during the autumn (Muntele 2022). For these reasons, Romania is one of the most affected states if we refer to the incidence of deaths caused by the pandemic (3465 deaths per 1,000,000 inhabitants, as of 1.07.2022, ninth place worldwide, according to the Coronavirus Resource Center database of Johns Hopkins University). During October 2021, Romania recorded the highest rate of deaths worldwide, reported per 1 million inhabitants (570) and one of the fastest growth rates of the number of cases (over 40% from 1.24 at 1st of October to 1.74 million cases at the beginning of November). Also, the overall mortality rate in Romania (relative to the number of cases) was constantly high for the whole timespan (COVID-19 Data Repository, 2022). The difficulties of managing the pandemic, especially in severe cases, indicate serious deficiencies in the decision-making process and in the functioning of the health care system. The assessment refers explicitly to the fall of 2021 when, amid a governmental crisis, the ability of the health system to handle severe cases generated an abrupt increase in deaths due to COVID-19 (Túri et al. 2022; Muntele 2022).

Fast-growing literature analyzes regional and local drivers of the spatially heterogeneous health impact of the COVID-19 pandemic. In Romania, some solid papers assess COVID-19 diffusion and effects at the national, regional and county scale (Goschin and Constantin 2021; Iordan et al. 2021; Mitrica et al. 2021; Muntele 2022; Enciu et al. 2022; Panazan and Gheorghe 2022). However, there are very few studies at the local level of administrative-territorial units such as cities, towns or communes (Matei et al. 2021; Cioban and Mare 2022). The present paper aims to find the territorial factors that can explain the higher mortality rate on both local and regional scales.

The current approach tackles the geography of excess mortality (EXCMORT) during the first two years of the pandemic by analyzing the drivers and patterns of spatial differentiation across Romania. The specific objectives of this study are:

1. To determine which sociodemographic, economic and environmental risk factors relate to COVID-19 EXCMORT rates at the local level and county level;
2. To investigate how the relationship between these factors and EXCMORT varies geographically.

The empirical contribution of the study is related to testing, comparing and evaluating a two-scale territorial model of diffusion to illustrate the evolution and impact of COVID-19 during a reasonably long period (two years). A factor analysis and a multiple regression model complemented by a geographically weighted regression were accomplished to obtain a local and regional spatially differentiated perspective that can help decision-makers take targeted, non-uniform technical measures depending on territorial aspects. The overall purpose is to identify the place-based drivers of resilience to pandemics to support governance and policies regarding potential future epidemics/pandemics.

2 Spatial determinants of excess mortality during COVID-19

The geography of COVID-19, which includes spatial distribution and features of spatial determinants, provides practical tools to understand the outbreak and the spread of coronavirus in different countries, regions, cities, towns or rural areas (Maiti et al. 2021). Spatial regression models are commonly used to quantify spatial dependence and the risk of disease progression in the territory and different communities (Ehlert 2021; Purhadi et al. 2021). Meanwhile, death rates and spatial diffusion, on one side, and the identification of the major driving forces of disease occurrence, on the other side, are intrinsically linked. Many approaches use spatial regression to explore environmental, socioeconomic and demographic factors that explain the territorial variability of COVID-19 incidents and consequences scales (Desmet and Wacziarg 2020; Ozyilmaz et al. 2022; Qi et al. 2020; Sannigrahi et al. 2020; Sun et al. 2021).

Some categories of factors are commonly included in multivariate analyses to explain the incidence of COVID-19 and the mortality rate. Most approaches consider sociodemographic factors, as "the spread of the COVID-19 pandemic is due to the social closeness and direct interaction between individuals" (Jasim et al. 2022: 51,508). Common factors include population size, density (Ramirez et al. 2022; Bashir et al. 2020), gender and educational attainment (Feldman and Bassett 2021). Also, the ethnic composition and the share of certain more vulnerable minorities might play an important role (Sá 2020; Feldman and Bassett 2021). Other indicators are more specific to the pandemic context. Population mobility, including circular migration, seasonal migration for agricultural work (Hâncean et al. 2020; Paul 2020), and international mobility strongly favor disease diffusion, at least in the first phases of the pandemic (Lee et al. 2021). The elderly population and people with pre-existing health conditions are generally considered more vulnerable to severe COVID-19 if infected with SARS-CoV-2 (WHO 2021; Zhang and Schwartz 2020, Ramirez et al. 2022).

Other scholars include economic factors when assessing COVID-19 mortality rates. Assessments at larger scales take gross domestic product (GDP) per capita as a background factor. There is also a considerable amount of papers relating COVID-19 impact on material conditions, household characteristics, and social inequalities. They include individual and household income, relative poverty, overcrowded housing and intergenerational co-residence (Basellini and Camarda 2020; Brandily et al. 2021; City Intelligence 2020, Sannigrahi et al. 2020).

Even more importantly, the health system's capacity is a fundamental resilience factor. It provides isolation and treatment for the infected population and protection for the non-infected (Liang et al. 2020), therefore supporting infection prevention policies (Lupu and Tiganasu 2022). Commonly used indicators are the number of hospital beds and physicians (McCabe et al. 2020; Ramirez et al. 2022; Basellini and Camarda 2020) and other variables such as the number of nurses (Mansour et al. 2021).

Environmental quality can also be a strong point or aggravating factor, e.g. air pollution by the concentration of particulate matter increases susceptibility to severe forms of COVID-19 (Ramirez et al. 2022; Bolano-Ortiz et al. 2020). On the contrary, the presence of forests (Roviello and Roviello 2021) or urban green areas can indirectly decrease the impact of COVID-19 (You and Pan 2020).

Overall, the geographic factors play a vital role in the resulting COVID-19 impact. Travelling distances are decisive during the outbreak periods (Fortaleza et al. 2020), and so is the proximity of other people while working (City intelligence

2020). More generally, highly dense and connected cities were the gates for COVID-19 entering the national territories, spreading and producing outbreaks due to the proximity of residents (Coelho et al. 2020; Rodríguez-Pose and Burlina 2021). However, these urban areas were also the best in implementing and sustaining mitigation measures (Gerritse 2020). Meanwhile, studies confirm that institutional quality and the effectiveness of public health care policies are decisive factors in controlling and decreasing the mortality rate during pandemics (Rodríguez-Pose and Burlina 2021; Jinjarak et al. 2021).

3 Methodological approach

There is still a gap in the literature which focuses on illustrating that the pandemic crisis was not just international and national but also regional and local (Bailey et al. 2020). In our study, we acknowledge that local COVID-19 impact is conditioned by specific (micro-scale) factors and by regional (county) determinants. These are the first two levels of an even larger hierarchically nested construct that is, finally, global (McCann et al. 2022). In our two-level assessment, we use excess mortality as a dependent variable and similar explanatory indicators at both scales to highlight their differentiated influence and weight in each context.

Most studies assessing the health impact of COVID-19 include incidence and the official number of deaths as the leading indicators. However, some authors signaled a certain misreporting of COVID-19 cases in many countries. For Romania, the excess mortality is estimated to be more than double when compared to the official COVID-19 deaths (Wang et al. 2022), which makes the official statistics on the number of cases and fatalities susceptible to bias. Plus, and more importantly, a complete database regarding COVID-19 mortality at the local level is not available in the case of Romania.

In the present paper, we propose excess mortality (EXCMORT) as a more solid indicator. It also captures deaths from other causes attributable to the overall crisis conditions that overwhelmed the health system, conditions which led to diverted resources from other health issues, and to fewer people seeking treatment for other diseases (Ritchie et al. 2020). Therefore, we have chosen EXCMORT as the dependent variable and proxy for COVID-19 impact during two years of the pandemics (March 2020–June 2022). EXCMORT includes the growth rate of mortality of all causes beyond what one would have expected to register under 'normal' conditions (Checchi and Roberts 2005). EXCMORT demands caution but can provide a robust indicator of human losses (OECD/European Union 2022; McCann et al. 2022). We measured the difference between the reported death rate in 2020–2021 and the trend set in the previous period (2015–2019). Besides EXCMORT another 12 explanatory variables where selected (Table 1).

Most of the indicators have already been used in different studies (see Sect. 2). One exception is the non-agricultural employed population (NONAGR). It can play a role in COVID-19 mortality because people employed in agriculture

Table 1 The selected indicators

Indicator	Acronym	Year/period	Description/unit	Sources
Excess mortality	EXCMORT	2015–2021	The excess mortality rate from the period 2020–2021, compared to 2015–2019 (average gross mortality, expressed per thousand inhabitants)	www.insse.ro/Tempo Online/
Population density	DENS	2020	Population density on July 1, 2020 (calculated based on the administrative area of 2020)	www.insse.ro/Tempo Online
Forest areas	FOREST	2018–2020	The degree of afforestation in 2018 and 2020	www.insse.ro/Tempo Online, Corine Land Cover 2018
Share of the ageing population	AGEING	2020	Ageing index on July 1, 2020 (+65 years/0–14 years)	www.insse.ro/Tempo Online
Employment in the non-agricultural sector	NONAGR	2020	The share of employees in non-agricultural activities from the total number in 2020 (%)	www.insse.ro/Tempo Online
Access to utilities	EDIL	2011	Share of the population with access to running water and sewage utilities	www.insse.ro/ 2011 Census
Share of the educated population	EDUC	2011	The share of the population with secondary and higher education	www.insse.ro/ 2011 Census
Income	INCOME	2020	Estimated income by reference to the employed population and the average income by category of employees in 2020, the average incomes of pensioners and beneficiaries of social allowances	www.insse.ro/Tempo Online
Access to physicians	PHYS	2020	The number of physicians per 100,000 inhabitants in 2020	www.insse.ro/Tempo Online
Health personal	HEALTH	2020	The number of average health personnel per 100,000 inhabitants in 2020	www.insse.ro/Tempo Online
Population mobility	POPMOB	2015–2020	Changes of residence (2015–2020) divided by total population /	www.insse.ro/Tempo Online
Percentage of Roma minority	ROMA	2011	Share of the Roma/gipsy population	www.insse.ro/ 2011 Census
Accessibility to cities with over 50,000 inhabitants	DIST50K	2020	The road distance to the closest city of over 50,000 inhabitants (Population on July 1, 2020)	www.insse.ro/Tempo Online

(predominantly subsistence in Romania) involve, by default, little social interaction, usually within the family circle. On the contrary, employees from industry or service activities generally interact more with other citizens, often in crowded spaces and requiring commuting. However, some scholars analyzed in depth the occupational structure of the population and its influence on COVID-19 incidence and mortality (Wang et al. 2022; Irlacher and Koch 2021). One can also distinguish between various occupations in terms of their potential for direct human contact or if they allow or do not allow teleworking (Baker 2020). Nevertheless, within the limits of our present study, we only consider NONAGR to make a rough differentiation between urban (or quasi-urban) and profoundly rural agricultural populations. This indicator is rarely used in other studies in this manner, because the share of the population employed in agriculture is meagre in most countries in Europe and North America. In contrast, Romania has a 46% rural population, of which 25% is engaged in subsistence farming activities.

There are two other indicators less included by other assessments: the share of forest areas and the share of the Roma minority. The first is relevant considering the ecological services of forests, for example, in lowering air pollution. The second relies on the vulnerability of certain minorities, especially the Roma population, as there are studies indicating a different behavior and social treatment of this minority compared to the general population (Crețan and Light 2020).

There are some other limitations of our study, which should be addressed by future studies. First, there are differences in the time frame of some data at the local level. Most of the indicators are from 2020, but some are available only from the last census from 2011 (the 2022 census still needs to be published). However, this information is relatively stable, at least in their territorial distribution, and we consider their use appropriate. Other issues are related to the need for other representative indicators (especially at the local level) and their lack of accuracy, which usually comes from errors in registration that is reflected in the lower degree of significance of the statistical models.

If referring to tools and methods, we used XLStat2019 and ArcGis Pro to conduct the (geo)statistical analyses and mapping. The EXCMORT was put in spatial perspective using Optimized Hotspot Analysis which identifies statistically significant spatial clusters of high values (hot spots) and low values (cold spots). This tool implemented in ArcGis Pro software creates a new Output Feature Class with a z-score, *p* value and confidence level bin (Gi_Bin) for each feature in the Input Feature Class.

In the next step, we correlated the selected factors, all tested and included in regression models. First, we applied Multiple Linear Regression (MLR), which is the extension of ordinary least-squares (OLS) regression involving multiple explanatory (independent) variables:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon$$

where, y_i = EXCMORT (dependent variable), x_i = independent variables, β = unknown parameters, β_0 = y-intercept (constant term), β_p = slope coefficients for each independent variable, ε = error terms (residuals)

Given the limitations of MLR, particularly when describing spatial realities by illustrating the relation between geographic drivers, a Geographically Weighted Regression (GWR) model was then applied. GWR highlights the non-stationarity of data and measures spatial heterogeneity by testing the regression model's logical factors with variability across space (Brunsdon et al. 1996; Jasim et al. 2022). The local estimate of the model parameters is obtained by weighting all adjacent observations using a distance decay function, assuming that values for closer units influence the regression more than the values for the more remote units.

Therefore, the model equation in the case of GWR becomes:

$$y_i(u) = \beta_0(u) + \beta_1(u)x_{i1} + \beta_2(u)x_{i2} + \cdots + \beta_p(u)x_{ip}$$

The notation (u) indicates that the variable describes a relationship around location u and is specific to that location u. A prediction may be made for the dependent variable only if values for the independent variables are also measured at the location u (Charlton et al. 2009).

4 Results

Romania showed different patterns of COVID-19 mortality when compared to the rest of Europe or to the world. Although the mortality rate was low in the first four months, from July 2020 until the end of 2021 the values were constantly higher than the European or World level, with a maximum of 1298 deaths/ million inhabitants in the last half of 2021. However, the incidence of coronavirus was roughly at the same level or even lower. If compared to other post-communist countries, Romania's COVID-19 death rates had a similar evolution to the Republic of Moldova, but overall, when also considering the dynamics of the number of cases, the Romanian model is relatively closer to those of the other EU members—Hungary and Bulgaria (Table 2).

Nevertheless, the registration of fatal cases of COVID-19 was defective in Romania, as illustrated by the evolution of general mortality in the years 2020–2021, recording one of the most significant excesses of deaths compared to the situation in the years 2015–2019. The underestimation of COVID-19 deaths is apparent, even if a large part of the surplus is due to other causes, against the background of the concentration of resources from the public health system to limit the pandemic.

Thus, the EXCMORT between 2020 and 2021 compared to 2015–2019 was 20.7%, close to that of other European states. Still, the deaths attributed to COVID-19 justify only 54.2% of this excess, compared to 90.5% in Spain. This fact shows the deficiencies in managing the health system and the precariousness of the media infrastructure (Bogos et al. 2021).

There are two categories of cases of excess deaths (Fig. 1): higher than the reported COVID-19 fatalities (ex. Bucharest, Hunedoara, Cluj, Constanta and Brasov), the second with counties where the estimated number of excess deaths is even lower than the number of victims caused by pandemics (Bihor, Dambovita, Suceava, Bistrita-Nasaud, Salaj, Caras Severin, Vaslui or Botosani).

Table 2 The incidence and the death rate of COVID-19 in Romania (Data source: COVID-19 Data Repository, 2022)

Periode (months, year)	Cases per 100,000 inhabitants					Deaths per 1,000,000 inhabitants				
	2020		2021		2022	2020		2021		2022
	Jan–Jul	Jul–Dec	Jan–Jul	Jul–Dec	Jan–Jul	Jan–Jul	Jul–Dec	Jan–Jul	Jul–Dec	Jan–Jul
Romania	***141***	***3147***	***2387***	***3800***	***5783***	***86***	***840***	***827***	***1298***	***367***
Republic of Moldova	463	2960	4387	4680	3942	150	673	874	1121	352
Ukraine	105	2371	2724	3342	3129	27	407	784	1016	292
Hungary	43	3294	4953	4597	6889	60	931	2085	943	765
Serbia	213	4679	5419	8407	10,495	40	427	546	819	487
Bulgaria	74	2927	3250	4834	6290	34	1092	1550	1913	929
EUROPE	338	3320	3356	5590	15,068	263	502	769	591	459
World	**137**	**1081**	**1262**	**1348**	**3204**	**72**	**173**	**264**	**187**	**114**

a-Nasaud, Salaj, Caras Severin, Vaslui or Botosani).

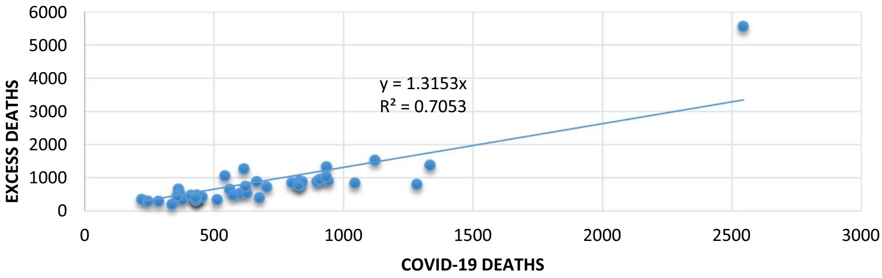


Fig. 1 COVID-19 reported fatalities and EXCMORT in Romanian counties (2020–2021)

The first category includes urbanized counties where social connections and interactions are powerful. In contrast, the second is predominantly rural, with lower population densities and chronic isolation phenomena, a form of "natural social distance". This difference is primarily due to the different degrees of urbanization and the steep urban–rural differences in Romania.

There is considerable spatial heterogeneity in EXCMORT during COVID-19 (Fig. 2). In the areas with high values of EXCMORT secondary and tertiary sectors predominate, doubled by the increased mobility (commuting and migration) that favored the spread of the virus. However, one can observe that in the southwest and northeast, the areas with a reduced surplus are more clearly defined,

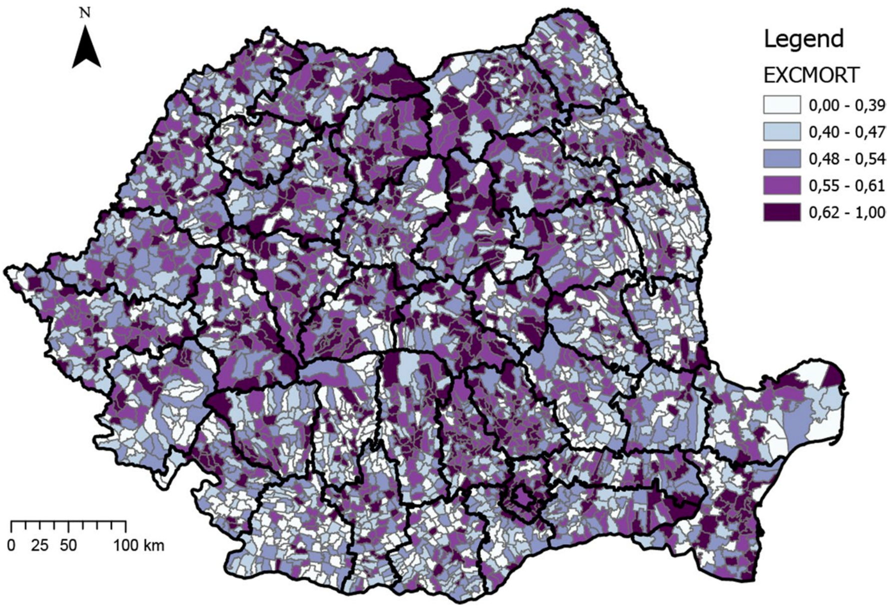


Fig. 2 Spatial distribution of EXCMORT 2020–2021 (normalized values)

closely linked to the same "natural" social distance and to the predominantly agricultural nature of the activities in the mentioned areas, oriented towards subsistence and with some more fragmented settlements. Rural abandonment, as a result of massive migration (internal and international), is frequent in these areas.

To better visualize the spatial clusters, Optimized Hot Spot Analysis (Fig. 3) identified the areas of high EXCMORT between 2020 and 2021. These areas are located in the Bucharest region and in the northern part of the capital city, including highly industrialized areas from Prahova, Brasov and Arges counties, the urbanized area of Sibiu and Hunedoara. Other hot spots of EXCMORT are, first, the industrial and tourism area of the seaside (Constanta) and, secondly, the northern part of Romania, i.e. Suceava, Bistrita and Maramures counties. The second one is related to the massive international emigration for seasonal work (which also generated an early infection in April 2020, out of control in the densely populated area of Suceava) (Muntele 2022). On the contrary, the low values (and even the lack of excess mortality) was registered in the poorest and more isolated areas from the periphery of some counties, i.e. Iasi-Vaslui, Teleorman-Giurgiu, Dolj-Mehedinti, Gorj-Valcea, south of Caras-Severin).

When correlating EXCMORT with each of the selected indicators (Table 3), the results show statistically significant associations for all indicators at the local level. At the same time, ten factors are also relevant at the county level. Most of these factors correlate positively to EXC_MORT, which shows that they are susceptible to increase human losses during the pandemic outbreak. The high positive correlation of EDIL, NONAGR, INCOME, EDUC and DENS shows a strong association

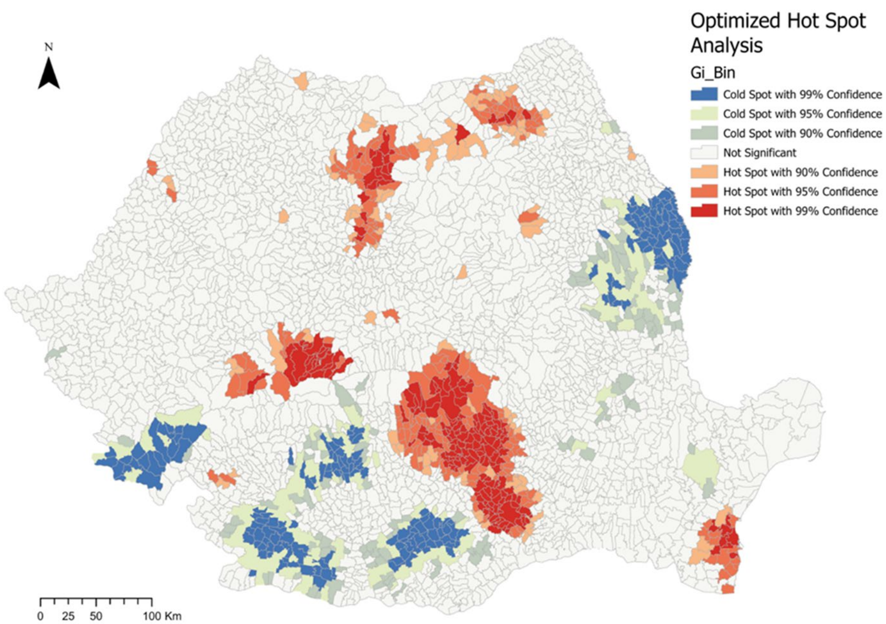


Fig. 3 EXCMORT—optimized hotspot analysis

Table 3 The correlation between EXCMORT and the selected factors at local and county level

Variables	EXCMORT_county level (42 units)	EXCMORT_ commune level (3181 units)
DENS	0.432***	0.251***
AGEING	−0.403***	−0.168***
NONAGR	0.608***	0.295***
INCOME	0.555***	0.273***
PHYS	0.340**	0.140***
HEALTH	0.261*	0.136***
POPMOB	0.297*	0.087***
ROMA	0.145*	0.057***
DIST50K	−0.242	−0.088***
EDIL	0.671***	0.328***
EDUC	0.516***	0.279***
FOREST	0.099	0.066***

*, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively

Table 4 Model parameters (EXCMORT): a. NUTS 3 level; b. LAU2 level

Source	Value	Standard error	t	Pr>|t|	Lower bound (95%)	Upper bound (95%)
(a)						
Intercept	0.489	0.026	18.511	**<0.0001**	0.435	0.542
AGEING	−0.163	0.045	−3.631	**0.001**	−0.255	−0.072
INCOME	0.224	0.129	1.731	0.092	−0.038	0.486
PHYS	−0.213	0.076	−2.796	**0.008**	−0.367	−0.058
EDUC	0.168	0.122	1.373	0.178	−0.080	0.416
(b)						
Intercept	*0.473*	*0.008*	*59.773*	***<0.0001***	*0.457*	*0.488*
DENS	0.117	0.022	5.396	**<0.0001**	0.074	0.159
AGEING	−0.088	0.012	−7.360	**<0.0001**	−0.111	−0.065
NONAGR	0.089	0.014	6.399	**<0.0001**	0.062	0.117
INCOME	0.071	0.023	3.069	**0.002**	0.026	0.116
PHYS	−0.021	0.016	−1.377	0.169	−0.052	0.009

Equation of the model (EXCMORT):

a) NUTS3 level

EXCMORT = 0.48 – 0.16 * AGEING + 0.22 * INCOME – 0.21 * PHYS + 0.17 * EDUC

b) LAU2 level

EXCMORT = 0.47 + 0.12 * DENS2020 – 0.09*AGEING + 0.09 * NONAGR + 0.07 * INCOME-0.02 * PHYS

Table 5 GWR—analysis details and model diagnostics

Territorial scale	NUTS3	LAU2
Number of features	42	3181
Dependent variable	EXCMORT	EXCMORT
Explanatory variables	AGEING, INCOME	DENS, AGEING, NONAGR, INCOME
Distance band (km)	276.3	138.7
R^2	0.683	0.174
AdjR^2	0.540	0.150
VIF	5.16	1.30
AICc	−161.5546	−4147.2681
AIC	−169.9130	−4053.0145
BIC/MDL	−154.0684	−3955.0954
Sigma-squared	0.0009	0.0157
Sigma-squared MLE	0.0006	0.0152
Effective degrees of freedom	29.2702	3090.1212

of socioeconomic development and urbanization to EXCMORT. One can infer that generally, the closeness of cities, agglomeration of population and social interaction were the main drivers of the high impact of COVID-19.

Meanwhile, mortality was lower in isolated areas remote from cities (DIST50K) despite a high share of the elderly population. The high incidence of COVID-19 does not associate significantly with accessibility or precariousness of medical services. What mattered more was maintaining appropriate behaviors for limiting contacts and, implicitly, increasing social distance, as the abundant literature in the field shows (Wang et al. 2022; Ramirez et al. 2022; Lupu and Tiganasu 2022).

To study these spatial patterns of EXCMORT, we applied multiple linear regression (MLR) and geographically weighted regression (GWR). The results were global and local regression models at each spatial scale.

At the county level (NUTS3), by including all the variables in MLR, five explanatory variables were detected (by the Best model method) that explain 57% ($R^2=0.57$) of the variability of the statistical information regarding EXCMORT, which is more than the simple average value would bring. The INCOME and EDIL positively (and strongly) correlate with EXCMORT, while AGEING and PHYS associate negatively (Table 4).

At the local (LAU2) level, five explanatory variables were detected that explain 12% ($R^2=0.12$) of the variability of the statistical information regarding EXCMORT, which is still statistically significant. MLR identified five indicators that can explain most of EXCMORT. At the county level, AGEING and PHYS decrease the values of EXCMORT, while INCOME and EDUC increase it. At the LAU2 level, DENS becomes the most critical driver together with NONAGR and

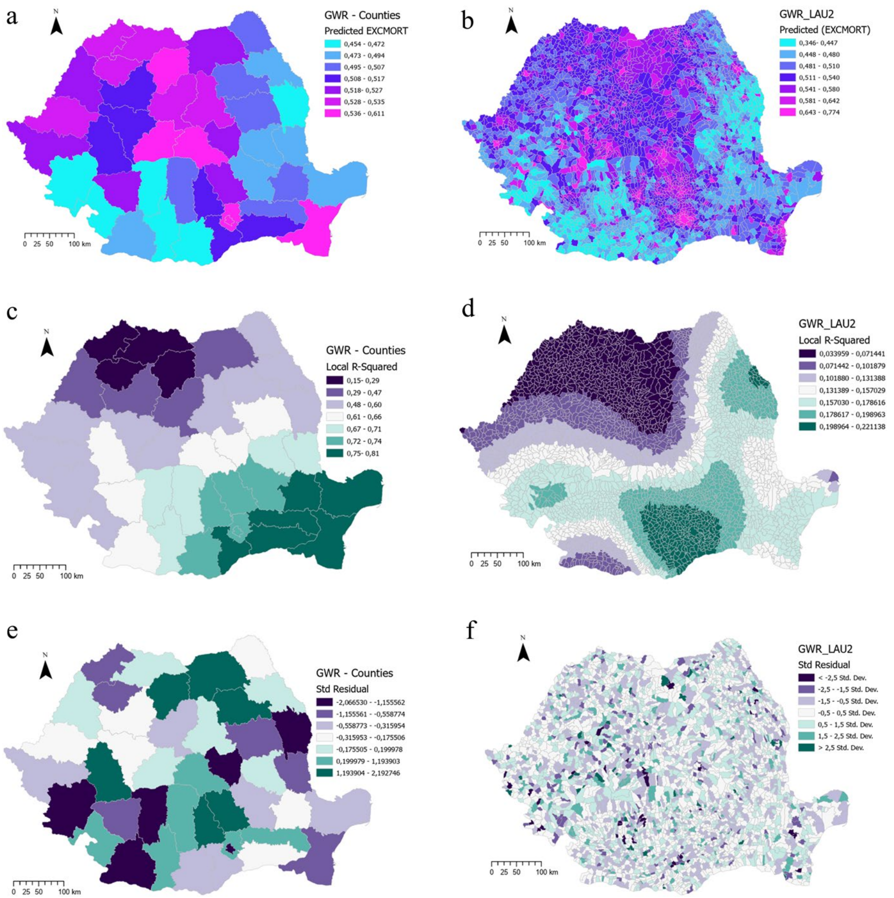


Fig. 4 GWR—the predicted values (**a**, **b**), Local R-squared (**c**, **d**) and standardized residuals of the model (**e**, **f**) at local (LAU2) and regional (NUTS3) levels

INCOME, while AGEING best describes the rural and isolated areas with lower EXCMORT. DENS and AGEING. Access to medical services (PHYS) has a minor influence on the proposed models.

Both models can be considered acceptable given the *p* value of the F statistic computed in the ANOVA table and the significance level of 5%, along with the fact that there was a large number of units included in the analysis. However, there is a significant bias as the model produces average parameters over the whole sample without considering their geographic variation. However, by calculating a global regressing model, the primary purpose of the assessment is not accomplished, i.e. the spatial distribution and differentiation.

Therefore, we used Geographic Weighted Regression (GWR) as a more powerful tool to assess spatial variations of EXCMORT, including in the model the best-fitted

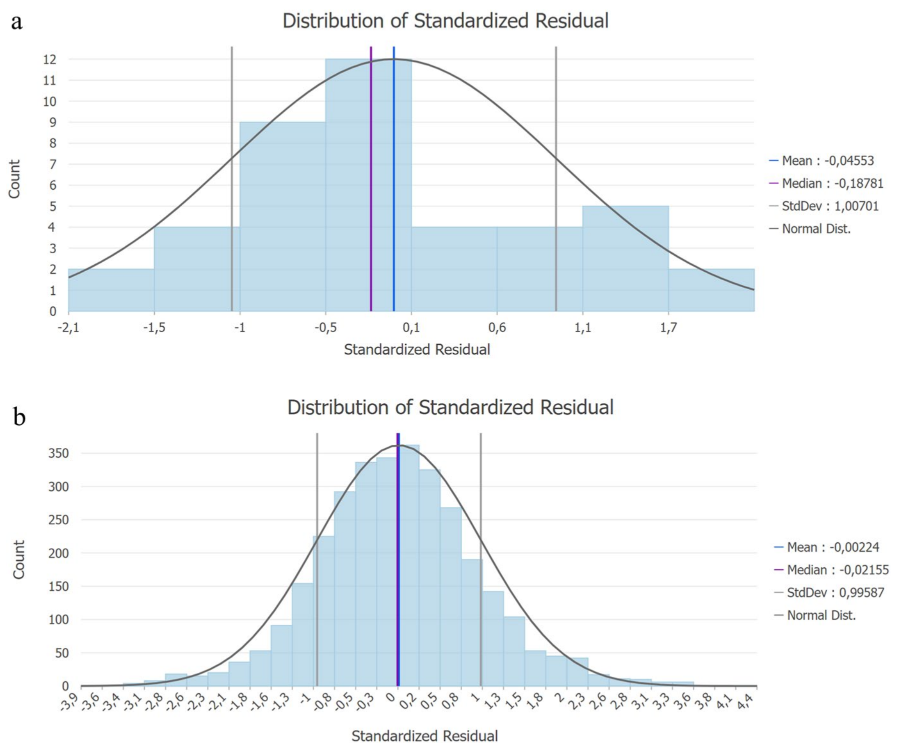


Fig. 5 GWR—the histogram of the standardized residuals at NUTS3 (**a**) and LAU2 (**b**) levels

variables, i.e. variables that explain the most the variance, while avoiding collinearity. The results of the analysis are detailed below (Table 5, Figs. 4 and 5):

The GWR included only two variables at the county level -AGEING and INCOME -whereas, at the local level, the model also adds DENS and NONAGR. For the first model, the total R-squared is much higher, 0.68 compared to 0.17, in the case of the second model, but overall the model at the local level, including 3181 units, is more suited (even though some explanatory variables are not avaialble). However, the local R^2 of GWR at the LAU2 level varies between 0.03 and 0.22. The model's predicted values show a southeast-northwest area and secondary hot spots of EXCMORT around big cities such as Iasi (in the northeast) or Constanta (in the southeast, at the seaside). However, the local R-square shows that the model best fits the southern areas around the capital city, to the northeastern region, but also for the seaside area (outside the Danube Delta) and southwest (Banat and Oltenia). The model is inconsistent for the northwestern part of Romania, where the prediction of the model is way above the real values, while other factors might better describe the drivers of EXCMORT from COVID-19. The presence of specific risk factors, such as those favoring the prevalence of cardiovascular diseases, in the context of a diet specific to Central Europe can also provide supplementary explanation for this area (Bunescu et al. 2008). The residuals show the heterogeneity of spatial dependencies and the contribution of specific local conditions that created higher or lower mortality than the models would predict. The distribution of the residuals is normal at the local scale (which indicates a more accurate model), whereas at the county level, there is an apparent left asymmetry.

5 Concluding remarks

The Romanian diffusion model and the impact of COVID-19 have specificities related to the intrinsic characteristics of the territory and to the rural and agricultural profile that differentiates it from the more urbanized and better-connected countries in Western Europe. Our findings indirectly (but consistently) show that social interaction is the main attribute that induced excess mortality in Romania. The most significant indicators at both local and regional scale that positively correlate to excess mortality are all related to urbanization and concentration of population. By contrary, even in localities with a high share of the elderly population, the isolation and remoteness decreased the impact of COVID-19, at least in the first two years. It is because most of the population is still rural and agricultural, while the urban–rural divide is still very pronounced. In the case of the pandemics, urban areas are disadvantaged as the physical and social distances are much smaller. In the case of other countries such as Hungary similar studies showed that rural isolation and deprivation was associated with lower COVID-19 incidence but with a higher mortality rate (Oroszi et al. 2021).

However, there are different outcomes at different scales and in different geographic areas. Outside the Carpathian area, there is high excess mortality in developed metropolitan areas and cold spots in rural areas and small towns. Meanwhile, the Transylvanian model is different because of the more urbanized territory, which also created premises for the faster virus spread.

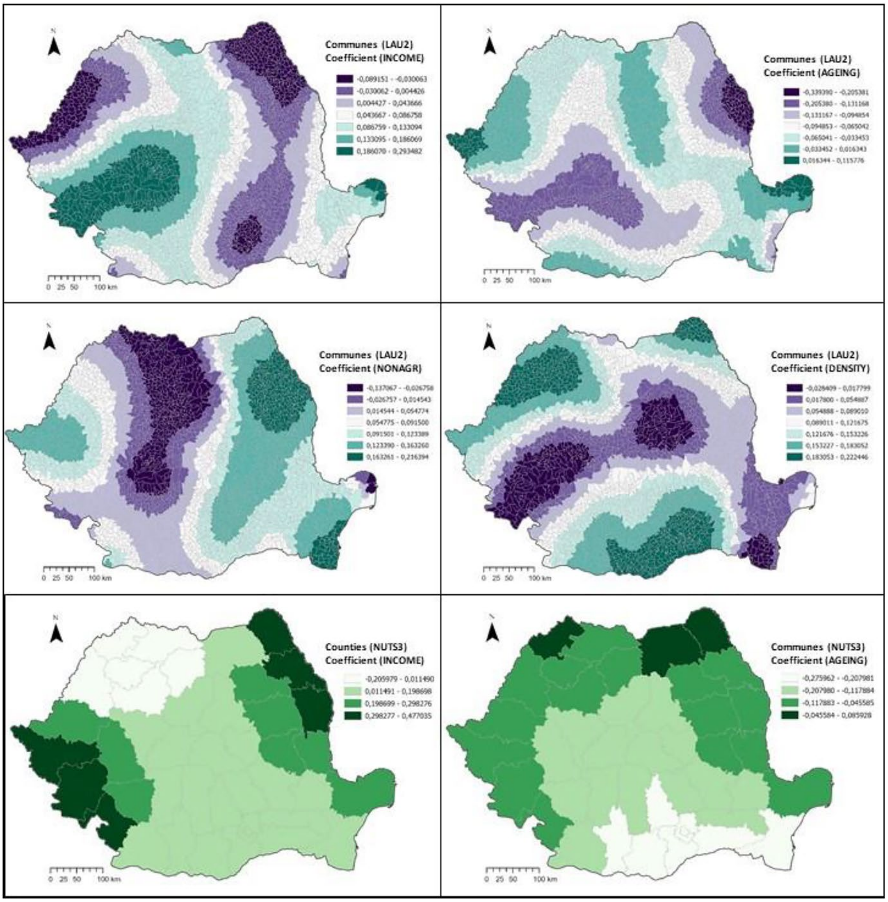
At the local level, both multiple linear regression and geographically weighted regression modelsare statistically significant. The southern and eastern parts of Romania seem to be very well described by the applied model, which positively links excess mortality to density, employment in the non-agricultural sector and the population estimated income, while negatively associates it with the share of the elder population. The outcome is less representative for northern and western Romania, which seem closer to a central European model, which we will assess in a forthcoming paper. Although the variables are better interrelated at the county level, the regression models are less significant and less conclusive at this scale.

Consequently, connections, social interactions, and mobility drive development, but they are also, especially in the first phases of the pandemic, the path for disease diffusion, which can create higher incidence and higher excess mortality. It comes not only from the direct losses but also from lower attention given to other disease causes.

Finally, resilience policies during pandemics should consider the specific situation of countries, regions and localities. On the one hand, the need to ensure a balanced social, economic and environmental development should not be neglected (with a particular focus on medical infrastructure and services). On the other hand, perhaps as significantly, at least in the first stages of a pandemic shock, the provision of practical possibilities to reduce social contact and mobility should be facilitated. Ensuring resilience by creating modularity, i.e. an autonomous operation of the spatial units capable of securing the resources strictly necessary for functioning at the local level, is a solution to protect the more vulnerable population and territories. Especially in cities and urban agglomerations, ensuring modularity by reducing unnecessary mobility, creating possibilities for access to services and amenities in the proximity (see the popular 15 min-city concept) and capacities to efficiently transition to teleworking, when needed, will be useful also in increasing social distance and, consequently, in reducing excess mortality in case of future pandemics. We conclude that Romania's situation is particular and different from many other European states. The local and regional territorial systems show distinct individualities that a single model cannot describe. For this reason, it is challenging to explain excess mortality during COVID by only taking the factors that are usually considered as the drivers of mortality in similar studies of more homogenous countries. Meanwhile, it is an interesting case study that can give a different perspective, illustrated by a particular combination of factors that act differently within Romania's territory and require place-specific measures. Our approach can be developed (by using more numerous and relevant indicators and by taking into consideration also other scales), replicated and applied in other geographic contexts.

Appendix

GWR model at communes (LAU2) and county (NUTS3) level—Coefficients of explanatory variables.



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Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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