Municipal waste management: a complex network approach with an application to Italy

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Abstract

The paper contributes to the debate concerning the management of municipal solid waste by providing an analysis of two key aspects of waste management -

namely, waste separation and dispatch to treatment plants. Our analysis aims at detecting the extent to which actual behavior in (close-by) municipalities is similar with respect to those two aspects. To pursue our scope, a complex network approach is followed. In particular, we conceptualize, explore and compare two networks, whose nodes are the municipalities, while weights synthesize in one network the percentage of sorted waste that is collected at a municipal level, and in the other one the distance from the waste processing plants used by each municipality. The theoretical network models are implemented through an empirical study based on a high quality dataset referred to Italian municipalities. In this regard, the detection of communities of municipalities and their geospatial contextualization are introduced as devices for a complete description of current practices of municipal waste separation and transfers in Italy.

Keywords: Municipal solid waste, waste management, waste separation, complex networks, Italian municipalities.

1 Introduction

Management of municipal solid waste (MSW) is one of the most relevant issues concerning human activities with social and environmental impact (Cervantes et al., 2018). As recently reported by the World Bank (Kaza et al., 2018), on average, in 2016, a person generated 0.74 kilogram of waste daily, but this had a wide range, from 0.11 kilogram per capita per day in Sub-Saharan Africa, to a maximum of 4.54 kilograms per capita per day in North America (which is close to 4.46 in Latin America and Caribbean, and 4.45 in Europe and Central Asia). Worldwide, only 19 percent of waste undergoes materials recovery through recycling and composting, and 11 percent is treated through modern incineration; moreover, municipal solid waste is expected to increase to 3.40 billion tonnes globally by 2050, in line with growth in prosperity and movement to urban areas (Kaza et al., 2018).

Separate waste collection and waste disposal services can help significantly in improving those figures and reducing environmental pollution due to waste (Passarini et al., 2011; Castillo-Giménez et al., 2019). However, the reduction of social and environmental impact due to waste-related negative externalities depends on a number of factors, as waste management is complex (Cervantes et al., 2018); indeed, it involves every individual, as well as a number of institutions and firms providing various waste management services (Achillas et al., 2013; Juul et al., 2013; Soltani et al., 2015; Agovino et al., 2016b).

Waste management is usually a responsibility of local authorities, which have limited resources, especially where municipalities are not populated by high-income individuals (Mazzanti et al., 2008; Chu et al., 2019). This has a negative bearing on the capacity of the authorities for waste management planning, contracting, operational monitoring, and so on. Moreover, inter-municipal government cooperation is in place in a minority of cities only; its impact on waste collection and sorting is overall limited, as it typically occurs through the use of shared assets for waste transfer, disposal, and city cleaning (Kaza et al., 2018). Municipal waste management offers therefore a fragmented picture at different geographic levels, globally as well as locally. Recent results suggest that, in the European Union-27, a rapid convergence in performance in the treatment of municipal waste by member states has occurred after the transposition into national law of the Waste Framework Directive of 2008; however, as far as convergence is not found, there may be clubs, or communities, that show similar patterns of behaviour (Castillo-Giménez et al., 2019). Furthermore, the concept of circular economy (Kirchherr et al., 2017; Korhonen et al., 2018) is currently viewed, by many practitioners and scholars, as a better way to approach a range of environmental issues, waste management emerges as one of the most relevant areas of economic circularity, especially in Europe (Merli et al., 2018; Zeller et al., 2019). Recent contributions to this literature have noted, on the one hand, that the transition to a circular economy needs to occur at the macro-, the meso-, and the micro-system levels (Kirchherr et al., 2017; Merli et al., 2018); on the other hand, that attainment of policy goals embedded in the concepts of circular economy and sustainable development require efforts by a plurality of actors – i.e., consumers, firms, institutions, governments, etc. – who should not be considered in isolation, but as agents in (circular) networks (Korhonen et al., 2018; Merli et al., 2018).

The aim of this work is to contribute to the analysis of how waste management takes place at municipal level, with focus on quantitative features of solid waste selection and subsequent delivery to waste treatment plants. In particular, we are interested in finding out whether granular data on waste sorting and treating help to detect somewhat homogeneous communities of municipalities, on the basis of features of local waste management practices. To pursue our scope, a complex network approach is followed (Boccaletti et al., 2006; Jacob et al., 2017), with a specific attention in building meaningful connections based on the similarity among the considered nodes. Indeed, complex networks are structures characterized by patterns of connections which are non-trivial when compared for instance to those of the regular graphs; thus, their analysis is particularly interesting. Furthermore, similarity-based networks can unveil important relationships among the nodes of a network as demonstrated in several applications related, for example, to social science (Liben-Nowell and Kleinberg, 2007) and finance (Tumminello et al., 2010; Martinez-Jaramillo et al., 2014)

Our paper lies in this strand of research by considering two networks whose links are weighted by using two different similarity scores. In particular, we conceptualize, explore and compare two networks whose nodes are the municipalities. The networks show different weights on the links. In one case, the weights synthesize that two nodes are more strongly connected when they share very similar percentages of selected waste; in the other one, weights are such that a strong connection is attained when the nodes exhibit similar distance from the waste processing plants used to treat waste. In our analysis, the weights are assumed to range in $[0, 1]$ in both of cases for comparison purposes (see Subsections 2.2.1 and 2.2.2). In so doing, we provide the analysis of two very different features of the waste collection process and we also deal with the relevant theme of the relation between the distance of a municipality from waste processing plants and from targets for waste selection. Indeed, the former network – that we will call $N^{(p)}$ – considers connections among municipalities according to their performance in implementing waste selection policies. Performance is higher when municipalities achieve higher percentage of selected waste. In this respect, we label as "virtuous" the municipalities achieving a high percentage of sorted waste. In the same line, we state that two municipalities are strongly connected when they have a similar high percentage of selected waste – hence, pointing to "virtuous" connections. As we will see below, meeting policy targets in separating waste – i.e., being virtuous – drives the communities detection. The second network is related to purely geographic connections, as it considers weighted means of the distances between each municipality and the plant(s) it uses for disposal of its separated waste. We will call such a network $N^{(d)}$. To the best of our knowledge, this approach has never been used before in analyses of waste management issues. Beyond its originality, the very important feature of the theoretical proposal is the adaptability to all cases for which data are available. Yet, different regional realities can be effectively discussed by means of the considered methodology.

The theoretical network models are implemented through an empirical study based on a high quality, publicly available dataset referred to Italian municipalities. Therefore, community detection and network centrality measures are introduced as devices for a complete description of actual municipal practices in Italy with regard to separate waste collection and transfer to waste plants. The community partitioning (i.e., the network clustering) is obtained using modularity maximization, since the modularity function well represents the definition of community and it is useful for evaluating the quality of a certain community partitioning. Indeed, modularity is a function which assigns a real value to any partition in communities of a given network. The name "modularity" refers to the "modules" – i.e., communities. The modularity is high if a significant fraction of the links of the network run between nodes of the same community. Basically, this means that a high modularity is associated to a partitioning of the network whose classes are weakly mutually connected but are formed by strongly interrelated nodes.

Empirical results show that clusters are quite different and they do not overlap when the two networks are considered. The most virtuous municipalities situated mainly in the Northern part of Italy. Moreover, there is evidence that virtuous clusters have a quite large number of elements, especially with regard to waste separation. However, we find a heterogeneous distribution of the distance-based clusters among Italian regions, which suggests that, in this case, community detection is less informative by itself.

The rest of the paper is organized as follows. In Section 2 we present the network models for waste management, along with the description of the employed community detection method. In Section 3 we define the boundaries of the problem of waste management in Italy. In Section 4 we illustrate the application of the theoretical framework to the paradigmatic case of Italy. The empirical results are discussed in

Section 5. In Section 6, we finally frame some conclusive remarks.

2 Network models for waste management and communities detection method

This section is devoted to the outline of the complex network approach that we will follow in our study. In the first place, we overview some key notation on networks and we present the method used for building the two networks employed for the analysis of separate waste collection and transfer to processing plants. Then, we discuss the complex nature of the two networks and we illustrate the community detection method.

2.1 Preliminaries on networks

A network represents a unified system able to model a set of elements along with their interconnections. The basis of the conceptualization of a network is a graph $G = (V, E)$, being V the set of n nodes and E the set collecting the m links. The generic nodes will be denoted hereafter as $i, j \in V$ or, similarly, $i, j = 1, \ldots, n$, and the link (i, j) formalizes the (possibly existing) connection between i and j.

With $\mathbf{A}$ we denote a n-squared binary matrix, taking values 0 or 1, where the element $A_{ij} = 1$ if nodes i and j are connected; the degree of the node i is $k_i = \sum_j A_{ij}$, and it quantifies the number of neighbors of the node i; the number of links in the graph G is $m = \frac{1}{2}\sum_{ij} A_{ij}$.

In our context, existing links are weighted. Such weights are nonnegative numbers which capture the strength of the connection between two nodes. We denote the weight associated to (i, j) by w_{ij}; we assume that $w_{ij} = 0$ if and only if the link (i, j) does not exist, i.e. $(i, j) \notin E$. Weights are collected in the n-squared weighted adjacency matrix $\mathbf{W} = (w_{ij})_{i,j \in V}$. Clearly, E is fully identified through the weighted adjacency matrix $\mathbf{W}$. The network N is the weighted graph, and it can be written as $N = (V, \mathbf{W})$.

In our framework, V collects municipalities. Thus, municipalities are here interpreted as the nodes of a network. Moreover, we present two network models by conceptualizing the weights in two different ways: on one hand, we refer to links based on the distance of the municipalities from the waste processing plants; on the other hand, we build links driven by the percentage of the waste sorting implemented by the municipalities. Details are provided in the next subsection.

2.2 The sorted waste collection and disposal networks

We consider a set V of n municipalities, which represent the nodes of two networks. The networks will be denoted by $N^{(p)} = (V; \mathbf{W}^{(p)})$ and $N^{(d)} = (V; \mathbf{W}^{(d)})$. For defining the weights, a similarity approach is followed. Specifically, as we will see in details below, we assume that the entity of the connections is high when the nodes are highly similar. The difference between the considered networks is based on the specific definition of the concept of similarity. In one case, two municipalities – i.e., nodes – are similar when they achieve similar percentages of sorted waste over total waste; in the other one, two municipalities are similar when they are geographically placed at a similar distance from the used waste processing plants.

2.2.1 Network $N^{(p)}$

We denote by $p_i \in [0,1]$ the share of separated waste collected by municipality i over the total amount of collected waste, for each $i \in V$.

We assume that two municipalities $i, j \in V$ have a strong connection when they show a similar behavior in sorting waste. Specifically, we define $\mathbf{W}^{(p)} = (w_{ij}^{(p)})_{i,j \in V}$, with

$$w_{ij}^{(p)} = \begin{cases} \frac{\min\{p_i, p_j\}}{\max\{p_i, p_j\}}, & \text{when } p_i + p_j > 0; \\ 0, & \text{when } p_i = p_j = 0. \end{cases} \tag{1}$$

Weights in (1) range in $[0,1]$. In particular, $w_{ij}^{(p)}$ is close to one when $p_i \sim p_j$, and it is null when p_i and/or p_j is null. Furthermore, in some sense, weights in (1) are built to assign stronger connections to nodes with higher percentages of sorted waste. To explain this statement, assume that $p^* > 0$ is such that $p_i = p_j - p^*$. Then (1) can be rewritten as follows:

$$w_{ij}^{(p)} = \frac{p_j - p^*}{p_j},$$

which is an increasing function of p_j. Substantially, weights are more sensitive to the distance between p_i and p_j as their values become smaller.

2.2.2 Network $N^{(d)}$

We proceed here as in the construction of $N^{(p)}$, with the remarkable distinction that we move from a different connection parameter.

We denote by $d_i \geq 0$ the distance measured in kilometers between the municipality and the waste processing plants (where waste disposal occurs). As we will point out in the Section 3, such a distance is a weighted mean of the distances between the municipality and the plant(s) it uses for treatment and disposal of its separated waste.

Also for this network, we assume strong connections in presence of similar distances from the plants used. Thus, in line with the definition of $\mathbf{W}^{(p)}$ in (1), we define the entries of $\mathbf{W}^{(d)}$ as

$$w_{ij}^{(d)} = \begin{cases} \frac{\min\{d_i,d_j\}}{\max\{d_i,d_j\}}, & \text{when } d_i + d_j > 0; \\ 0, & \text{when } d_i = d_j = 0. \end{cases} \tag{2}$$

Weights in (2) share the same features of the $w^{(p)}$'s: they are contained in $[0, 1]$, they are close to one when the involved d's have similar values, they are null in presence of at least one null distance d. Moreover – as for the case of the weights $w^{(p)}$'s, see Subsection 2.2.1 – a high value of $\max\{d_i, d_j\}$ is associated to a high value of the weight, once the distance $\max\{d_i, d_j\} - \min\{d_i, d_j\}$ is taken constant.

2.2.3 Complexity of $N^{(p)}$ and $N^{(d)}$

One of the most important elements used to estimate the complexity of a network is represented by its degree distribution, i.e. the distribution of the number of the connections of the single nodes. The most well-known example of complex networks – i.e., the scale-free networks (Barabási and Albert, 1999) are considered complex mostly because they show a very heterogenous degree distribution that responds to a power law. In order to capture the heterogeneity of the degree distribution of $N^{(p)}$ and $N^{(d)}$, we use the Shannon's Entropy measure in its normalized version (Shannon, 1951). It is worth noting that other measures of heterogenity like the Gini coefficient (Kunegis and Preusse, 2012), could be used to pursue such a scope. The entropy of the actual networks $N^{(p)}$ and $N^{(d)}$ is tested against a set of 100 random networks per actual network, with the same number of nodes and links. The concept of entropy introduced by Shannon refers to the average level of information inherent in a random variable's possible outcomes. The entropy equation for discrete probability distribution is:

$$H = -\sum_{i=1}^{n} p_i log_2(p_i) \tag{3}$$

and the normalized entropy:

$$H_n = -\frac{1}{log_2(n)} \sum_{i=1}^{n} p_i log_2(p_i) \tag{4}$$

where n is the number of degree values. For a vector $p_i = 1/n \, \forall \, i = 1, ..., n$, the Shannon entropy is maximized. Normalizing the entropy by $log(n)$ gives $H_n \in [0, 1]$. Therefore, a network with constant degree values – i.e., a regular network – would have null entropy, while a network with n different degree values would have unitary entropy. If we compute the normalized entropy of our networks, we obtain $H_n(N^{(p)}) = 0.92$ and $H_n(N^{(d)}) = 0.81$. If we respectively compare such values to two sets of randomized networks, one for each real network, we note that the actual entropy values are about 183 and 76 standard deviations away from the mean of the entropy distributions for random networks, being $\mu_H^p = 0.676$, $\sigma_H^p = 0.0013$ and $\mu_H^d = 0.695$, $\sigma_H^d = 0.0015$.

2.3 Community detection method

Community detection is the task of partitioning a network into groups of nodes that are densely connected inside their group – which is the community – and sparsely connected to the rest of the network (Newman, 2018). Being the definition of community qualitative, the problem of community detection is open to different mathematical interpretations (Newman, 2018; Peel et al., 2017). One of the most popular approaches to the task of community detection is represented by modularity maximization (Newman, 2006).

Modularity maximization is an optimization problem that has the modularity function Q as objective function and the network as input. The modularity Q quantifies the quality of a certain community partitioning by means of the following expression:

$$Q = \frac{1}{2m} \sum_{ij} (A_{ij} - \frac{k_i k_j}{2m})\, \delta(g_i, g_j) \in [-0.5, 1] \tag{5}$$

where g_i and g_j are two integers which label the community i and j, respectively, for $i, j = 1, \ldots, N$, $i \neq j$, and with $N \leq n$. The case $N = 1$ means that we have just one community containing all the nodes, while $N = n$ means that we have n communities, each of them with only one node. The Kronecker function $\delta(g_i, g_j)$ is one when $g_i = g_j$ and zero otherwise.

Given the definition of community – i.e., a group of nodes that are densely connected inside their group and sparsely connected to the rest of the network – the optimized value of modularity is considered to provide the most meaningful community partitioning – according to the prefixed criterion driving the construction of the adjacency matrix of the network. Indeed, such a value corresponds to a partitioning of the network in which the number of links among nodes belonging to the same community is substantially higher than the number of links among nodes belonging to different communities. Such an aspect is mathematically represented by the difference in Equation (5), that counts the actual number of links among nodes assigned to the same community versus its expected value.

Given a certain assignment of nodes into groups, expressed by the vector $\mathbf{g}$, the modularity value represents the deviation of the number of links among nodes of the same type – which is represented by $\sum_{ij} A_{ij}\delta(g_i, g_j)$ – from the expected number of links among such nodes, given their degree. Indeed, given two nodes with degree k_i and k_j respectively, the expected number of links between i and j is k_i times $\frac{k_j}{2m}$, that is, k_i times the probability of being connected to j. The modularity function is normalized to range between -0.5 and 1. It assumes low values when there are less links than expected among nodes in the same group, whereas it assumes high values in the opposite case. For instance, in Figure 1 we report different partitioning in communities and values of modularity for the same network. We observe that the highest value of modularity occurs when the assignment of nodes into communities well reflects the structure of the network.

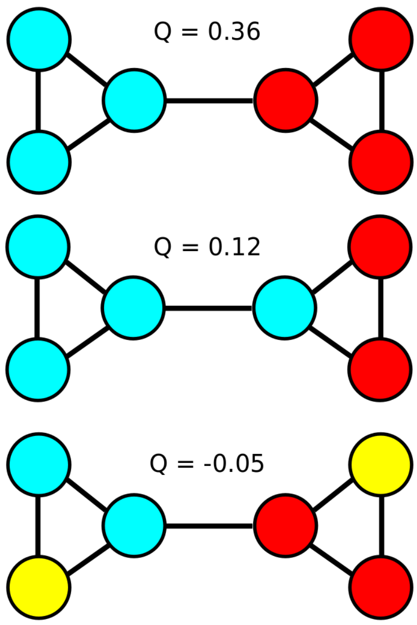

Figure 1: Three examples of community partitioning of the same network with six nodes and seven links. The values of modularity change in accordance with the quality of the partitioning. The Louvain algorithm returns the first community partitioning reported at the top of the figure.

The problem of maximizing modularity, being the problem of dividing the network into an arbitrary number of groups of arbitrary size, ranging from 1 to n, is a NP-hard problem (Brandes et al., 2008), and several heuristics of modularity maximization have been proposed in recent years. In this paper we will exploit a state-of-the-art community detection algorithm called the Louvain algorithm (Blondel et al., 2008). The algorithm follows an agglomerative greedy approach that optimizes modularity, firstly finding small agglomerates – i.e., communities – of nodes that provide the highest value of modularity; secondly, considering such agglomerates as single nodes in order to re-iterate the first step. In more detail, the algorithm is divided in two phases that are repeated iteratively. The first phase starts with assigning a different community to each node of the network. So, in this initial partition, there are as many communities as there are nodes. Then, for each node i, its neighbors are taken into account, together with the gain of modularity that would take place by removing i from its community, and by placing it in the community of one of its neighbors. The node i is then placed in the community for which the gain is maximum, but only if this gain is positive. If no positive gain is possible, i stays in its original community. This process is applied repeatedly and sequentially for all nodes, until no further improvement can be achieved and the first phase is then complete. The first phase of the Louvain algorithm stops when a local maxima of the modularity is attained, i.e., when no individual move can improve the modularity.

The second phase of the algorithm consists in building a new network whose nodes are the communities found during the first phase. To do so, the weights of the links between the new nodes are given by the sum of the weights of the links between nodes in the corresponding two communities. Links between nodes of the same community lead to self-loops for this community in the new network. Once this second phase is completed, it is then possible to reapply the first phase of the algorithm to the resulting weighted network in an iterative way.

The outcome of the employed community detection algorithm is a modularity value Q, a vector of integers reporting the assignment of nodes into communities g and a number of communities.

3 Waste management in Italy

In this section, we present the problem of MSW in Italy and the dataset used for the study.

3.1 The problem of municipal solid waste ~~in Italy~~

As in other European countries, waste management performance in Italy is strictly related to EU recycling targets (Greco et al., 2015). Over the last two decades, European Union (EU) Directives have set waste policies and targets to deal with waste issues in a coordinated way. Those regulations have been moving municipal waste management in Europe up the waste hierarchy – laid down by the Waste Framework Directive 2008/98/EC – which prioritises waste prevention, followed by preparing for reuse, recycling, and other recovery, thus leaving disposal as the least desirable option. Waste management in the EU has improved considerably in recent decades (Bourguignon, 2018). Furthermore, the EU is also making the requirements about separate waste collection more stringent, for instance, by specifying exemptions in further detail and requiring separate collection for textiles and hazardous waste from households by 2025.

The most relevant pieces of Italian legislation date back to the Legislative Decree no. 22 of 1997 – the so-called 'Ronchi Law', after the name of the Minister of Environment –, that aimed at introducing a number of remedies to salient environmental issues arising from waste management ~~in Italy~~. Those issues included a remarkable increase in the amount and variety of waste; growing demand for waste disposal; increasing risk of negative environmental, health and social impacts of waste management practices. The Italian Decree of 1997 followed a few European directives of 1991 and 1994, which provided frameworks for waste management in the EU (see the directives 91/156/CEE, 91/157/CEE, 91/689/CEE, and 94/62/CE). The Italian legislation promoted a model of aggregated waste management between several municipal administrations and a reduction of waste movement across Italian regions, according to principles of proximity and regional self-sufficiency in managing local waste. Therefore, regional governments hold the responsibility for drawing up waste management plans and strategies to promote waste reduction. Municipalities are included in so-called optimal territorial areas (ATO-Ambiti Territoriali Ottimali), approximately corresponding to areas of Italian provinces, to improve municipal waste management (Di Foggia and Beccarello, 2018).

The 'Ronchi Law' set chronological targets for separate waste collection, to be achieved by ATOs, as percentages of total municipal waste generation: 15% by 1999, 25% by 2001, and 35% by 2003. In 2006, the Legislative Decree no. 152 repealed the 'Ronchi Law', but retained its main provisions and set new targets for separate waste collection, i.e., 35% by 2006; 45% by 2008; 65% by 2012. To meet those targets, a system of incentives and sanctions was adopted, in order to reduce (increase) municipal waste tariffs where targets are (not) met (Greco et al., 2015; D'Amato et al., 2018). However, the deeply heterogeneous design of ATOs and their organizational differences have determined dissimilar efficiency standards in waste management across Italy (Agovino et al., 2016b; Di Foggia and Beccarello, 2018). In a recent empirical study using national data (Agovino et al., 2017), the authors state that separate waste collection increased from 7.2% in 1996 to 42.3% in 2013. This finding was significantly below the 65% target set by Italian laws for 2012. Moreover, Northern regions proved to be more reactive to waste management legislation than Central and especially Southern regions, and achieved higher separate waste collection rates (Agovino et al., 2017). Nevertheless, empirical analyses show also a convergence process in terms of separate waste collection rates across Northern, Central and Southern regions, that could result from the slowdown recorded in the separate waste collection process in Northern Italy (Agovino et al., 2018); see also (Agovino et al., 2016b).

The Italian ISPRA (Istituto Superiore per Protezione e Ricerca Ambientale, a national agency for environmental protection and research) reported that per capita annual generation of municipal waste declined, on average, from 550 to 505 kilograms between 2006 and 2012, while it has been floating around 490 kilograms afterwards. It noted that in 2017 waste generation declined notwithstanding increases in gross national product and household expenditure, whereas correlation among those socio-economic indicators were usually positive (see ISPRA (2018), ch. 2). Their report showed that the regions in Northern Italy generated a per capita amount of sorted waste higher than that of other Italian regions. Moreover, it increased from 266 to 333 Kilos per year in 2013-2017 in the North, while for Southern Italy the same quantity grew from 129 to 185. Furthermore, in 2013-2017 the percentage of sorted waste over total waste increased from 54.4 to 66.2 in the North, while it increased from 28.8 to 41.9 in the South. Figures for Central Italy were in between; for instance, the proportion of sorted waste increased from 36.4 in 2013 to 51.8 in 2017.

3.2 Data

The theoretical network models, as specified above, are implemented through an empirical study based on a high quality dataset referred to Italian municipalities. The dataset is available from Ministry of Economy and Finance (MEF) and collects data about 6605 municipalities, thus covering around 85 percent of the Italian municipalities – in 2016 Italy had 8100 municipalities – as those located in autonomous regions with special statute are not included (the Italian Constitution grants home rule to five regions, namely Valle d'Aosta, Friuli-Venezia Giulia, Sardegna, Sicilia, and Trentino-Alto Adige, allowing them different degrees of legislative, administrative and financial power). We use data on year 2016, which is the most recent data on municipal waste management in Italy available from the dataset. MEF has been improving its methodology to calculate so-called standard municipal expenditure needs for municipal services (SOSE, 2016) and has therefore produced a reliable dataset, which is an advantage of this work.

Indeed, waste management data are critical to creating appropriate policy and planning for the local context; however, solid waste data should usually be considered with a degree of caution because of inconsistencies in definitions, data collection methodologies, and availability (EEA, 2016; Simões and Marques, 2012; Kaza et al., 2018).

The dataset provided by MEF includes data on the following variables, about MSW management, for each municipality: the number of annual tonnes of solid waste generated excluding hazardous waste); the percentage of sorted waste over solid waste; the average distance in kilometers between the municipality centre and the waste treatment plants used by the local waste carriers – who collect municipal waste – weighted by the number of tonnes of treated waste.

Table 1 reports summary statistics that are useful in order to understand the general properties of the distributions that we take into account.

We first note that the distribution of Solid waste displays a strong heterogeneity with respect to the distributions of both Sorted waste and Distance. Such a difference is well represented by the difference between the mean and the median, that suggests the

	Solid waste (tons)	Sorted waste (%)	Distance (Km)
Min	17.49	0	1.1
Max	1689206	97.25	148.34
Mean (μ)	3916	56.11	31.74
Median	1044.45	60.88	27.31
Standard Deviation (σ)	25842.52	22.02	19.89
Standard Error	317.98	0.27	0.24
Excess kurtosis	2846.47	-0.35	3.25
Skewness	47.3	-0.66	1.57

Table 1: Summary statistics for the variables Solid waste, Sorted waste and Distance.

presence or large deviations in the right tail. This is also confirmed by the measures of excess kurtosis – i.e., the difference between the kurtosis of the variable distribution and that of Gaussian distribution – and skewness (see e.g. Ausloos and Cerqueti (2018)). The distributions of Sorted waste and Distance are more well-behaved resembling two Gaussian distributions with a slight skewness to the left in the former case and to the right in the latter.

MEF considers also other variables, which are not used to validate our theoretical network models – e.g., the type of plants, if any, built on the municipal land. Moreover, MEF uses a k-means cluster analysis to detect homogeneous groups of municipalities by looking at their geographic, social and economic characteristics (see SOSE (2016), Appendix D). According to their analysis, each municipality belongs to one of the 15 clusters identified by MEF.

4 Results of the complex network analysis

4.1 Sorted waste analysis – Network $N^{(p)}$

As described in Section 3.2, network $N^{(p)}$ is the one in which two municipalities have a strong connection $w_{ij}^{(p)}$ when they sort similar proportions of their waste. In order to study the network, first we compute all possible similarity scores among the $\binom{n}{2}$ couple of nodes, then we threshold the resulting network in a way such that only links displaying high similarity are kept. The reason behind thresholding low similarity values is twofold: the first reason is discarding connections that do not have a relevant similarity; the second reason is to exploit the full potential of the tools of network science that mostly require sparse networks.

The process of thresholding discards all the links with a similarity score below a threshold $t^{(p)}$ that we set at $t^{(p)} = \mu^{(p)} + \sigma^{(p)}$, where $\mu^{(p)}$ and $\sigma^{(p)}$ are the mean value and the standard deviation of the entries of $\mathbf{W}^{(p)}$, respectively. We consider only the largest connected component – i.e., the largest subgraph made up of interconnected nodes – of the resulting network, which has $n = 6549$ nodes, $m = 3738919$ links and a density of $\rho = \frac{2m}{n(n-1)} \sim 0.17$. The reason behind choosing the largest connected component is to filter out from the analysis isolate nodes, whose importance cannot be quantified by network-based measures. The communities, that are retrieved with the algorithm described in Section 2.3, are five and they are labeled from a to e. The number of nodes in each community is relatively homogeneous and around 1500 nodes

– i.e., municipalities – except for community a that displays a lower number of nodes. The number of nodes of the communities is 466, 1572, 1409, 1421 and 1681 for a, b, c, d and e, respectively. The retrieved communities are highly cohesive, as confirmed by their relatively high value of modularity $Q^{(p)} = 0.47$, and such a partition of the network can be considered of high quality also because it is associated to groups displaying very similar proportions of separated waste. In Figure 2 we observe how each community is associated to a specific range of waste sorting. In more detail, we observe different instances starting from municipalities with low proportions of separated waste – e.g., community a – to increasingly more virtuous municipalities – e.g., community e.

The obtained partition in communities can be also mapped over the Italian territory to show to which extent municipalities belonging to different communities are distributed across the country. Figure 3 reports the distribution of the different nodes over the Italian territory. We observe a relatively homogeneous distribution, except in a few cases. See, for instance, the community described in panel e of Figure 3. In this community we observe, firstly, the region Lombardia, where there is a high concentration of virtuous municipalities sorting a high proportion of their waste (see the deviation of the red color of Lombardia from the colors of the other regions); secondly, the regions Puglia and Molise, where we observe the opposite situation, with low concentration of virtuous municipalities.

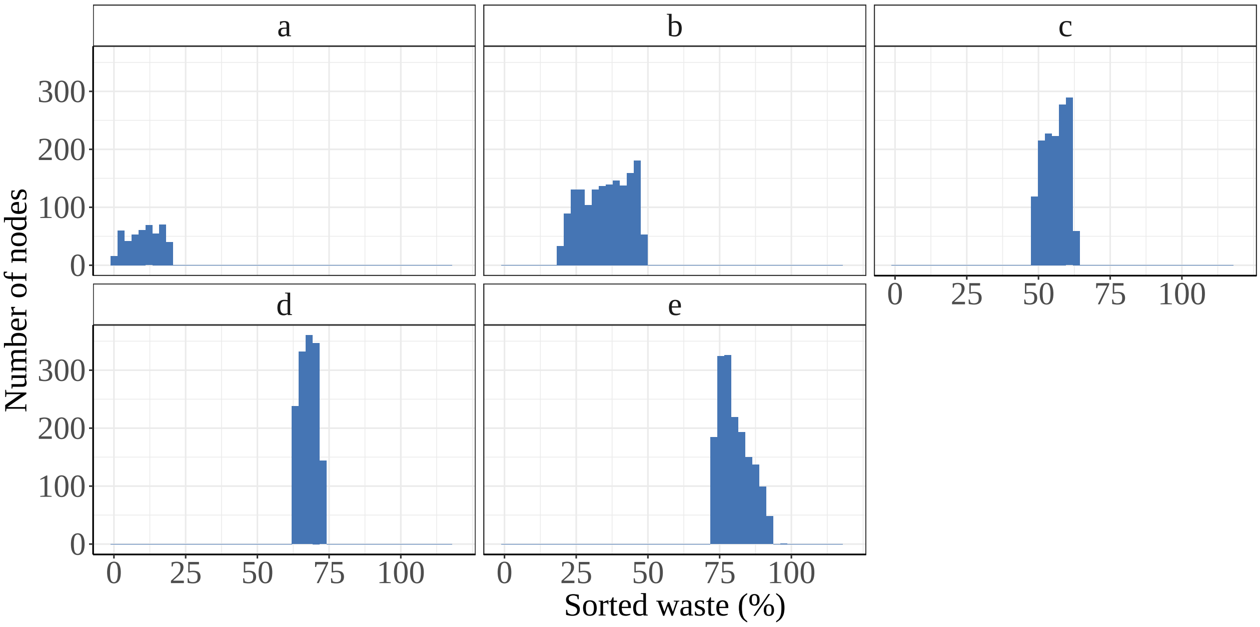

Figure 2: Number of nodes – i.e., municipalities – per communities, given their percentage of sorted waste – i.e., network $N^{(p)}$ –. We note that the partition in communities unveils different classes of municipalities based on their percentages of sorted waste. In more detail, the proportion of sorted waste spans approximately between $0 - 20\%$ for community a, $20 - 50\%$ for b, $50 - 65\%$ for c, $65 - 75\%$ for d and $75 - 100\%$ for e.

4.2 Distance analysis – Network $N^{(d)}$

In network $N^{(d)}$ two municipalities have a strong connection if they are located at a similar distance from the waste treatment and disposal plants that they use. Also in this case, we apply a thresholding procedure, with threshold $t^{(d)} = \mu^{(d)} + \sigma^{(d)}$, where $\mu^{(d)}$ and $\sigma^{(d)}$ are the mean value and the standard deviation of the entries of $\mathbf{W}^{(d)}$. The resulting network, of which we consider only the largest connected component as for the previous network, has $n = 6541$ nodes, $m = 2066843$ links and a density of $\rho = \frac{2m}{n(n-1)} \sim 0.1$. The communities, as retrieved with the algorithm described in Section 2.3, are three and they are labeled from a to c. The number of nodes of

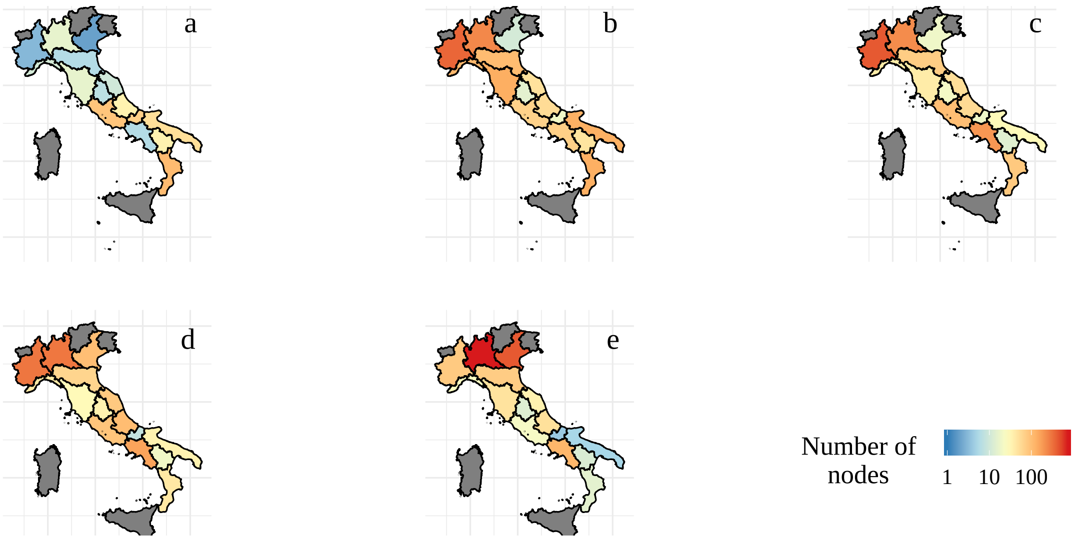

Figure 3: Distribution of the nodes – i.e., municipalities – belonging to different communities over the Italian territory for network $N^{(p)}$. Colors are scaled using a logarithmic function. The distribution of community members over the country is relatively homogeneous, although panels a and e show more heterogeneity across Italian regions.

the communities is 2860, 1672 and 2009 for a, b and c, respectively. The retrieved communities are relatively cohesive, as confirmed by their value of modularity $Q^{(d)}=$ 0.22. In Figure 4 we observe how each community is associated with different, yet similarly distributed, distances from plants. This partition in communities can be mapped over the Italian territory, as we did in the case of $N^{(p)}$, in order to evaluate to which extent municipalities belonging to different communities are distributed across the country. Figure 5 reports the distribution of the different nodes over the Italian territory. We observe a relatively heterogeneous distribution; for instance, community a includes several municipalities located in the region Lombardia, while a few Italian regions have no municipality in that community. Conversely, community c includes municipalities from all over Italy in similar proportions.

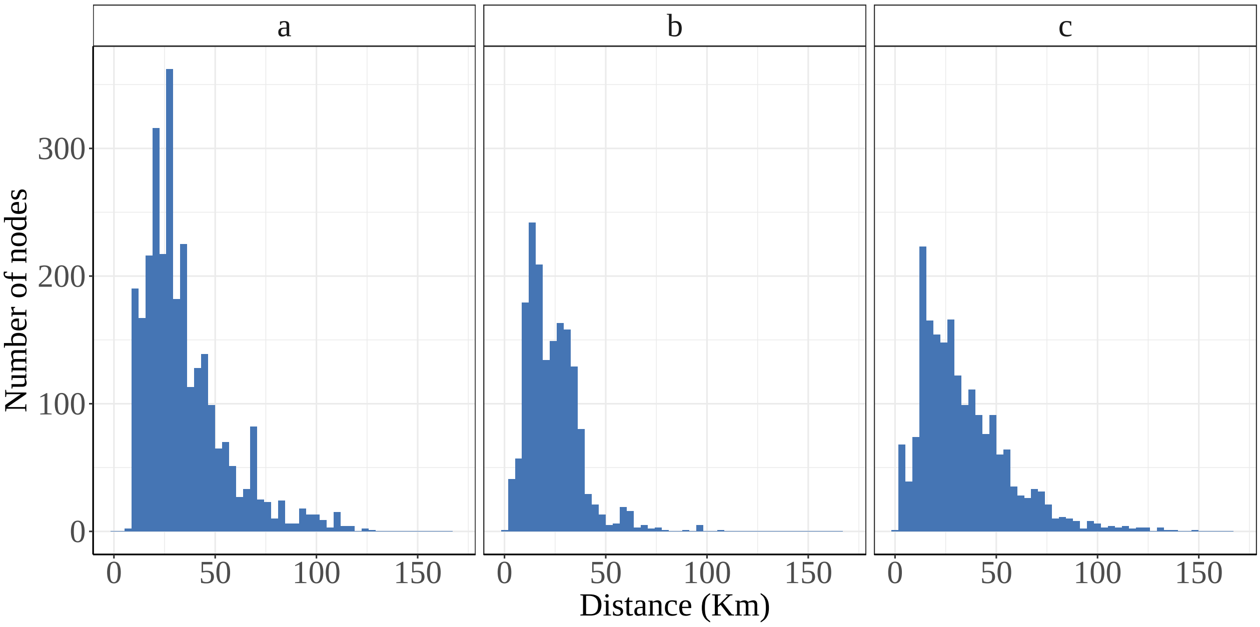

Figure 4: Number of nodes – i.e., municipalities – per community, given their distance from waste processing plants – i.e., for the network $N^{(d)}$ –. In any case, the three communities display similar distribution of such distances that recall a normal distribution with right skewness.

5 Discussion

Municipal governments are in charge of the provision of waste management services for their local communities, however, their choices on waste management have consequences that are seldom limited to their administrative borders, for instance because part of the waste generated by their local community is transferred and processed somewhere else. Moreover, local governments are in a position to set incentives for their citizens to improve waste management, e.g., by pushing better waste separation at household level, or sanctioning illegal waste disposal (D'Amato et al., 2018; Marques et al., 2018; Sastre et al., 2018). A number of studies have highlighted the complexity of waste management systems and have suggested the adoption of comprehensive ap-

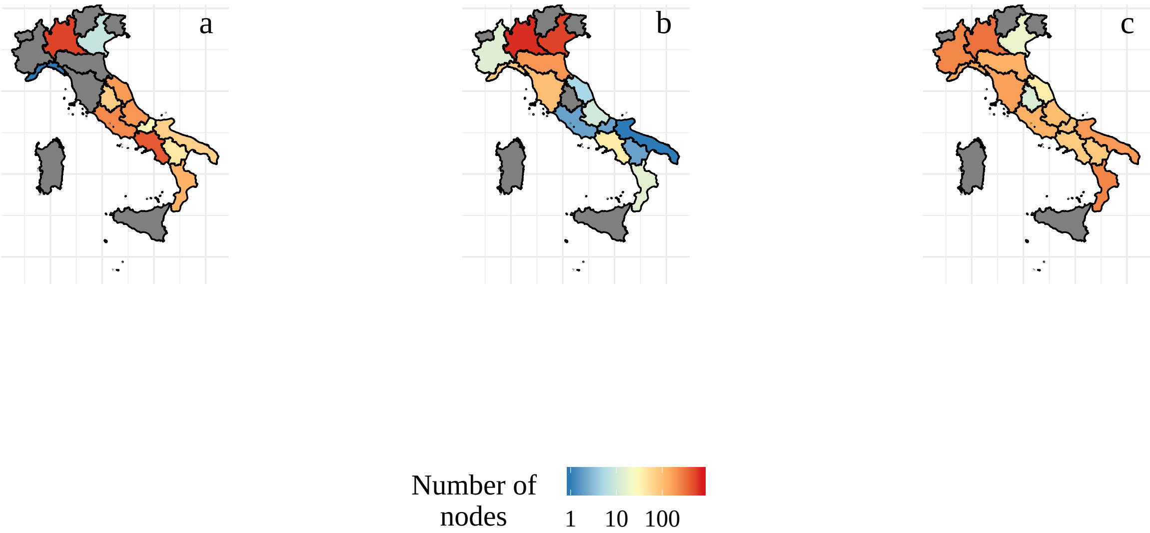

Figure 5: Distribution of the nodes – i.e., municipalities – belonging to different communities over the Italian territory for network $N^{(d)}$. Colors are scaled using a logarithmic function. The distribution of communities members over the country can be either strongly heterogeneous (see community a) or weakly heterogeneous (see community c).

proaches in the analysis of their effectiveness (Bertanza et al., 2018; Cervantes et al., 2018; Zeller et al., 2019). This study has proposed a novel approach, as we use the theory of complex networks and apply it to waste management. The results that we get for the two networks $N^{(p)}$ and $N^{(d)}$, using our data on municipal waste management in Italy, are quite different. Our analysis leads, on the one hand, to the detection of five communities of Italian municipalities according to the proportion of waste separation achieved in their local area; moreover, the quality of this partition is relatively good as $Q^{(p)} = 0.47$ in the case of network $N^{(p)}$. On the other hand, three is the number of communities detected in the case of network $N^{(d)}$, which considers the (weighted) distance between each municipality and the waste processing plants used by it; in addition, $Q^{(d)} = 0.22$, that is lower than the previous one, thus suggesting much weaker connections and similarities among Italian municipalities with regard to this feature of waste management practices in their territories.

Second, community detection in $N^{(p)}$ seems to be much more informative than in $N^{(d)}$. In fact, from the analysis carried out for network $N^{(p)}$, we get a partitioning of municipalities into five relatively homogeneous communities according to the percentage of waste selection in each community. Municipalities that fall in the same community share a very similar performance as regards their percentage of waste separation. Moreover, those in community a, i.e. the less "virtuous" ones in terms waste separation are a few. The number of municipalities falling in communities c, d, or e – where sorting is more than 50% – is about 4511, i.e. almost 70% of the Italian municipalities in the network, including around 25% of top performers, which separate more than 75% of their waste.

As the average amount of sorting across the whole network – i.e., by taking into account all the municipalities – is around 56% of waste, our analysis enables an improvement of the quality of the information we have about municipal waste management in Italy, by showing distributions of municipalities according to their specific performances. Furthermore, from a technical perspective, it can be argued that this partitioning into five communities is a better result than the k-means partition proposed by MEF, as our findings are more in line with the original structure of the data and no ex-ante decision on the number of communities is introduced in this complex network analysis.

A closer look at community e shows that the more virtuous Italian municipalities are located mostly in Lombardia. On the other hand, municipalities that do very poor waste separation – i.e., those in community a – are located mainly in Lazio and Mezzogiorno, where the virtuous ones are almost absent indeed. This suggests that there is an uneven distribution of the ability to achieve good performances in terms of waste separation across Italy. At the same time, however, our analysis offers additional information on the North vs. Center-South Italian divide in waste separation: for instance, Campania (in South Italy), has few nodes in panel a, and performs relatively well in the other panels of Figure 3. To increase the proportions of selected waste, it might help to investigate further the conditions which enable better performances in some municipalities than others, especially those located in similar or close geographic areas (Passarini et al., 2011; Sastre et al., 2018; Castillo-Giménez et al., 2019).

Turning to a discussion of results for network $N^{(d)}$, which considers distances from plants, we have already noted that those results provide much less clear-cut information. This is revealed, firstly, by the different values that measure the densities of the two resulting networks (around 0.1 of $N^{(d)}$, which is lower than 0.17 of $N^{(p)}$; see Section 4 above): in the case of $N^{(d)}$, the algorithm has detected communities using only 10% of all possible connections among nodes. Secondly, the shape of the three distributions of the municipalities in the three communities, as can be observed in Figure 4, is similar: those distributions are right-skewed ones, as their median value is lower than their mean value. Moreover, our network analysis detects three communities of municipalities that, according to the distance from plants, have a distribution also similar to the distribution that can be inferred from the summary statistics presented in Table 1.

The algorithm used in the analysis, in considering similarity scores among nodes, detects communities of municipalities where most of them use plants located within 50 kilometers, approximately; furthermore, results show that municipalities in community b concentrate below 40 kilometers, compared to the other two communities. Nevertheless, behaviour of Italian municipalities remains heterogeneous inside communities, as each community includes municipalities that use waste treatment plants located very far – i.e., above 100 kilometers away; see Figure 4. Heterogeneity inside each community in $N^{(d)}$ is especially apparent when the partitioning of this network is compared to the one resulting for $N^{(p)}$ (see Figure 2). We note here that, however, this result might be worth of consideration in policy design, as it suggests it might be less effective than waste selection targets in the improvement of waste management.

Further investigation of the results in Figure 4 reveals that the number of municipalities allocated to the tails of the three distributions differs across the three communities in $N^{(d)}$. Compared to communities b and c, community a has the distribution with more variety in its tail; conversely, the distribution for community b shows the least variety in its tail. This suggests that community b, which is the one where distances from plants concentrate below 40 kilometers, can be also considered more cohesive than communities a and c. Moreover, Figure 5 shows that the three communities are variously spread on the Italian territory. In fact, community a includes, above all, municipalities in Central and Southern Italy, with the notable exception of Lombardia; municipalities in community b can be located especially in Northern Italy; there is no geographic area prevailing in the case of community c, which is nevertheless of interest, as this adds another perspective to the usual Italian imbalance between North vs. Center-South.

Taking into consideration the three communities, the case of Lombardia emerges as an interesting one at regional level, as each community includes a high number of nodes: although geographically close to each other, the community detection method splits those regional municipalities into three dense groups according to distance from waste treatment plants. This suggests that more fine-grained analyses into local practices might provide further knowledge see (Oppio and Corsi, 2017; Passarini et al., 2011), with regard to Lombardia and Emilia Romagna, respectively).

In order to test the meaningfulness of a network approach we compare our results to those obtained using a different clustering approach that is the k-means method (Kaufman and Rousseeuw, 2009). It is worth reminding that the procedure of community detection on a network is just another type of cluster analysis performed under the assumption that data points – nodes, in our case – are interconnected. Therefore, from a purely technical point of view, the network approach is a type of cluster analysis that may provide a different viewpoint on the problem. Such a different view point is given by the construction of a network structure using the initial data.

We implemented two instances of the univariate k-means clustering considering the variables Sorted waste p and Distance d separately, in accordance to the fact that we built two networks $N^{(p)}$ and $N^{(d)}$. The main issue of certain clustering methods – including, among them, also the k-means – is deciding how many clusters should be extracted. A handy way to solve such a problem consists in finding a function that determines the quality of the clustering output. In line with the literature of k-means clustering, we chose to use the Average Silhouette (AS) function as a quality function for the chosen number of clusters. High values of AS indicate the presence of an explanatory number of clusters and consequently the best partition is that showing the highest AS. For both our variables, we find that the optimal number of clusters is $k = 2$. Figure 6 displays the AS function for different values of k in the left panel and the partitioning obtained for $k = 2$ in the right one.

	Cluster 1	Cluster 2
μ_p	69.1	29.5
σ_p	10.7	13.8
μ_d	62.0	18.3
σ_d	23.4	9.48

Table 2: Results of the k-means clustering with $k = 2$. The values of average and the standard deviation are indicated as μ_p and σ_p in the case of Sorted Waste and as μ_d and σ_d in the case of Distance.

The AS suggests to divide the data into two components for each variable and by computing the average sorted waste and distance for both clusters we find the values displayed in Table 2. The values reported in the Table suggest that the algorithm is

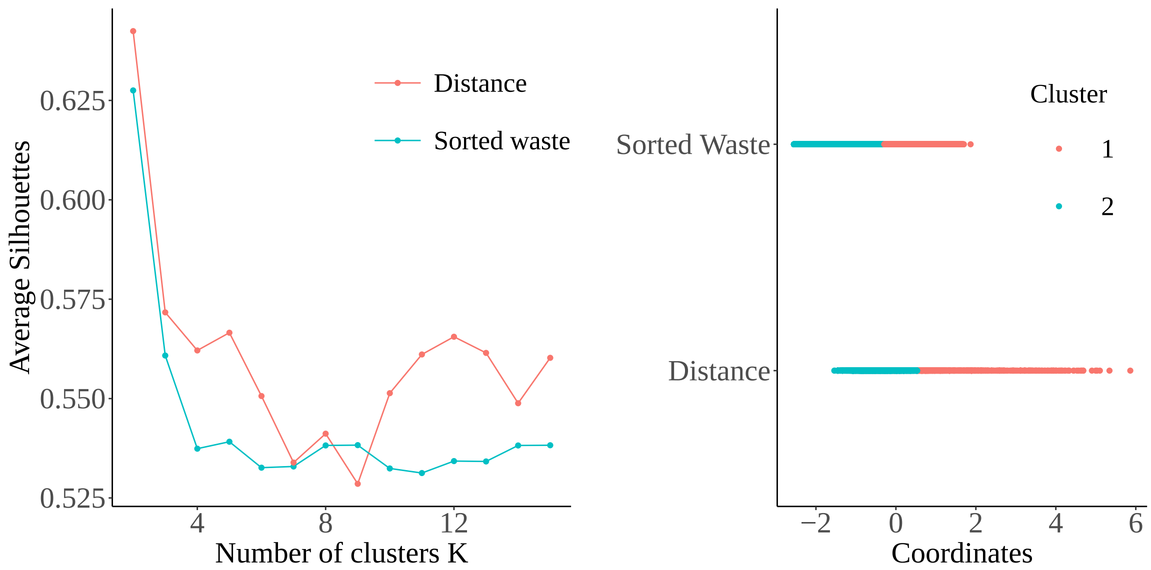

Figure 6: Sorted waste: 4436 points – i.e., municipalities – belonging to cluster 1 and 2169 points belonging to cluster 2. Distance: 1428 points – i.e., municipalities – belonging to cluster 1 and 5177 points belonging to cluster 2. It is worth to note that the span of the x-axis does not imply a higher number of data points. It is also worth noting that the dimension of the two variable is rescaled in order to have $\mu = 0$ and $\sigma = 1$ in accordance with the good practises of the k-means method.

differentiating high and low values in a somewhat dichotomous way. In comparison to the results provided by the community detection algorithm – i.e., of the network-based cluster analysis – the results deriving from the k-means look quite coarse-grained.

As a further test, we compare the results of the community detection algorithm with those of the k-means clustering by implementing the latter method with $k = 5$ clusters in the case of sorted waste and $k = 3$ clusters in the case of distance. In other words, we compare the results of the two clustering methods setting the number of clusters for the k-means method equal to the number of communities retrieved by the community detection algorithm. The measure used to compare the two clustering methods is the

Rand Index (Rand, 1971), $RI \in [0, 1]$, that counts the frequency of occurrence of agreements over the total pairs of elements. Values of RI close to 1 indicate high agreement between the two clustering results while values of RI close to 0 indicate low agreement. In the case of sorted waste we obtain $RI^{(p)} = 0.88$ indicating a high agreement while in the case of distance we obtain $RI^{(d)} = 0.51$ indicating a substantially lower agreement. Overall, despite some evident overlap between the clustering methods the results could be useful for at least two purposes that are: *i*) cross-validating the results of a certain clustering algorithm; *ii*) exploiting the differences between the results to obtain potentially novel insights about the considered system. More in general, exploiting networked data and data-driven approaches could be useful in a wide range of situations characterized by sudden changes and variations in the structure of interconnections and for implementing scenario analysis as shown, for instance, in applications related to finance (Gale and Kariv, 2007) and other socio-economic systems (Bonaccorsi et al., 2020).

This study offers two main limitations. First, empirical results are valid only for the Italian case and for 2016, which is the considered year. Second, the proposed network models describe the cases of connections among municipalities driven by the distance from the waste processing plants and the percentage of sorted waste. However, the analysis maintains a high level of generality, and the employed methodological instruments can be applied to empirical data taken from any type of regional reality. Furthermore, the structural conceptualization of the complex network models allows to adapt the theoretical framework to explorations of other features of MSW management beside those two considered here.

6 Concluding remarks

In this article, we have conceptualized and analyzed two networks, with respect to two different features of MSW management – namely, the proportion of sorted waste over total waste, and the distance between a municipality and the waste processing plants that it uses to dispose of its MSW. Our network-based methodology offers an original perspective in the support of bottom-up decisions on waste management, and it is driven by data. Therefore, we have also proposed its application to the case of Italy, using a high quality and fresh dataset for 2016, including all Italian municipalities with the exception of those located in autonomous regions. Elaborating this data by means of an algorithm, our two network models (one for each feature of MSW management) have detected five communities of municipalities in the network with waste separation, and three communities in the network with distance between municipalities and waste processing plants. With regard to other studies of waste management practices in Italy, our results offer a less fragmented picture. Furthermore, our work is a contribution to recent analyses that look at proximity effects on waste management behavior (Agovino et al., 2016a; Oppio and Corsi, 2017) and we do this by a network approach, which is naturally suited for this purpose. Our results are enriched by graphical presentations of the regional distribution of all Italian municipalities within each community, that provide further insights for waste management in Italy, considering regional governments' responsibilities in this country. As discussed above, our data-driven community detection method adds information to the well-known North vs Center-South imbalance, and may suggest changes in regional regulations and definition of so-called optimal areas for waste management. In this perspective, our study may also contribute to meta-analyses of waste management, especially in the evaluation of converging processes towards desirable practices or targets set by policy makers at national or international level (see Crociata et al. (2016); Castillo-Giménez et al. (2019); Sastre et al. (2018)). Many empirical studies consider waste separation. However, optimal reduction of the environmental impact of waste requires to account for distance travelled by vehicles used to transport it. Relatedly, decisions on placement and capacity of waste plants are strategic ones that involve relevant investment (see Kuudela et al. (2019); Juul et al. (2013); Soltani et al. (2015)). Our distance-based network analysis provides decision-making support and additional information for further actions, building on the heterogeneity observed in the three communities (recall the tails in the distributions in Figure 4): municipal behavior dissimilar from that prevailing inside each community may be due to critical saturation or absence of close-by MSW plants, which, in turn, may derive from not-in-my-backyard obstacles, or, more generally, from poor levels of environmental pro-sociality and crime (see Agovino et al. (2016a); D'Amato et al. (2018)). Furthermore, the complex network methodology enables to calculate an indicator (Q) of the quality of the results obtained. Our application to Italy shows that communities detected in the network that considers the proportions of separated waste are more cohesive than those in the other network. This result is worth of consideration in policy making (a process that is increasingly supported by intensive use of data including networks): it suggests, with regard to the Italian case, that an effort aimed at increasing waste selection can be more effective than an effort aimed at reducing municipal distance from waste plants (which is actually harder). At the same time, community detection may play a very important role with regard to waste selection targets: while such targets are usually set by exogenous regulations, the five cohesive communities that were detected are bottom-up aggregations of municipalities; these municipalities implement waste separation according to five clear-cut percentage intervals that result from data on local behavior (see communities in Figure 2). This may suggest, on the one hand, data-driven reconsideration of waste separation targets, and, on the other hand, further investigation of specific characteristics of MSW management in municipalities around interval borders. For instance, one might find existence of scale economies favoring efficiency of waste management companies in few circumstances only, whereas calling for subsidies in others (see Bartolacci et al. (2019); Passarini et al. (2011)).

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