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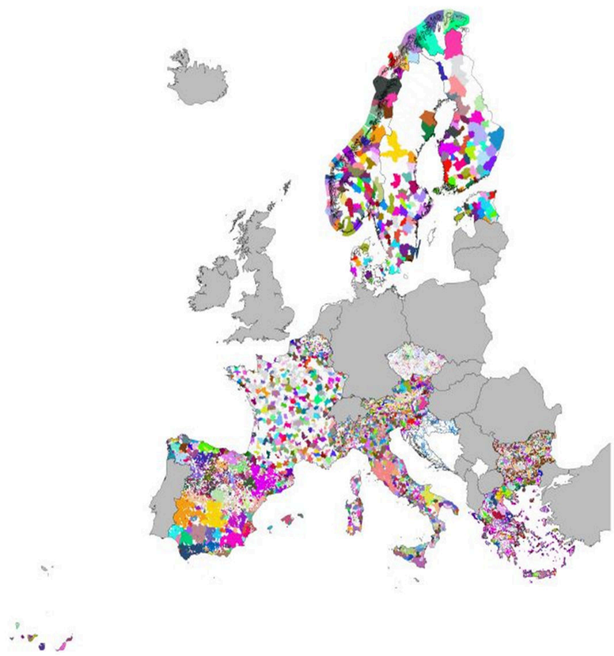
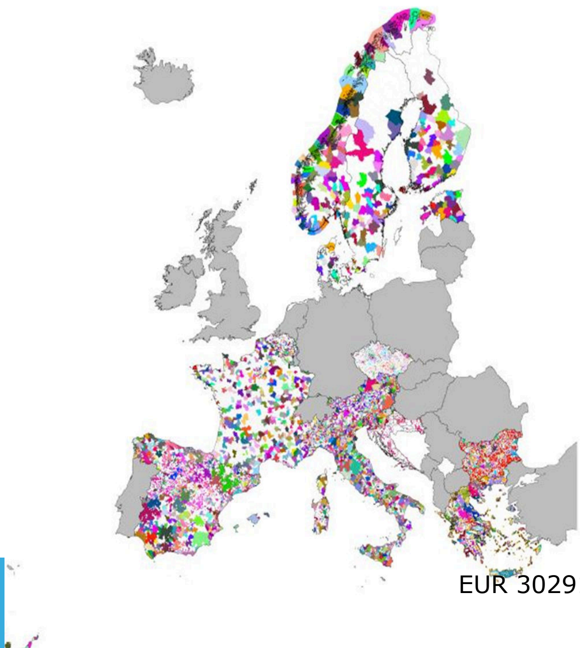
Mapping Mobility Functional Areas (MFA) by using Mobile Positioning Data to Inform COVID-19 Policies

A European Regional Analysis

Iacus, S. M., Santamaria, C., Sermi, F., Spyratos, S., Tarchi, D., Vespe M.

2020





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Contents

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[1]GSMA is the GSM Association of Mobile Network Operators.
[2]DG Connect: The Directorate-General for Communications Networks, Content and Technology is the European Commission department responsible to develop a digital single market to generate smart, sustainable and inclusive growth in Europe.
[3]Eurostat is the Statistical Office of the European Union.
[4]ECDC: European Centre for Disease Prevention and Control. An agency of the European Union.

Abstract

This work introduces the concept of data-driven Mobility Functional Areas (MFAs) as geographic zones with high degree of intra-mobility exchanges. Such information, calculated at European regional scale thanks to mobile data, can be useful to inform targeted re-escalation policy responses in cases of future COVID-19 outbreaks (avoiding large-area or even national lockdowns). In such events, the geographic distribution of MFAs would define territorial areas to which lockdown interventions could be limited, with the result of minimising socio-economic consequences of such policies. The analysis of the time evolution of MFAs can also be thought of as a measure of how human mobility changes not only in intensity but also in patterns, providing innovative insights into the impact of mobility containment measures. This work presents a first analysis for 15 European countries (14 EU Member States and Norway).

Highlights

— Human mobility naturally shapes MFAs in time and space;

— lockdown measures have shown an overall ”shrinking” effect on the MFAs across Europe;

— MFAs are persistent in time with intra-weekly recurrent patterns

— MFAs can be used to inform targeted mobility containment measures in case of new outbreaks, providing a balance between epidemiological and socio-economic impact.

1 Introduction

In April 2020, the European Commission (EC) asked European Mobile Network Operators (MNOs) to share fully anonymised and aggregated mobility data in order to support the fight against COVID-19 (European Commission, 2020a, European Commission, 2020b) with data driven evidence.
The value of mobile positioning *personal data* to describe human mobility has been explored (Csáji et al., 2013) and its potential in epidemiology studies demonstrated (Wesolowski et al., 2012, Jia et al., 2020, WU et al., 2020, Kraemer et al., 2020) in literature.
The new initiative between the Commission and the European MNOs relies on the effectiveness of using *fully anonymised and aggregated mobile positioning data* in compliance with 'Guidelines on the use of location data and contact tracing tools in the context of the COVID-19 outbreak' by the European Data Protection Board (EDPB, 04/2020).
This work introduces an innovative way to map *natural* human mobility through fully anonymised and aggregated mobile data. Maps showing *natural* mobility are based on the usual patterns of citizens' mobility and can be compared with maps of administrative areas.

Indeed, the mapping of human mobility patterns has a long tradition in settlement geography, urban planning and policy making. The idea behind mobility patterns is the identification of a network of aggregated inbound and outbound movements across spatial structures for a given time scale (for example, daily, intra-weekly, seasonally, etc) according to the scopes of their use. These patterns have been called in several ways; the followings list includes just a few variants of the same concept:

— *'commuting regions'*: the identification of relatively closed regions of daily moves of residing population based on commuting data from censuses (Casado-Díaz, 2000, Van der Laan, 1998).

— *'functional regions'*: a tool used to target areas of specific national and European policies (OECD, 2002). There are several natural areas of application of functional regions including employment and transportation policies, environmentally sustainable spatial forms, reforms of administrative regions, strategic level of urban and regional planning and a wide range of geographical analyses (migration, regionalisation, settlement system hierarchisation) (Andersen, 2002, Ball, 1980, Casado-Díaz, 2000, Van der Laan, 1998).

— *'functional urban areas'*: cities with their commuting zone (Eurostat, 2106, Dijkstra et al., 2019). They are generally identified by a densely inhabited city, together with a less densely populated commuting zone whose labour market is highly integrated with that of the city.

— *'overlapping functional regions'* (Killer and Axhausen, 2010).

The most common data sources for the above-mentioned studies are by far the population censuses and *ad hoc* pilot surveys.
This study proposes an alternative method to define highly-interconnected spatial regions (i.e., forming dense sub-networks); only fully-anonymised and aggregated mobility data are used to this end. The data-driven regions identified through the proposed method are referred to as *'Mobility Functional Areas'* (MFA).
Although mobile data has been used in the past in a pilot-study on mobility in Estonia (Novak et al., 2013), the present study adopts a new technique to define mobility functional areas (MFA), which is based only on aggregated data, and extends the research to 15 European countries (14 member states: Austria, Belgium, Bulgaria, Czechia, Denmark, Estonia, Spain, Finland, France, Greece, Croatia, Italy, Sweden, Slovenia, plus Norway).

In a policy making perspective, especially related to the COVID-19 pandemic, the insights resulting from this analysis may help governments and authorities at various levels:

a) to limit all non-essential movements across specific geographic areas, especially in the initial phase of a future outbreak of the virus, to limit spread while also limiting the economic impact of such measures outside the MFA;

b) to apply different physical distancing policies in different areas, according to their specific epidemiological situation.

In the absence of any other information, most of the governments are forced to use administrative areas, such as regions, provinces and municipalities to impose physical distancing measures and mobility restrictions. Nevertheless, administrative boundaries are static and do not reflect actual mobility. On the other hand, both the potential spreading of the virus and the territorial economy strongly depend on local mobility (Iacus et al., 2020). Although these aspects cannot be taken into account in this work, the hypothesis is that the implementation of different physical distancing strategies (such as school closures or other human mobility limitations) based on MFA instead of administrative borders might lead to a better balance between the expected positive effect on public health and the negative socio-economic fallout for the country. Despite the evident potential benefits, it must be noted that while administrative areas (hard boundaries) are well recognised by citizens and make it easy for the administrations to implement physical distancing and mobility restrictions, further coordination efforts would be needed to apply such limitations based on MFAs.

This work is organised as follows. Section 2 describes the data sources used in the analysis. Section 3 explains in details the concept of MFAs and, along with Section 4, describe the methodological approach to identify MFA pre- and post- lockdown measures; the evolution in time of the MFAs is presented through a case study for Spain. Section 5 is a quick review of the results for each of the remaining 14 countries considered and finally Section 6 shows an overall view of the MFAs across Europe (15 countries analysed).

2 Mobile Positioning Data

The agreement between the European Commission and the Mobile Network Operators (MNOs) defines the basic characteristics of fully anonymised and aggregate data to be shared with the Commission's Joint Research Centre (JRC[5]). The JRC processes the heterogeneous sets of data from the MNOs and creates a set of mobility indicators and maps at a level suitable to study mobility comparatively across countries; this level is referred to as 'common denominator'.

This section briefly describes the original mobile positioning data from the MNOs; the following section introduces the mobility indicator derived by JRC and used in this research.

Data from MNOs are provided to JRC in the form of Origin-Destination-Matrices (ODMs) (Mamei, 2019, Fekih, 2020). Each cell $[i - j]$ of the ODM shows the overall number of *'movements'* (also referred to as 'trips' or 'visits') that have been recorded from the origin geographical reference area i to the destination geographical reference area j over the reference period. In general, an ODM is structured as a table showing:

— reference period (date and, eventually, time);

— area of origin;

— area of destination;

— count of movements.

Despite the fact that the ODMs provided by different MNOs have similar structure, they are often very heterogeneous. Their differences can be due to the methodology applied to count the movements, to the spatial granularity or to the time coverage. Nevertheless, each ODM is consistent over time and relative changes are possible to be estimated. This allows defining common indicators (such as 'mobility indicators' (Santamaria et al., 2020), 'connectivity matrices' (Iacus et al., 2020) and 'mobility functional areas' that can be used, with all their caveats, by JRC in the framework of this joint initiative.

Although the ODM contains only anonymised and aggregate data, in compliance with the EDPB guidelines (EDPB, 04/2020), upon the reception of each ODM, the JRC carries out a *'Reasonability Test'*. Both the reasonability test and the processing of the ODM to derive mobility indicators take place within the JRC's *Secure Platform for Epidemiological Analysis and Research* (SPEAR).

[5]The Joint Research Centre is the European Commission's science and knowledge service. The JRC employs scientists to carry out research in order to provide independent scientific advice and support to EU policy.

3 Mobility Functional Areas

The construction of the MFAs starts from the ODM at the highest spatial granularity available. Table 1 shows the characteristics of the different sets of data used for to calculate the MFAs. Although the applied methodology is very similar for all the 15 considered countries, without any loss of generality, only the case of Spain is used to provide practical examples. because it is covered by two MNOs data sets. For Norway ODM data are available from two different operators, and slightly different among them, although the analysis shows that the identified MFAs are almost equivalent (see Section 5.12).

Country	(ISO2)	highest granularity cell	used	NUTS 3	used	date range
Austria	(AT)	grid 16-18 km^2	5129	districts	35	01/02/2020 - 29/06/2020
Belgium	(BE)	postal code areas	1131	regions	44	11/02/2020 - 29/06/2020
Bulgaria	(BG)	grid 16-18 km^2	4615	provinces	28	01/02/2020 - 27/06/2020
Czechia	(CZ)	regular grid	4014	regions	14	01/01/2020 - 28/06/2020
Denmark	(DK)	municipalities	98	provinces	12	02/02/2020 - 07/06/2020
Estonia	(EE)	municipalities	79	counties	5	14/02/2020 - 07/06/2020
Spain	(ES)	municipalities	6893	provinces	59	01/02/2020 - 29/06/2020
Finland	(FI)	municipalities	310	provinces	19	02/02/2020 - 07/06/2020
France	(FR)	municipalities	1426	departments	96	01/01/2020 - 23/06/2020
Greece	(GR)	grid 25 km^2	6240	prefectures	53	15/05/2020 - 30/06/2020
Croatia	(HR)	grid 17 km^2	1384	counties	22	01/02/2020 - 19/06/2020
Italy	(IT)	census areas	8051	provinces	110	01/01/2020 - 29/06/2020
Norway	(NO)	municipalities	422	counties	18	02/02/2020 - 07/06/2020
Norway	(NO)	municipalities	356	counties	18	20/01/2020 - 21/06/2020
Sweden	(SE)	municipalities	290	counties	21	02/02/2020 - 07/06/2020
Slovenia	(SI)	grid 16-18 km^2	1248	provinces	12	01/02/2020 - 29/06/2020

Table 1: Data used in the analysis of the MFAs. Some areas (like overseas territories) are excluded.

Let $ODM_{d,i,j}$ an element of the ODM matrix for date d representing the number of movements from cell i to cell j, $i,j = 1,\ldots,n$

$$ODM^*_{d,i,j} = \frac{ODM_{d,i,j}}{\sum_{j=1}^{n} ODM_{d,i,j}}, \quad i,j, = 1,\ldots,n.$$

where n is the total number of rows and columns of the ODM (which is a $n \times n$ matrix) and let $ODM^*_{d,i,j}$ the corresponding element of the ODM normalised by row.
Now we transform the ODM^*_d matrix into a 0/1 proximity matrix P_d as follows

$$P_{d,i,j} = \begin{cases} 1, & ODM^*_{d,i,j} > \text{threshold}, \\ 0, & \text{otherwise}, \end{cases}$$

where the threshold has been set[6] to 15% according to several studies (Novak et al., 2013, Eurostat, 2106, Dijkstra et al., 2019). As the ODM matrix is not symmetric, so is the proximity matrix, which is transformed into an adjacency matrix A through the following expression:

$$A_d = \frac{1}{2} \cdot \left(P_d + P_d^T\right)$$

so that each element of A_d can take only three values:

- $A_{d,i,j} = 0$ if there are no movements from i to j and viceversa (i.e. the two cells are not connected);
- $A_{d,i,j} = 0.5$ if there are movements only in one direction, either i to j or j to i.
- $A_{d,i,j} = 1$ if there are movements in both directions, from i to j and from j to i;

From the adjacency matrix we construct a directed[7] graph where the vertex represent the cells $i = 1,\ldots,n$ and the edges are weighted according to the matrix A. The MFAs are calculated using a community detection technique called *walktrap* algorithm (Pons and Latapy, 2006), which finds communities through a series of short random walks[8]. The idea is

[6]We tested different thresholds above and below 15% and also a uniform distribution threshold, but the 15% seems to be the most effective in isolating stable MFAs for all the countries analysed.

[7]An undirected graph could be used as well, but we use a directed graph in view of the community detection algorithm used later on.

[8]This approach is different from the *intramax* algorithm used in (Killer and Axhausen, 2010, Novak et al., 2013)

that these random walks tend to stay within the same community. The goal of the walk-trap algorithm is indeed to identify the partition of a graph that maximises its modularity[9], which is exactly the same concept of clusters of fully interconnected cells where most of the movements are internal.
All the communities with only one member, i.e. those without inbound and outbound movements over 15%, are collapsed into a single big fictitious area representing the territory that either cannot be identified as a pure MFA, or it is just a collection of atomic (mobility-wise) cells. Figure 1 shows a representation of the MFAs in Spain for two weekdays: before (left) and after (right) the lockdown, which was in force since 14 March 2020.

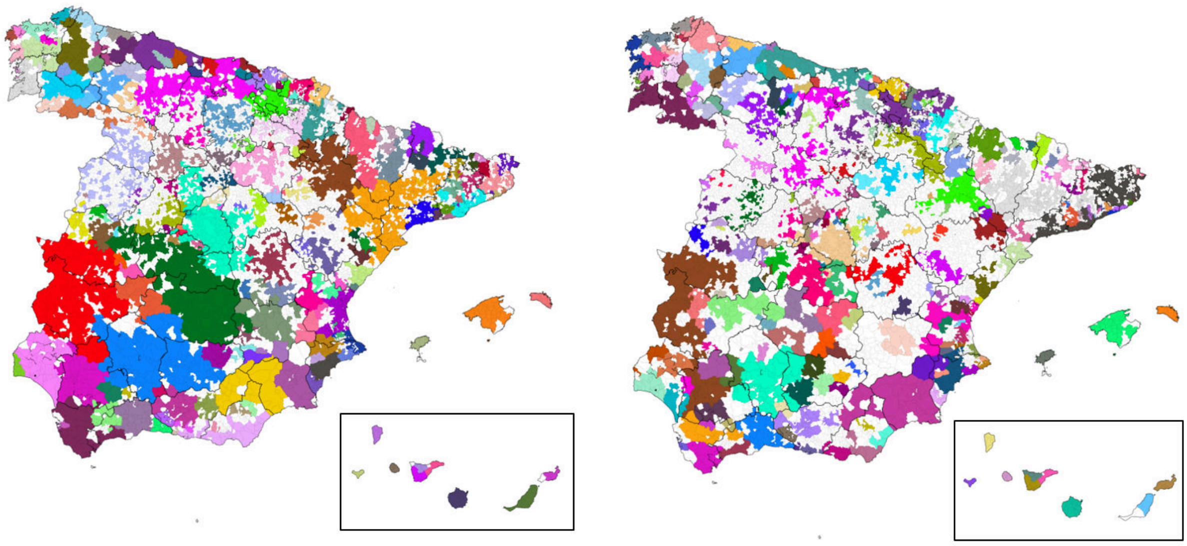


Figure 1: Spain - MFAs before (Monday 3 February 2020, left) and after (Monday 16 March 2020, right) the lockdown of 14 March 2020. For visualisation reasons, Canaries islands are not in scale and have been moved close to the mainland. Black lines represents the borders of provinces (administrative areas). Whereas before the lockdown the MFAs extend across provinces, after the lockdown their area generally reduces and they mostly lay within provinces' borders. Areas where connectivity is below 15% (no apparent stable direction is observed in the mobility flows) are in white. The remaining colours are randomly assigned.

It is well known and expected that mobility changes between weekdays, weekends and holidays, but there might be also an internal variability within the working week as well as across weeks (e.g., not all Mondays are *exactly* the same in terms of mobility); this is why we need to measure how much MFAs are stable and consistent in time.

In order to evaluate the persistence of MFAs' structure in time, we make use of the following similarity index (Gravilov et al., 2000) between two sets of groups of labelled $G = \{G_1, \ldots, G_K\}$ and $G' = \{G'_1, \ldots, G'_{K'}\}$, where K and K' are not necessarily equal. The similarity index is defined as

$$\text{Sim}(G, G') = \frac{1}{K} \sum_{i=1}^{k} \left\{ \max_{j=1,\ldots,K'} \text{sim}(G_i, G'_j) \right\} \tag{1}$$

where

$$\text{sim}(G_i, G'_j) = 2 \frac{|G_i \cap G'_j|}{|G_i| + |G'_j|}, \quad i = 1, \ldots, K, \quad j = 1, \ldots, K'.$$

with $|B|$ the number of elements in set B.
The similarity index is such that $\text{Sim}(G, G') \in [0, 1]$ but it is not symmetric, therefore in order to have a symmetric measure we consider

$$\overline{\text{Sim}}(G, G') = \frac{1}{2} \left(\text{Sim}(G, G') + \text{Sim}(G', G') \right).$$

[9]The modularity of a graph is an index designed to measure the strength of division of a network into modules (also called groups, clusters or communities).

Figure 2 is a heatmap representation of the matrix of similarity index among all MFAs for the period 1 February 2020 - 10 June 2020. Darkest-bluish zones are most different, whereas lighter-reddish are the most similar. It is interesting to observe the difference between pre- and post- lockdown (14 March 2020), then a slow recovery to normality. It is also worth noticing that holidays and weekends have clearly different mobility patterns than weekdays and that these MFAs are differ from the administrative borders (Spanish provinces), especially during weekdays (see Figure 3).

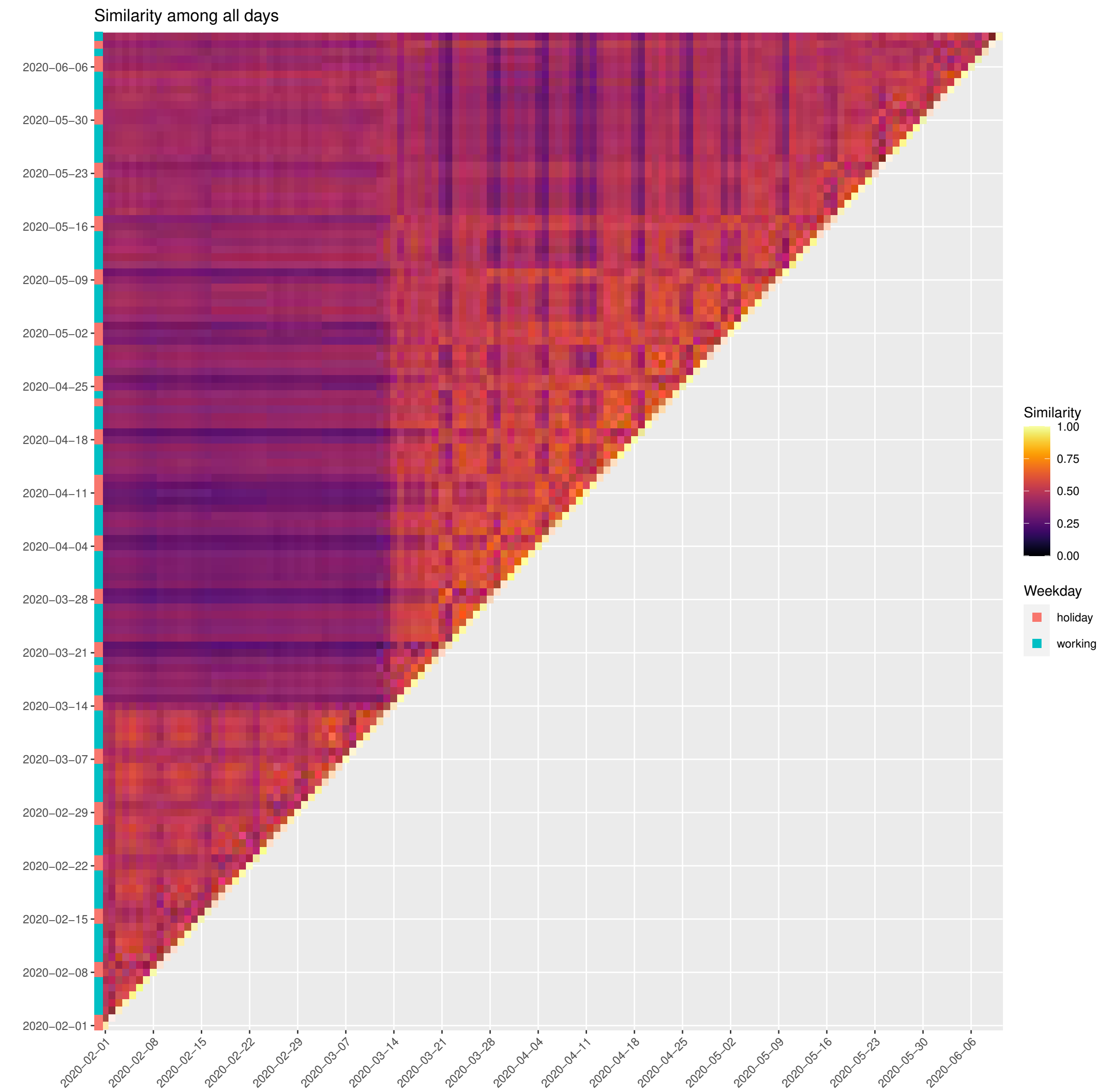


Figure 2: Similarity index matrix of all MFAs in Spain. Period: 1 February 2020 - 10 June 2020.

4 Detecting the persistent MFAs

As seen in the previous section, the MFAs have daily patterns, they change between before and after the lockdown is in force and tend to go back to their original shapes after the ease of containment measures. Moreover, MFAs shows time-variability also for the same weekday; thus, in order to fully exploit their potential, a stable version of the MFAs needs to be identified. Since the number of MFAs changes day by day and the same cell may move from an MFA to another (changing the MFA label associated to it), we apply a CO-association method. The CO-association method (CO) avoids the label correspondence problem. It does so by mapping the ensemble members onto a new representation where

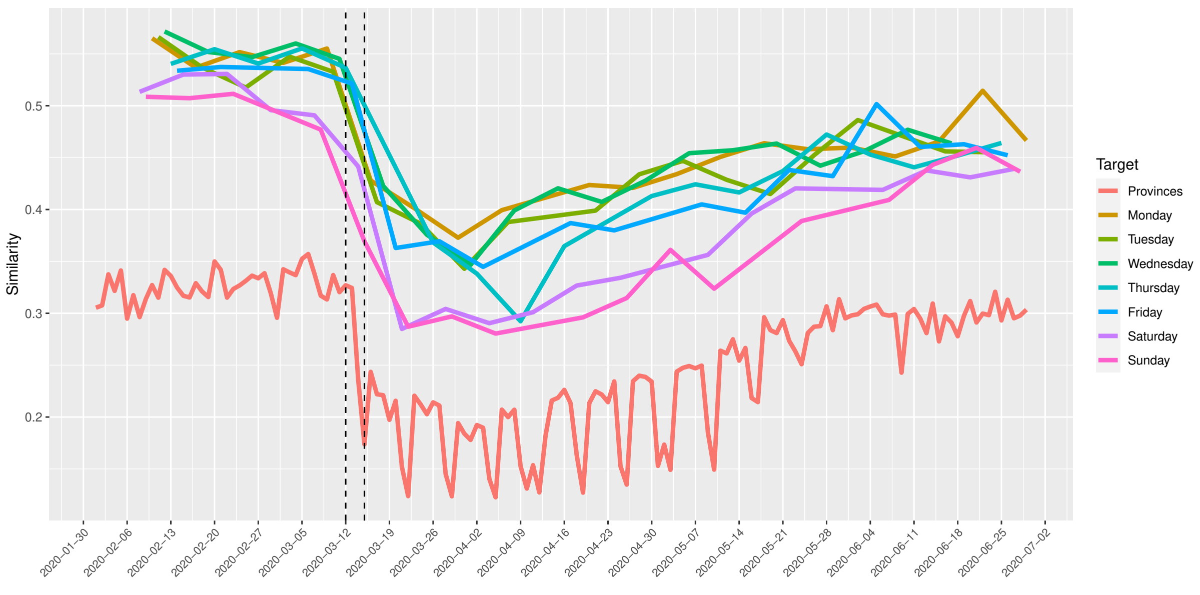


Figure 3: Intra week similarity of daily MFAs and with respect to the Spanish provinces (red).

the similarity matrix is calculated between a pair of objects in terms of how many times a particular pair is clustered together in all ensemble members (Fred and Jain, 2005). In other words, CO calculates the percentage of agreement between ensemble members in which a given pair of objects is placed in the same mobility functional area.
As the first lockdown in Spain was enforced on 14 March 2020, we focus on the weekdays[10] from 1 February 2020 to 14 March 2020.
Let d be the data of one of these D weekdays and MFA$_d$ the set of mobility functional areas obtained on day d. We then evaluate the *co-association matrix*

$$CO(x_i, x_j) = \frac{1}{D}\sum_{d=1}^{D} \delta\left(MFA_d(x_i), MFA_d(x_j)\right)$$

where X_i and x_j are the cells (e.g., municipalities) and MFA_d is the set of MFAs for day $d = 1, \dots, D$ and $\delta(\cdot, \cdot)$ is defined as follows:

$$\delta(u, v) = \begin{cases} 1, & \text{if } u \text{ and } v \text{ belong to the same mobility functional area,} \\ 0, & \text{otherwise.} \end{cases}$$

Then, as our scope is to obtain a persistent version of the MFAs, we further threshold the CO matrix so that all entries below 50% are set to 0 and those higher or equal 50% are set to 1 (it means that only cells falling in the same MFA at least 50% of the times are associated with that MFA[11]) leading to a new matrix $\overline{CO}$.
Then again a directed graph is built with this matrix using the entries of the $\overline{CO}$ matrix to weight the edges and applying the walktrap algorithm to obtain the final persistent MFA. The same procedure is replicated for the post lockdown dates, ending up with a different set of persistent MFAs that we denote by Post-MFA. With these two persistent sets of MFAs at hand, we further test if they are meaningful to the analysis. It turns out that these persistent MFA are in fact reasonably well defined.
We then apply the symmetric similarity index $\overline{\text{Sim}}(\cdot, \cdot)$ for all the daily MFAs against the persistent MFAs, the Post-MFA and the provinces (NUTS3). Figure 4.

[10]For the other countries we take into account the actual time span of the daily data in respect to the given date of the national lockdown.
[11]Though, for some countries, like France and Italy, this threshold has to be increased. See Sections 5.8 and 5.11.

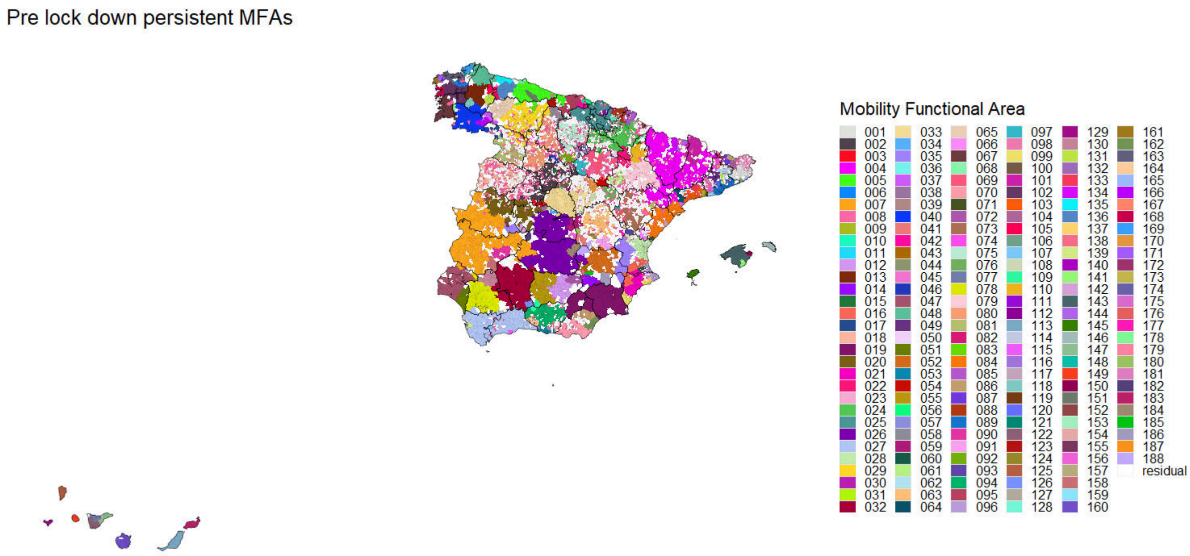


Figure 4: Shapes of the pre lockdown persistent MFAs for Spain.

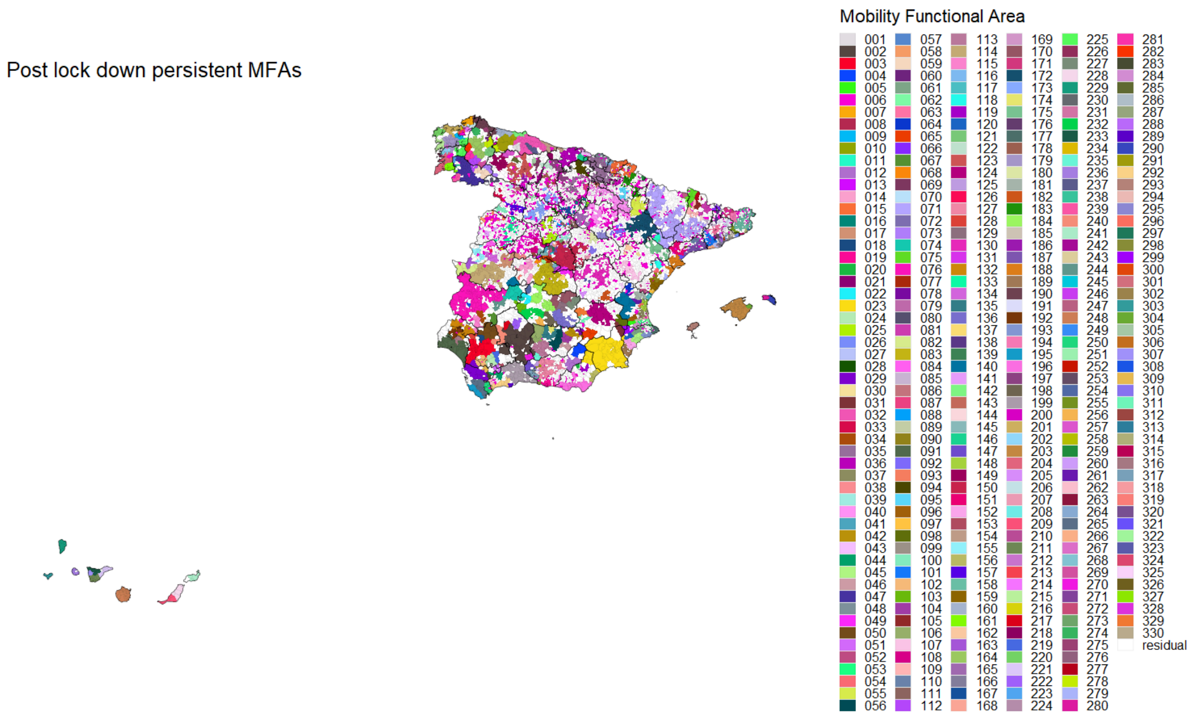


Figure 5: Shapes of the post lockdown persistent MFAs for Spain.

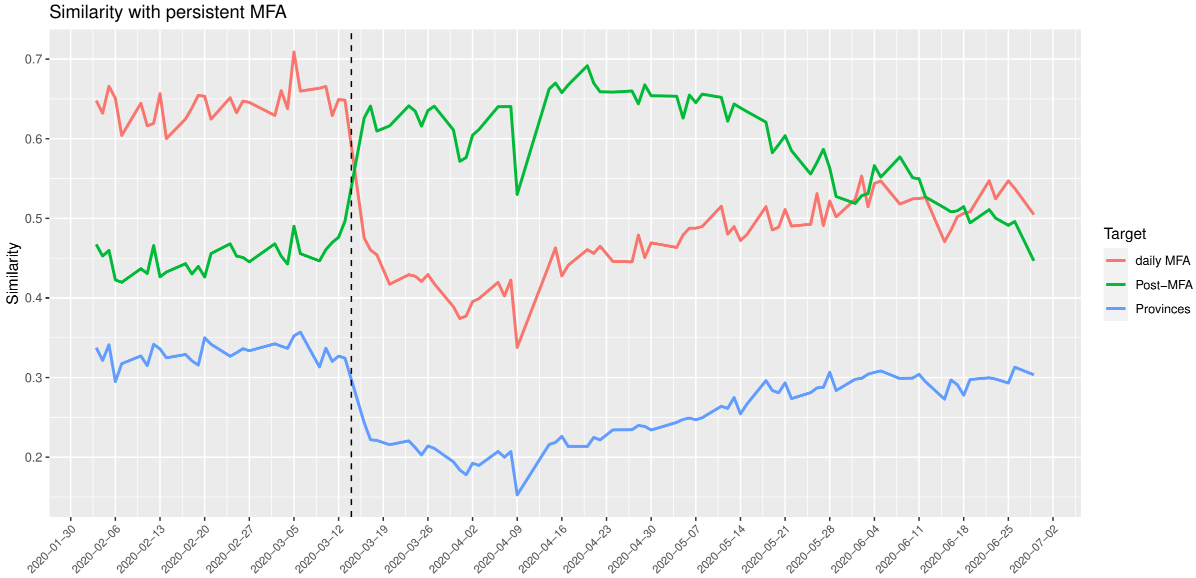


Figure 6: Similarity by day of the week of the MFAs with respect to persistent and post lockdown MFAs and Spanish provinces. Daily MFAs are very similar to the persistent MFAs before lockdown, whereas they are more similar to post-lockdown MFA after. A return to normality is slowly appearing. Once again, provinces are in between before lockdown.

5 MFA by country

We now review, without commenting it, the additional 14 countries with a special split in case of Norway where data from two different MNOs are available. Odd peaks and anomalies are due to different kinds of error in the original data; since these outliers are not considered in the definition of the persistent MFA, they do not affect the analysis, but only the graphical patterns (see, e.g., Figure 21). Although the graphics are self-explanatory, we can suggest the reader to focus on some common and diverging evidence in what follows. Common, and vastly expected, evidence can be summarised as follows:

— intra-weekly patterns, i.e., workdays are different from weekends days and holidays;

— persistence of the MFAs across countries is clear;

— pre- and post- lockdown MFAs are different, meaning that mobility has been effectively reduced when lockdown measures have been implemented;

— administrative areas are, on average, much different from MFAs

— persistent MFAs spreads across more than one administrative though not covering an entire administrative area;

— lockdown MFAs are smaller that persistent MFA, usually confined with an administrative area and their number is larger than the persistent MFAs.

On the contrary, it is worth noticing that in some countries the dissimilarity matrixes are darker than for other countries, meaning that the mobility have been more affected by lockdown measures than other countries (see also Figure 36). The shading of the intensity is also a sign of the speed of reversion of the human mobility to pre-crisis level. This is also expected, as there are different types and intensities of lockdown measures.

Further, for those countries in which nation-wide measures have not been enforced but only self-restrictions to mobility, the shapes of the pre- and post-lockdown MFAs are only slightly different.

5.1 Austria

Figure 7: AUSTRIA: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Austrian districts (middle). Full similarity matrix among daily MFAs (bottom).

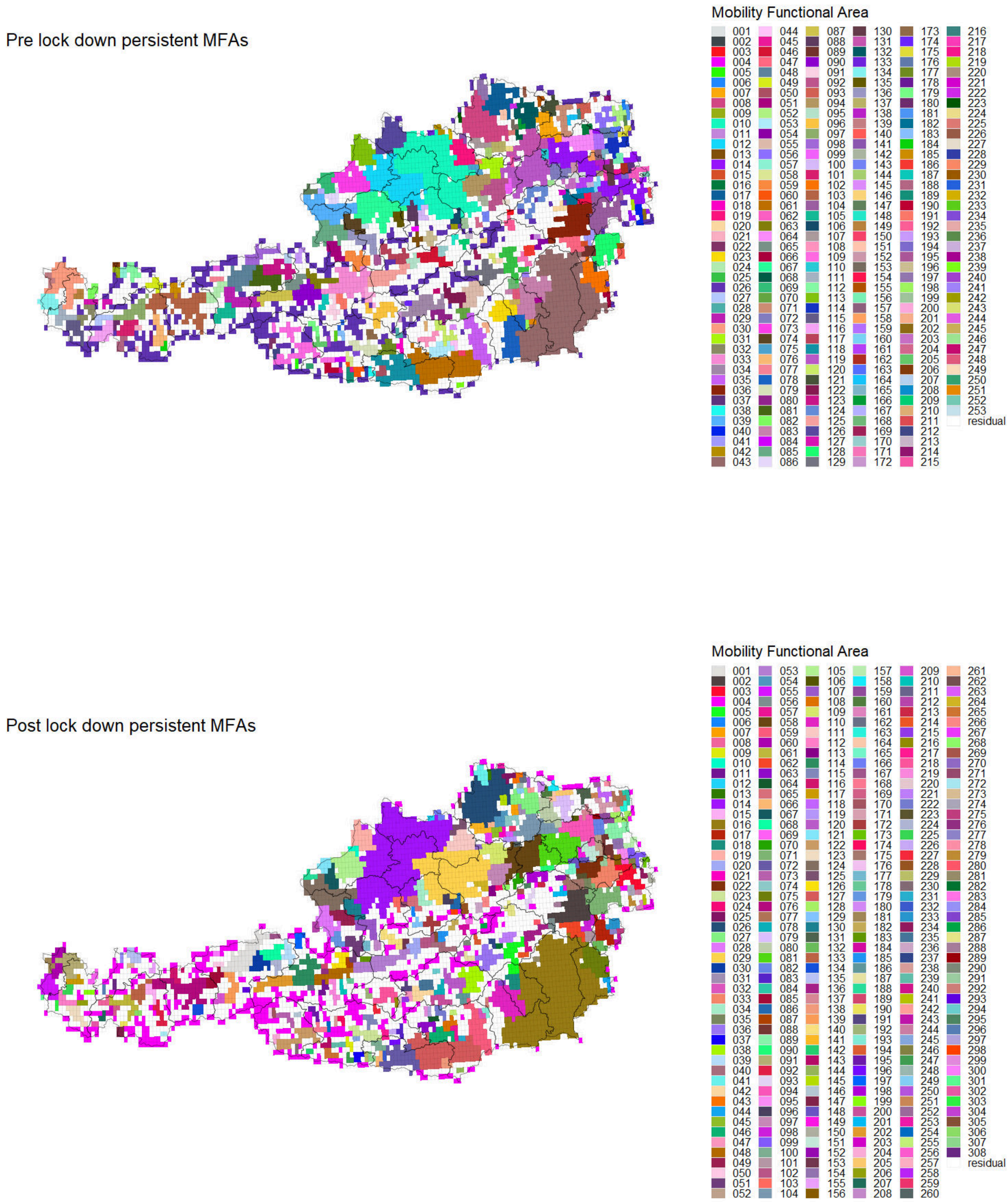


Figure 8: AUSTRIA: Pre (up) and post (bottom) lockdown persistent MFAs.

5.2 Belgium

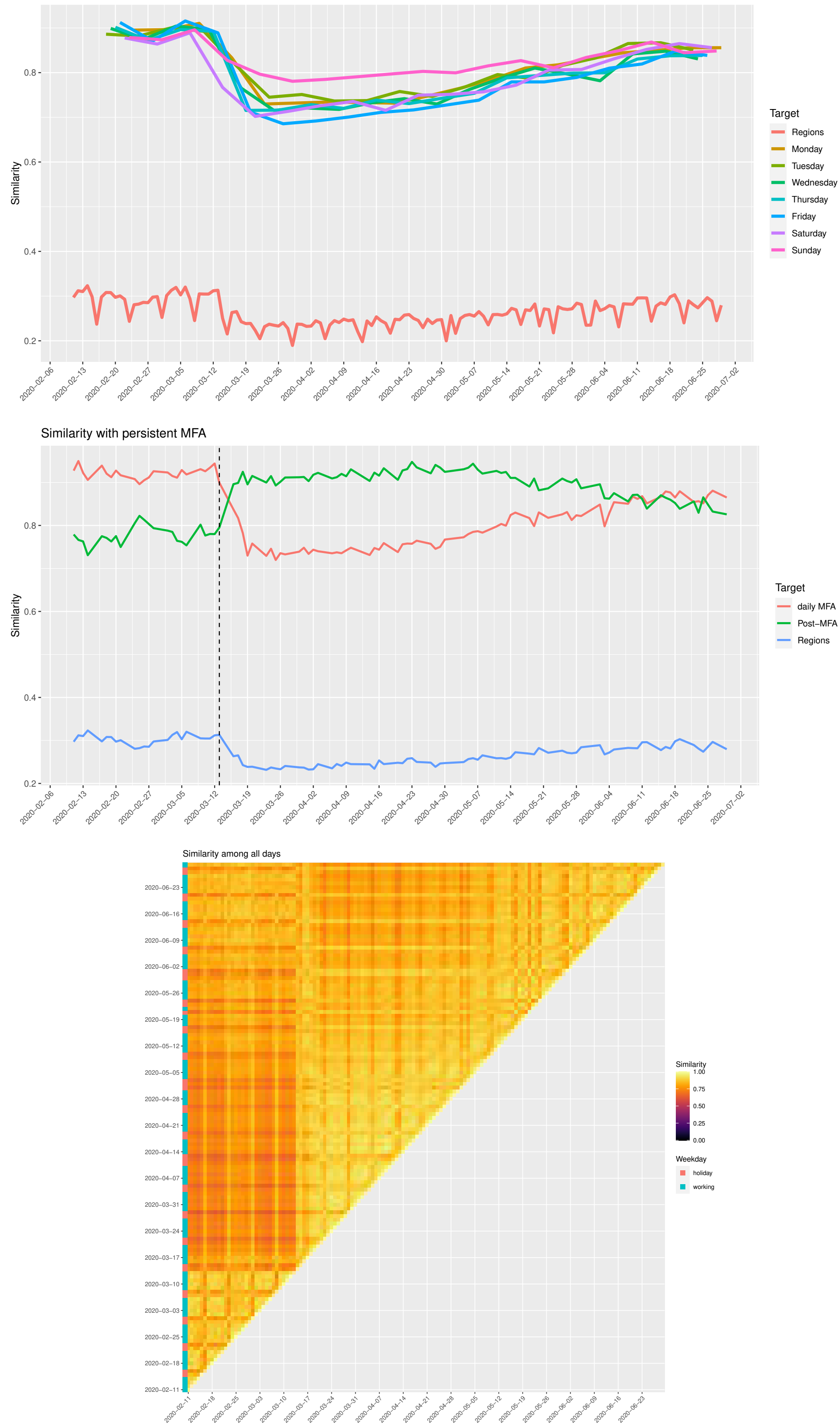


Figure 9: BELGIUM: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Belgian regions (middle). Full similarity matrix among daily MFAs (bottom).

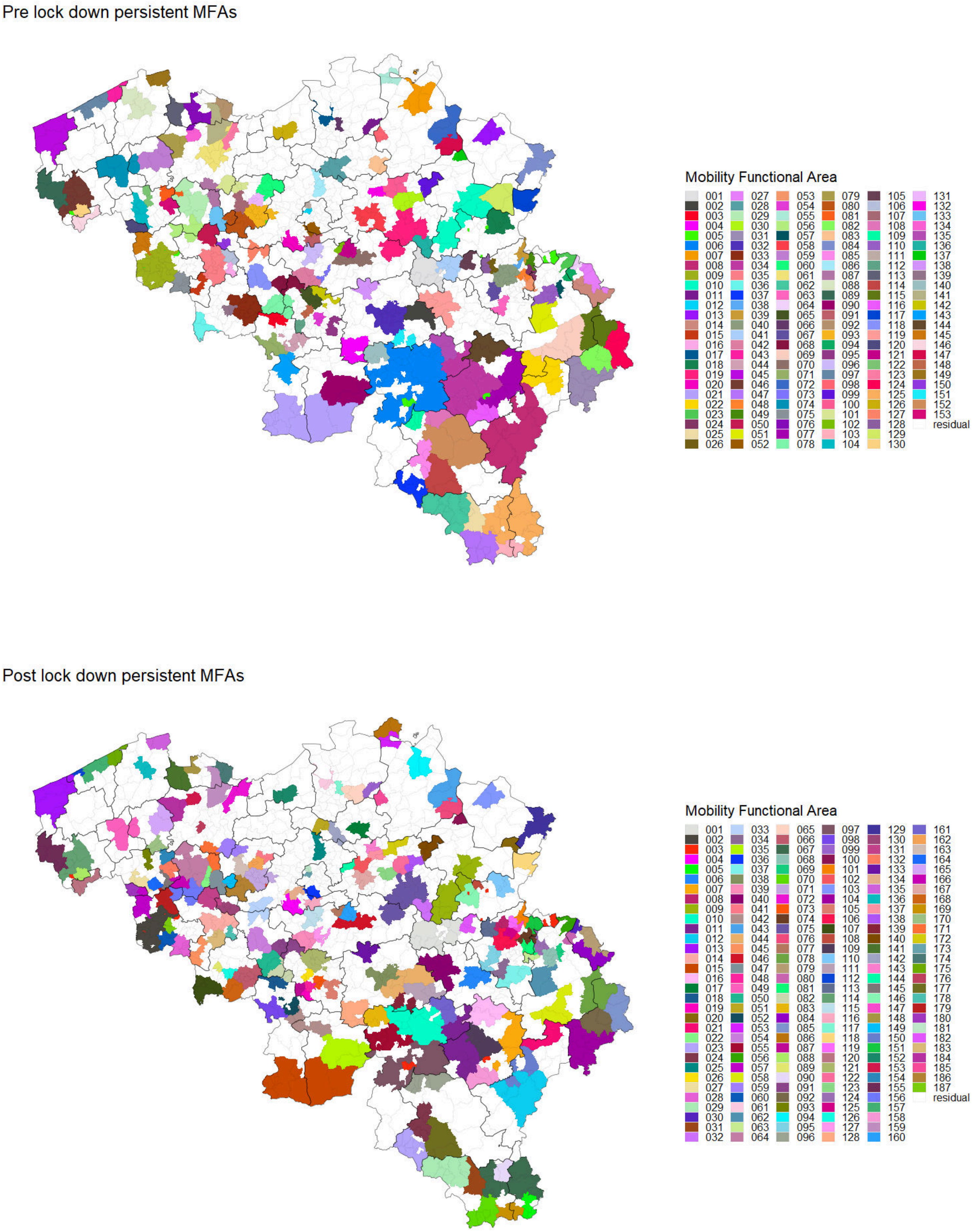


Figure 10: BELGIUM: Pre (up) and post (bottom) lockdown persistent MFAs.

5.3 Bulgaria

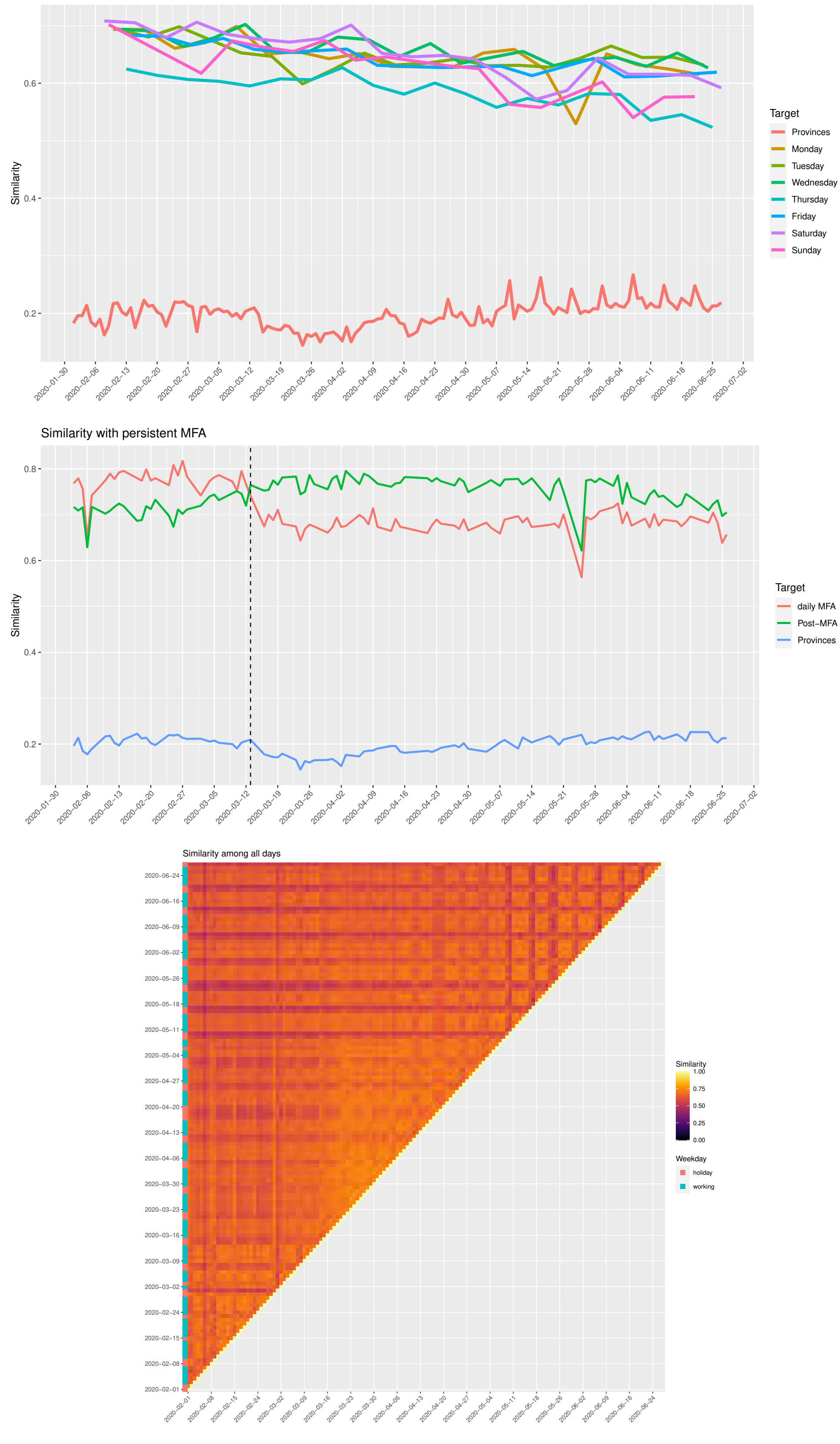
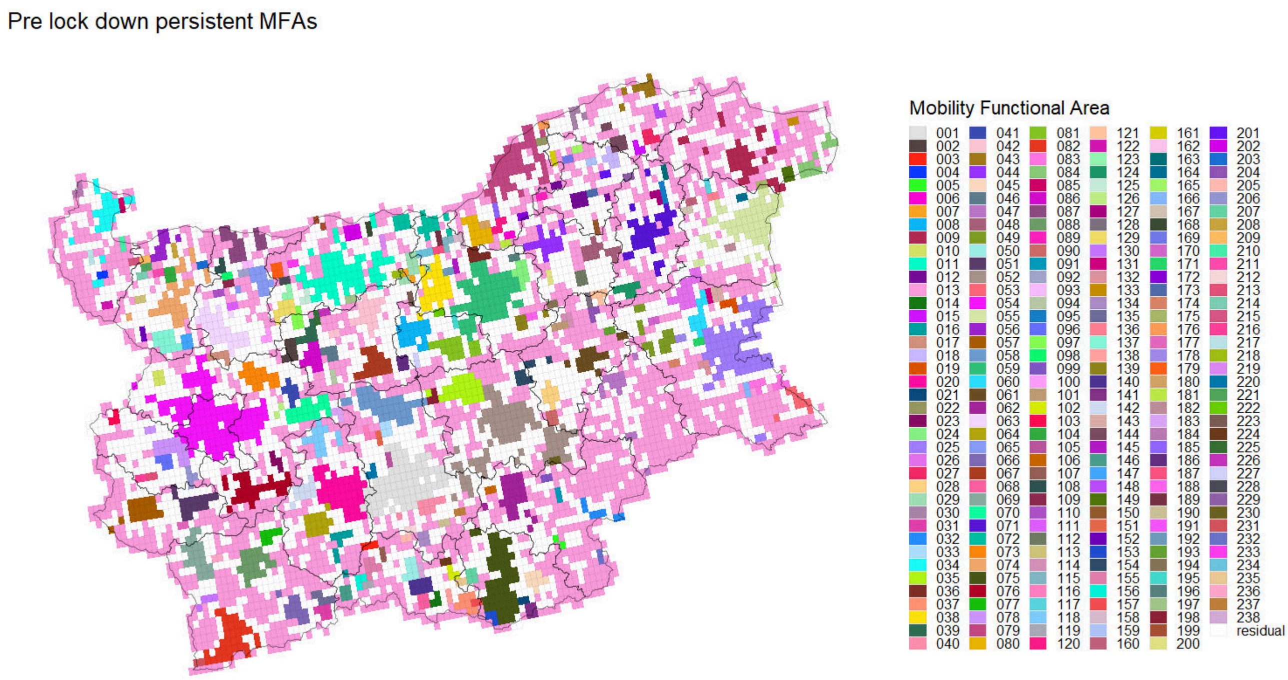


Figure 11: BULGARIA: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Bulgarian provinces (middle). Full similarity matrix among daily MFAs (bottom).



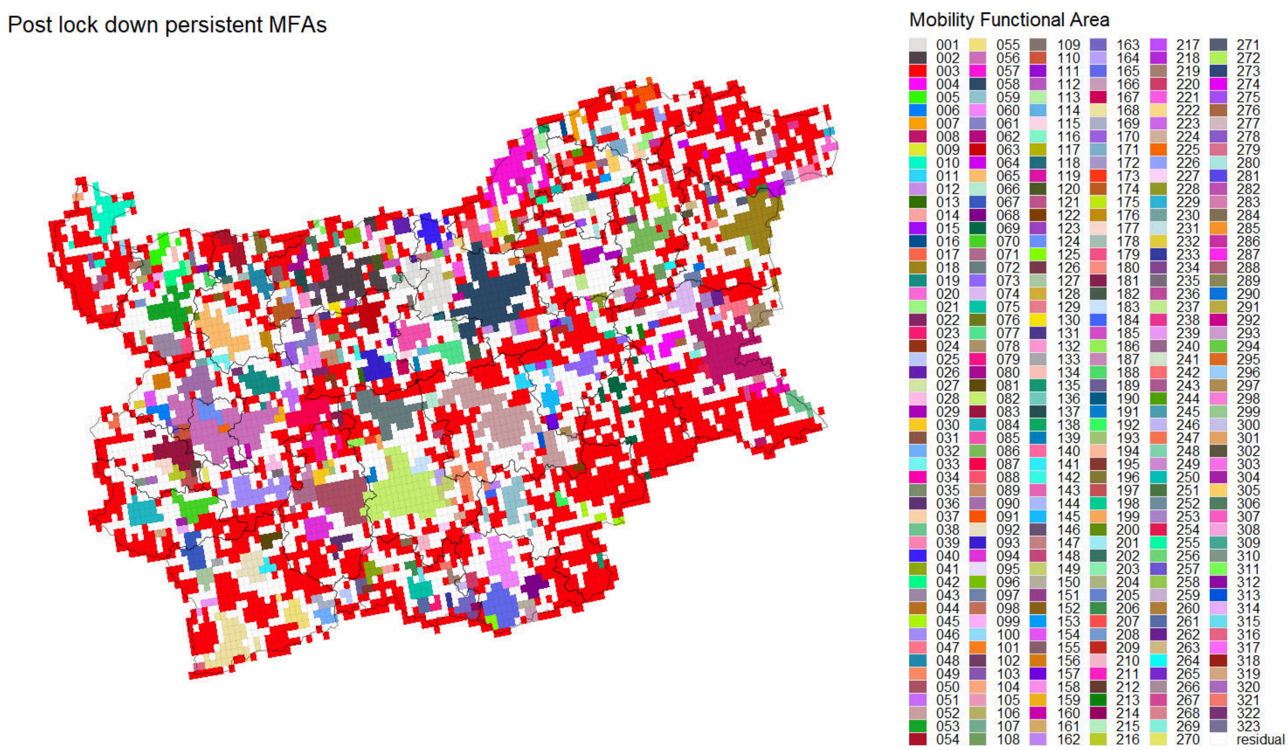
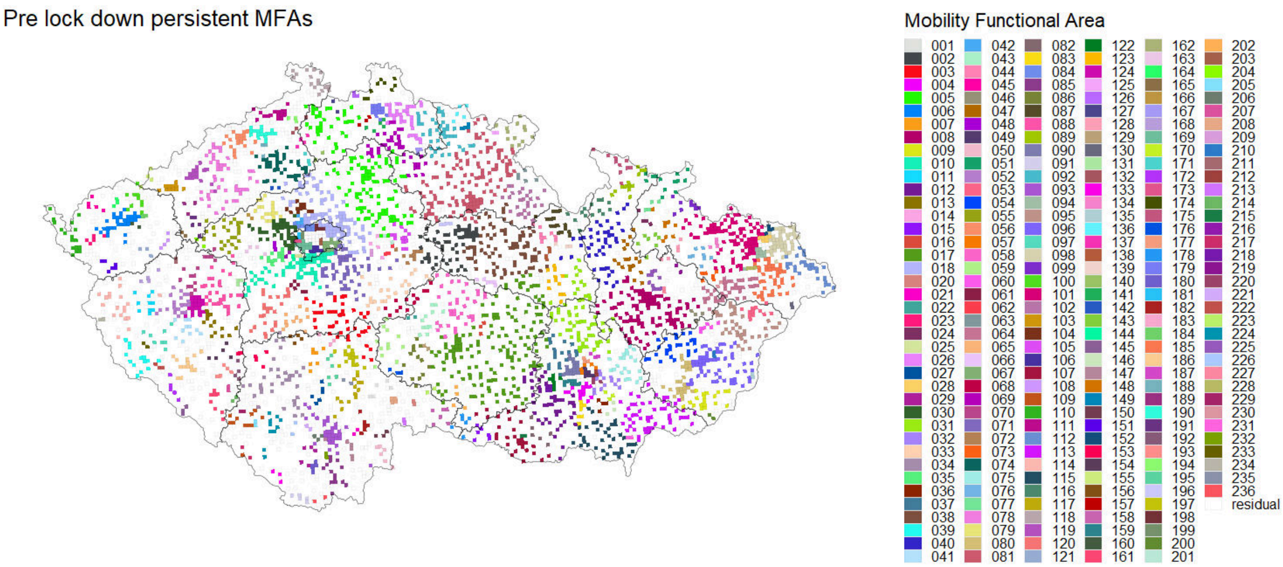


Figure 12: BULGARIA: Pre (up) and post (bottom) lockdown persistent MFAs.

5.4 Czechia

Figure 13: CZECHIA: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Czech regions (middle). Full similarity matrix among daily MFAs (bottom).



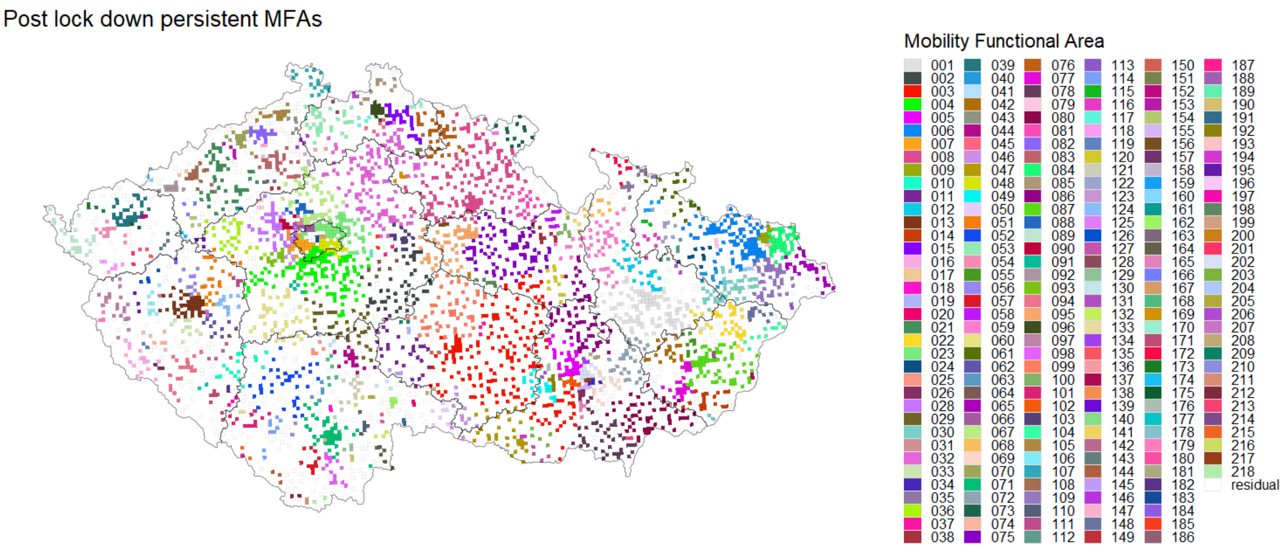


Figure 14: CZECHIA: Pre (up) and post (bottom) lockdown persistent MFAs.

5.5 Denmark

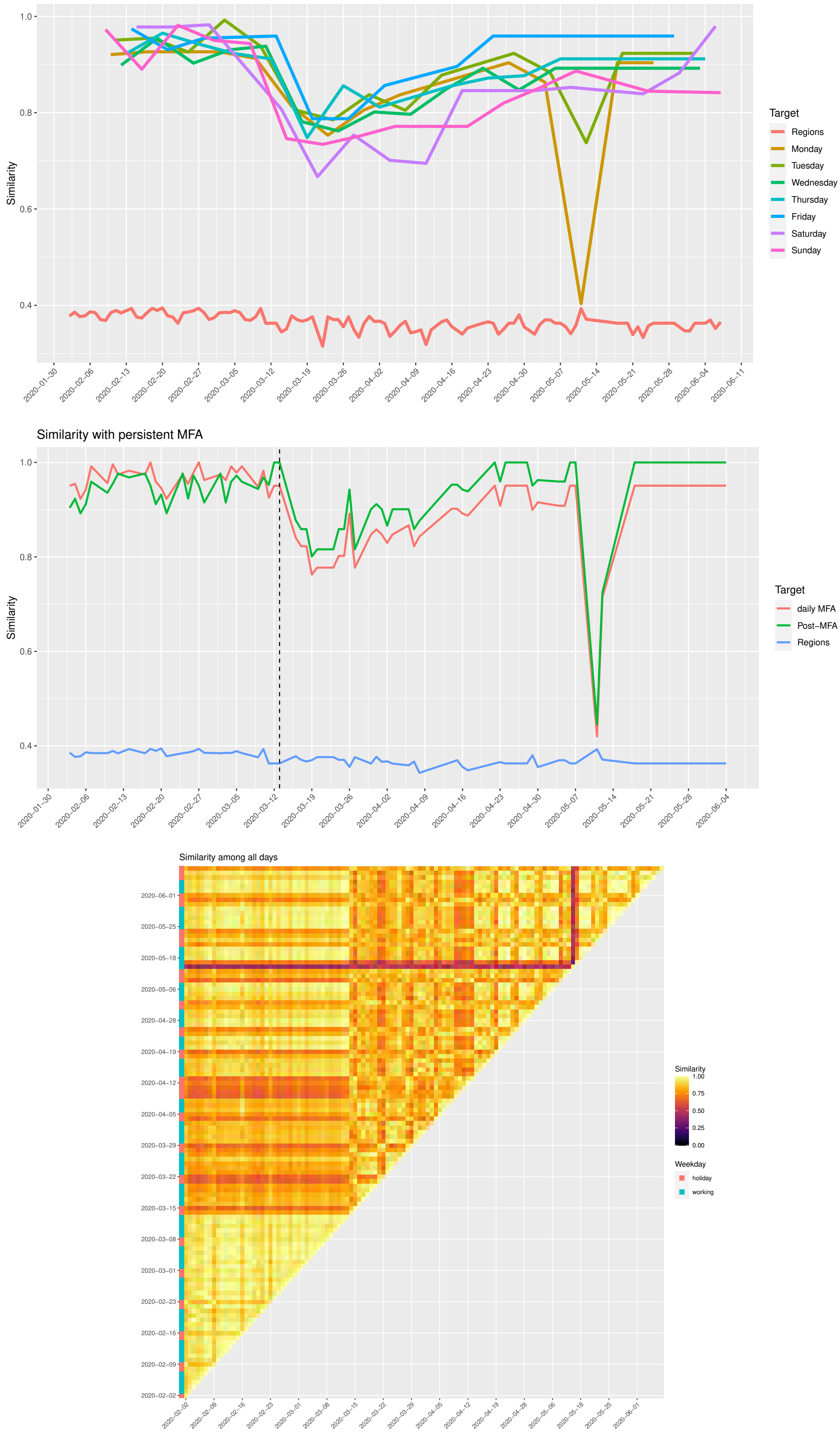
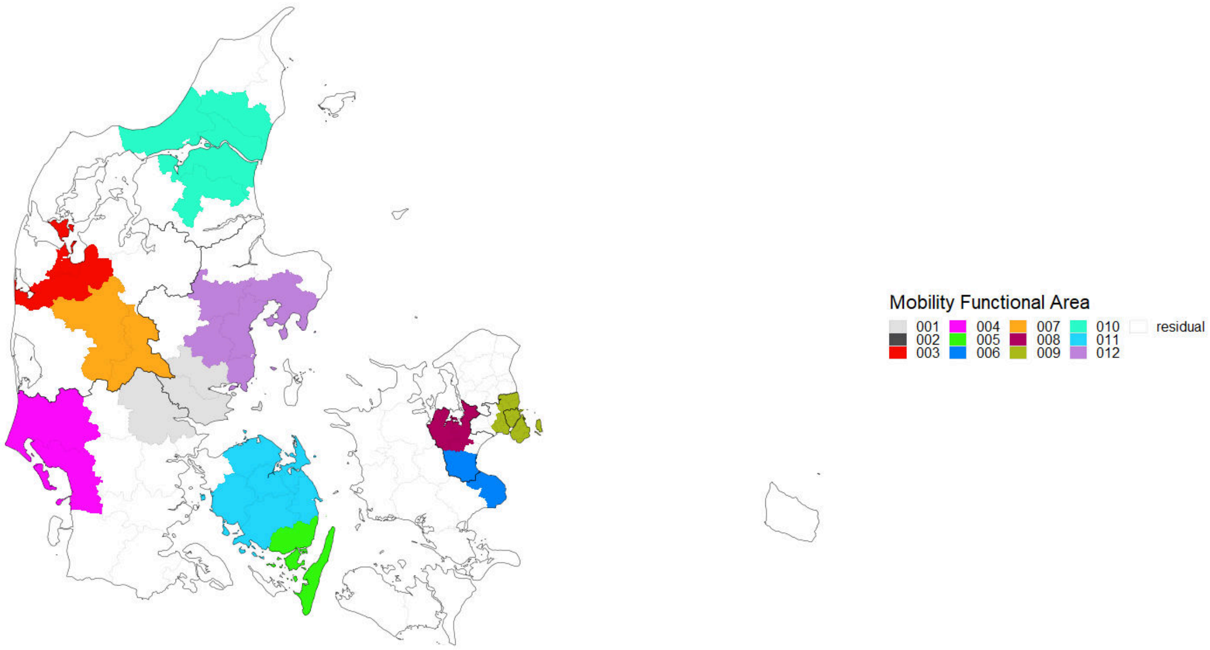


Figure 15: DENMARK: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Danish regions (middle). Full similarity matrix among daily MFAs (bottom).

Pre lock down persistent MFAs



Post lock down persistent MFAs

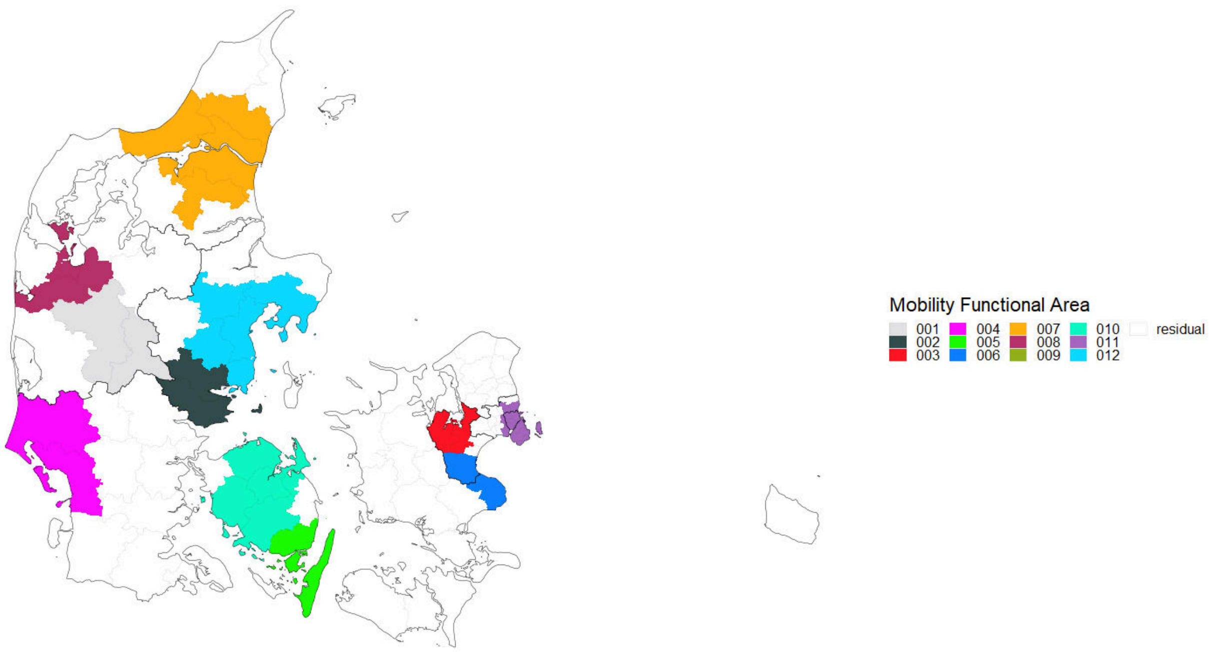


Figure 16: DENMARK: Pre (up) and post (bottom) lockdown persistent MFAs.

5.6 Estonia

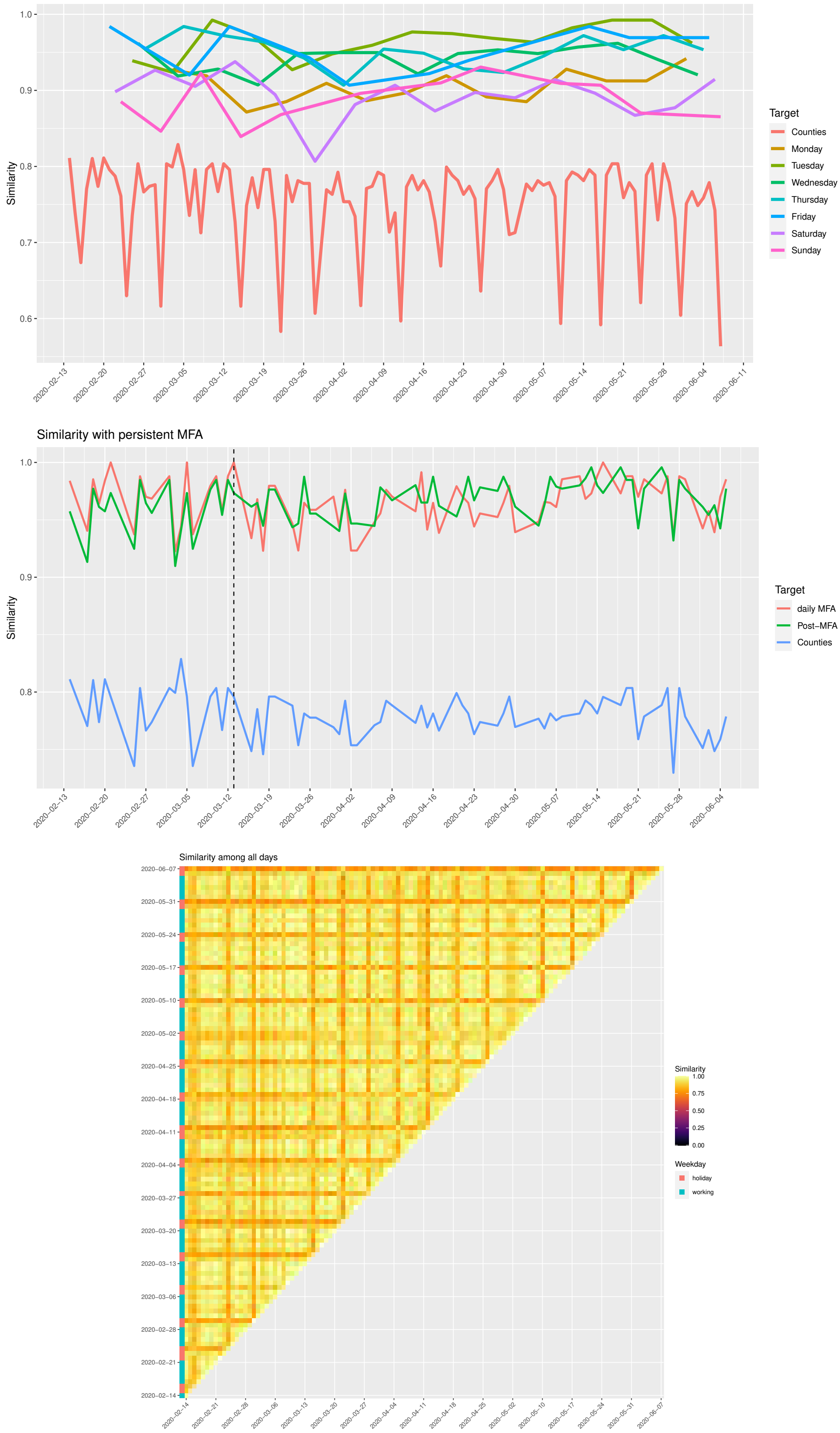
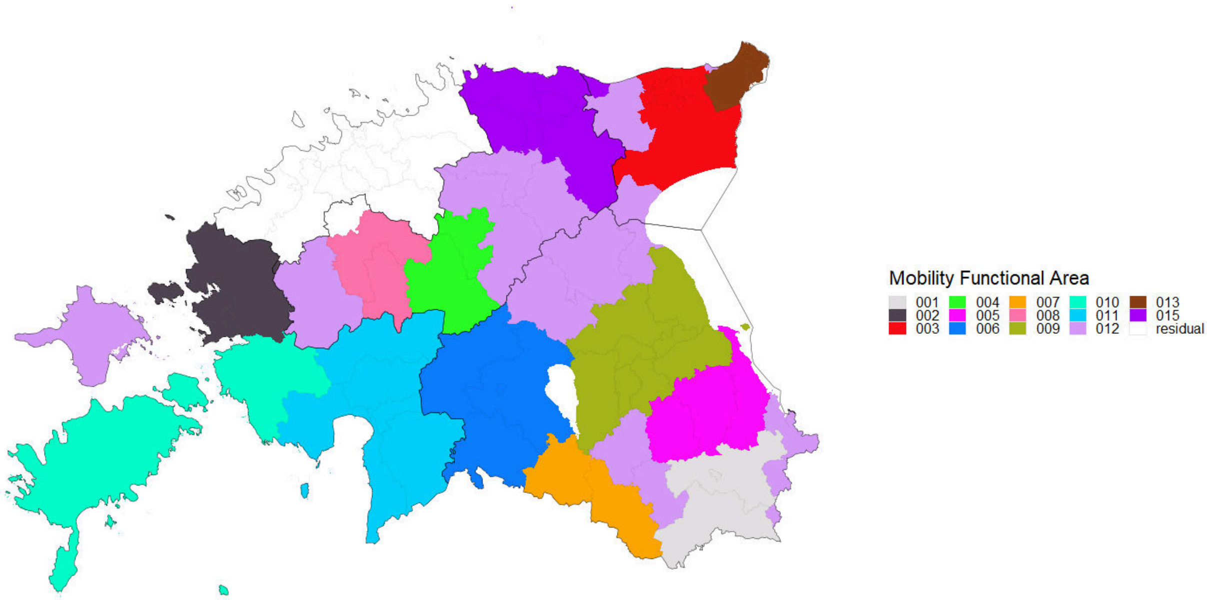


Figure 17: ESTONIA: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Estonian counties (middle). Full similarity matrix among daily MFAs (bottom).

Pre lock down persistent MFAs



Post lock down persistent MFAs

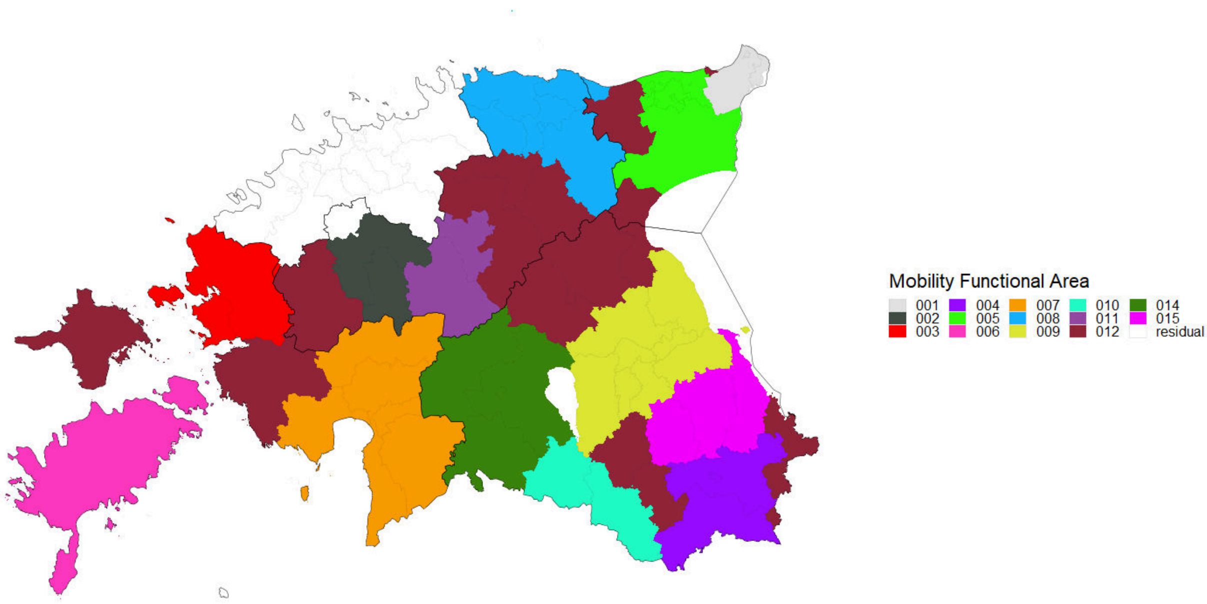


Figure 18: ESTONIA: Pre (up) and post (bottom) lockdown persistent MFAs.

5.7 Finland

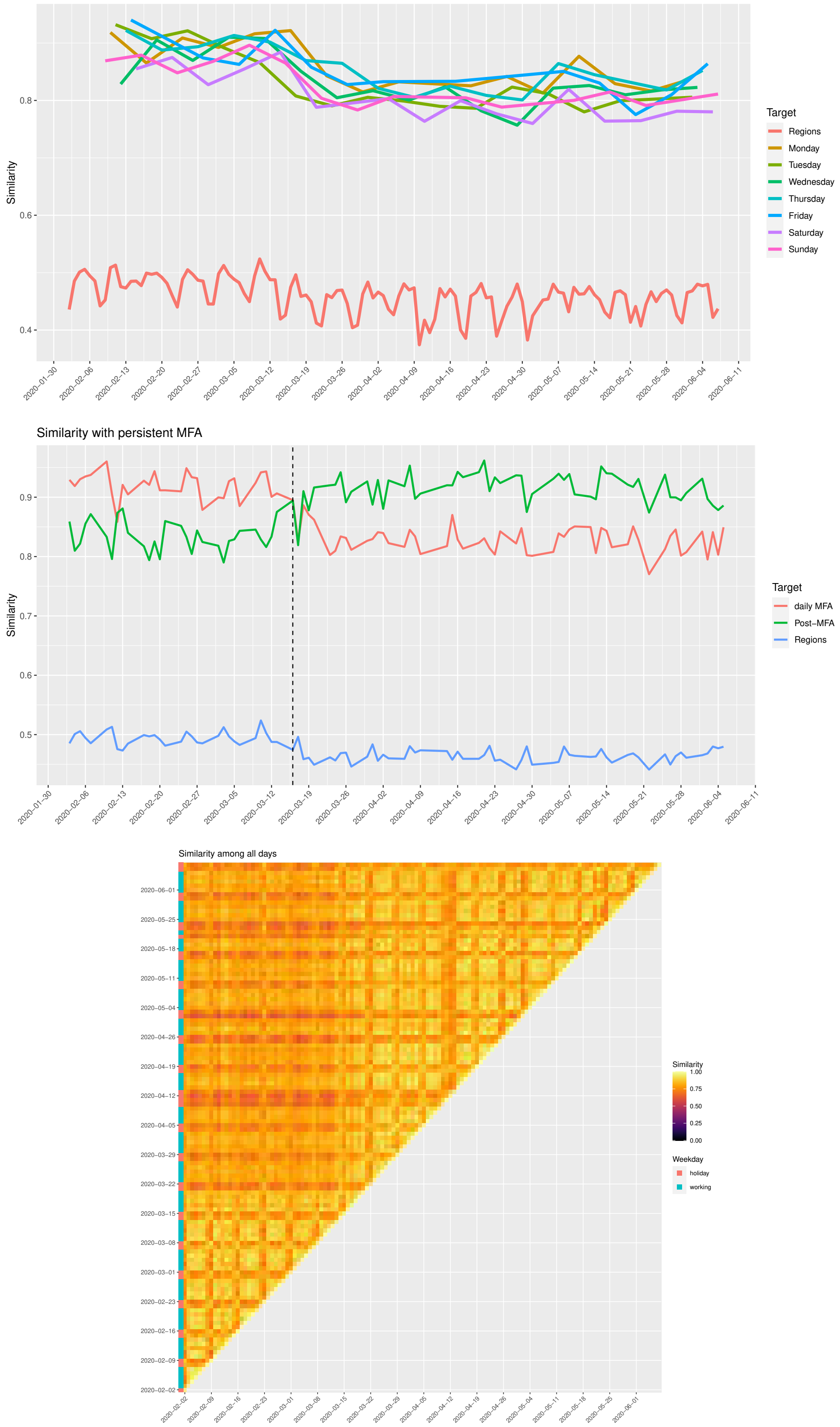


Figure 19: FINLAND: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Finnish regions (middle). Full similarity matrix among daily MFAs (bottom).

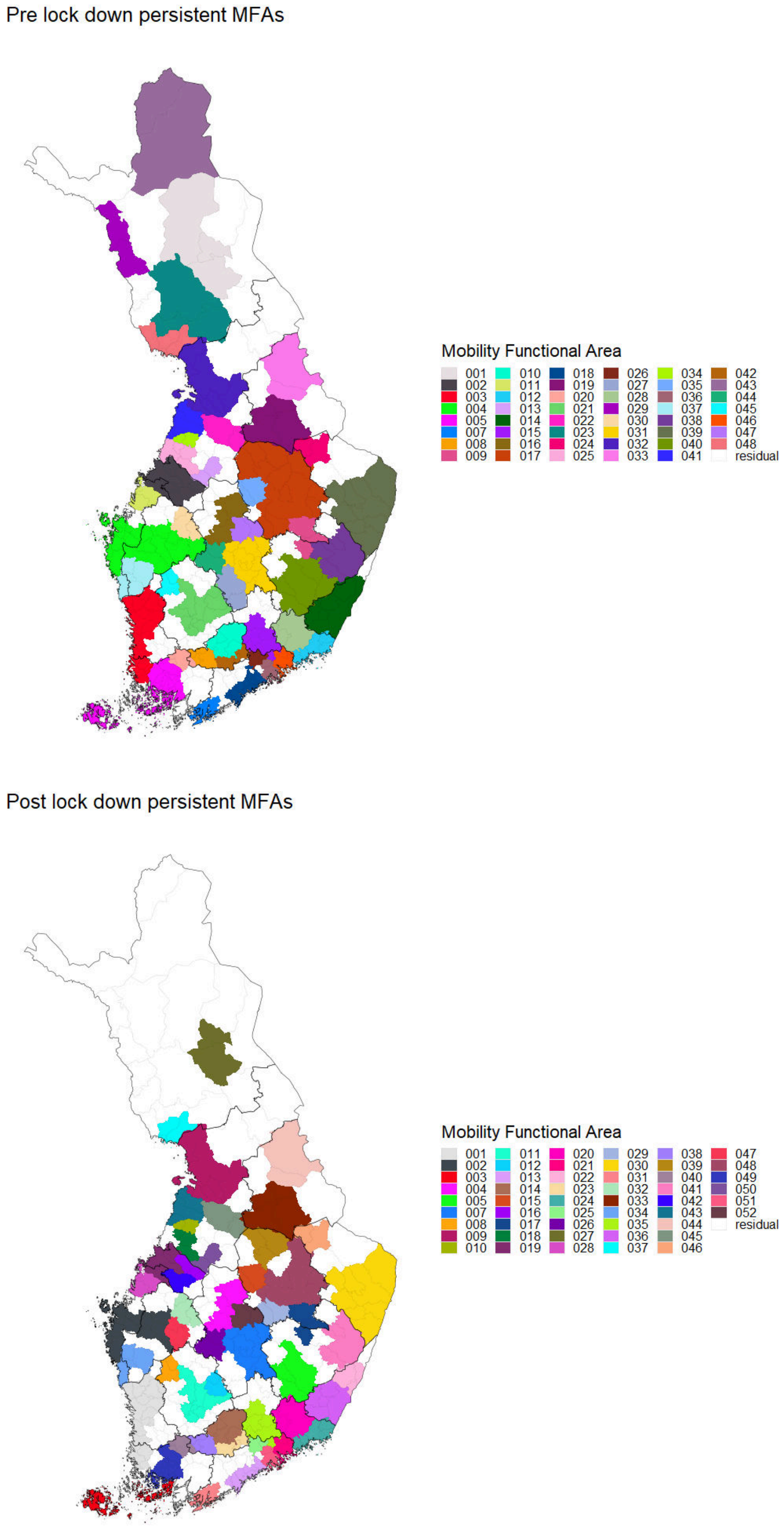


Figure 20: FINLAND: Pre (up) and post (bottom) lockdown persistent MFAs.

5.8 France

France is one special case, being Paris highly interconnected with many other areas. To avoid too much fuzziness in the the definition of the MFAs, we increased the filtering threshold on the CO matrices of Section 4 from 50% to 98% in order to select sharper persistent MFAs.

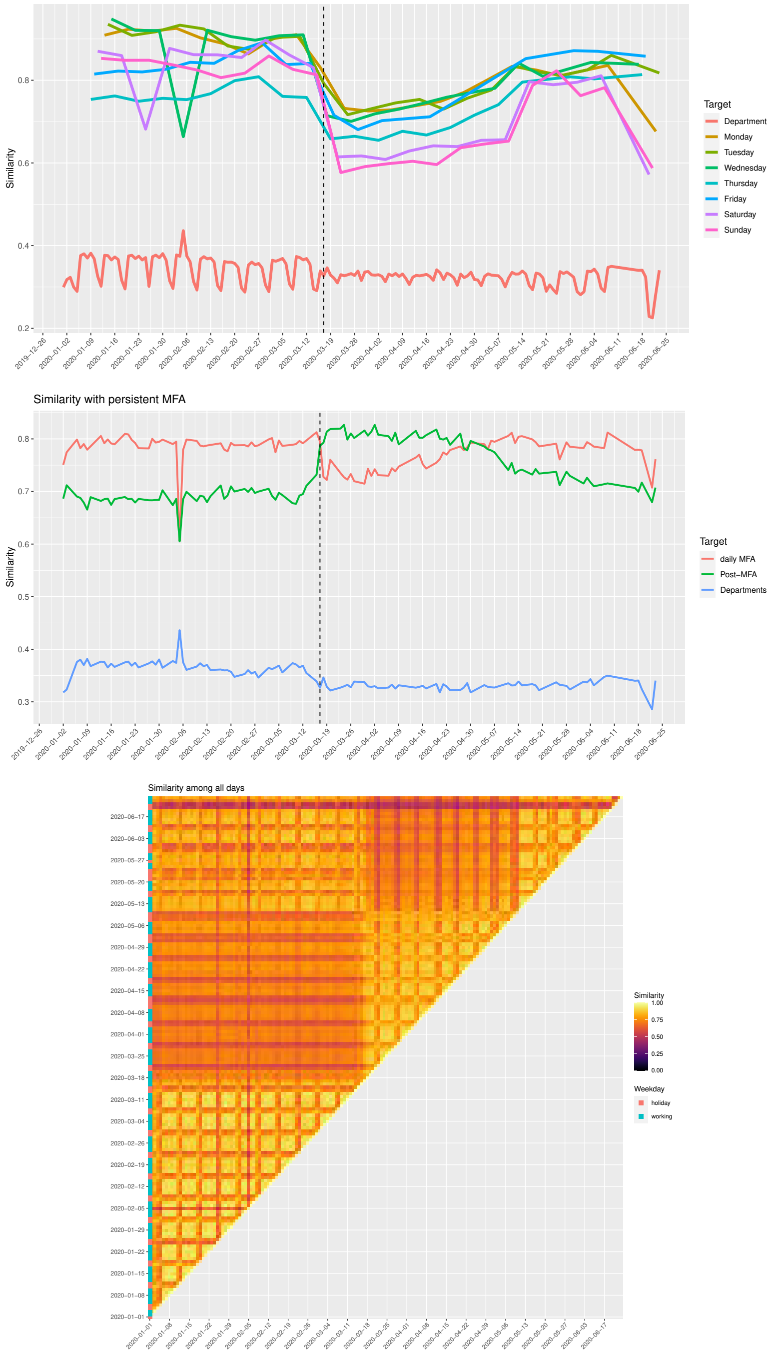


Figure 21: FRANCE: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and French departments (middle). Full similarity matrix among daily MFAs (bottom).

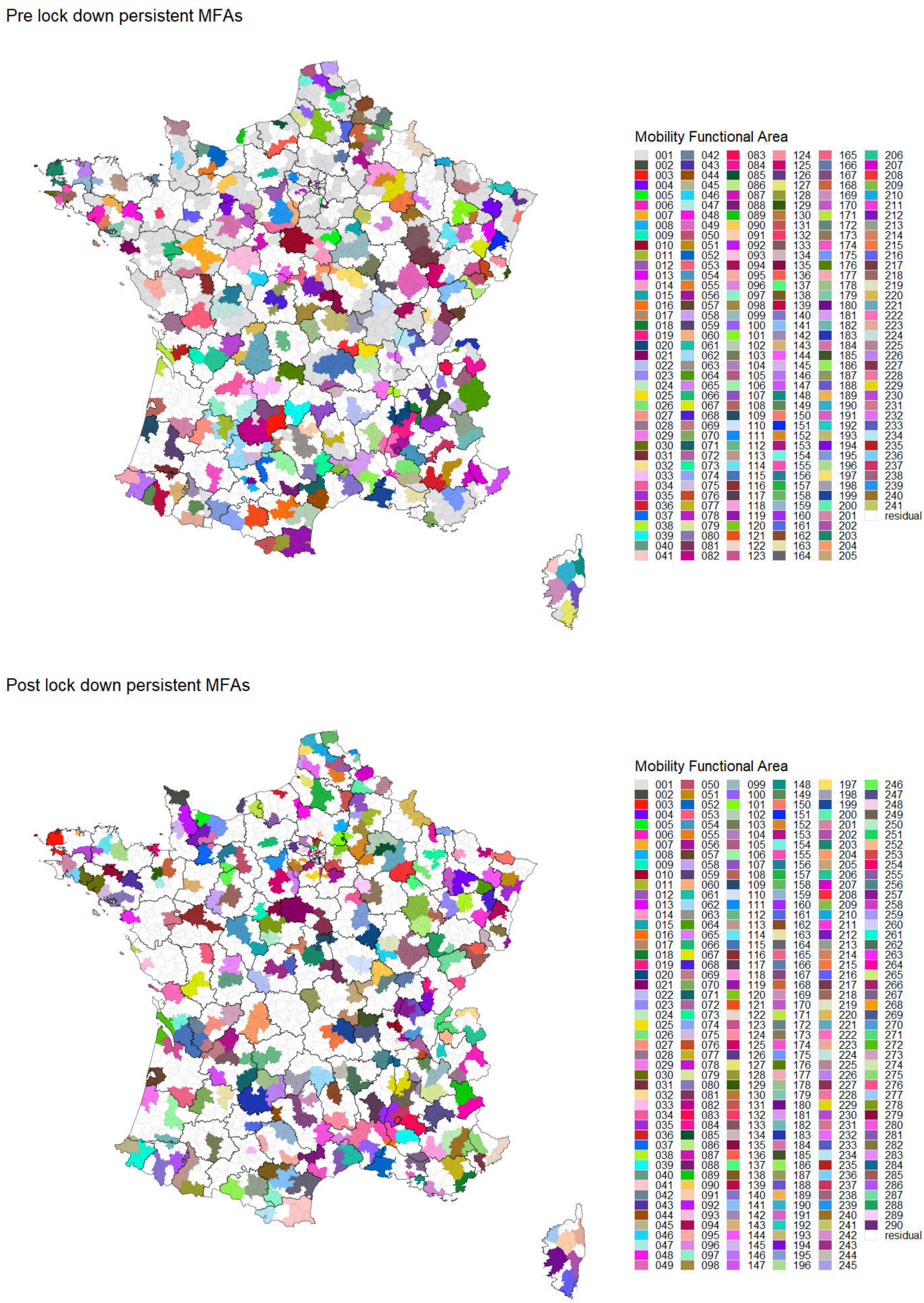


Figure 22: FRANCE: Pre (up) and post (bottom) lockdown persistent MFAs. Notice that Paris area, before lockdown, is interconnected with many other municipalities far from it.

5.9 Greece

Given that the data for Greece are available since 15 May 2020 (see Table 1), the persistent MFAs are calculated looking at the very last data after the ease of lockdown measures. Indeed, on the 4th of May, free circulation within NUTS3 areas was allowed and on the 18th of May, circulation across NUTS3 was possible with the exclusion of islands (with the exception of Crete). Further, on the 25th of May free circulation also to and from the islands was permitted. We look at persistent MFAs from 25 May 2020. This is also reflected in the legend of Figure 23.

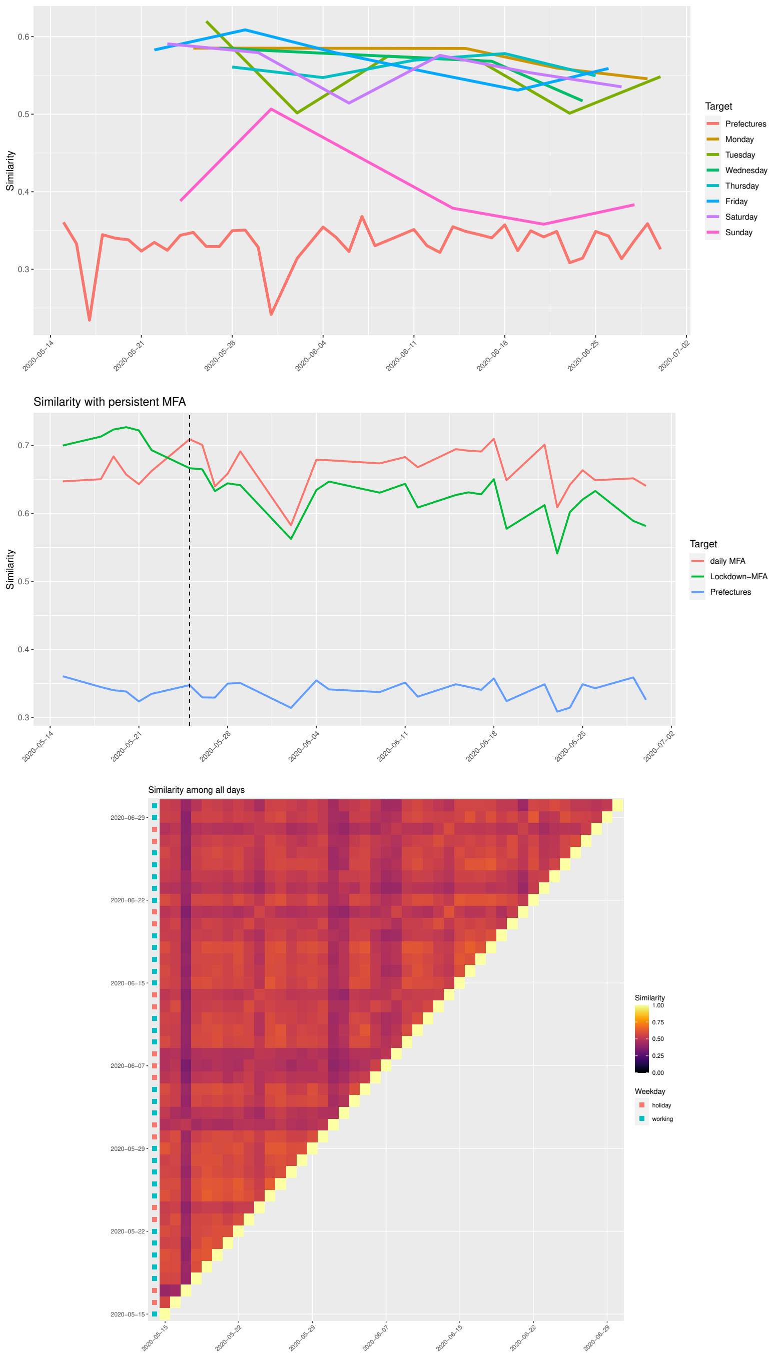
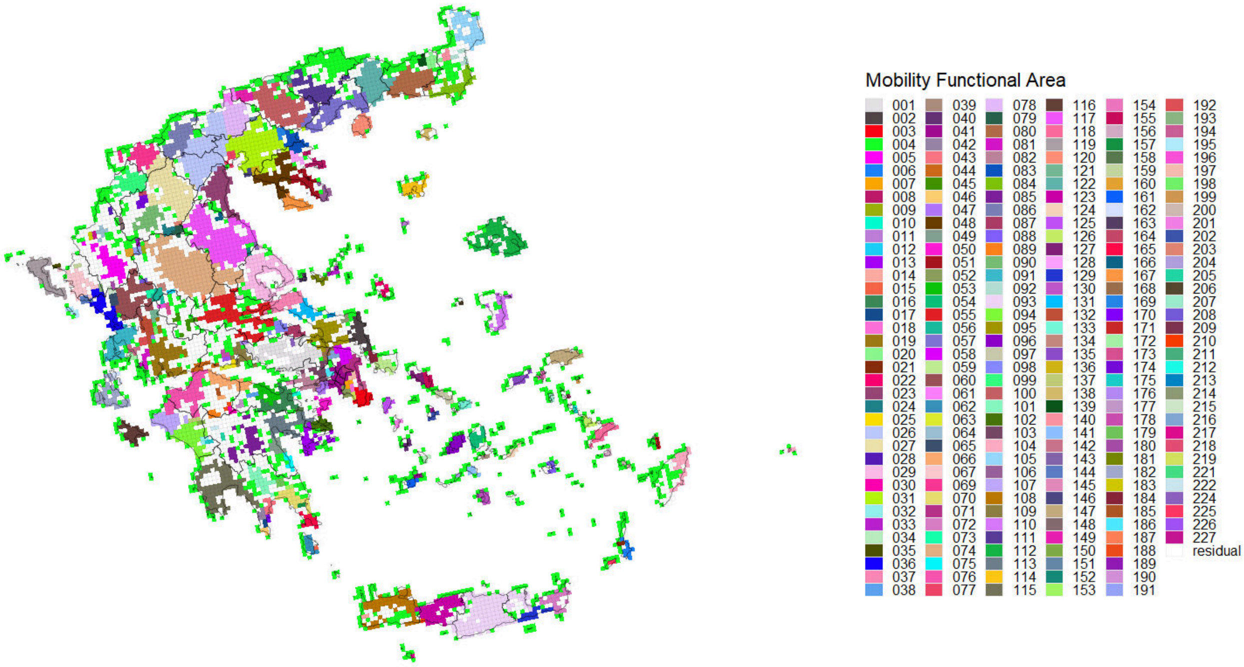


Figure 23: GREECE: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Greek prefectures (middle). Full similarity matrix among daily MFAs (bottom).

Pre lock down persistent MFAs



Post lock down persistent MFAs

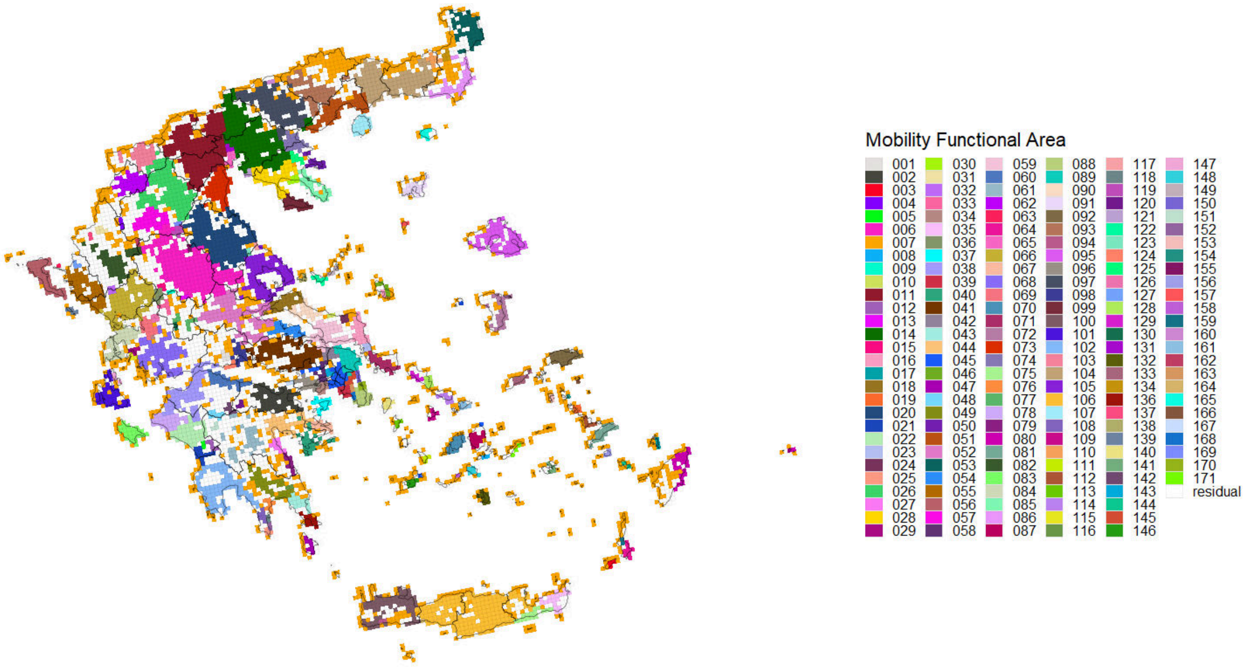


Figure 24: GREECE: Pre (up) and post (bottom) lockdown persistent MFAs.

5.10 Croatia

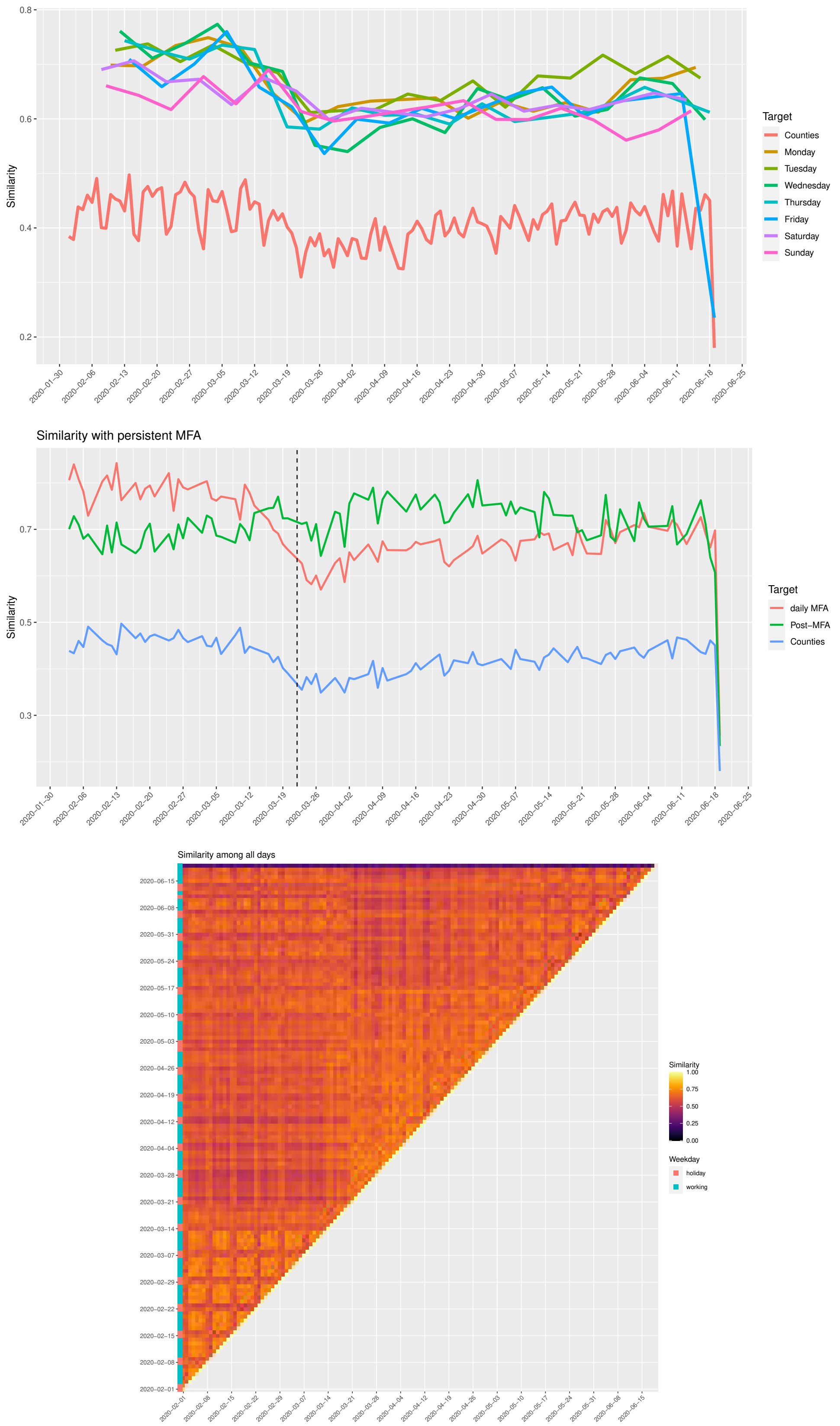
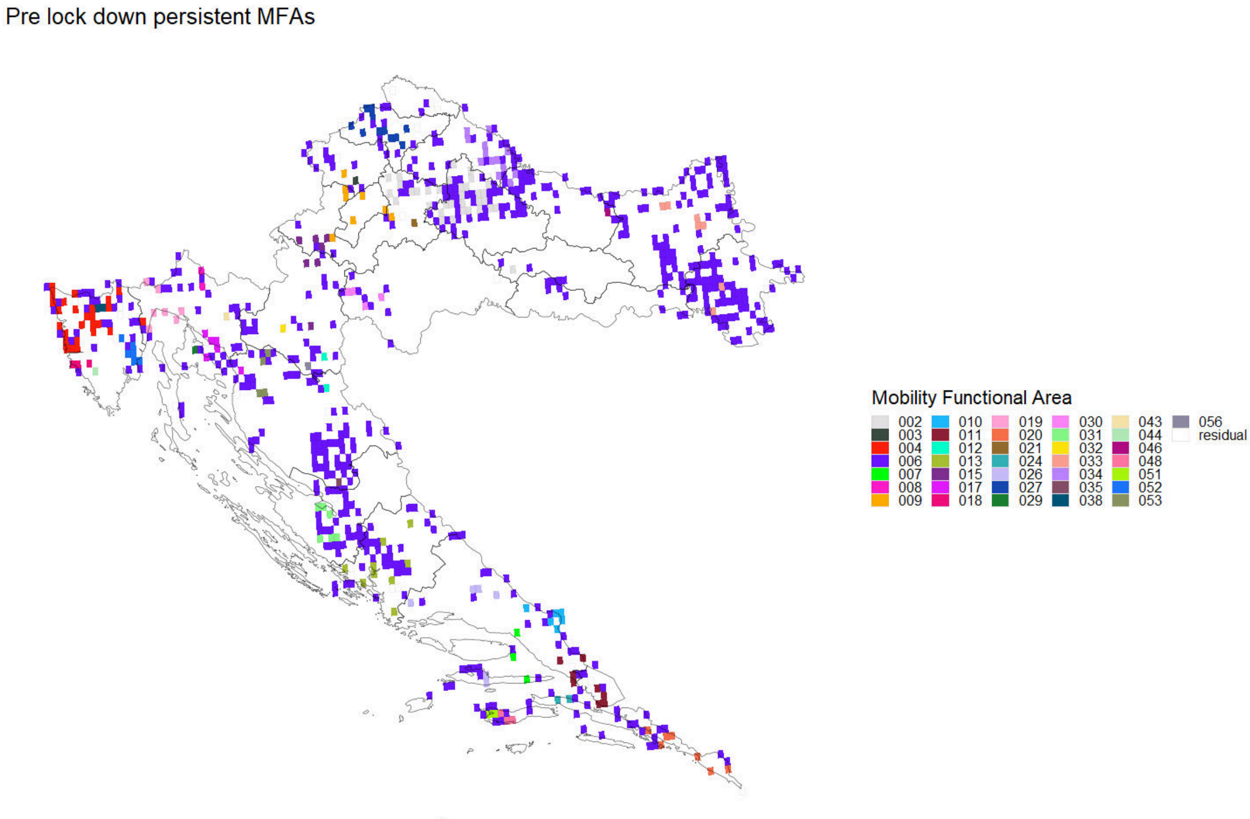


Figure 25: CROATIA: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Croatian counties (middle). Full similarity matrix among daily MFAs (bottom).



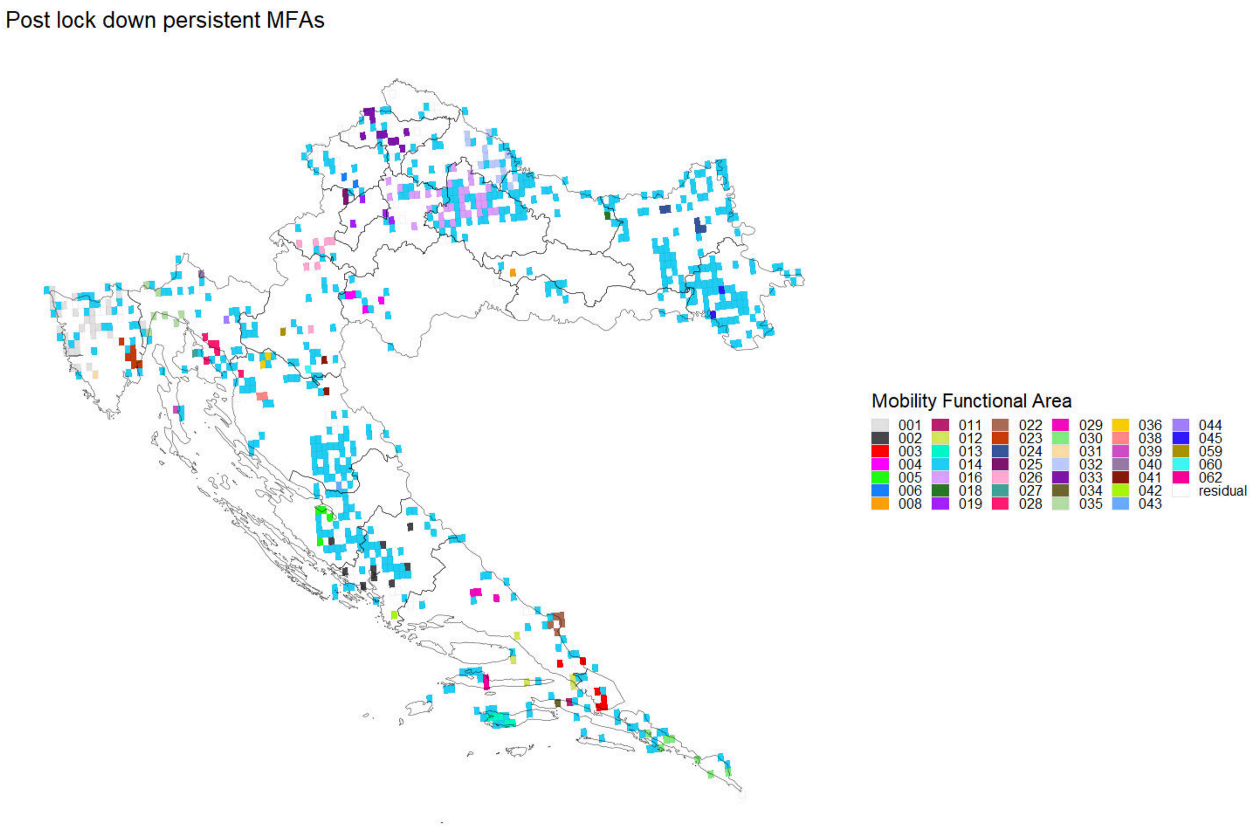


Figure 26: CROATIA: Pre (up) and post (bottom) lockdown persistent MFAs.

5.11 Italy

Italy is the second special case of municipalities highly interconnected with many areas, therefore also for Italy, we increased the filtering threshold on the CO matrices of Section 4 from 50% to 98% in order to select sharper persistent MFAs. Figure 29 shows the effect of reducing the threshold from 98% to 50%: geographically closer and distinct MFAs tend to group together. This is not an effect of the clustering algorithm, but an effect of thresholding the CO-occurence matrices. Remind that the thresholdings isolates regions that occurs to fall in the same MFA more that 98% (Figure 28) or 50% (Figure 29) of the times respectively. The daily MFA do not change their shapes, only the persistent ones.

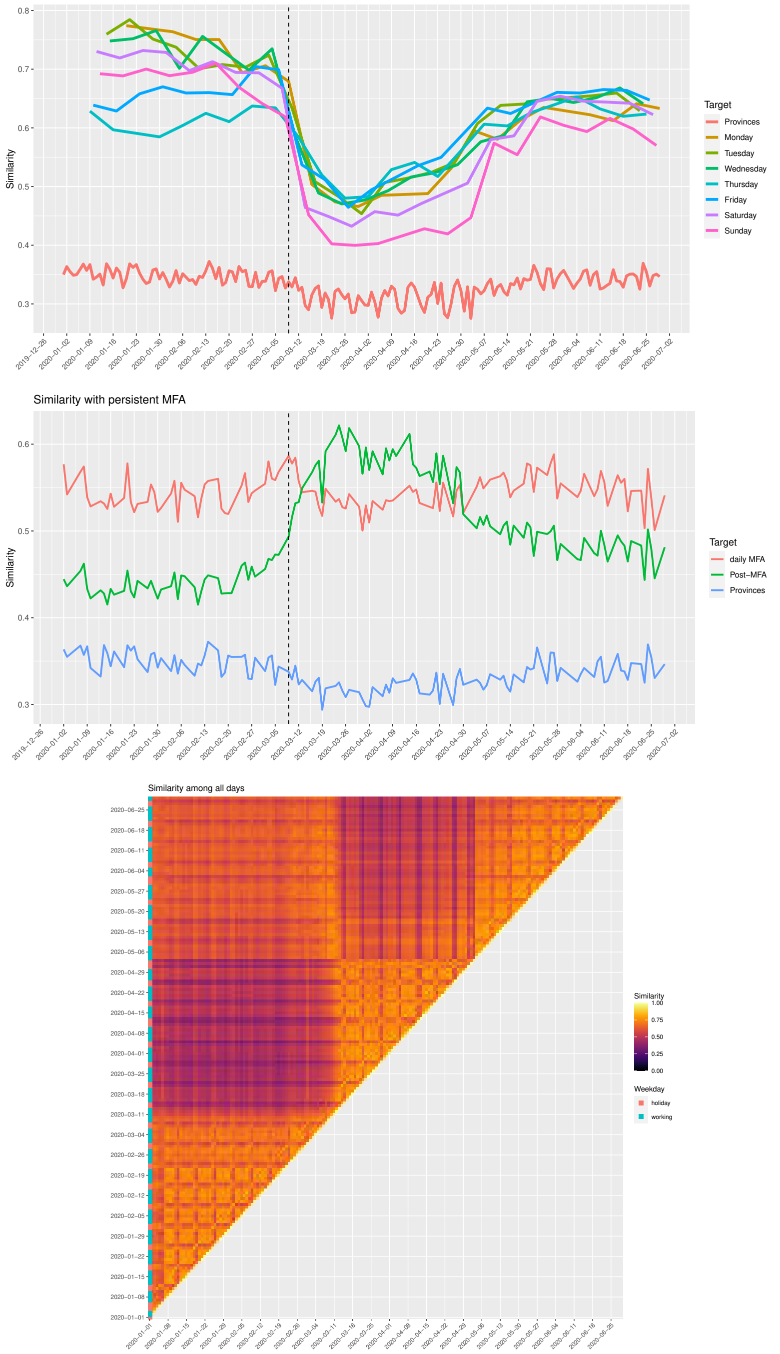


Figure 27: ITALY: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Italian provinces (middle). Full similarity matrix among daily MFAs (bottom).

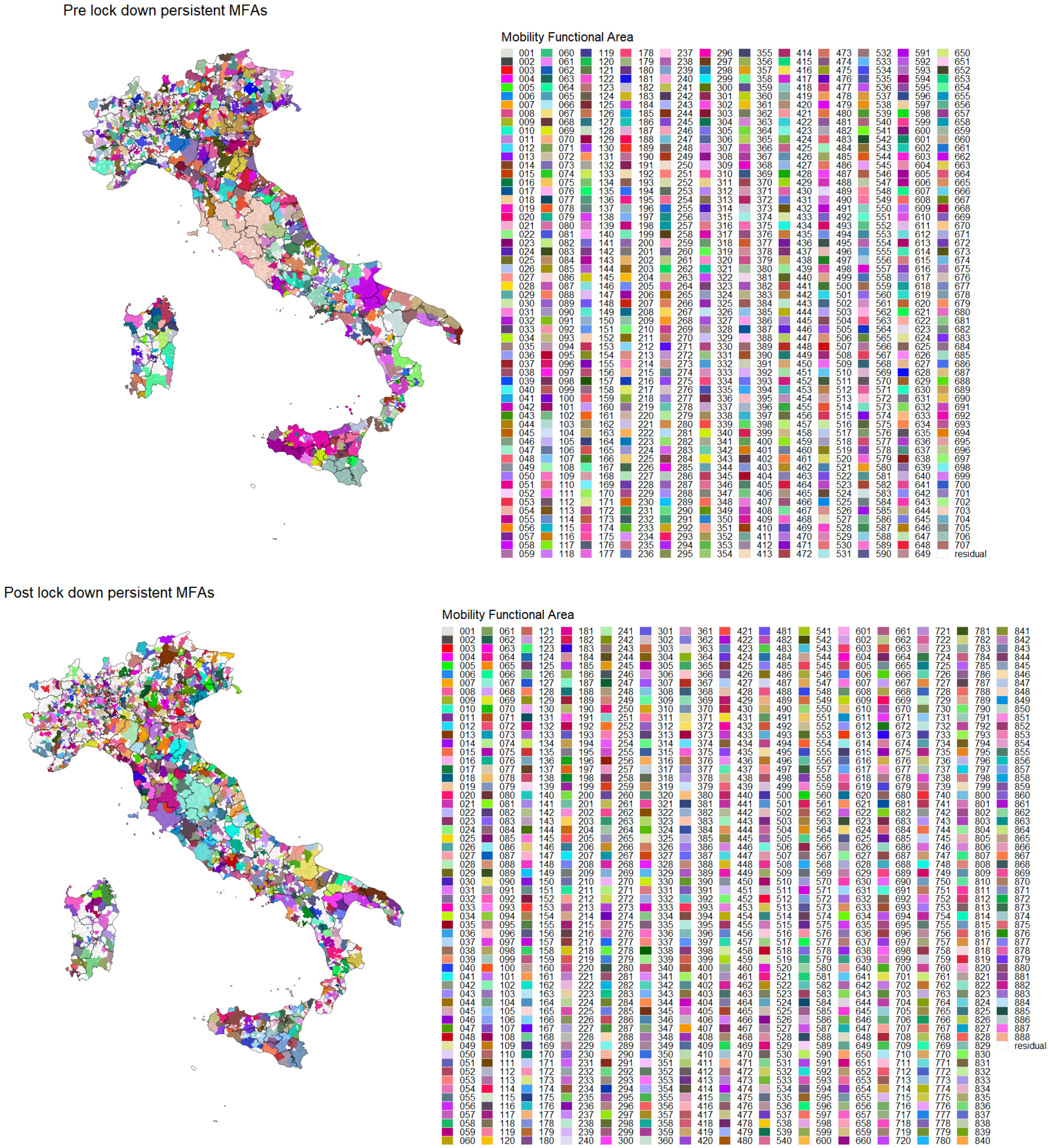


Figure 28: ITALY: Pre (up) and post (bottom) lockdown (sharper, i.e. 98% threshold on the CO matrices) persistent MFAs.

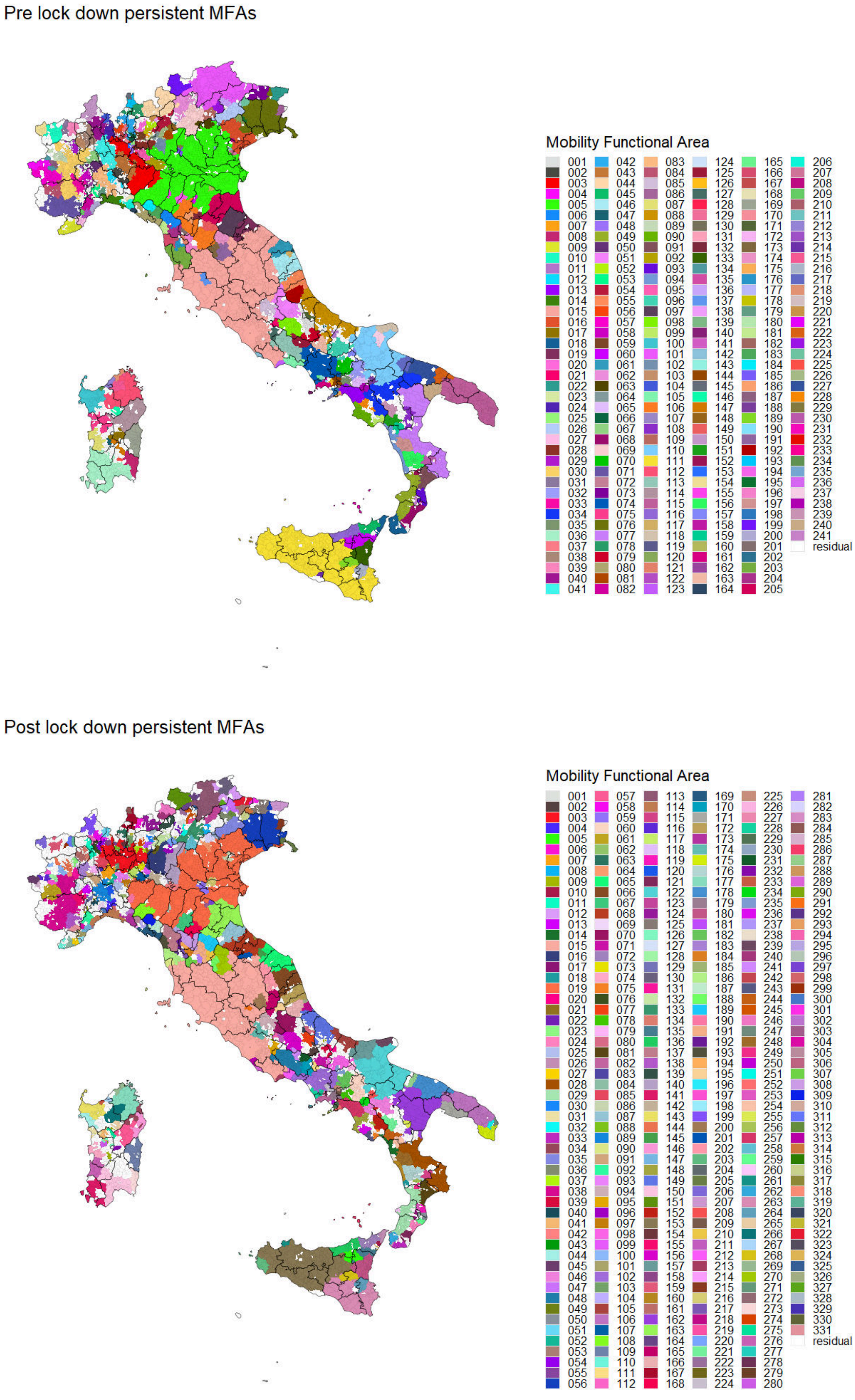


Figure 29: ITALY: Pre (up) and post (bottom) lockdown (fuzzier, i.e. 50% threshold on the CO matrices) persistent MFAs.

5.12 Norway

For Norway we have analysed two ODMs (both at municipality level) from different MNOs, as shown in Table 1. For these two data sets we looked at the similarity between the two sets of persistent MFAs, obtaining a similarity index of 98.2% confirming that the patterns of human mobility, observed on two sets of mobile user groups, are quite stable and similar. Since there are no substantial differences in the results relative to the two sets of data, only the analysis for one MNO is presented in Figures 30 and 31.

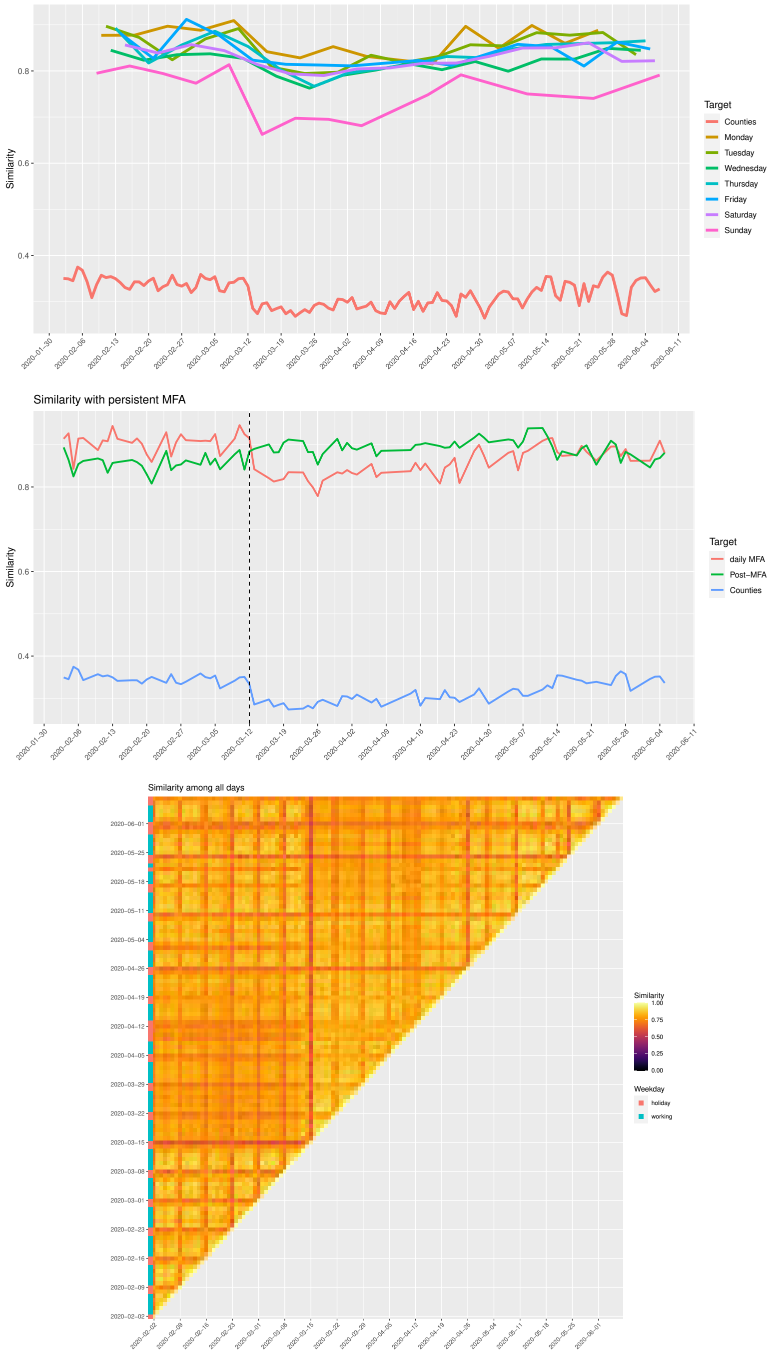


Figure 30: NORWAY: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Norwegian counties (middle). Full similarity matrix among daily MFAs (bottom).

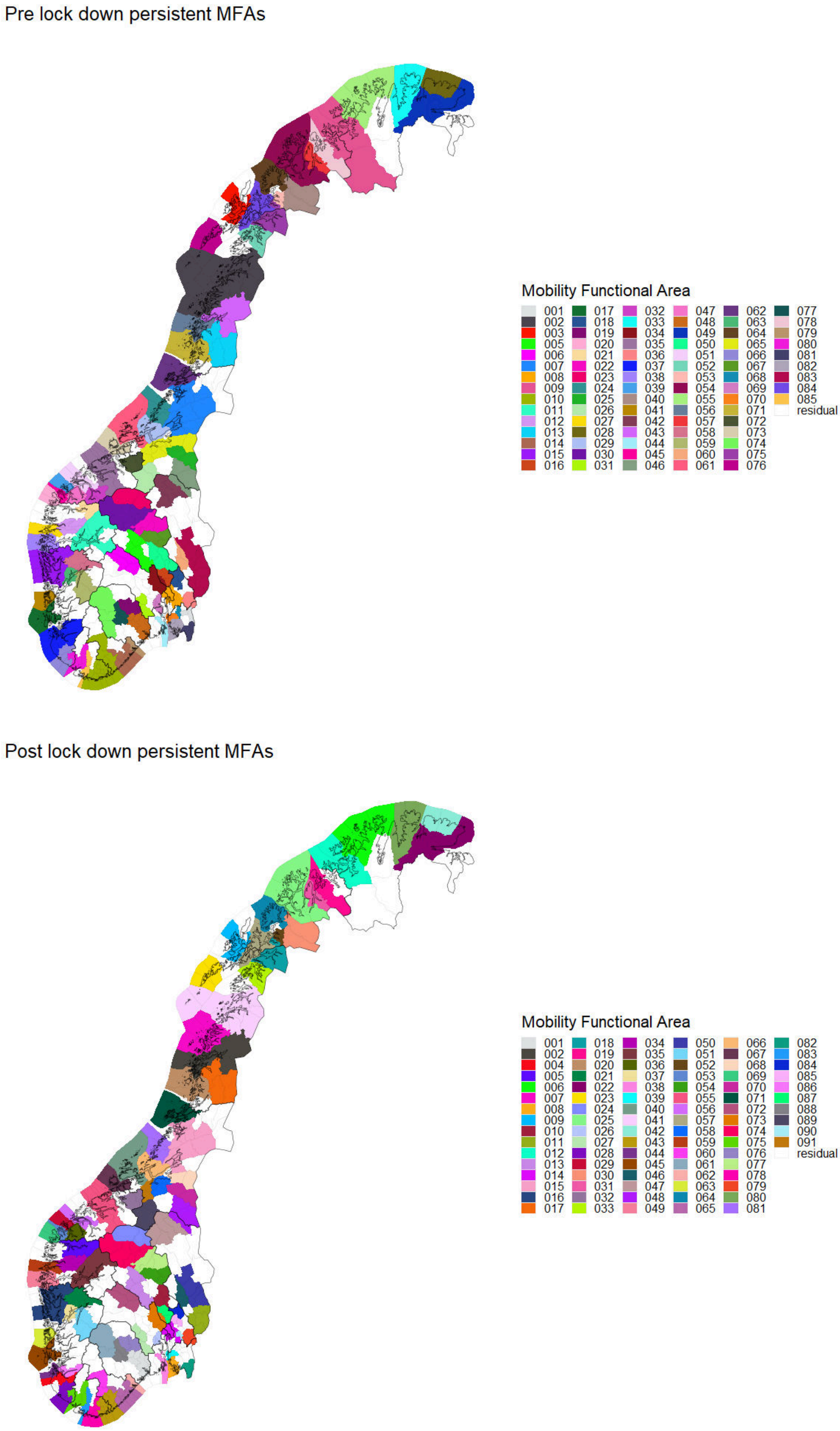


Figure 31: NORWAY: Pre (up) and post (bottom) lockdown persistent MFAs.

5.13 Sweden

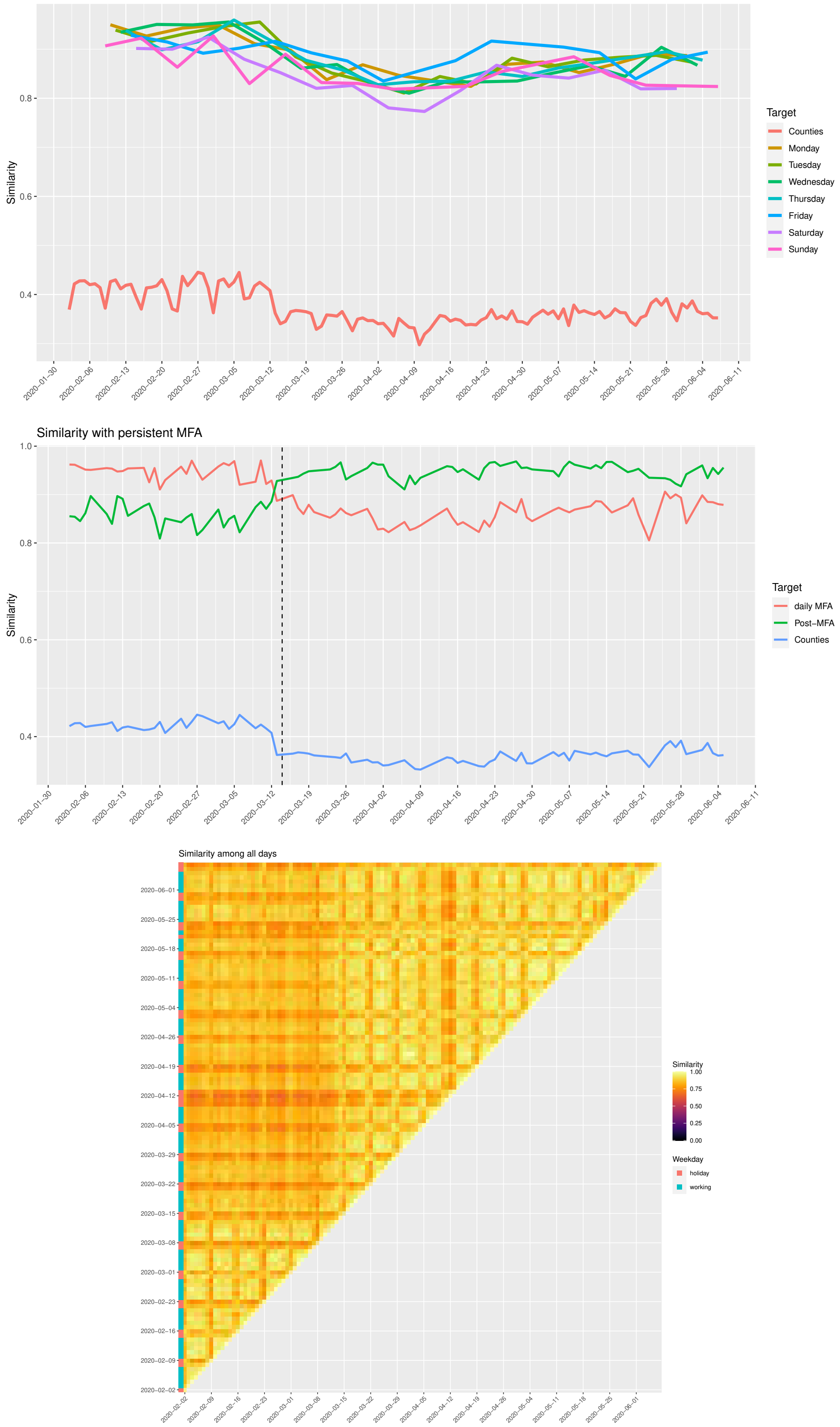


Figure 32: SWEDEN: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Swedish counties (middle). Full similarity matrix among daily MFAs (bottom).

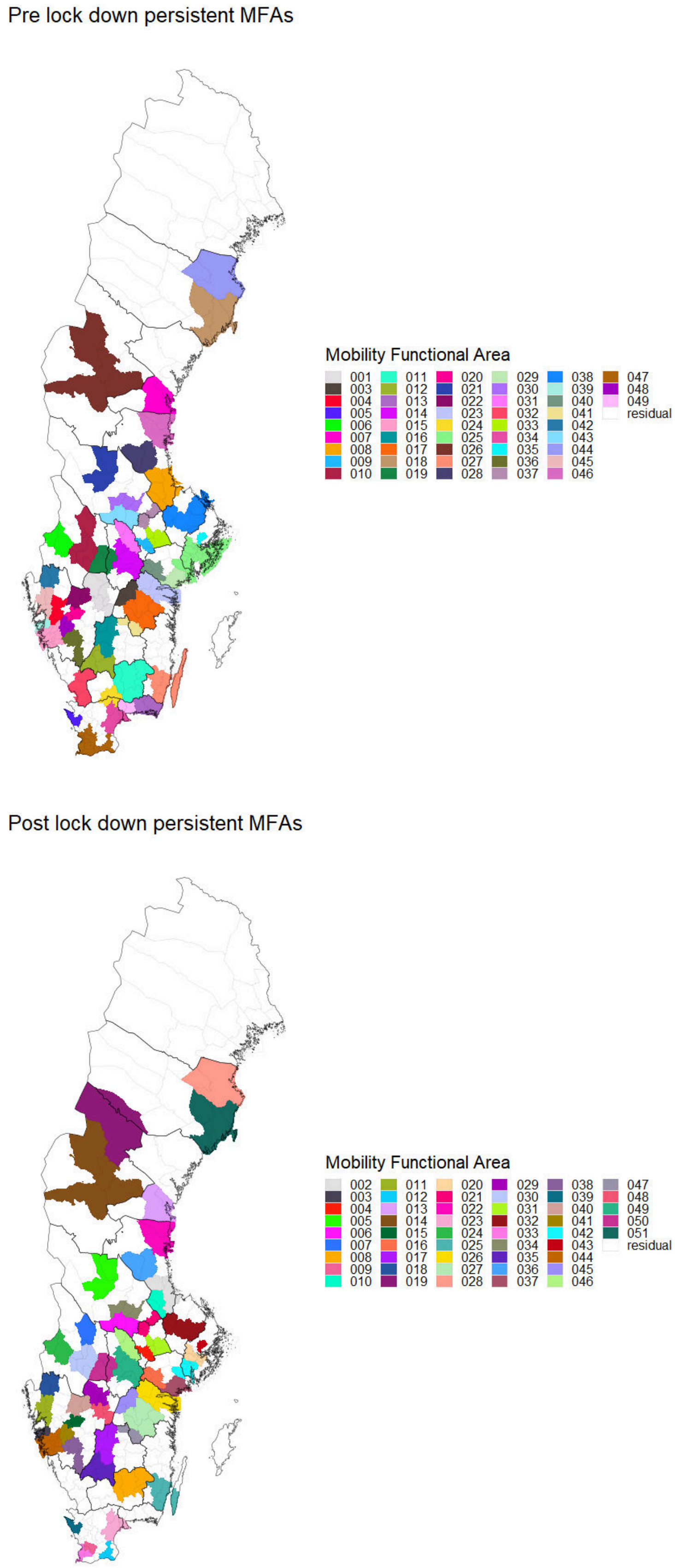


Figure 33: SWEDEN: Pre (up) and post (bottom) lockdown persistent MFAs.

5.14 Slovenia

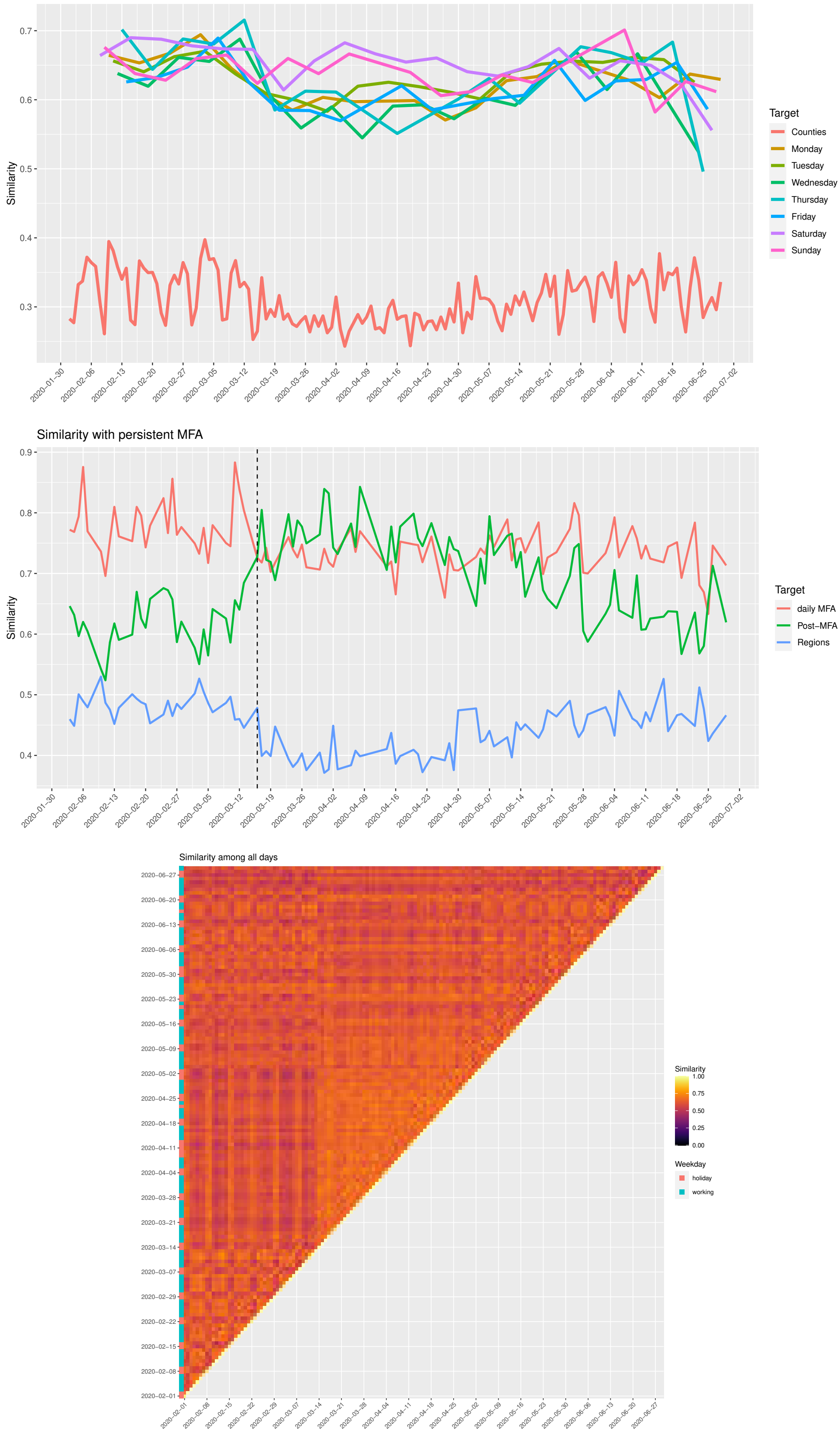
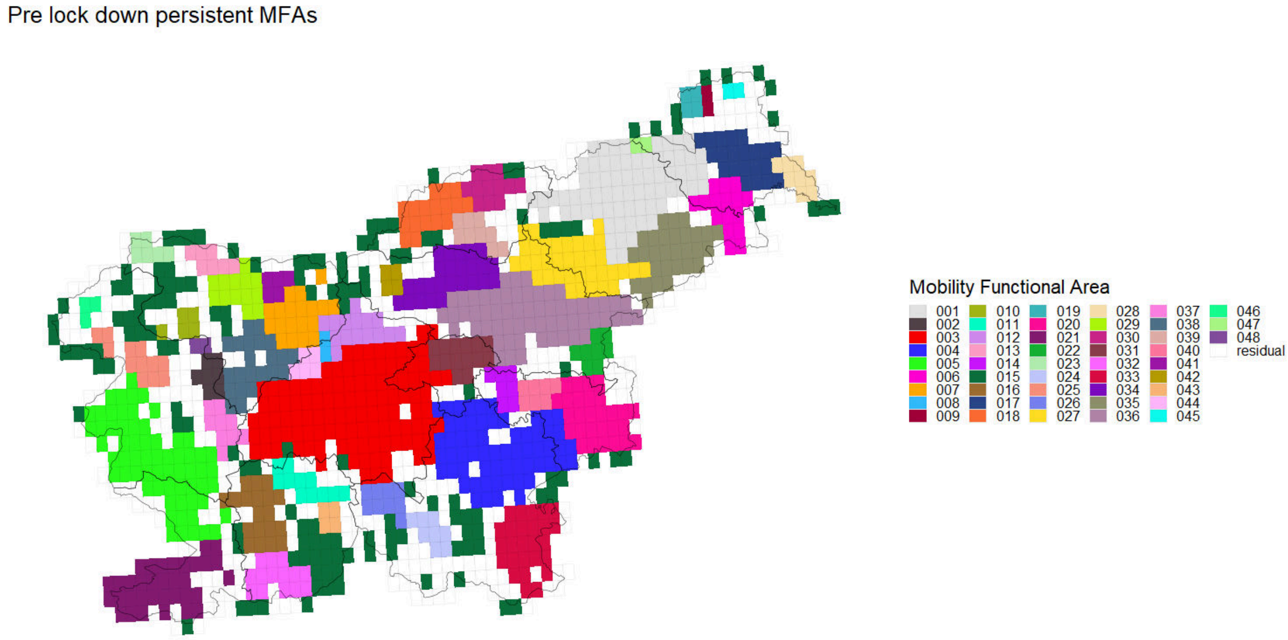


Figure 34: SLOVENIA: Intra-weekly similarity of MFAs (top) and daily similarity of the MFAs with respect to persistent and post lockdown MFAs and Slovenian regions (middle). Full similarity matrix among daily MFAs (bottom).



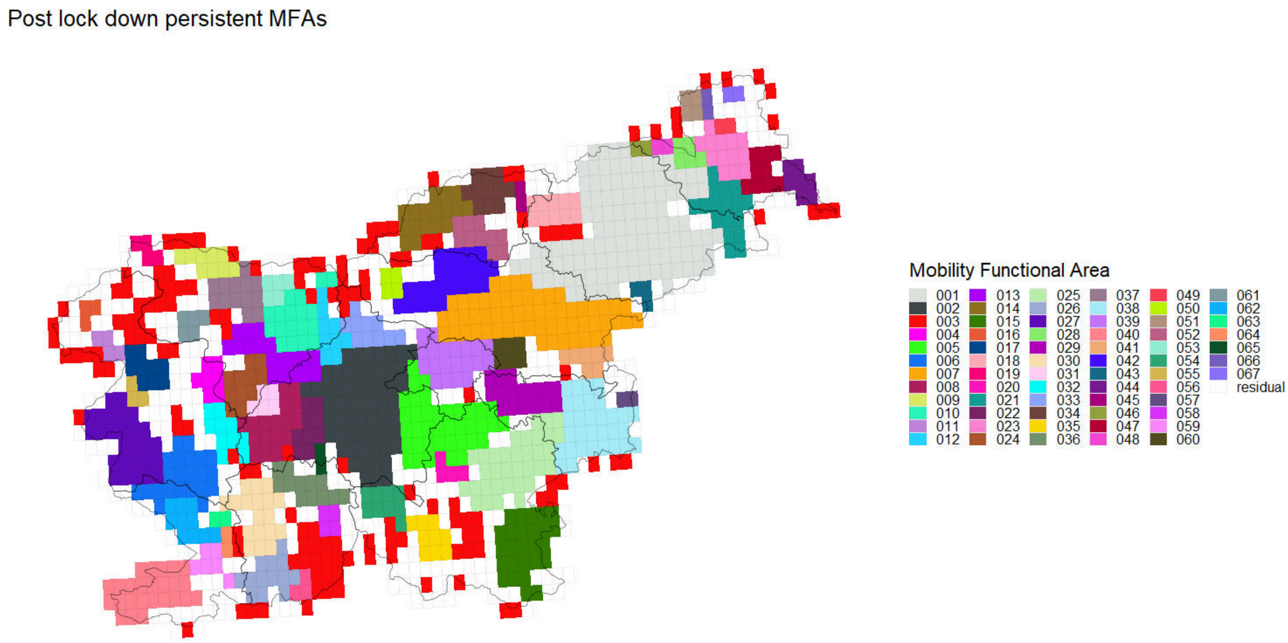


Figure 35: SLOVENIA: Pre (up) and post (bottom) lockdown persistent MFAs.

6 An overview of MFAs across Europe

This section provides an overview of the MFAs calculated for 15 European countries (Norway plus the 14 member states: Austria , Belgium ,Bulgaria,Czechia, Denmark,Estonia,Spain, Finland,France,Greece,Croatia,Italy,Sweden ,Slovenia). It is worth to remark that, since the project in support of the joint initiative to explain the recent COVID-19 outbreak in Europe and support exit strategies through mobile data and apps is still in progress, and more MNOs are continuously joining the initiative by providing ODMs, the coverage of European countries is destined to increase. For the same reason, MFAs will be calculated for the same country using data from more than one MNO, in order to validate the very encouraging results obtained for Norway. Figure 36 gives a comprehensive view of how much the lockdown measures have affect human mobility, as measured by MFAs. The shading of the intensity of the similarity matrices, also show the speed of reversion of the mobility to a pre-crisis level. The two maps of Figures 37 and 38 show the overall shrinking and shaping effect of lockdown measures. The white color just means that mobility is happening mostly within each given municipality, while similar colors across countries are meaningless because color scales are from country to country.

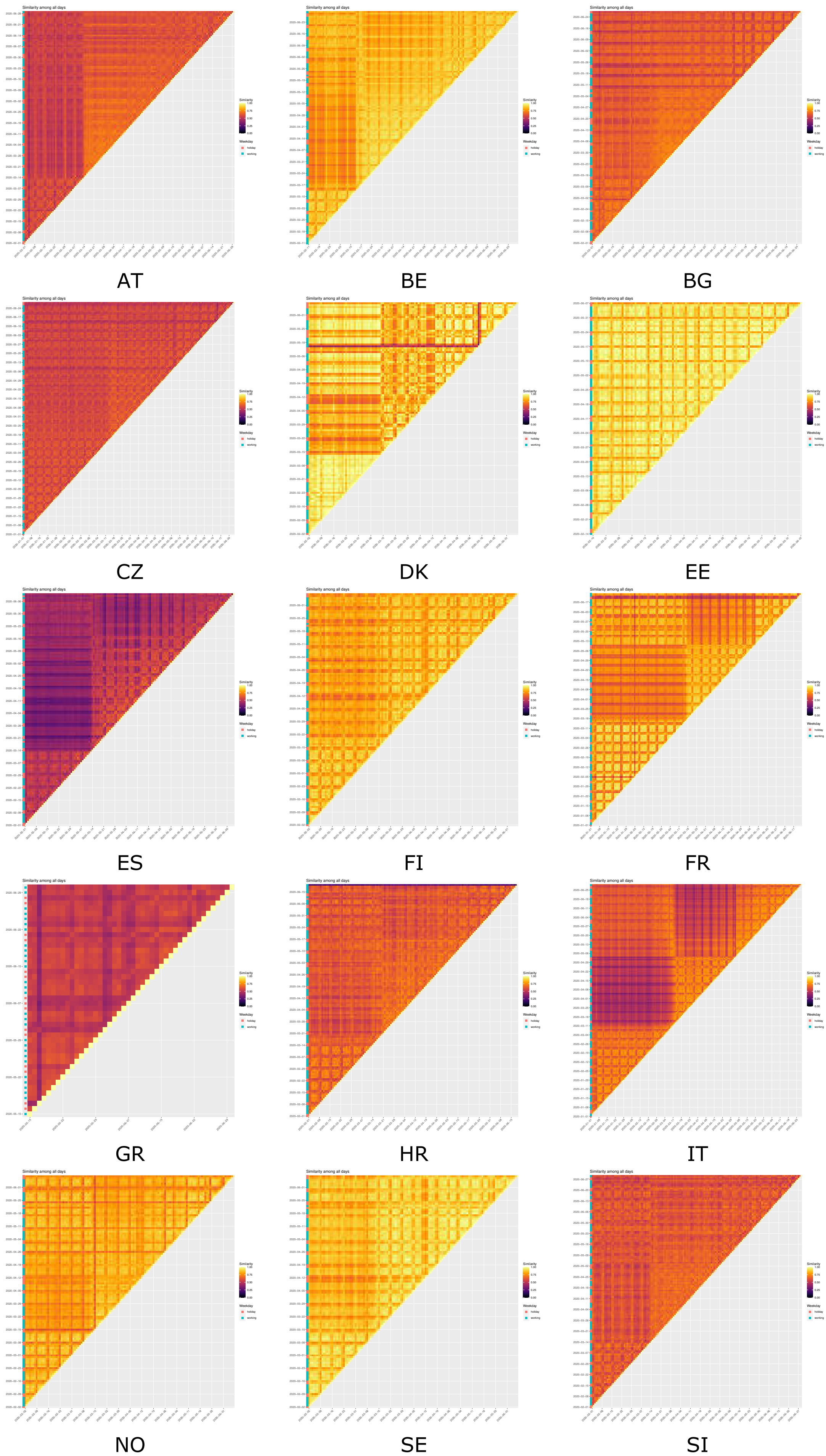


Figure 36: Overview of similarity of the daily MFAs for the 15 countries.

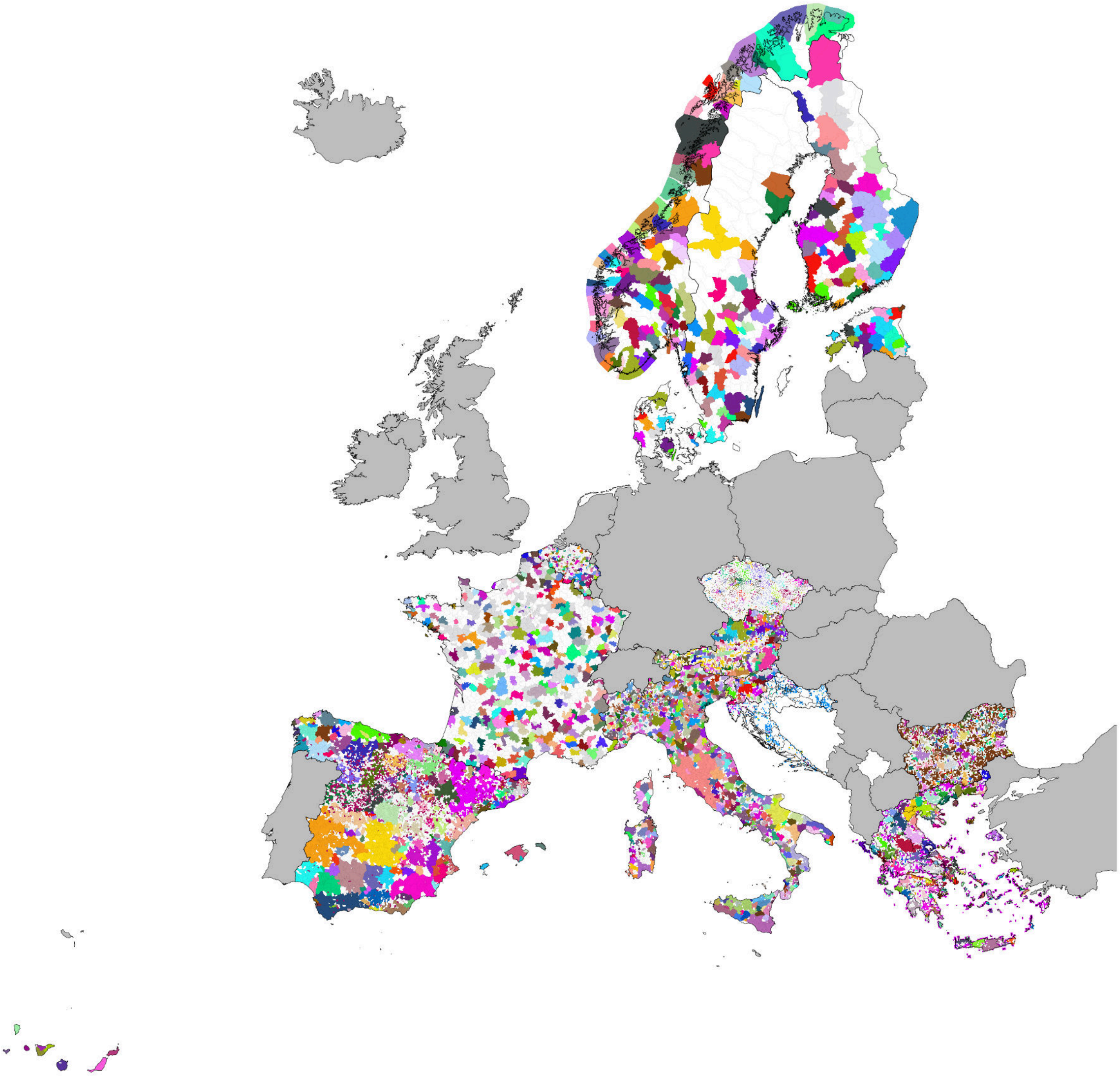


Figure 37: Persistent (pre lockdown) MFA for the 15 countries analysed. Same colors in different countries do not mean they are the same MFA.

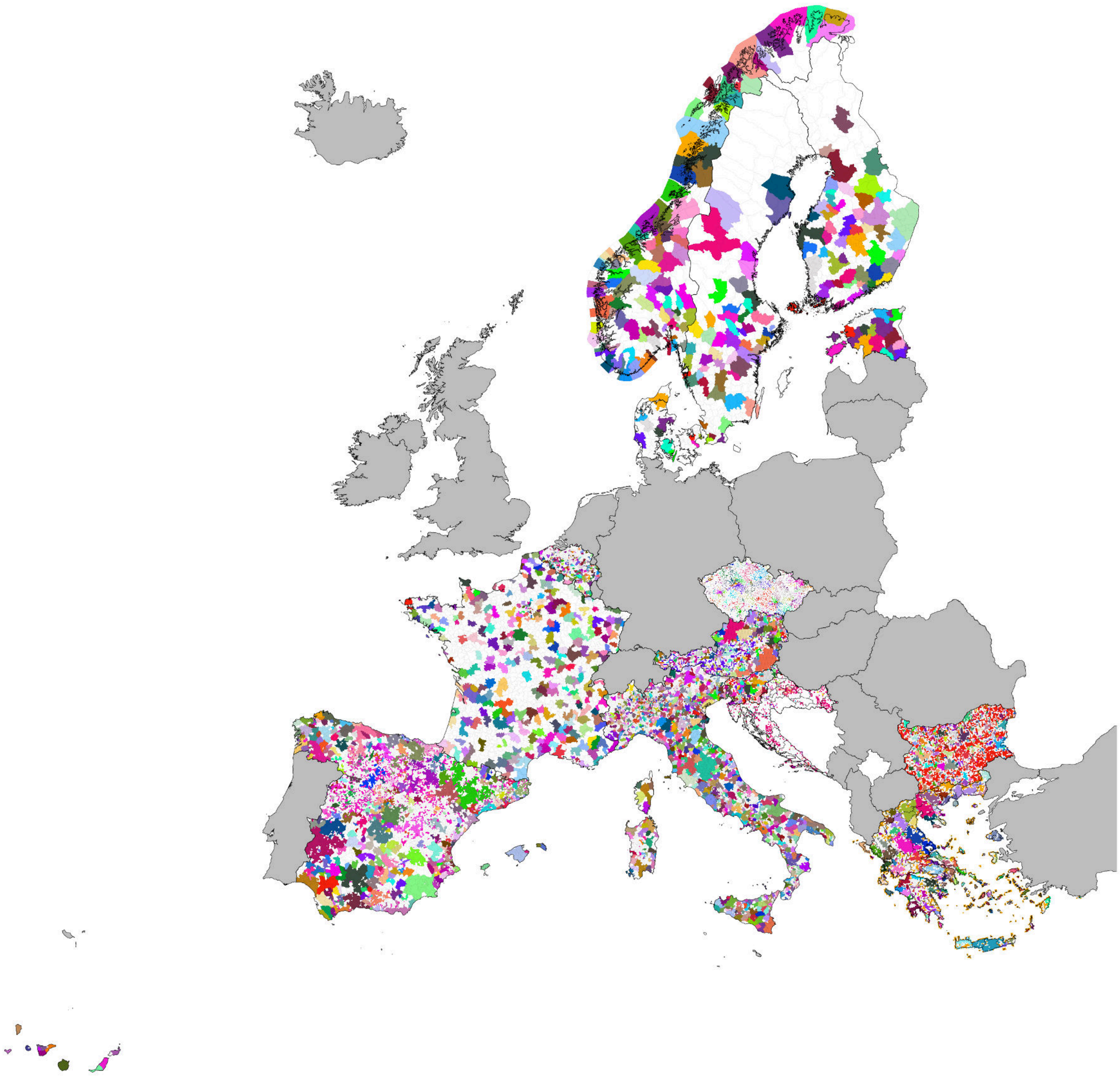


Figure 38: Post lockdown MFA for the 15 countries analysed. Same colors in different countries do not mean they are the same MFA.

7 Conclusions

The present work, in line with the literature on functional regions, puts in evidence on how administrative borders are often different from the commuting patterns. Indeed, human mobility naturally shapes these patterns. In this study, fully anonymised and aggregated data provided by several European MNOs are used to identify a data-driven concept of functional areas, named 'Mobility Functional Areas' (MFAs). By analysing 15 different countries (14 member states: Austria, Belgium, Bulgaria, Czechia, Denmark, Estonia, Spain, Finland, France, Greece, Croatia, Italy, Sweden, Slovenia, plus Norway) , we observe common evidence. Though slightly changing every day, MFAs are essentially persistent in time and present clear intra-weekly patterns. The mobility-restriction measures (lockdown) implemented in different countries to limit the COVID-19 outbreak, have not only reduced the volume of mobility but have had also a clear impact on the shape of the MFAs, showing a clear "shrinking" effect as expected. The level of enforcement of these measures can be compared across countries by looking at the overall similarity matrices.

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