WP4 – Technical Report

Smart-working and smart cities: data collection and indexes construction

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WP4 –Technical Report

Data sources review: mobility of population

The problem of the population mobility during the COVID-19 pandemic was one of the scientific topics that presented a major interest, in the early research associated with the epidemic diffusion. Three major datasets describing the dynamics of the mobility were identified during the process of data collection:

- the Google Community Mobility Reports (available at https://www.google.com/covid19/mobility/)
- the Facebook datasets (available at https://dataforgood.facebook.com/dfg/tools/movement-range-maps)
- the Apple dataset - COVID-19 Mobility Trends (from April, 14, 2022 the data is no longer available at https://covid19.apple.com/mobility). However, the data for 2020 was downloaded earlier than the deprecation date, for investigations in the project.

Each of datasets has its own "philosophy" of indicators' presentation. For example, the Google datasets contains 6 indicators describing the mobility of population:

G1. Grocery and pharmacy (it includes markets, pharmacies, drug stores, etc.)
G2. Parks
G3. Transit stations
G4. Retail and recreation (it includes shopping centers, restaurants, cafes, museums etc.)
G5. Residential
G6. Workplace

In the analysis provided in the country and thematic reports we used the indicator G.6, excluding the other five for several reasons – low connection with the smart-working topic, data gaps or limited coverage for some regions or metropolitan areas.

The Facebook datasets are also of major interest for the investigation of the population mobility, even if the number of indicators is much more reduced:

F.1 – proportion of people that are fixed in their location ("stay put", in the Facebook methodological description of the data)
F.2 – proportion of people that move from their location to other location.

The Facebook mobility data has limitations for the purpose of our research. The main limit is given by the fact that, when compared to Google dataset, there is no assessment of the mobility for workplace and, in this case, the connection with the smart-working diffusion is basically an approximation. For example, the proportion of the population that is spatially mobile contains contingents of persons that might be moving for other objectives – shopping, leisure, medical care etc. In the same time, the proportion of population that is considered immobile ("stay put") might be composed by persons that have integrated different patterns of activities (mixed forms of working – remote and at the office, people that have the workplace nearby, students in campus etc.).

The data provided by Apple was also explored during the mobility indicators collection process. Even if it is interesting from a geographical perspective (mobility declined by modes of transportation), for the general objective of the project it was less useful. A second limitation for the integration in the project was given by the unbalanced level of territorial coverage, with a fair amount of information for some of the case study countries (Italy, France, Spain or Poland), but extremely restrictive for Romania.

The territorial level of data availability varies from dataset to dataset. The Facebook mobility reports are based on the Database of Global Administrative Areas Project (GADM spatial delineation), with its own nomenclature and geometry. The Google files make use of the NUTS nomenclature, being easier to integrate in the mapping and analysis process. In both cases, independently from the mapping area (EU or a selected set of countries) there are challenges related to the geometry consistency. For example, at European level, the basic administrative units that can be mapped vary from the former LAU1 (e.g. Poland) to NUTS1 (France or Germany), according to the dataset. The chronological extent of the two data sources (Google and Facebook) is also not perfectly overlapping. Facebook data starts on the 1st of March 2020 and it ends on the 22 of May 2022, while the Google mobility reports begin on the 15 of February 2020, ending in 15 of October 2022. Given the extent of the data, the mapping of all the indicators can be imagined only in a dynamic context (map animation). However, this animation, despite of being spectacular, has little scientific added-value. A better understanding of the mobility trends is possible when the indicators are summarized using monthly or weekly averages. This procedure also helped us to deal with the missing data and to eliminate the "week-end" trends.

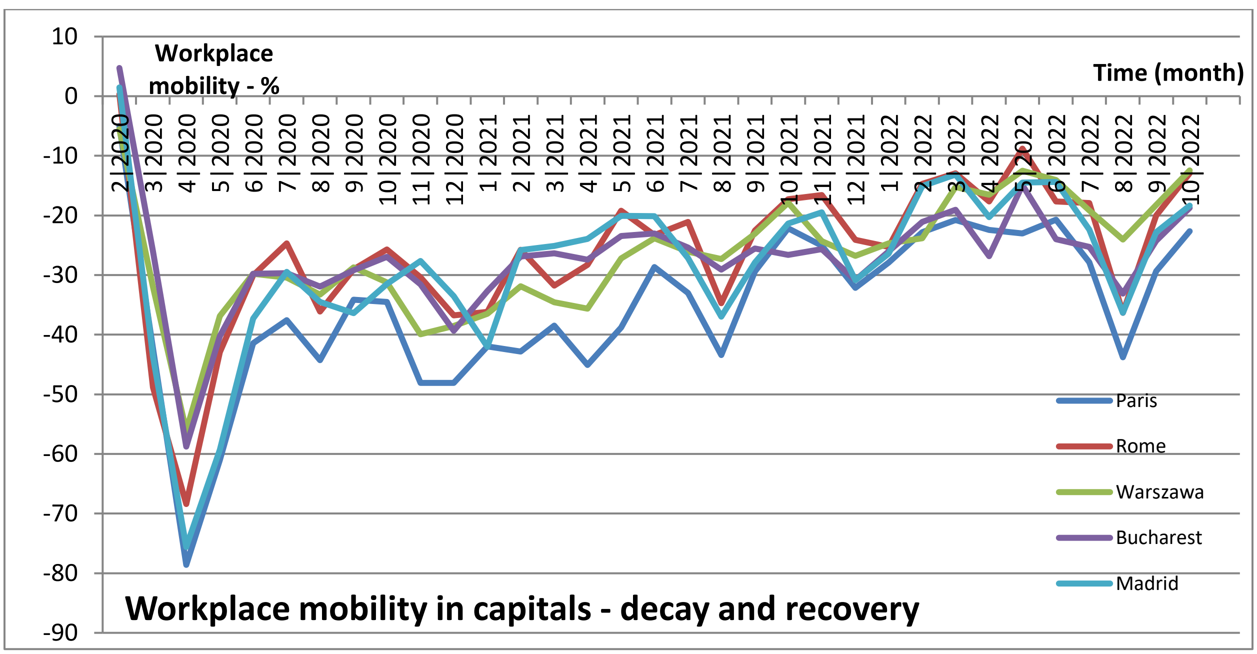


Fig. 1 Comparing capitals – mobility trends between February 2020 – October 2022 (Y axis = mobility description for workplace frequentation; X axis = time/months). Illustration based on the Google Community Mobility Reports.

In the case of Spain, one supplementary data source was found during the implementation of the WP4 – an assessment of the internal mobility in 2020 and 2021, at LAU level, based on an experimental methodology applied by the Spanish National Statistics Institute and available at https://www.ine.es/en/experimental/movilidad/experimental_em_en.htm. The data describes the flows of population between each Spanish LAU and their destinations, allowing comparisons for selected days of the year. Being an experimental dataset, refining the data and the methodology is an ongoing process, but it is clearly an excellent example of how to provide relevant data for policy design. The review of similar data providers for France, Italy, Poland and Romania did not succeeded in finding comparable daily flows information, making the Spanish case remarkably singular.

Data sources review: ITC endowment

The analysis of the ITC endowment at local scale strongly depends on the quality of data and indicators used in the research process. If the superior administrative scales (NUTS3 and NUTS2) are rather well documented and covered by indicators, the local level is barely explored, given the complexity of the task. The Eurostat datasets can provide some insights at regional scale, based mainly on the data describing the internet use or the households' endowment.(https://ec.europa.eu/eurostat/statistics-xplained/index.php?title=Digital_economy_and_society_statistics_-_households_and_individuals.). The attempts to identify a proper methodology of investigation of the internet endowment are still a scientific embryo, with an emphasis on the identification of sources and the data integration on a spatial frame. From a policy perspective, these attempts are not new – Territorial Dynamics in Europe. Trends in the Internet roll-out. Territorial Observation, no. 4, 2011, ESPON, showing that an interest for this topic was a constant during the last two decades. From a scientific perspective, the existing literature is rather limited and technically oriented (computer science and regional planning). In the main flow of publications, few articles focus on the local[1] dimension.

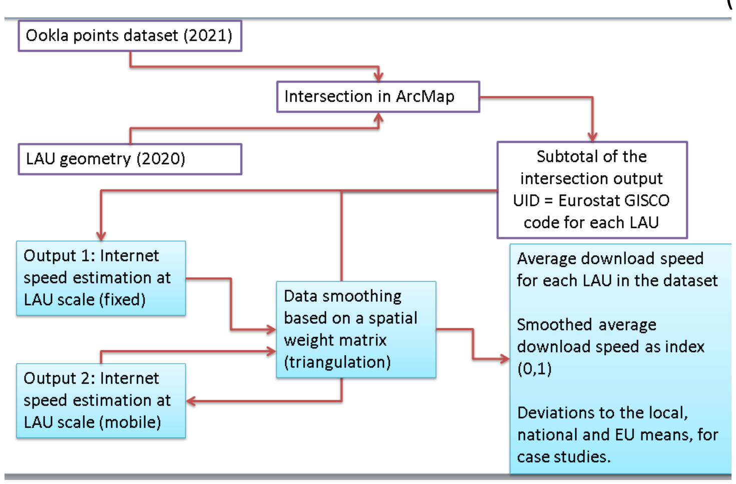
Our investigation managed to identify two major sources of data for the evaluation of the IT endowment at LAU level. The first database contains the geolocation of the IP addresses (https://db-ip.com/db/), but the results of the data integration in a territorial frame are rather limited. Most of the addresses concentrate into cities, with an extremely sparse coverage of the rural regions, even in the metropolitan areas. This first approach of data collection was finally abandoned. The second attempt to create a spatial database of IT endowment used the Ookla Internet Speed Measure data, available on the Kaggle repository (https://www.kaggle.com/datasets/dhruvildave/ookla-internet-speed-dataset) or at https://registry.opendata.aws/speedtest-global-performance/. This second database was clearly much more useful than the simple description of the IP stocks. The data can be declined in two categories – mobile and fixed speed evaluation, with a complex chronological extent (2019-2021, by quarter).The main advantage of Ookla DB use is given by the fact that the location of the internet speed measurement polygons (tiles) is doubled by a set of descriptive indicators:

[1] Janc, Krzysztof, Ilnicki, Dariusz and Jurkowski, Wojciech. "Spatial regularities in Internet performance at a local scale: The case of Poland" Moravian Geographical Reports, vol.30, no.3, 2022, pp.163-178. https://doi.org/10.2478/mgr-2022-0011

- average download speed (kbps.)
- average upload speed (kbps.)
- latency (ms.)
- number of devices used in the measurement process
- number of speed tests implemented

From a technical point of view, the challenges of the data integration are rather limited, but given the complexity and the data granularity, the task is time consuming. Even if one will have the option to download all the three years of reference 2019, 2020, 2021, we limited the data acquisition to 2021 for a better matching with the other indicators collected in WP 4 (employment, for example) Basically, after the indicators were downloaded, the polygons were eliminated and the information was conserved in centroids, lighting the total amount of "information on the disk". The point cloud was intersected with the LAU delineation (the most recent one – GISCO Eurostat). The output of this operation allowed as recreating the internet speed measures for each local administrative Europe in the Eurostat GISCO/Eurogeographics covered area. The initial study area (EU, EFTA, Western Balkans) contains 80 000 000 points, equally declined between fix and mobile Internet speed estimations.

(1)



(2)

Fig. 2 Sampling points distribution in the Naples area (1). Work-flow schematics for the data integration from Ookla DB.

Despite the complexity of the dataset, the GIS methodology applied for the evaluation of the internet speed at local level is simple. In this stage, two outputs of the GIS intersection were ready for mapping: fixed and mobile internet speed estimation. The next step took into account the level of incertitude in the data distribution across the LAU, especially in areas with geographical specificities (mountain areas, islands, sparsely populated regions etc.).The solution was to smooth the indicators using a spatial weight matrix based on a Delaunay triangulation, instead of contiguity between the LAU polygons. This option was retained because some of the Italian and French LAU are islands, without a common administrative border with other LAU.

From a cartographic perspective, the degree of the phenomenon visibility on the map is fair to high. The next set of illustrations show the outputs of the steps described in the data collection and data integration methodology.

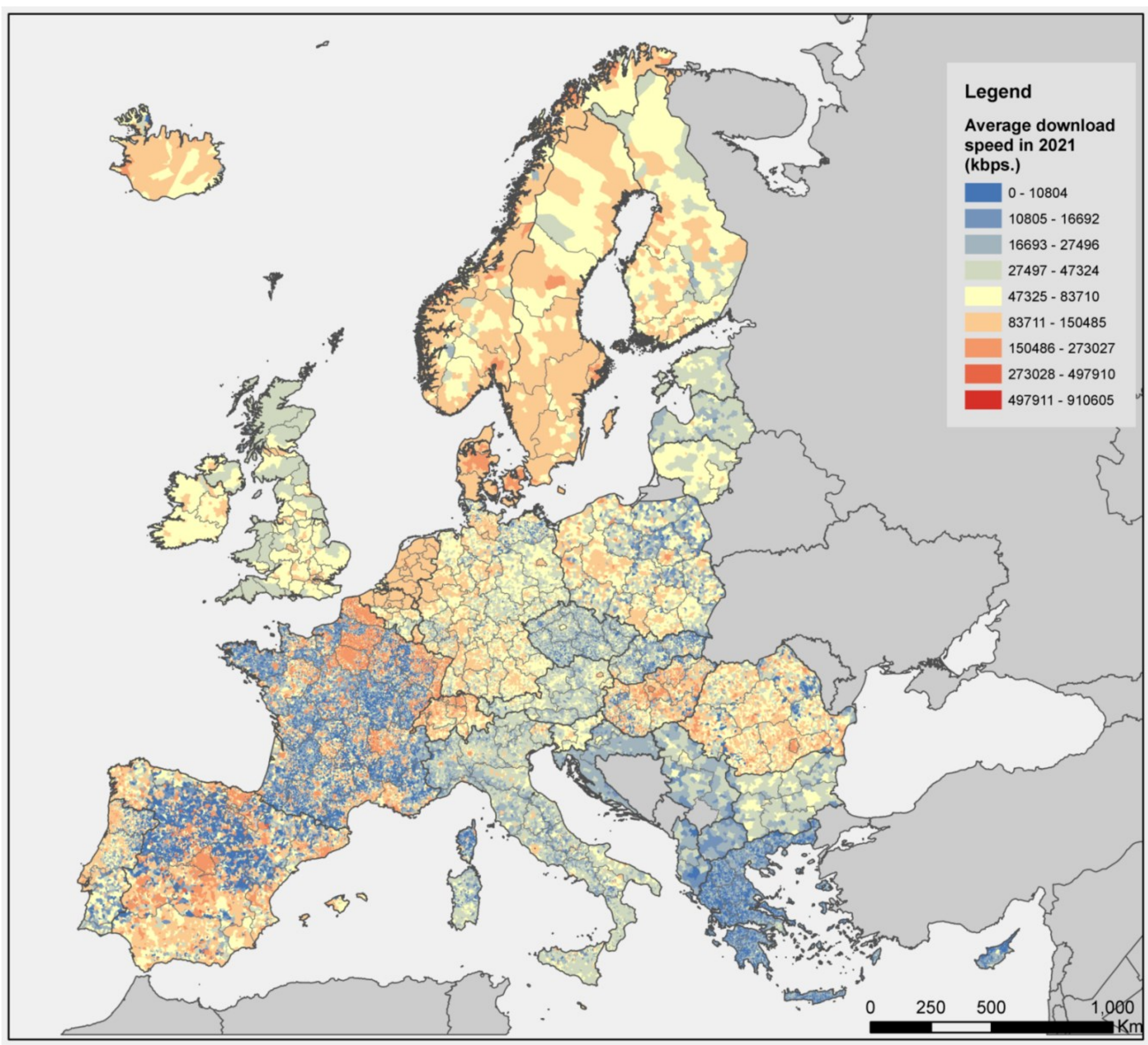


Fig. 3 Data integration results before applying a local smoothing – average download speed in 2021 (local level, fixed connection).

The raw results give access to a more restrictive analysis of the spatial repartition of the internet download speed. Even in this stage some key-findings relevant for policy design might be extracted. First, the digital divide in Europe seems to be organized by a North-South opposition between states, with some regional exceptions, mainly in Spain. The case of the European Eastern countries is interesting, as they were introduced later in the diffusion process. This delay is rather a territorial advantage because the technical infrastructures are newer, than in the core states, with an impact on the internet speed.

When a local smoothing technique is applied, the territorial stakes become clearer. In this second case, the metropolitan areas are easier to identify and the regional or sub-regional forms of digital divide are better shaped on the European map. Some of the problems of speed connection in the rural areas that are endemic in the north of Spain or in France are not so unique at the scale of Europe. For a better understanding of the differences between the LAU, the average speed of internet was transformed in an index ranging from 0 to 100 (maximum).

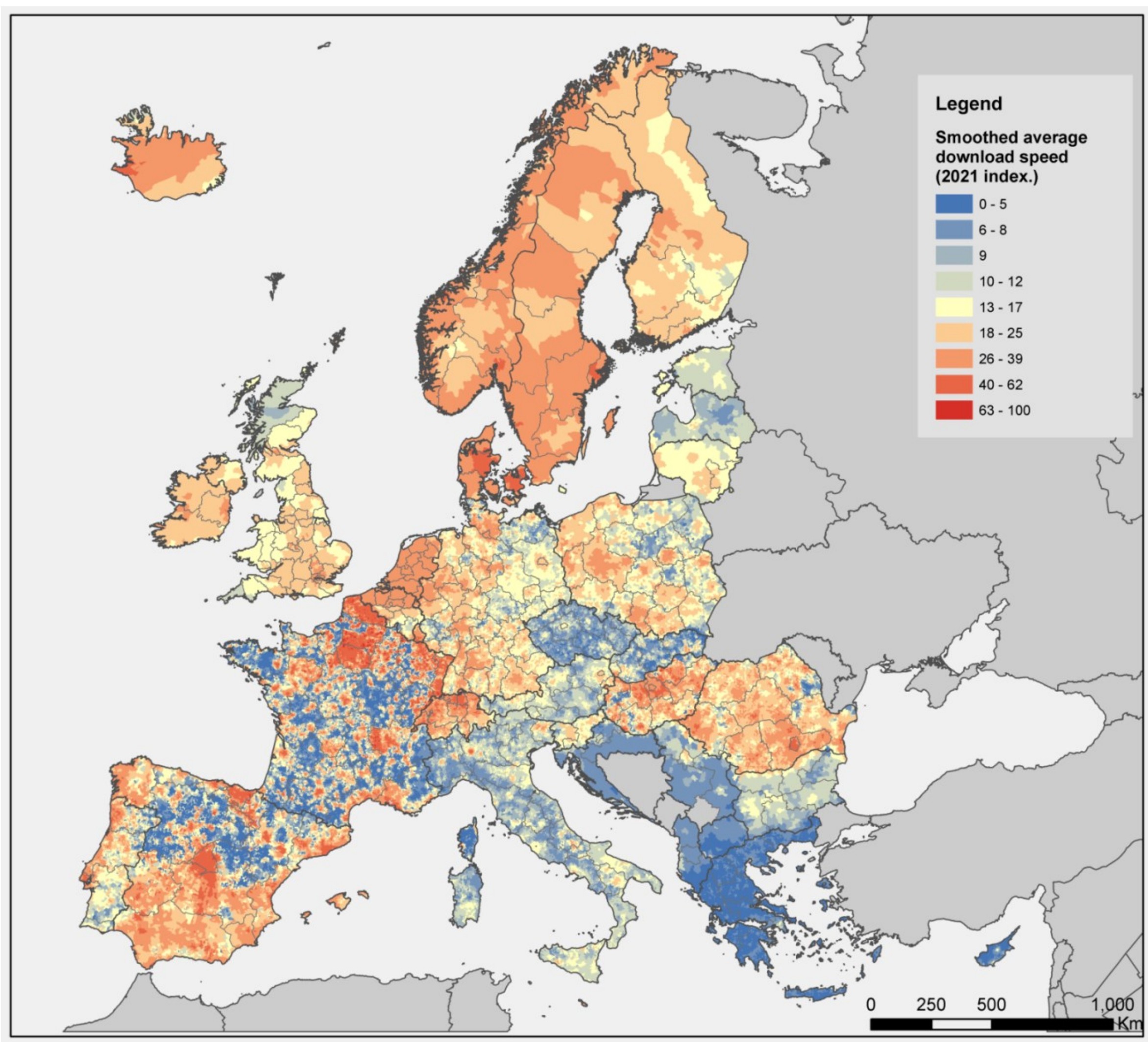


Fig. 4 Data integration results after applying a local smoothing technique – average download speed in 2021 (local level, fixed connection, transformation into an index).

The same approach was used for the evaluation of the internet speed via mobile connections. In this case, the results of the analysis depict a different territorial situation. Some of the countries that have a fair or good to excellent fixed Internet connection are now in a lower position in the European hierarchy, like Romania and Hungary. The analysis of the data and the map also shows that the mobile connections speed might be associated with the density of metropolitan areas in a country, responding to some obvious market logics. In some cases, one might suspect even the existence of distance decay patterns acting in and around some of the European metropolitan areas. For example, in France, the speed is decreasing as a distance function to the metropolitan core of Paris, Lyon, Bordeaux or Nantes. It is difficult to investigate how this decay functions and what are the parameters associated to it, but the progressive decay in speed might by a relevant topic for policy design in these countries. The same geographical pattern might be observed in Spain, Italy or Poland, with a lesser extent. In the Romanian case, the speed decay creates strong disparities between the metropolitan areas and the rural territory and the explanation has a technical nature – the local endowment with 3G and 4G antennas.

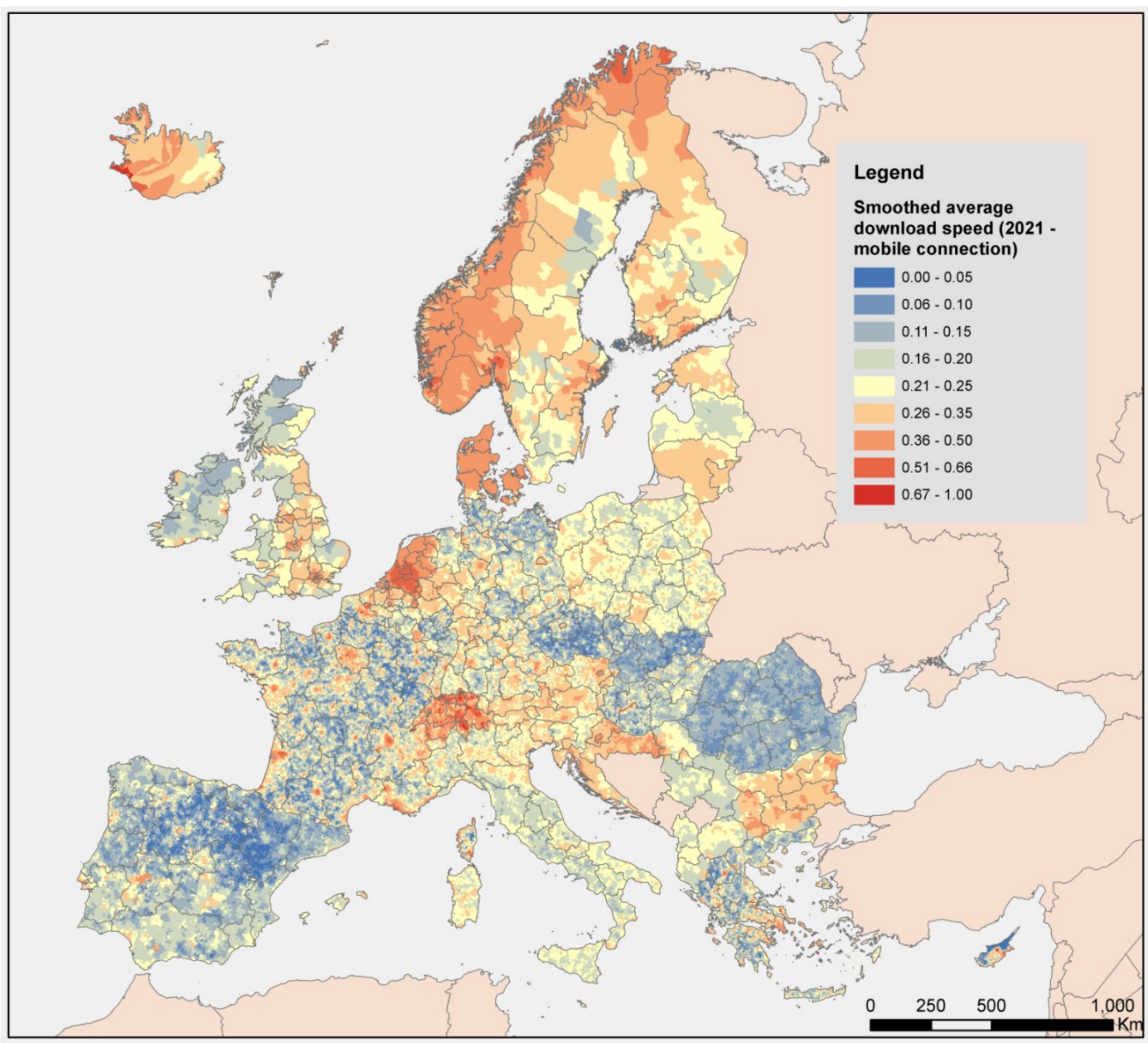


Fig. 5 Data integration results after applying a local smoothing technique – average download speed in 2021 (local level, fixed connection).

Given the complexity of the data needed to describe this endowment, an exploration of this hypothesis was implemented only for Romania. Using the data provided by OpenCelliD (https://opencellid.org/downloads.php), our investigation was successful in mapping almost exhaustively the mobile phones cells (antennas) present in the Romanian territory. As the density of cells creates unreadable maps, the location data was transformed in an index that measures the theoretical distance between the cells, under the assumption that they would have been uniformly distributed, in a theoretical space (Euclidean, uniform and with perfect isotropy).

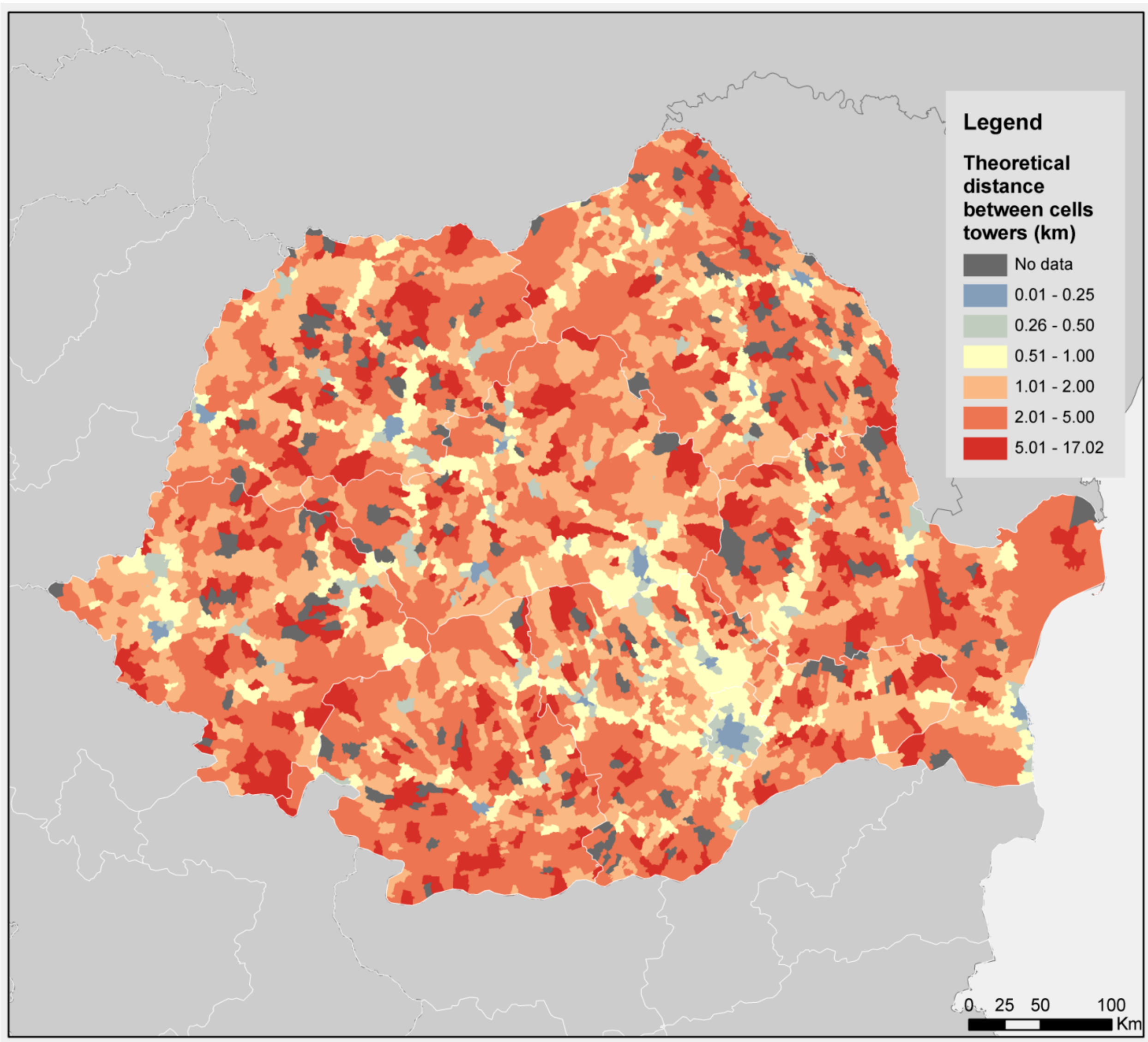


Fig. 6 Theoretical distance between the mobile phone antennas (3G and 4G) in Romania - 2022

The data indicates that the local clustering of cells/antennas is significantly higher in the Romanian metropolitan areas and it has sparse densities in the rural territory. Also, the main transportation corridors are well endowed, but this endowment interferes with some geographical specificities, that impede the diffusion of the technical support for mobile internet communication – mountain areas, territories with an intense terrain fragmentation or the Danube Delta. The map we obtained can be compared with the cartographic product describing the spatial repartition of the mobile Internet speed connection, based on the Ookla Database. It confirms the fact that the Romanian position in the EU hierarchy is affected by laggings in the technical endowment, especially in the case of the 4G antennas. This deficit of connectivity might be a topic of interest for the policy making, as it impacts the local potential for smart-working diffusion in the local territories that have, from the perspective of other indicators, a fair chance to promote it.

Data sources review: environmental indicators

The main problem in approaching the correlation between the smart-working diffusion and the environmental benefits is not the access to data sources, but rather the quality and the heterogeneity of the indicators provided. After the evaluation of different data providers, our strategy of indicators collection focused on the data extraction from the official source of EEA (European Environment Agency) – Air Quality Statistics. The reasons for this option are:

- the spatial resolution of the data. EEA –AQS gives access to data describing a high quality sampling points from all Europe, with a good coverage of the metropolitan areas. In this case, the data could be compared with the mobility indicators obtained from Google mobility Reports, allowing supplementary directions of research.
- the data quality. The indicators provided by EEA-AQS are validated in a sound process of quality check, making them extremely useful for scientific and academic research. One minor problem is the time needed for accessing validated data, especially in particular chronological contexts like 2020 – 2021.
- the variety of indicators that can be used for analysis. In the frame of our investigation, we were particularly interested in observing a potential association between the diffusion of smart-working during the Covid 19 closure period and the decrease of atmosphere concentration of some harmful compounds, like the NO2 or CO. EEA-AQS have a good coverage with data for these two precise chemical substances associated with the urban traffic and mobility.
- finally, the EEA-AQS databse allowed us to investigate this association for all the 5 stated included in the project – France, Italy, Poland, Romania and Spain.

Once the indicators source was identified, an extensive process of data collection was implemented. For each state a bulk-download of the .csv files describing each air monitoring station was implemented, using specific tools. In a second step, the data downloaded was merged in national tabular files. Finally, in order to eliminate the noise induced by particular causes (national holidays, meteorological conditions and local economic context), a monthly data smoothing was applied on the indicators information. For spatial outliers' detection, a large amount of the data we obtained was geo-located. However, after testing the data for geographical anomalies, it was impossible to conclude if the quality of the data was affected. Dealing with the data visualization was a separate problem, one that forced us to select representative case studies for each state, at city level. As the state capitals almost depict particular patterns, in the Romanian example, we have excluded Bucharest and included some representative metropolitan areas that have different economic specializations.

When the data quantity obtained is large (Poland or France, e.g.), the data visualization process needs to be adjusted. This adjustment can be done by selecting comparable spatial units like the large metropolitan areas. The choices can be crossed with the objective of the data visualization. For example, in order to detect heterogeneous trends and patterns, one might want to plot cities with different economic orientations or demographic mass.

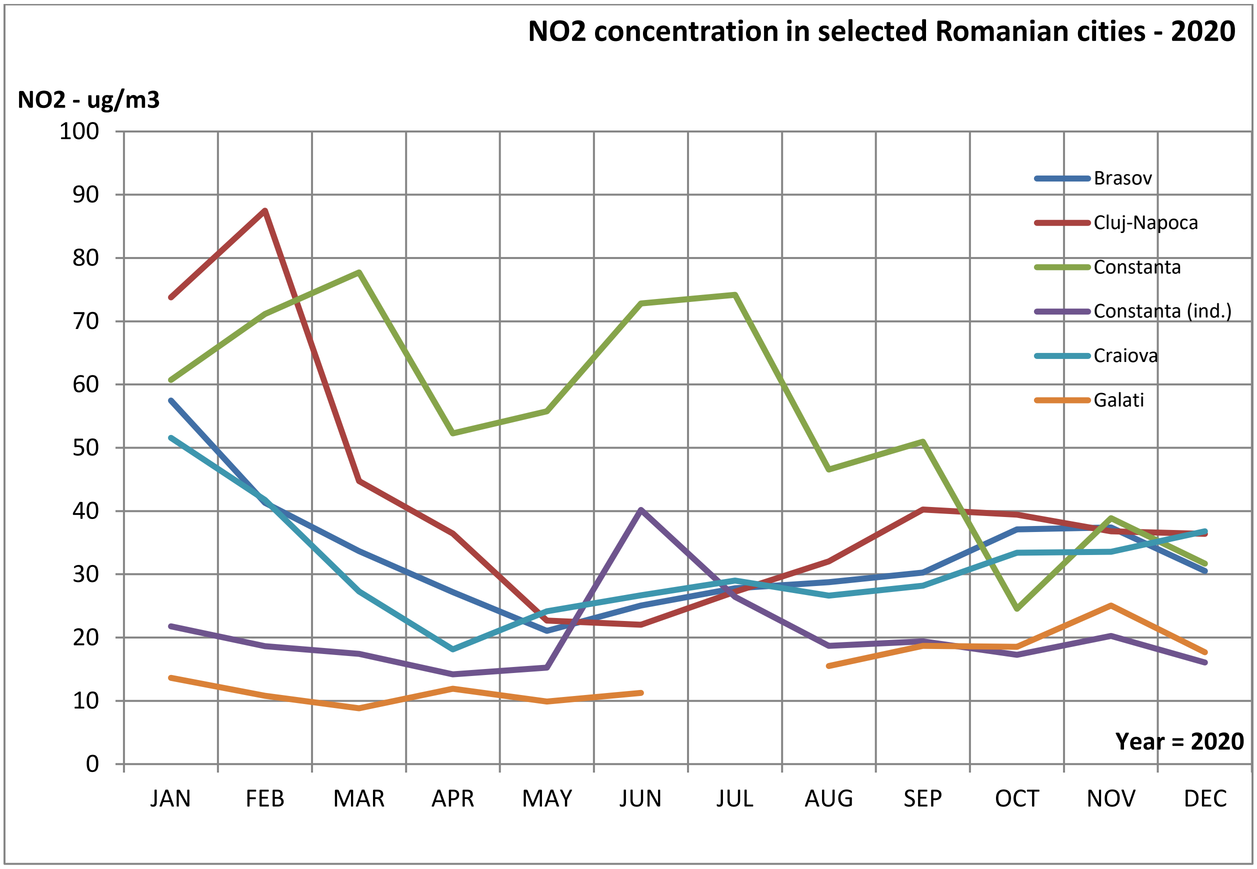


Fig. 7 Dynamics of the NO2 concentration at urban scale (2020 – Romanian selected cities). Monthly average concentrations.

Data source: https://discomap.eea.europa.eu/App/AirQualityStatistics/index.html#, EEA

All the datasets integrated for the description of the environmental benefits of the smart-working diffusion are chronologically harmonized for 2020. The information describing the evolution of the environmental indicators after 2020 is not available for all the states included in the case studies (missing data for Romania). Even if it possible to plot the dynamics of the compounds for some states, the comparative frame will be missing.

Data sources review: smart-working index

Retrieving relevant indicators for the assessment of the smart-working diffusion at local and regional level was the most challenging task during the process of data collection. This difficulty is explainable by multiple factors:

– no official data collection on relevant indicators (like the description of economic occupancy in a territorial frame)
- the data exist but is covered by statistical secrecy (microdata and surveys)
- the access to information is based on payment
- the topic is new and the statistical interest only recently began to focus on it
In this case, in order to build an image of the territorial patterns of the smart-working diffusion in the 5 studied states, we used proxy indicators retrievable at LAU (local administrative unit) level – the number of employees by NACE sector or, when not available, the number of business entities classified by the same nomenclature. Each state presents particularities in relation with the data collection process:

Spain. The main source for this state is the Nationals Statistical Institute. It provides data describing the structure of the business entities stocks at local level. There is no available data describing the spatial distribution of employees for an administrative frame lower than the NUTS3. Some of the data is covered by statistical secrecy, making the analysis an approximation of the local situation and not a description of it. Even in these conditions, the indicators are still useful to understand how the local economic systems adopted potential smart-working practices.

Main data source: https://www.ine.es/jaxiT3/Tabla.htm?t=4721

Italy. Again, the data collection was based on official sources - the Nationals Statistical Institute of Italy, which allows the free use and download of relevant indicators, like the number of employees structured by NACE classification. The most recent period covered is 2020, comparable with the case of Spain. No significant problems were detected during the indicators collection, excepting the size of the unique file that describes the LAU.

France. The French INSEE provides some data for the local administrative units, but the level of detail is limited to the NACE level 1 nomenclature, at least for our attempts to collect the information. This is possibly explained by the need to conserve a reasonable size of the download files, given the large number of French communes (more than 36000). The description of the smart-working diffusion is based on the stocks of employees locally recorded. The most recent available year is 2020.

Poland. The main source of information is https://stat.gov.pl/en/ (the Nationals Statistical Institute). Just like in the case of Spain, data on the spatial distribution of employees was not retrieved. In compensation, we used the stock of business entities for 2021 (the most recent available year as filter in the dataset). As the level of detailing was high, the NACE 4 digits sectors were aggregated in NACE level1. No significant impeding factors obstructed the data collection and data integration process.

Romania. There is no official data source for an assessment of the smart-working diffusion in the Romanian NSI. In this case, we used the information provided by the Romanian Registry of Commerce for a governmental institution that manages the official open-data portal in Romania (https://data.gov.ro). More than 600000 records were summarized in order to approximate the stocks of employees by NACE sectors, at local level. The data concerns only the private sectors of the economy, ignoring the potential smart-working positions in public activities (education, for example). The year of reference is 2020.

Overall, after the data was collected and integrated in tabular files for GIS use, elementary tests for data quality check were implemented. These tests focused mainly on the outliers' detection from a spatial perspective. The results of these tests provided a massive number of false positive outliers and we concluded that the level of data quality is sufficiently high for further analysis and for mapping. The indicators were coded and aggregated for a better interoperability of the datasets. The table contains an example of the operation for Italy, but the same approach was used for the other states.

DESCRIPTION OF IT9, IT10 AND IT11.

LEN	NACE	NACE_DESCR	SWO
1	A	Agriculture, forestry and fishing	0
1	B	Mining and quarrying	0
1	C	Manufacturing	0
1	D	Electricity, gas, steam and air conditioning supply	0
1	E	Water supply; sewerage; waste management and remediation activities	0
1	F	Construction	0
1	G	Wholesale and retail trade; repair of motor vehicles and motorcycles	0.5
1	H	Transporting and storage	0
1	I	Accommodation and food service activities	0
1	J	Information and communication	1
1	K	Financial and insurance activities	1
1	L	Real estate activities	0.5
1	M	Professional, scientific and technical activities	1
1	N	Administrative and support service activities	1
1	O	Public administration and defense; compulsory social security	0.5
1	P	Education	1
1	Q	Human health and social work activities	0
1	R	Arts, entertainment and recreation	1
1	S	Other services activities	0
1	T	Activities of households as employers; undifferentiated goods and services	1
1	U	Activities of extraterritorial organizations and bodies	1

Table 1 Indicators coding and data aggregation for Italy

For each country, an indicator labeled SWO (smart-working oriented stocks of employees or business entities) was created. The indicator is based on the summing up of the observed values of the NACE sectors that can be considered permeable for the smart-working diffusion (value 1 in the SWO column of Table 1). As the values of the SWO indicator present a limited interest for mapping, a quantitative transformation was needed and this transformation allowed us to elaborate two indexes of smart-working diffusion in the national contexts:

Index 1 – local Z scores for the smart-working diffusion. The index depicts the relative deviations of the local stocks of employees/business entities to the local mean. The formalization of the index is simple, but it gives access more information and interpretation than the simple mapping exercise of the SWO indicator. As any Z score, it is based on the ratio between the differences to the local mean and the local standard-deviation, for each LAU in the study area. Values close to 0 are associated to situations of normal diffusion of the smart-working practices in the local territory. Significantly large positive and negative values can be translated as particular situations of strong concentration (or absence, when negative) of smart-working employees and business entities. The size of the local territory for each a z score was calculated is a 90 minutes negative-exponential kernel around each LAU (see illustration below). The estimation of the 90 minutes limit is based on a network dataset provided by Eurogeographics as open-data.

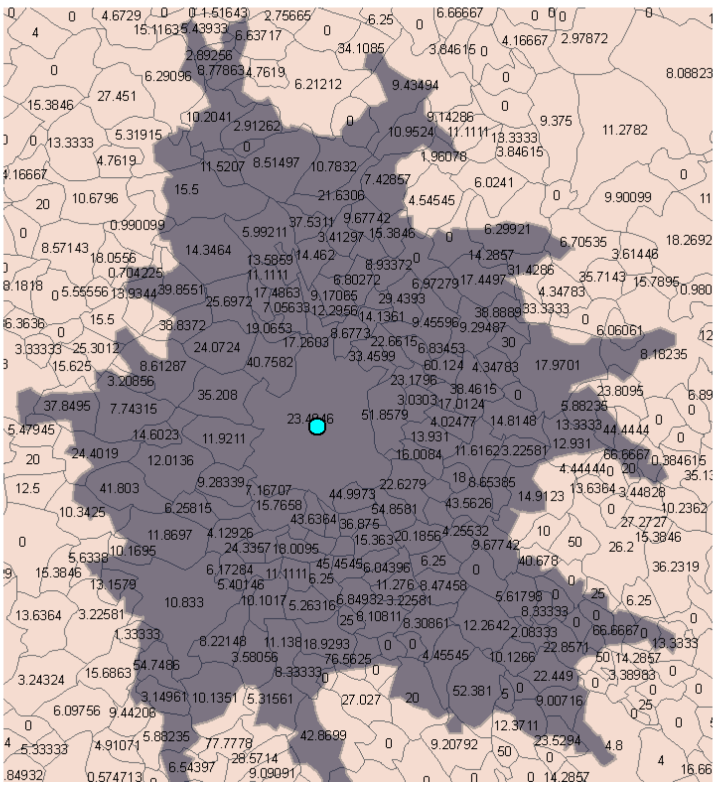


Fig. 8 Territorial context for the calculation of a local Z score (Toulouse, France – 90 minutes isochrones). The values labeled on the illustration represent the share of the SWO in the total amount of employees, at LAU level.

When mapped, the local Z score is able to detect the potential territorial disparities in the distribution of the smart-working employees or business entities. In the case of Poland, for example, the relatively high values of the indicator (Z>1) are usually associated with the urban endowment, at local and regional level. All the cities of Poland that have a metropolitan vocation are also strongly oriented to smart-working, independently of their geographical position. Szczecin is the only exception to this regularity and its particular position might be explained by the functional patterns of urban economic specialization acting in place. The opposition between the city-cores and the near rings of LAU is quite strong, but not as strong as in the case of Romania. At the opposite, the low values of the indicator (Z < -1) are located in areas that might be labeled as traditional rural areas (the triplum confinum of Pomorskie, Kujarsko-Pomorskie and Mazovieck regionalny), in some of Poland's inner-peripheries (the peripheral areas of Pomorskie and Zachodnio-Pomorskie) or near borders. The same pattern of territorial distribution, with a strong concentration of smart-working employees or business entities in cities, is also present in the other 4 states. The differences are given by the administrative local frame and by the incorporation of smart-working in the national context. Measuring this concentration was the main intention of the Index 2 – potential accessibility to smart-working employees/business entities.

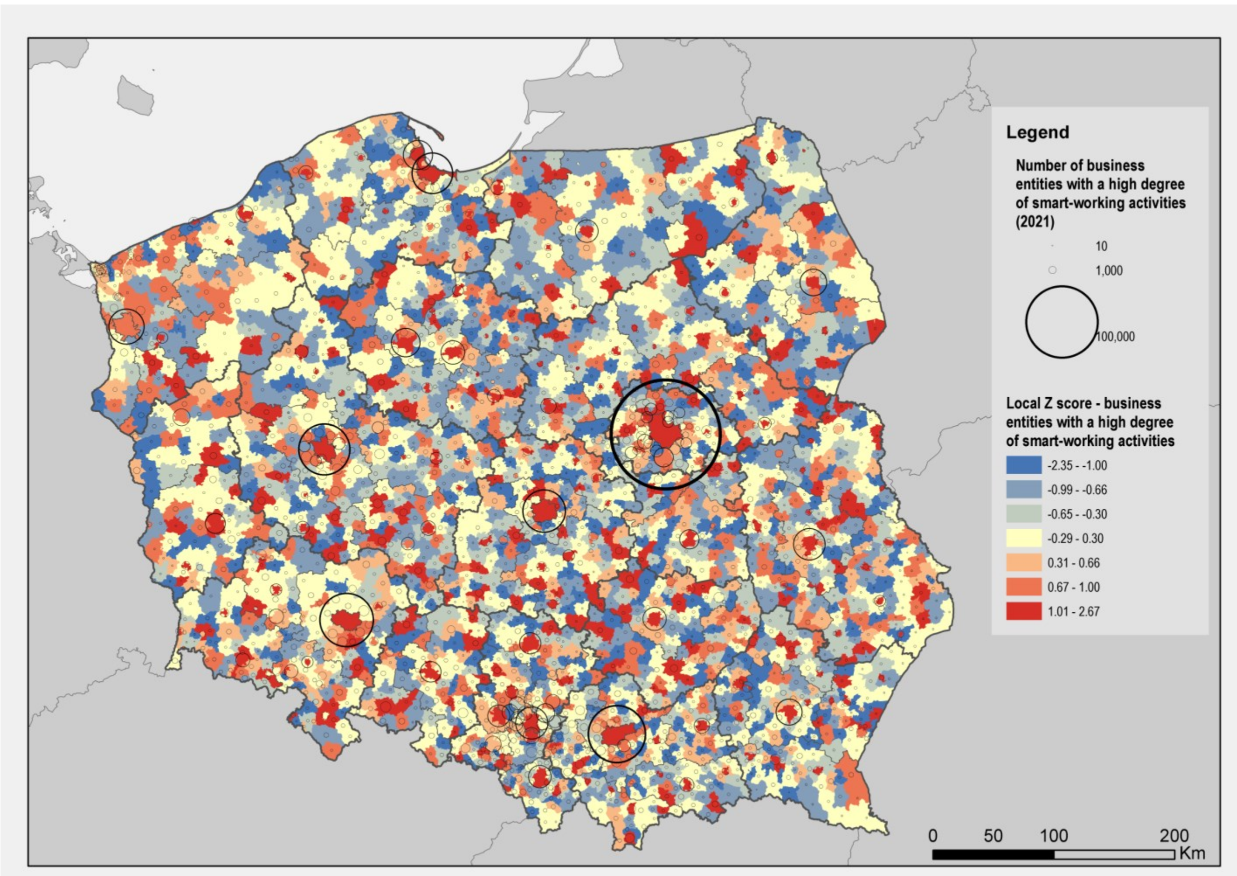


Fig. 9 Local Z score for smart-working activities in Poland

Index 2 – potential accessibility to smart-working employees/business entities. If the local disparities in the distribution of the smart-working employees or business entities can be measured by the local Z scores, the intensity of the spatial concentration invites the researcher to find other solutions. Our option was for the elaboration of a potential accessibility measure of this concentration, using a local negative-exponential kernel of 90 minutes. This kernel evaluates and weights the distance between a target LAU i and all its neighbors, using time-distances estimated in the road network. The formalization of the model is:

$$PA_i = \sum_i^j (e^{\alpha * Dij^{\beta}} * SWO_j)$$

PA_i = the potential accessibility of an LAUi to the stocks of employees/business entities, in a negative exponential kernel of 90 minutes.

α= a parameter describing the distance where the distance weights reach 0.5

Dij = the distance between the target LAU i and its neighbors in a range of 90 minutes. B=2, a usual value in this model. Once the distances are estimated and the SWO values are known, the calculation of the potential accessibility models resumes to a weighted sum. The shape of the kernel is illustrated bellow, in figure 10.

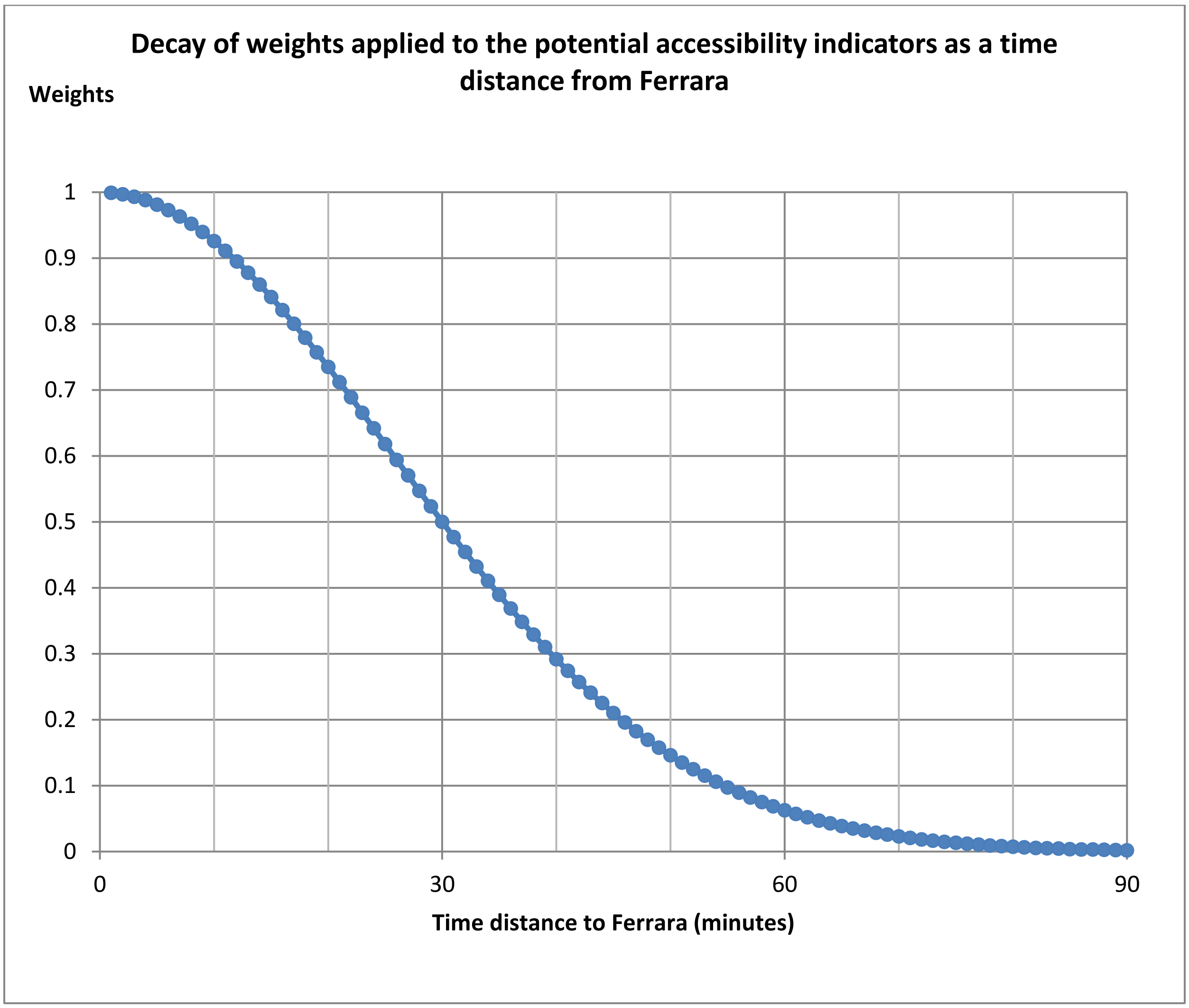


Fig. 10 Negative-exponential kernel based on the target LAU of Ferrara

The assumptions of the model are simple. We consider that the level of spatial interactions between the LAU of a chosen state are distance decay controlled. It means that the distance can be used as a filter, in order to estimate a weighted sum of the smart-working employees stocks around each local administrative unit. Without having access to empirical data and with a limited theoretical discussion of this topic, we considered reasonable to adjust the kernel at 30 minutes distance of each LAU. This is an optimal distance for commuting even if, the limit of 30 minutes is in many cases ignored. Of course, other types of distance functions might be used for this index of concentration, but this is a usual one and highly supported by the literature. Four of the countries included in the project as case studies allowed the implementation of this model, excepting France. For France, we needed to adjust the spatial resolution of the data, as calculating distance matrixes for 36 000 was technically impossible. In this case, we have calculated the potential accessibility of smart-working employees in the frame of the French cantons (an intermediate scale between the LAU and the NUTS3).

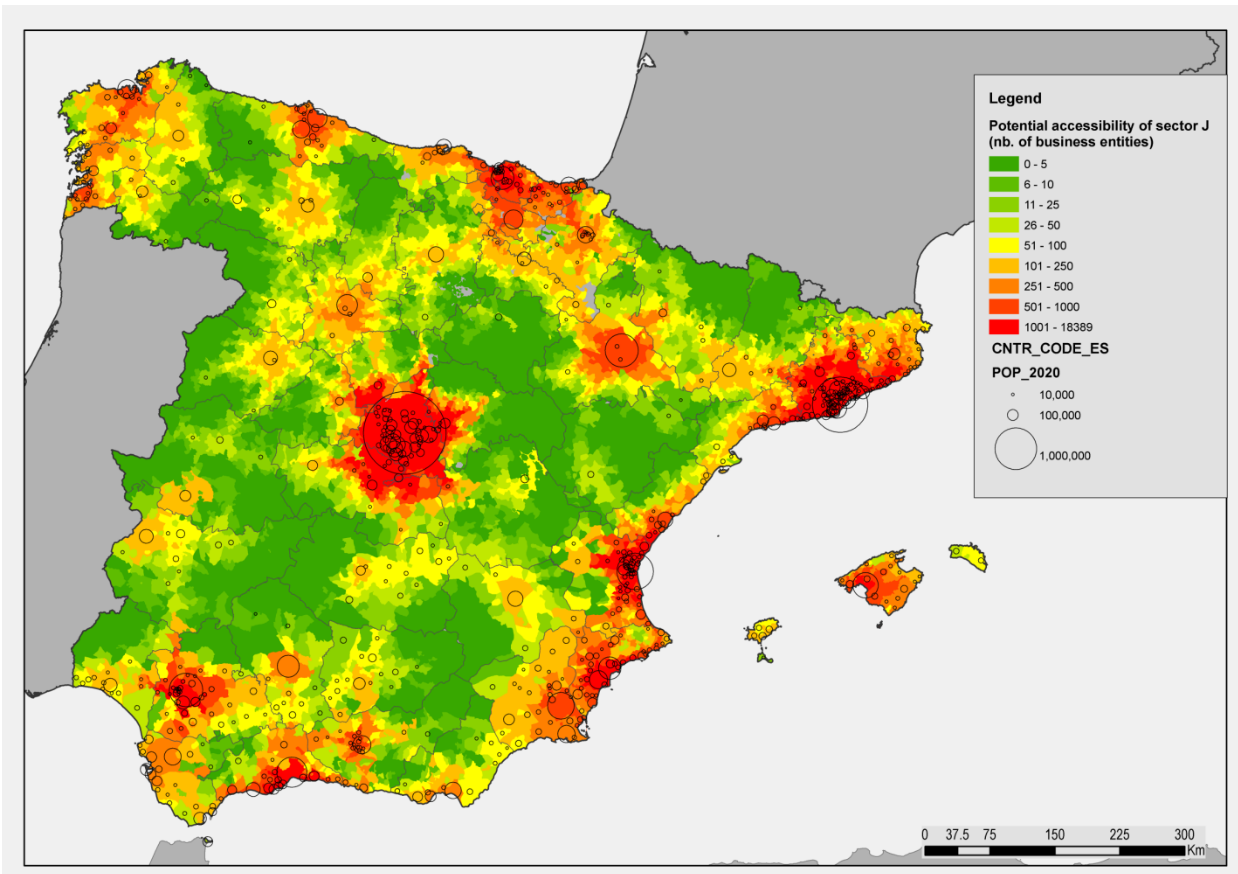


Fig. 11 Potential accessibility to smart-working business entities in Spain – the NACE J sector

The map depicting the potential accessibility of companies that are active in the J NACE economic sector, in Spain, is relevant for the concentration trends at work in this country. Compared to the local Z scores, the potential accessibility indicators highlight better the relation between the presence of metropolitan areas and the distribution of companies enrolled in potentially smart-working sectors. The map shows that the metropolitan area of Barcelona, almost faded on the previous cartographic illustrations, is an attractive area and it might compete Madrid in size and density of enterprises. The other large Spanish cities and metropolitan areas (Murcia, Seville, Valencia, Malaga and Bilbao) are also functional for the installation of business entities in the J sector, but on a smaller extent. The transportation corridors of Spain are responsible for the apparition of the intermediate values on the map (see the transportation axis form Madrid to Seville and Malaga, by Linares, Cordoba or Granada). The territories located outside this transportation grid are significantly less invested by the J sector, forming the first two classes of the legend (marked with green).

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