Rethinking core-periphery model: waves of COVID-19 in Russian regions[1]

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Abstract—Studies of the COVID-19 pandemic have repeatedly demonstrated that the role of spatial factors in the transmission of infection is significant. However, there is no universal spatial model thoroughly describing COVID-19 spread patterns. The paper proposes an original view on the centre-periphery model: regions are classified according to settlement pattern (static component) and openness (closedness) (dynamic component) characterising intensity of inter-regional human interactions (population flows). A total of 8 types of Russian regions are distinguished by the parameters of openness (closedness), population density and average size of a settlement. The course of the pandemic in the regions is analysed using the monthly trend of excess mortality, divided into three waves (acute phases) of COVID-19 spread. Empirical evidence shows that regions differ significantly in terms of the impact of the pandemic. Polarisation is the highest in the first wave, suggesting a greater role for spatial factors in the early stages of coronavirus outbreak. During the second and third waves, differences between regions begin to level out, probably influenced by internal socio-cultural and economic factors. The COVID-19 pandemic in the Russian regions allows us to rethink the traditional hierarchical concept of centre-periphery space. New dimensions are emerging: in addition to classical centres, there are remote frontier regions with similar functionality. Alongside the periphery is the outback ("glubinka"), close to the centre but paradoxically almost unaffected by its influence.

Keywords: COVID-19 pandemic, centre-periphery model, human interactions, transport openness, settlement pattern, Russian regions

INTRODUCTION

The centre-periphery concept, which has been discussed in academia for about half a century, derived mainly from the concept of innovation diffusion (Gritsay et al., 1991). If we look at the novel coronavirus spread across the planet in 2020 as a kind of "negative" innovation, then the COVID-19 pandemic can be seen as a tragic but rather insightful experiment to test the existing centre-periphery model. Compared to the tailored works on the geography of technological innovation, the coronavirus transmission with population flows seems to take us back to the origins of the concept of innovation developed by Hägerstrand on the example of migration (Hubbard et al., 2008). In contrast to migrations, the rapidly spreading novel coronavirus provides a cross-section of essentially the entirety of human movements, contacts and personal interactions. They include commuting (both within a centre and urban agglomeration), business trips, fly-in/fly-out migrations, seasonal movements to and from recreational sites, etc. The role of a wide range of movements in the initial outbreak of the infection on a particular territory has been widely reported in the press and, at this stage, arguably requires no additional evidence. For further research, we assume that the spread of coronavirus between settlements is an indicator of the intensity of all population traffic between them.

To make it clear, we emphasise that the initial transmission of coronavirus infection should be considered in the first place. This has also been confirmed in multiple studies. The work (Linka et al., 2021) is particularly notable here: it provides a detailed analysis using data from airlines (for air travel) and mobile network providers (for road traffic). The crucial finding of this paper for our study is that traffic flows are only associated with the initial introduction of infection into an area.

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Subsequently, the statistical link between incidence rates and traffic flows disappears and morbidity develops due to other factors no longer associated with transport openness.

Of course, the link with transport openness to a certain extent might also be seen at later stages, mainly, apparently, when new variants of virus emerge or new carriers arrive[2]. However, other factors begin to play an increasingly important role. These factors include primarily the introduction or non-introduction of quarantine measures and other anti-epidemic restrictions, the willingness of the population to comply with them, as well as a range of measures affecting the intensity of personal interactions within the territory: the configuration of settlements, characteristics of the retail and public transport networks, economic specialisation, etc. In particular, such results have been received in studies within our research project (Goncharov et al., 2023). Some of these factors are partly determined by position within the centre-periphery dichotomy, e.g. economic specialization. The semi-periphery usually has many manufacturing enterprises, where it is almost impossible to organize efficient distancing, unlike offices, which are easily transferred to a remote mode. However, in general, the link with the transport situation as well as with the centre-periphery system apparently becomes feeble. This fact is confirmed by low correlation of excess mortality during the pandemic with various transport system parameters (Kotov et al., 2022).

This paper therefore sets out to distinguish particular waves of the COVID-19 pandemic in contrast to the majority of works by geographers and economists. We hypothesise that *the spatial distribution patterns of the first wave of the COVID-19 pandemic reflect fundamental properties of the structure of space (and in particular centre-periphery linkages reflected in the intensity of human interactions of all kinds cumulatively) to a greater extent than those of subsequent waves.*

COVID-19 AND CENTRE-PERIPHERY MODEL

Returning to the origins of the centre-periphery concept, we cannot ignore its connection to the gravity model. This phenomenon is widely discussed by contemporary authors in centre-periphery studies. A. Copus, the key researcher of centre-periphery linkages in contemporary Europe, inter alia, points it out in his work on the EU periphery index (Copus, 1999). According to the gravity model, two settlements normally interact more intensively the larger their population size and the smaller the distance between them. Of course, this is a relatively simplified assumption, but this model de facto explains the Hägerstrand hierarchical diffusion, which is connected both with the hierarchy of settlements by population size and the distance from the centre to the periphery that accepts the innovation.

In later studies, many factors have been taken into account to differentiate the centre from the periphery, such as the cost of transportation, the agglomeration effect, the cost (and hence accessibility) of services, population density, settlement density, etc. (Copus, 2001). Works on the diffusion of technological innovation (Feldman and Kogler, 2010; Baburin and Zemtsov, 2014) have gained prominence, where the notion of a centre is narrowed down to essentially a highly specialized centre of innovation (usually the centre of concentration of scientific organizations and laboratories). This idea allows us to understand the mechanism of distribution of economic activity and population, but the result may well be precisely the gravity model. The level of interconnection between settlement centres in it is determined by the size of their population and the distance between them. Although, as Copus observed, in fact "true" peripherality is marked by poor links to the outside world, and this can be found even close to the centre which is an important point for our research.

However, it is not surprising that the coronavirus pandemic, as in a sense an "ideal innovation" reflecting the totality of inter-settlement human links (and not just, let us assume, the spread of patent

[2] The chief physician of the Kalarsky district hospital in Zabaykalsky krai described the impact of the shift work factor on the local coronavirus situation in an interview with one of the authors. "COVID-19 had a slightly different course in our district than in other districts of Zabaykalsky krai and in Chita. It started a little later but we had it for a very long time because there were many shift workers from a lot of different regions... We just decided to close, less than five or ten people came. Then suddenly two or three of them arrived from other regions. They were examined on arrival. As soon as they were examined, they were placed in quarantine here" (interview by N.Yu. Zamyatina, Novaya Chara, May, 2022. The respondent estimated the total number of shift workers (from various organisations, including Russian Railways) in the area to be around 10 thousand).

references, as in the modern geography of innovation) has prompted a number of attempts to relate it to the Hägerstrand hierarchical diffusion (Fig. 1).

Expectedly, many researchers noted that Hägerstrand model works to some extent in the first phase of a pandemic (Klapka et al., 2020; Poom et al., 2020; Zemtsov and Baburin, 2020). Thus, most major global cities were hit rather quickly, with the virus literally crossing oceans faster than neighbouring areas. Moscow and St. Petersburg, expectedly, appeared as the first hotspots of the coronavirus in Russia. However, atypical patterns emerged already in the first months of the pandemic. Firstly, it is the rapid spread of the disease to very remote areas (e.g. Yamalo-Nenets autonomous okrug). Secondly, COVID-19 appeared later and/or inflicted milder damage in some areas that could well be considered central. These are, for instance, some major cities in Siberia or, conversely, some regions in Central Russia located close to Moscow as the main hotbed of infection.

Undoubtedly, a direct detection of population flows (e.g. through data from mobile operators (Linka et al., 2021)) leading to the above-mentioned oddities in the spread of the coronavirus would be the most precise option to choose for our study. The task of defining the centre and the periphery in this case would be to identify zones with different total volume of population flows. However, the authors do not possess such detailed data.

Therefore, we set a *goal to provide a new insight into the features of the centre and the periphery considering them through the prism of human interactions drawing on data on the course of the COVID-19 pandemic as a proxy indicator of population flows of different genesis in the Russian space.*

To achieve this goal, we examine the COVID-19 spread patterns during the first wave as the main indicator (set of indicators) of population flows (personal interactions), and attempt to find statistical indicators that describe the mechanism causing these flows. We focus mainly on the spatial features of centre and periphery evolution, on how the centre and periphery manifest themselves in the space of flows. We do not aim to describe all the factors causing these flows. Thus, for example, obviously, the ideal centre should be characterised by higher per capita incomes than the periphery, etc. (in particular, there was an attempt to link income with mobility during the lockdown period (Dokhov and Topnikov, 2021)).

DATA AND METHODS

The methodical part of the work is divided into two main stages. At the first stage we select a basic indicator to measure the impact of coronavirus in regions and to periodise pandemic waves for each region. At the second stage we choose the number of parameters to assess the scale of external and internal population flows directly or indirectly. In addition, field interviews were used for analysis (references in the footnotes are provided in each case). They were conducted by participants in our grant project in several regions of the country. Before moving to a detailed description of the methodology, the authors should emphasize that the goal of this study was not to build a comprehensive factor model explaining the distribution of COVID-19 mortality. Such attempts were made in numerous works by Russian researchers (Zemtsov and Baburin, 2020; Kravchenko and Ivanova, 2021; Makarova and Pyshmintseva, 2021; Pilyasov et al., 2021; Kotov et al., 2022; Goncharov et al., 2023). They led to different results, but certain spatial factors mattered in every model. The article aims only to identify key spatial features of Russian regions influencing the course of the pandemic. Other factors, e.g. socio-economic, medical, are not considered intentionally.

The first stage: selection of basic indicator and detection of pandemic waves for each region. The general idea of this article is to evaluate the influence of spatial factors that can shed light on mechanisms of the infection transmission on different stages across Russian regions. As the basic indicator describing the consequences of COVID-19 we use ratio of monthly number of deaths for the period from April, 2020 to December, 2021 relative to the five-year average monthly number of deaths during 2015–2019 (five closest pre-pandemic years):

$$EM_x = \frac{M_{2020;2021x}}{0{,}2 \times \sum_{2015-2019} M_x},$$

where EM – ratio indicating excess mortality in a certain month from April, 2020 to December, 2021, M – number of deaths in this month, x – month. Accordingly, all values above 1 indicate an excess mortality relative to the preceding five-year average. Some researchers measure excess mortality as a deviation from the forecast based on a recent trend in mortality (Wang et al., 2022). We rejected this method of calculation despite the fact that yearly number of deaths fell by 1.5% between 2015 and 2019. In some regions, mostly with small population, the trend tends to be unstable and subject to significant fluctuations year to year, so that aggregate values for previous years appear to be more robust than the trend projections. Also, excess mortality per capita, i.e. increase in mortality rate (%), was tested as an alternative basic parameter. Expectedly, this indicator is highly correlated with the share of population older than 65 years: linear correlation coefficient equals 0.62, $p\text{-}value < 0.0001$. Modelling the excess mortality per capita across Russian regions in 2020 has shown that this factor has the highest predictive ability (Kotov et al., 2022). The "simple" excess of mortality used in this work, on the contrary, is weakly related to the age structure of the population and allows us to better evaluate the factors stimulating COVID-19 spread and the pandemic impact on healthcare systems of different Russian regions.

After calculating monthly excess mortality for 21 months of the pandemic from April, 2020 to December, 2021 relative to previous five-year average, the issue of identifying waves of COVID-19 has arisen. For this purpose, we analyse the monthly fluctuations of mortality in the regions (year-over-year) in 2015–2019. We calculate a median value of 1.14 from the sample of maximum excess mortality values (extreme fluctuations). This means that the number of deaths per month in the average Russian region did not increase by more than 14% relative to the number of deaths in the same month in the previous year during the pre-pandemic period. In fact, this threshold shows in which range mortality can fluctuate in regular conditions. All values higher, especially observed for two or more consecutive months, should be attributed to the COVID-19 effect, and are likely to indicate the acute phase of the infection spread in a region. At the next stage the trend of excess mortality was divided into three periods indicating three waves of the pandemic (Fig. 2).

However, the first wave cannot be identified in 29 regions (excess mortality from April, 2020 to August, 2020 less than 1.14 – threshold value). The second and third waves of the pandemic are detected in all regions without exception.

For each wave we calculate four parameters (Fig. 3, 4, 5).

1. Basic: average excess monthly mortality (based on unified national periodisation of waves).
2. Peak excess monthly mortality (maximum monthly mortality during the wave, but not less than the threshold (1.14)).
3. Start time of the wave (month when monthly mortality surpasses the threshold (1.14) for the first time).
4. Duration of the wave (number of months with excess mortality higher than the threshold (1.14)).

The first wave of the COVID-19 pandemic (April, 2020 – August, 2020) is the shortest and lowest. Regions show extremely different patterns in excess mortality. Some central regions, especially those with million-plus cities, faced exponential growth of infections despite harsh restrictive measures being induced, while in many peripheral regions the coronavirus spread slower or arrived very late. The most striking contrasts are in the time of onset and duration of the first wave. Among the most affected are the regions of Central Russia, St. Petersburg and Leningrad oblast, the republics of the North Caucasus and the oil and gas-producing Yamal-Nenets autonomous okrug and Khanty-Mansi autonomous okrug in West Siberia. There is also a high polarisation in terms of mortality. The excess mortality rate during the first wave in the Chechen Republic located in densely populated region of the North Caucasus reaches 44%, while in the remote Tyva Republic on Siberian periphery it is only 6%.

The second wave (September, 2020 – March, 2021), on the contrary, is the most coherent and homogenous one with a distinctive peak in December. Regions demonstrate almost synchronous dynamics and scope of excess mortality, while its dispersion is decreasing (the standard deviation of the average excess mortality is 6.1% compared to 11.8% in the first wave). The second wave is on average 40% higher than the first one. At this stage the pandemic permeates among every region, new hotbeds emerge in the Far East. The Russian economy cannot sustain strict lockdowns anymore which facilitates the spread of infection. The strictness of the lockdowns, mainly for economic reasons, begins to soften. As the result, the barrier and inertia effects of Russia's centre-peripheral space are gradually levelled out.

The third wave (June, 2021 – December, 2021) has similar regional projection to the second wave. The dynamics of excess mortality are different, though, with two mortality peaks. The first was in July, 2021. After a slight decline and stabilisation, mortality soared to a record high (national average: 1.75) in November due to the SARS-CoV-2 delta variant spread. Adult vaccination rate was still at around 40% in November, 2021, which is insufficient to reduce mortality from COVID-19. Although the regions pass the third wave relatively homogeneously according to average parameters (standard deviation of average excess mortality is 8.5%), the mortality dynamics are inconsistent. Most regions follow a standard pattern, repeating the general trend with two mortality peaks and record values in November-December, 2021 (up to 2.4). However, some regions have only one prominent peak in late autumn, while some (mostly Siberian and Far Eastern regions) feature the summer peak which is higher than the autumn peak. Such discrepancies specifically in the third wave are most likely due to interference of pandemic waves. At the time the delta variant of SARS-CoV-2 began to spread in Russia (June, 2021) regions of European Russia and some open regions of Siberia, which had passed through two full waves, were in the opposite phase to the peripheral regions of Siberia and the Far East, where the virus came with a delay.

The second stage: selection of indicators for assessing population flows as ways of COVID-19 spread. The first group of indicators directly describes *transport openness (closedness) of a region*, the choice of this group is the most obvious. In this case, special attention was paid to air transport: a number of works show a link between primary transmission of infection and air transport, which, in theory, provides the longest passenger connections – up to global ones (it is no coincidence that the role of air transport in the spread of infections was described even before the COVID-19 pandemic (Nicolaides et al., 2012)). Media analysis as well as our interviews confirm the importance of air transport in the initial transmission of infection[3]. Some studies on COVID-19 have found air traffic to be insignificant (Zemtsov and Baburin, 2020) but the authors' methodology in this case was fundamentally different.

We test different indicators of air passenger flows: relative and absolute. The logic behind using the absolute (rather than just per capita) indicator is the importance (in the context of our study) of the primary entry of infection into an area, i.e. the risk of COVID-19 outbreak is higher when the gross number of air passengers is high (Tarkhov, 2022). Thus, for example, the probability of occurrence of an infected person among the passengers arriving in Moscow is higher than among the passengers arriving, let us assume, in Igarka (here the number of air passengers reaches 50 per city resident annually due to the shift workers, but their total number is significantly lower than the total number of passengers passing through major airports of the country, and therefore, the possibility of appearance of infection carrier among them is lower proportionally to their absolute number). The indicator of total passengers handled at airports per capita was also taken for comparison.

In addition, we consider the indicator of integral transport accessibility. The calculated values of the indicator were taken from the article (Lavrinenko et al., 2019):

$$transport\_index_x = \sum_y P_y \div total\_cost_{x-y} ,$$

where *transport_index* – integral index of transport accessibility of a region x; P_y –population of a region y (million people); $total\_cost_{x-y}$ – the total transport costs of travelling from region x to all other regions y (roubles).

[3] "The COVID came to Chita with a Moscow flight! A woman, a local woman, was returning from holiday and turned out to be sick. So, while she went to the doctors, someone from her flight was found, and someone was not found, people who was flying with her left, and so the COVID began" (interview by N.Yu. Zamyatina, Chita, May, 2022).

Transport costs consist of a weighted average of direct and indirect (time) costs for all modes of passenger transport, adjusted for modal structure of transportation. An important advantage of the integral transport accessibility indicator for characterising the openness or closedness of a region is that it is based on the principle of the gravity model. Not only transport costs for inter-regional movements are taken into account, but also "weights" of regions expressed through population size. Accordingly, a location in a densely populated part of the country increases transport accessibility, as the factor of proximity to large regions in terms of population has an impact.

Migration indicators are less useful for assessing the transmission of the coronavirus because migrants constituted only a small flow of potential carriers of the virus (holidaymakers and travellers are much more significant given their greater proportion in the overall population). However, migration indicators are included in the analysis to show not so much the flow of potential carriers of the virus during the pandemic as to reflect indirectly the potential for such flows. Presumably, the migration situation is "fractally" reflected in the population flow pattern as a whole. A wide scope of migration in general might indicate a high intensity of other flows up to daily commuting. The analysis is based on five-year average migration volume (2015–2019) (number of departures and arrivals per capita and only arrivals per capita) and the proportion of intraregional migrants in the total number of migrants as a potential indicator of the overall closedness of the region[4].

In addition, unusual indicators are introduced into the analysis: the share of the population born in a region but living outside of it in the total population born in a region and the share of the population born in a region in the total population of the region (according to the 2010 census). The choice of the first one is based on the assumption that regions with a high share of locals living outside are a specific type of chronically depopulated regions (a typical example is Kirov oblast), a kind of "absolute outback ("glubinka")". We hypothesise that such "chronic" features of a region may be indicative of weak regular connections with other regions. The second indicator rather shows the degree of autochthony of a region or embeddedness of local residents which could also be a sign of a marker of an outback ("glubinka"). High shares of the population born in a region and living in it are typical for national republics where close social ties are preserved. Low shares are typical for regions specialising on mineral resources and major centres of migrants' attraction (Moscow, St. Petersburg, Krasnodar krai, etc.).

As already mentioned, the estimation of average per capita income could presumably produce similar results. Wealth could be seen as another proxy for mobility (financial opportunities and limitations of mobility) and such attempts have been made. However, in this case the authors refrain from introducing economic parameters, aiming at identifying exactly spatial ("flow") characteristics of centrality and peripherality, especially since income indicators have already been considered by many researchers (Zemtsov and Baburin, 2020; Kotov et al., 2022), and have not came to more or less unambiguous results.

The second group of indicators describes *settlement pattern*. It is logical to assume that areas with a sparse settlement network were less susceptible to the spread of the infection, because of the natural difficulty of contacts between individual settlements. In addition, we suggest that the consequences of COVID-19 are linked to the concentration of population within a region (monocentric regions are expected to be affected faster and more severely than polycentric ones). We consider a number of indicators, including the Herfindahl-Hirschman index for population of all settlements showing the concentration level of population in a region (calculated for settlements with a non-zero population from the database by the Research Development Infrastructure (RDI) online platform), the proportion of the population living in cities with more than 250 thousand residents, urbanisation level, average size of a settlement, settlement density, indicators of transport availability of the area by road network: road density and Engel coefficient (road density weighted by population). Among others, the indicator "share of the population living in remote mono-specialised towns or centres servicing rural areas" requires commentary. We proposed it previously in another paper (Zamyatina and Nikitin, 2020). Here we are referring to cities with a population of less than 100 thousand people, while not being satellites of agglomerations of cities with a population over 100

[4] Indicator suggested by A.N. Pelyasov.

thousand (delimitation of agglomerations was carried out according to the radius of transport accessibility of the centre by road: from 50 to 100 km, depending on the population of the centre). In fact, in the vast majority of cases, these are mono-specialised industrial towns or municipal centres and other small towns focused on serving the adjacent rural areas. The relative isolation of the city itself, and its (generally) poor links to the major centres (in contrast to satellite towns in agglomerations), is expected to facilitate later appearance of the new infection. However, such towns may become hotbeds in the later stages of the pandemic as coronavirus infection gradually spreads within a region. Mono-specialised towns can also be affected by the factor of close interactions between employees of the city-forming enterprise in the production facilities (especially in the manufacturing industry).

The complete list of the studied indicators is shown in table 1.

RESULTS: DESIGNING THE TYPOLOGY OF RUSSIAN REGIONS BASED ON THEIR PLACE IN THE SPATIAL STRUCTURE OF INTERREGIONAL POPULATION FLOWS

Selected indicators describing openness (closedness) and settlement patterns of regions are examined in order to establish their correlation with the basic indicators responsible for the impact of the COVID-19 pandemic. For this purpose, pairwise Pearson correlation coefficients of all indicators with average excess mortality are calculated for the whole study period from April, 2020 to December, 2021, as well as for each of the three waves. The results are presented in Table 2.

We did not find a high degree of statistical correlation in any of the cases. The highest correlation coefficients with excess mortality over the entire pandemic are -0.4 for the share of the population born in a region but living outside of it and 0.4 for the average size of a settlement. The results of the correlation analysis clearly demonstrate the difference between the first wave and the more similar second and third waves: on average, the first wave features higher correlation coefficients, particularly with the openness (closedness) indicators.

Some initial hypotheses have not been confirmed: for example, no significant correlation has been found between the damage from the pandemic during any of the waves and the polycentric or monocentric settlement pattern of the region expressed through the Herfindahl-Hirschman index calculated for population of all settlements. Indicators describing some attributes of spatial density, such as the availability of roads (Engel coefficient) and the density of settlements, have also proved to be insignificant. Paradoxically, some indicators of the migration situation and the level of urbanization have proved to be unrepresentative for the analysis of excess mortality distribution.

For further study, we select only those indicators for which the probability of a random statistical relationship (*p-value*) with the average excess mortality over the entire period is less than 0.05. The indicator of share of the population living in remote mono-specialised towns or centres servicing rural areas, although meeting this criterion, is excluded because a similar indicator weighted by the number of the urban population showed a higher correlation coefficient with the basic indicator.

A matrix of pairwise Pearson correlation coefficients is calculated for the selected indicators (Table 3).

A high degree of correlation was found between population density and road network density (0.9). We can calculate population density with greater accuracy, so the latter indicator is excluded from the analysis.

As a result, there are four indicators that characterise the openness (closedness) of the region: total passengers handled at airports (*air_passenger*), integral index of transport accessibility (*transport_index*), the share of the population born in a region but living outside of it in the total population born in a region (*outside_population*), the share of migrants (departures and arrivals on average over 5 years) in the total population (*migration_scope*). After *z*-normalisation of indicators:

$$x_i' = \frac{x_i - x_{avg}}{\sigma_x},$$

where x_i' – normalised value (*z-score*), x_i – value, x_{avg} – sample average, σ_x – standard deviation for the data set x_i, the region's openness (closedness) index was calculated:

$$accessibility\_index = 0{,}25 \times air\_passanger + 0{,}25 \times transport\_index + 0{,}25 \times (-outside\_population) + 0.25 \times migration\_scope\ .$$

We take the values of the share of the population born in a region but living outside of it with the opposite sign, because the higher they are, the more closed the region hypothetically. Accordingly, high values of the integral index indicate that the region is open and low values indicate that it is closed.

Population density (*population_density*), average size of a settlement (*settlement_size*), the share of urban population living in remote mono-specialised towns or centres servicing rural areas (*remote_urban*), share of the population living in cities with more than 250 thousand residents (*share250*) remained in the list of indicators describing settlement pattern. The last two indicators were excluded, as they, like the second, more general indicator, are based on population density. Thus, as a result, the settlement pattern is assessed using two indicators: population density and the average size of a settlement. We do not calculate the integral index in order to highlight the paradoxes of space, which can be both dense and dispersed, and on the contrary, sparse but concentrated.

The consolidated typology is designed by dividing the regions according to the values of the openness (closedness) index, population density and average size of a settlement, in each case into two classes. We use histograms to determine the threshold values separating classes (Fig. 6). For the openness (closedness) index, the median value is chosen, so, the regions are divided into two equal groups. The histograms for population density and average size of a settlement demonstrate distinct skewed right pattern, so, the threshold values are chosen with regard of natural breaks: 18 people per km^2 and 1.5 thousand people, respectively.

Thus, the regions are divided into open and closed, densely and sparsely populated, with large and small settlements. The consolidated typology is based on the combination of these classes, the regions fell into each of the eight possible types.

1. Dense + large settlements + open (16 regions).
2. Dense + small settlements + open (19).
3. Sparse + large settlements + open (3).
4. Sparse + small settlements + open (4).
5. Dense + large settlements + closed (4).
6. Dense + small settlements + closed (8).
7. Sparse + large settlements + closed (12).
8. Sparse + small settlements + closed (19).

Table 4 illustrates the differences in the course of the COVID-19 pandemic in different types of regions.

DISCUSSION

Overall, we can highlight the following trends. To start with, the most open regions were the first to be affected by COVID-19 – they have the highest mortality rates in the first wave. Further on, differences between open and closed regions in terms of excess mortality rates diminish but each of the waves tends to be longer in open regions than in closed ones. Let us point out that if the wave in region A is substantially longer than in region B, and the mortality in region A, only slightly higher than in region B, then it appears that overall, open regions paradoxically do better in coping with the pandemic than closed regions which could often face shortages of medical personnel, medicines, etc. This observation definitely deserves more detailed analysis in further studies. The difference in the duration of the waves seems to be attributable to persistent infection "flow" into more open regions, whereas in closed ones an initial coronavirus transmission causes an outbreak that becomes localised more rapidly than in open regions (see field study materials in the footnotes above).

It is noteworthy that the closed regions in our typology include both remote, classic peripheral regions (Zabaykalsky krai) and some regions of Central Russia (Smolensk oblast, Bryansk oblast, Ivanovo oblast, etc.). The latter group is of particular interest. Many regions in Central and Northwest Russia have relatively low mortality throughout the pandemic. Here we witness a kind of a paradox. Located relatively close to the main infection hotspots (Moscow and St. Petersburg), with a large proportion of elderly population (more vulnerable to the disease), etc., these regions were expected to show higher excess mortality rates. Apparently, it was the “chronic” closedness that prevented them from infection inflow. A lower level of excess mortality is observed only in very hard-to-reach groups of regions: types 4 and 7 in table 5, like Nenets autonomous okrug, Chukotka autonomous okrug, Magadan oblast, etc.) In fact, COVID-19 exposes the classical “inner periphery” in this case (or, using the “matrix” designed by V.L. Kaganski the outback (“glubinka”) (Kaganski, 2001)). Interestingly, the link with the coronavirus infection is clearly evident both in terms of transport openness and social parameters. Regions within inner periphery suffer from an outflow of population, which is a marker not so much of actual population flows with which the virus could spread, but of their absence. Migration flows here go one way: from the region, stagnant depression hinders development of business travel, commuting, etc. Among closed regions, however, a small group is more vulnerable to the pandemic. These are closed, dense systems with polycentric settlement pattern, such as Kemerovo oblast or the Republic of Ingushetia. Although these regions do not receive persistent inflow of the infection from the outside, there is a swift internal spread of the virus after its appearance in the region due to high connectivity and the presence of many large centres.

Another valuable observation also relates to a specific type of region, like the central regions, the first to be exposed in the course of the pandemic. They are open, as the centre should be, but, unlike the classical centre, they are sparsely populated which is usually an attribute of the periphery (Copus, 2001). If a sparse and open region in the same time has large settlement pattern, then it tends to have a high excess mortality rate during the pandemic. Such regions, having features of both centre and periphery, seem to represent a special type of region rarely distinguished in classical works on territorial structure – a frontier, or an area with rapid extraction of large amounts of natural resources. The distinctive feature of a frontier is precisely the speed and scale of development. It is no coincidence that major oil and gas producing regions in West Siberia (Yamal-Nenets autonomous okrug and Khanty-Mansi autonomous okrug) fall into this type in our study, but not every resource-dependent region[5]. Regions with already inertial, more sluggish development (e.g. Magadan oblast or Zabaykalsky krai) do not demonstrate similar features in terms of transport openness. On the contrary, the frontier, being a resource periphery, is acquiring the features of the centre due to an intensive inflow of population (the same is relevant to some innovations, as the study has shown).

CONCLUSIONS

The novel coronavirus infection, as a specific negative innovation, clearly manifests the division of the Russian space into “open” and “closed” zones, centre and periphery. Open regions (in terms of transport and apparently social sphere) are the first to be affected by the pandemic, showing higher excess mortality rates in the first wave, and a longer duration of the consequent waves. Closed regions with weaker links by air transport, low transport accessibility and, specifically, persistent outbound migration are less vulnerable in the first phase, but gradually level out with the centres of mobility by the third wave. These regions mark the inertial, systemic nature of the region's place in the territorial system of the country. The regions of the “inner periphery”, or the outback (“glubinka”) of Central Russia, on the one hand, and the remotest ones, on the other, stand out especially in this case. On the contrary, rapidly industrially developing regions with intensive air communications and established major urban centres are acquiring some of the functions of centres (in particular, openness to innovation while being relatively underdeveloped and underpopulated). They should be allocated to a specific type (“frontier” is proposed).

Thus, the coronavirus infection has unexpectedly demonstrated the need for a more flexible approach to Russia's space than the traditional centre-peripheral dichotomy. It contains at least twice as many options. We propose to identify the main types of regions in terms of their place in the structure of spatial development as centre, hinterland, periphery and frontier. This classification can be potentially considered as specific application of centre-periphery model for large heterogenous

[5] Novosibirsk oblast falls into the same type, which indicates that the suggested typology is still rather specific, characterising to a greater extent the features of COVID-19 distribution. Although the typology reveals many fundamental blocks of Russia’s space, it is obviously insufficient for its thorough conceptualisation.

territories with striking differences in terms of level of development, economic profile and human mobility. Undoubtedly, suggested conceptualisation requires further development up to a detailed capture of intra-regional population flows at the micro level. Russian regions are extremely heterogenous and therefore in many ways incomparable, so further refinement of the typology, e.g. for individual parts of regions or municipalities, could shed light on the multifactorial mechanisms of the infection spread.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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TABLES

Table 1. List of indicators

Indicator	Description	Unit	Time period	Class
total	average excess mortality (April, 2020 – December, 2021) relative to 5-year average pre-pandemic mortality (2015–2019)	share	2015-2021	basis
avg1	average excess mortality during the first wave (April, 2020 – August, 2020)	share	2015-2021	basic
avg2	average excess mortality during the second wave (September, 2020 – March, 2021)	share	2015-2021	basic
avg3	average excess mortality during the third wave (June, 2021 – December, 2021)	share	2015-2021	basic
square	total area	km^2	2022	supplementary
population	population	thousand people	2021	supplementary
share_urban	urbanisation level	share	2021	settlement pattern
air_ passanger	total passengers handled at airports	people per year	2016-2017	openness (closedness)
air_ passanger_pc	total passengers handled at airports per capita	people per year	2016-2017	openness (closedness)
remote_ urban	share of urban population living in remote mono-specialised towns or centres servicing rural areas	share	2020	settlement pattern
remote_total	share of the population living in remote mono-specialised towns or centres servicing rural areas	share	2020	settlement pattern
transport_ index	integral index of transport accessibility	index	2019	openness (closedness)
outside_ population	share of the population born in a region but living outside of it in the total population born in a region	share	2010	openness (closedness)
local_ population	share of the population born in a region in the total population of the region	share	2010	openness (closedness)
migration_ scope	share of migrants (departures and arrivals on average over 5 years) in the total population	share	2015-2019	openness (closedness)
migration_ arrivals	share of migrants (arrivals on average over 5 years) in the total population	share	2015-2020	openness (closedness)
inner_ migration	share of intraregional migrants in the total number of migrants	share	2015-2019	openness (closedness)
population_ density	population density	people/km^2	2021	settlement pattern
road_density	road density	km/km^2	2021	settlement pattern
engel_roads	availability of roads (Engel coefficient)	index	2021	settlement pattern
share250	share of the population living in cities with more than 250 thousand residents in the total population of the region	share	2021	settlement pattern
settlment_ size	average size of a settlement	thousand people	2020	settlement pattern
settlement_ density	settlement density	number/ 100 km^2	2020	settlement pattern
settlement_ herfindal	Herfindahl–Hirschman index for population of all settlements	index	2020	settlement pattern

Table 2. Pairwise correlation coefficients between the indicators describing openness (closedness), settlement pattern and basic indicators

	total	*avg1*	*avg2*	*avg3*
share_urban	-0.043	-0.094	-0.030	0.014

air_passanger	0.290*	0.316*	0.145	0.144
air_passanger_pc	0.176	0.218*	0.037	0.140
remote_urban	-0.283*	-0.298*	-0.222*	-0.185
remote_total	-0.252*	-0.279*	-0.192	-0.165
transport_index	0.278*	0.306*	0.175	0.156
outside_population	-0.409*	-0.298*	-0.273*	-0.337*
local_population	-0.015	-0.030	0.038	-0.041
migration_scope	-0.226*	-0.002	-0.242*	-0.233*
migration_arrivals	-0.176	0.031	-0.203	-0.207
inner_migration	-0.127	-0.312*	-0.011	-0.005
population_density	0.266*	0.325*	0.123	0.117
road_density	0.275*	0.322*	0.156	0.126
engel_roads	-0.173	-0.170	-0.107	-0.137
share250	0.280*	0.030	0.321*	0.249*
settlment_size	0.399*	0.442*	0.236*	0.202
settlement_density	-0.137	0.048	-0.108	-0.213*
settlement_herfindal	0.172	0.162	0.076	0.127

* p-value < 0.05

Table 3. Matrix of pairwise correlation coefficients for selected indicators

	air_ passanger	*remote_ urban*	*transport_ index*	*outside_ population*	*migration_ scope*	*population_ density*	*road_ density*	*share250*
remote_ urban	-0.166							
transport_ index	0.612	-0.274						
outside_ population	-0.230	0.285	-0.143					
migration_ scope	0.066	0.318	-0.213	0.289				
population_ density	0.751	-0.183	0.472	-0.235	0.059			
road_density	0.664	-0.271	0.645	-0.232	0.008	0.903		
share250	0.292	-0.223	0.441	-0.123	-0.293	0.487	0.541	
settlment_ size	0.442	-0.169	0.068	-0.326	0.150	0.654	0.545	0.303

Table 4. Typology of Russian regions according to combination of openness (closedness) and settlement pattern characteristics

Type	Description	Average excess mortality				Average duration of the wave. months			
		total	1st wave	2nd wave	3rd wave	total	1st wave	2nd wave	3rd wave
Openness (closedness)									
1a	open	1.285	1.137	1.318	1.459	13.7	1.3	6.0	6.4
2a	closed	1.249	1.073	1.294	1.419	12.2	0.8	5.1	6.2
Settlement pattern									
1b	dense + large settlements	1.304	1.172	1.330	1.471	13.6	1.5	5.9	6.3
2b	dense + small settlements	1.273	1.125	1.313	1.446	13.7	1.2	5.9	6.6
3b	sparse + large settlements	1.251	1.082	1.296	1.419	12.4	1.1	5.1	6.2
4b	sparse + small settlements	1.237	1.037	1.283	1.416	11.7	0.6	5.1	6.1
Consolidated typology									

1	dense + large settlements + open	1.294	1.135	1.329	1.465	13.6	1.3	6.1	6.3
2	dense + small settlements + open	1.284	1.135	1.320	1.463	14.2	1.4	6.2	6.7
3	sparse + large settlements + open	1.333	1.229	1.361	1.500	15.0	2.3	6.0	6.7
4	sparse + small settlements + open	1.220	1.086	1.232	1.389	10.8	0.8	4.5	5.5
5	dense + large settlements + closed	1.345	1.320	1.336	1.493	13.5	2.5	4.8	6.3
6	dense + small settlements + closed	1.248	1.099	1.295	1.408	12.6	0.9	5.4	6.4
7	sparse + large settlements + closed	1.230	1.045	1.279	1.398	11.8	0.8	4.9	6.1
8	sparse + small settlements + closed	1.240	1.027	1.294	1.422	11.9	0.5	5.2	6.2
Total		1.267	1.105	1.306	1.439	12.9	1.1	5.5	6.3

Table 5. Centre-periphery conceptualisation of suggested typology of Russian regions

Type	Description	Position within the centre-periphery model (typical)	Examples of regions
1	dense + large settlements + open	centre	Moscow, Krasnodar krai, Sverdlovsk oblast
2	dense + small settlements + open	centre and adjacent territories	Ryazan oblast, Belgorod oblast, Tatarstan, Bashkortostan
3	sparse + large settlements + open	frontier (developed)	Khanty-Mansi autonomous okrug, Yamalo-Nenets autonomous okrug
4	sparse + small settlements + open	frontier (off-road)	Nenets autonomous okrug, Chukotka autonomous okrug
5	dense + large settlements + closed	closed polycentric local system	Kemerovo oblast, Chechen Republic
6	dense + small settlements + closed	near-capital outback (“glubinka”)	Smolensk oblast, Ivanovo oblast, Bryansk oblast
7	sparse + large settlements + closed	remote dispersed periphery	Murmansk oblast, Irkutsk oblast, Kamchatka krai, Magadan oblast
8	sparse + small settlements + closed	far-from-centre outback (“glubinka”)	Kirov oblast, Vologda oblast, Zabaykalsky krai

FIGURE CAPTIONS

Fig. 1. Classical scheme of a pandemic diffusion through a global transportation network (Rodrigue and Luke, 2022).
Fig. 2. Dynamics of excess mortality (April 2020 – December 2021) in Russian regions (bold black line indicates overall dynamics in Russia).
Fig. 3. The first wave of COVID-19: average monthly excess mortality, peak excess mortality, start time of the wave, duration of the wave: regional projection.
Fig. 4. The second wave of COVID-19: average monthly excess mortality, peak excess mortality, start time of the wave, duration of the wave: regional projection.
Fig. 5. The third wave of COVID-19: average monthly excess mortality, peak excess mortality, start time of the wave, duration of the wave: regional projection.
Fig. 6. Histograms showing distribution of Russian regions by accessibility index (a), population density (log scale) (b) and average size of a settlement (c)[6].
Fig. 7. Types of regions according to combination of openness (closedness) and settlement pattern characteristics.

FIGURES

[6] In graphs (b) and (c) federal cities (Moscow, St. Petersburg and Sevastopol) are excluded.

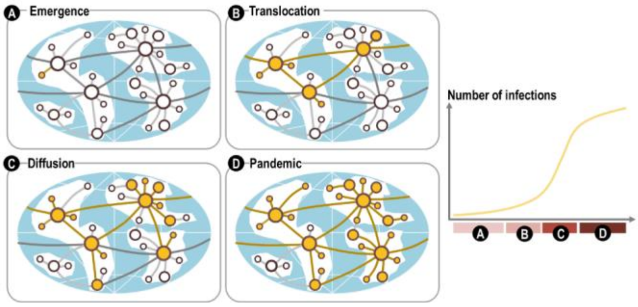

Fig. 1

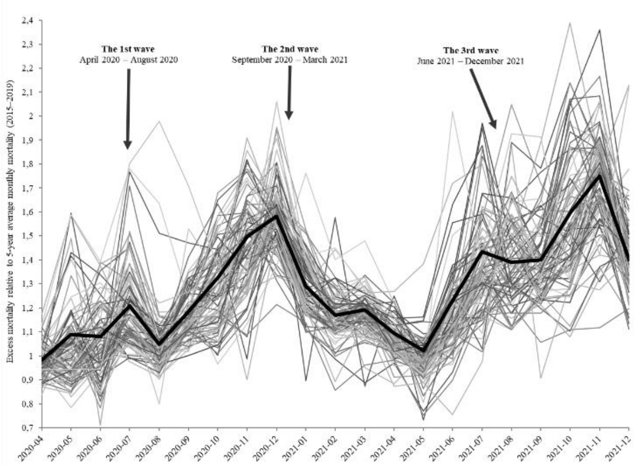

Fig. 2

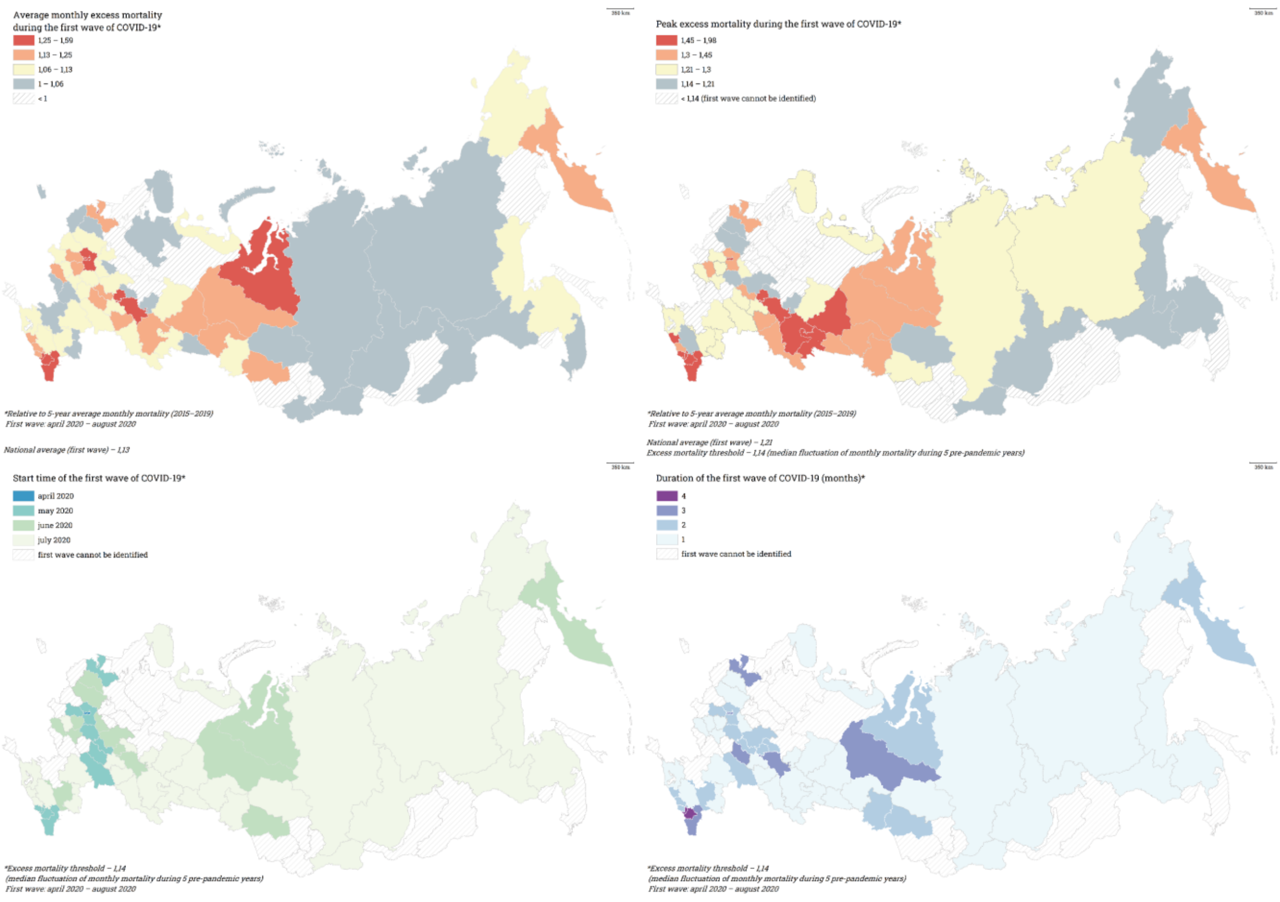

Fig. 3

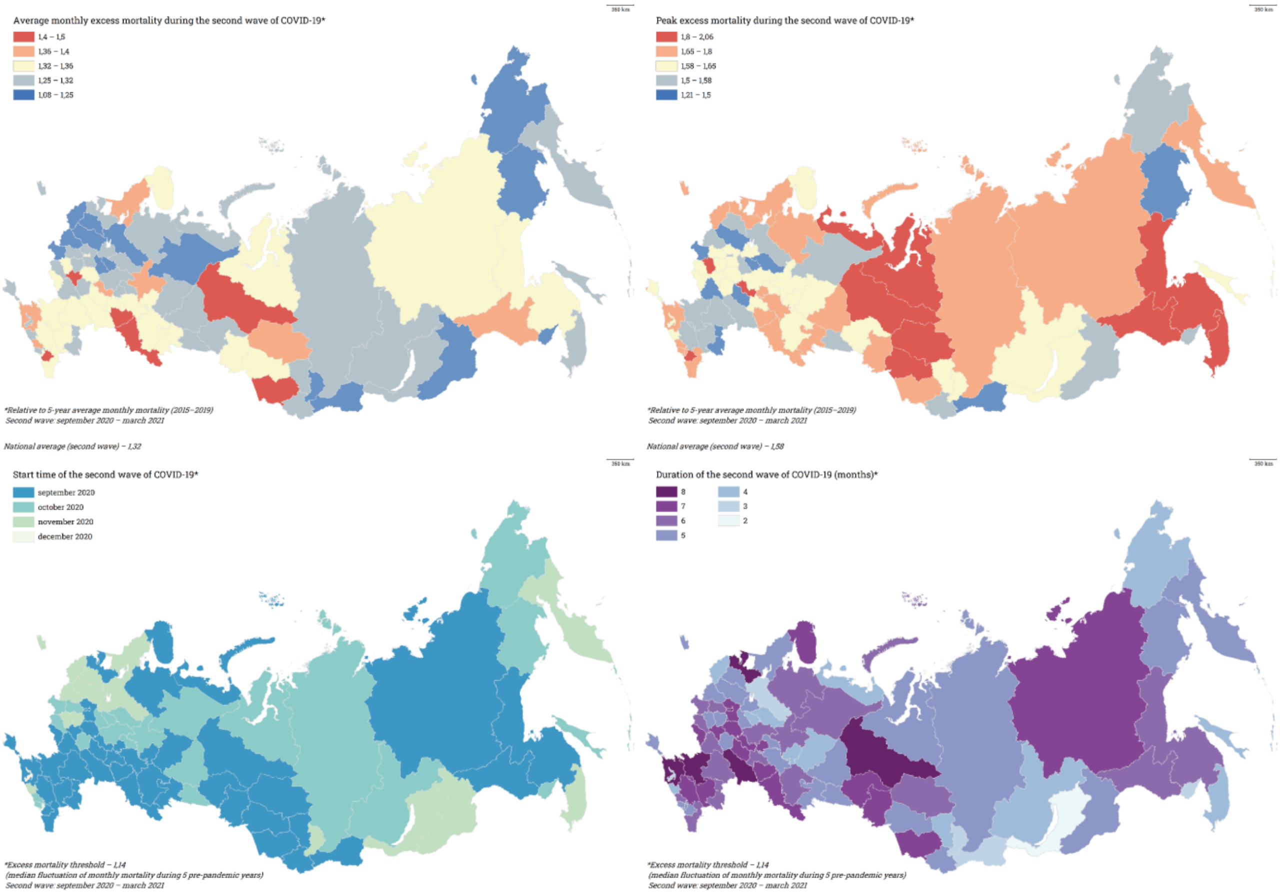
Average monthly excess mortality during the second wave of COVID-19*
1,4 – 1,5
1,36 – 1,4
1,32 – 1,36
1,25 – 1,32
1,08 – 1,25
*Relative to 5-year average monthly mortality (2015–2019)
Second wave: september 2020 – march 2021
National average (second wave) – 1,32
Peak excess mortality during the second wave of COVID-19*
1,8 – 2,06
1,65 – 1,8
1,58 – 1,65
1,5 – 1,58
1,21 – 1,5
*Relative to 5-year average monthly mortality (2015–2019)
Second wave: september 2020 – march 2021
National average (second wave) – 1,58
Start time of the second wave of COVID-19*
september 2020
october 2020
november 2020
december 2020
*Excess mortality threshold – 1,14
(median fluctuation of monthly mortality during 5 pre-pandemic years)
Second wave: september 2020 – march 2021
Duration of the second wave of COVID-19 (months)*
8
7
6
5
4
3
2
*Excess mortality threshold – 1,14
(median fluctuation of monthly mortality during 5 pre-pandemic years)
Second wave: september 2020 – march 2021

Fig. 4

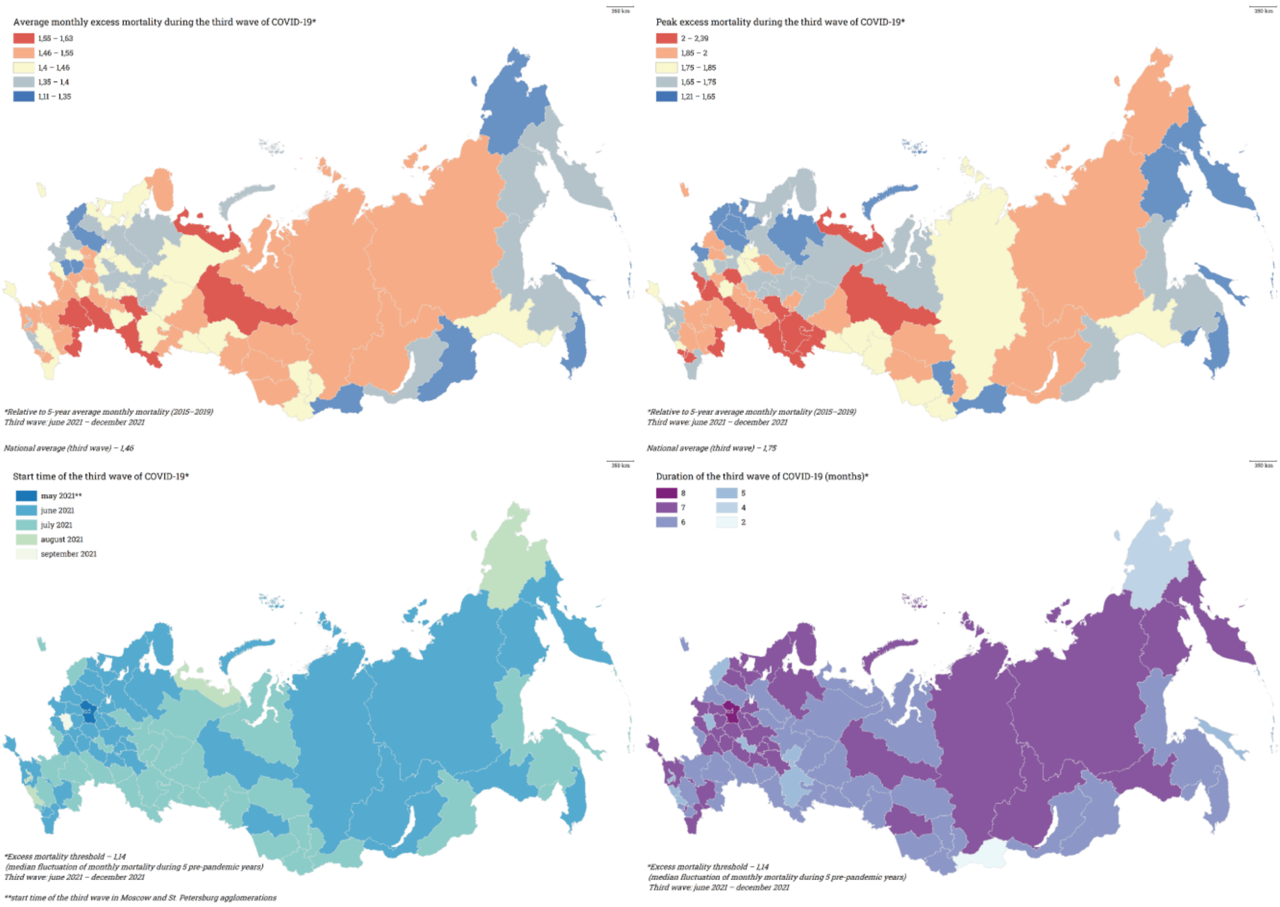
Average monthly excess mortality during the third wave of COVID-19*
1,55 – 1,63
1,46 – 1,55
1,4 – 1,46
1,35 – 1,4
1,11 – 1,35
*Relative to 5-year average monthly mortality (2015–2019)
Third wave: june 2021 – december 2021
National average (third wave) – 1,46
Peak excess mortality during the third wave of COVID-19*
2 – 2,39
1,85 – 2
1,75 – 1,85
1,65 – 1,75
1,21 – 1,65
*Relative to 5-year average monthly mortality (2015–2019)
Third wave: june 2021 – december 2021
National average (third wave) – 1,75
Start time of the third wave of COVID-19*
may 2021**
june 2021
july 2021
august 2021
september 2021
*Excess mortality threshold – 1,14
(median fluctuation of monthly mortality during 5 pre-pandemic years)
Third wave: june 2021 – december 2021
**start time of the third wave in Moscow and St. Petersburg agglomerations
Duration of the third wave of COVID-19 (months)*
8
7
6
5
4
2
*Excess mortality threshold – 1,14
(median fluctuation of monthly mortality during 5 pre-pandemic years)
Third wave: june 2021 – december 2021

Fig. 5

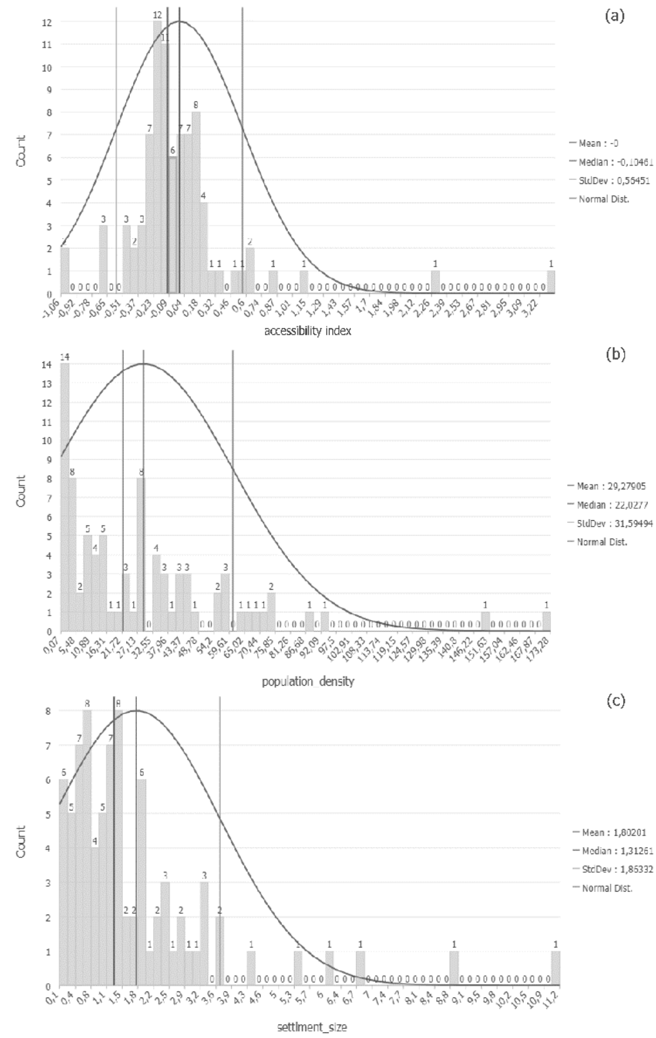
(a)
Count
accessibility index
Mean : -0
Median : -0,10461
StdDev : 0,55451
Normal Dist.
(b)
Count
population density
Mean : 29,27905
Median : 22,0277
StdDev : 31,59494
Normal Dist.
(c)
Count
settlment_size
Mean : 1,80201
Median : 1,31261
StdDev : 1,86332
Normal Dist.

Fig. 6

350 km
Region type
1. dense + large settlements + open (16)
2. dense + small settlements + open (19)
3. sparse + large settlements + open (3)
4. sparse + small settlements + open (4)
5. dense + large settlements + closed (4)
6. dense + small settlements + closed (8)
7. sparse + large settlements + closed (12)
8. sparse + small settlements + closed (19)

Fig. 7