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CIRCTER – Circular Economy and Territorial Consequences

Applied Research

Final Report

Annex 2

Material and waste patterns and flows in Europe:

Data regionalization

Version 09/05/2019

Final Report

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Abbreviations

B2B	business-to-business
B2C	Business to Consumer
C2C	Consumer to Consumer
CBM	Circular Business Model
CDC	Caisse des dépôts et consignations
CE	Circular Economy
CEAP	Circular Economy Action Plan
CER	European Remanufacturing Council
CLD	Causal Loop Diagram
DE	Domestic Extraction
DMC	Domestic Material Consumption
DMI	Direct Material Input
EC	European Commission
EEA	European Environmental Agency
EMAS	European Monitoring and Audit Scheme
EMF	Ellen MacArthur Foundation
EPR	Extended Producer Responsibility
ERDF	European Regional Development Fund
ESPON	European Territorial Observatory Network
EU	European Union
GDP	Gross Domestic Product
GPP	Green Public Procurement
GWR	Geographically Weighted Regression
JRC	Joint Research Centre
IS	Industrial Symbiosis
LMM	Last Minute Market
MBT	Mechanical-Biological Treatment
MFA	Material Flow Analysis
MS	Member States
MSW	Municipal Solid Waste
NACE	Nomenclature of Economic Activities
NUTS	Nomenclature of Territorial Units for Statistics
OLS	Ordinary Least Squares/Linear Regression
OVAM	Public Waste Agency of Flanders
P2B	Peer-to-business
P2P	Peer-to-peer
PPP	Purchasing Power Parity
RMC	Raw Material Consumption
RMI	Raw Material Input
ResCoM	Resource Conservative Manufacturing
SME	Small and Medium Enterprises
RIS3	Regional Innovation Strategies for Smart Specialisation
ToR	Terms of Reference
WEEE	Waste from Electrical and Electronic Equipment

1 Datasets and indicators that have been collected or regionalized in CIRCTER

Given the novelty of the circular economy (CE) approach, there are not generally accepted set of indicators for measuring the progress toward closed-lopp production-consumption systems. Only recently, the European Commission published a first attempt to provide a Monitoring Framework for a Circular Economy (COM(2018) 29 final) wherein they proposed a selected set of indicators (Figure 1-1).

Figure 1-1: Set of indicators provided by the EC

Production and Consumption

- EU self-sufficiency for raw materials (EU figures only)
- Generation of municipal waste per capita
- Generation of waste excluding major mineral wastes per GDP unit
- Generation of waste excluding major mineral wastes per domestic material consumption

Waste Management

- Recycling rate of municipal waste
- Recycling rate of all waste excluding major mineral waste
- Recycling rate of packaging waste by type of packaging
  - Plastic
  - Wood
- Recycling rate of e-waste (low data coverage)
- Recycling of bio-waste (composted/digested municipal waste (in mass unit) over the total population (in number)
- Recovery rate of construction and demolition mineral waste (data for 2010 only)

Secondary raw materials

- Contribution of recycled materials to raw materials demand- End-of-life recycling input rates (data for 2016 only)
- Circular material use rate (data for 2010 only)
- Trade in recyclable raw materials (Imports from EU, import from non-EU, export…)

Competitiveness and innovation

- Private investments, jobs and gross value added related to circular economy sectors
- Patents related to recycling and secondary raw materials

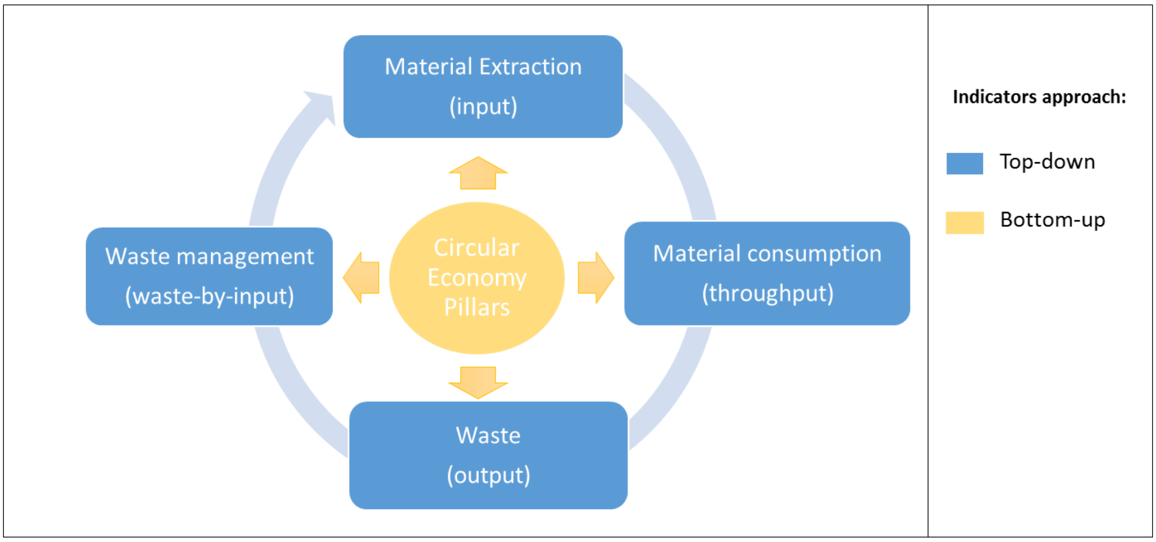
Source: own elaboration based on (European Commission, 2018)

After a detailed review of EC's indicators, the CIRCTER team came up with a slightly different selection which, to some extent, we believe better address the analysis of the temporal evolution toward a circular economy at aggregated economic and territorial levels. In fact, due to the highly aggregated level of EC indicators (i.e. national and European level) and the limited temporal availability (i.e. they mostly start from 2010), it is likely that historical regional patterns will go unobserved.

The project made a comprehensive indicators selection by integrating two different and complementary approaches: top-down approach which analyses material and waste patterns from indirect and aggregated data; and bottom-up approach which relies on the collection of direct evidence from CE pillars. While the first presents a kind of state-of-affairs of regional waste and material trends, the second focuses on the enablers and conditions which could potentially move forward the CE transition.

The selection of top-down indicators is based on a product life-cycle perspective, and as such it covers all relevant steps of product's life – extraction, production-consumption, waste generation – plus the last piece coming from the circularity paradigm, namely waste as a resource. Figure 1-2 resumes the CIRCTER indicators approach, while following tables present selected top-down indicators for each category; namely Table 1-1 refers to material consumption indicators, Table 1-2 to material extraction indicators, while Table 1-3 and Table 1-4 show indicators on waste generation and municipal waste treatment respectively.

Figure 1-2: CIRCTER's approach to CE indicators selection



Source: own elaboration

Table 1-1: Material consumption flows

Indicator	Eurostat coding	Subcategories	Description
Domestic Material Consumption	Env_ac_mfa	Biomass + Fossil fuels + metal ores + construction minerals	It covers the total amount of materials directly used by an economy, defined as the annual mass of raw materials extracted from the domestic territory, plus all physical imports minus all physical exports.
Biomass	Env_ac_mfa – MF1	Food + Feed + Animals + Wood +other biomass	It covers the total amount of biomass directly used by an economy, including: (1) Food: all potentially edible biomass from cropland plus traded food products; (2) Feed: all biomass from grassland, by-products and crops exclusively used for feeding livestock plus traded fodder; (3) Animals: all caught "wild" animals (in particular fish catch) and all traded livestock and animal products, including fish; (4) Wood: harvested wood and traded wood-based products including paper, furniture, etc.; (5) Other biomass: fibres

			and highly manufactured traded products predominantly from biomass.
Metal Ores	Env_ac_mfa – MF2	Industrial minerals + Ores	It covers the total amount of metal ores and industrial minerals actually consumed by an economy, namely: (1) Industrial minerals: all types of metallic ores and metal-based products; (2) Ores: all non-metallic minerals used predominantly for industrial processes (excluding fossil fuels).
Non-metallic minerals	Env_ac_mfa – MF3	Construction minerals	It covers the total amount of non-metallic minerals (excluding fossil fuels) actually consumed by an economy; mostly composed by construction materials.

Source: own elaboration

Table 1-2: Material extraction flows

Indicator	Eurostat coding	Subcategories	Description
Domestic Extraction (DE)	Env_ac_ mfa – DE	Biomass + Fossil fuels + metal ores + construction minerals	It covers the annual amount of raw material (except for water and air) extracted from the natural environment to be used as input in the economy

Source: own elaboration

Table 1-3: Waste categories

Indicator	Eurostat coding	Subcategories	Description
Total waste1 **generation, excluding major mineral wastes**	env_wasgen: TOT_X_MIN	Total waste generated by households and the following economic activities (NACE) and households: Agriculture, forestry and fishing; mining and quarrying; manufacturing; energy; waste/water; construction; other sectors; excluding mineral waste	It covers the waste produced locally, including the waste produced by waste treatment activities (sorting, composting, incineration), and covering both hazardous and non-hazardous waste; This category does not cover mineral wastes or soil[2].

1 Directive 2008/98/EC Article 3(1) defines waste as ‘any substance or object which the holder discards or intends or is required to discard’.

2 Over 90% of these come from the mining and construction sectors, which are subject to considerable fluctuation over time. By excluding major mineral wastes, this indicator reflects general waste trends more accurately than statistics on total waste generated. The indicator is one of the EU sustainable development indicators. It is also a resource efficiency indicator.

Total Waste generated by Households	env_wasgen: EP_HH	Total waste generated by households	It covers the waste produced locally by households' activities, including both hazardous and non-hazardous waste; This category also includes mineral wastes or soil.
Total Waste generated by agriculture, forestry and fishing	env_wasgen: A	Total waste generated by agriculture, forestry and fishing (NACE A)	It covers the waste produced locally by NACE A activities, including the waste produced by waste treatment activities (sorting, composting, incineration), and covering both hazardous and non-hazardous waste; This category also includes mineral wastes or soil.
Total Waste generated by mining and quarrying	env_wasgen: B	Total waste generated by mining and quarrying (NACE B)	It covers the waste produced locally by NACE B activities, including the waste produced by waste treatment activities (sorting, composting, incineration), and covering both hazardous and non-hazardous waste; This category also includes mineral wastes or soil.
Total Waste generated by manufacturing	env_wasgen: C	Total waste generated by manufacturing (NACE C)	It covers the waste produced locally by NACE C activities, including the waste produced by waste treatment activities (sorting, composting, incineration), and covering both hazardous and non-hazardous waste; This category also includes mineral wastes or soil.
Construction and demolition waste generated by construction	env_wasgen: W12-13 by F	Demolition and construction waste generated by the construction sector (NACE F)	It covers the subtotal of mineral and solidified wastes categories, namely: W121 + W12B + W124 + W126 + W127 + W128_13 generated by construction economic activity (NACE F).
Food Waste	env_wasgen: W091+ W092+ W101* 0.253	Animal and mixed food waste; Vegetal waste; Household and similar waste (25%);	It covers the food waste generated by all NACE activities plus households: this includes the subtotal of animal and vegetal wastes generated by economic activities and a 25% of total household waste (it is assumed that only 25% of household waste is food waste)[3].
Plastic Waste	env_wasgen: W074	Plastic waste	It covers the total plastic waste generated by all NACE activities plus households.
Electric and Electronical Waste (WEEE)	env_waselee	Electrical and electronic equipment waste	It covers the total electrical and electronic equipment waste that is collected4 locally

Source: own elaboration

Table 1-4: Municipal waste generation and treatment

Indicator	Eurostat coding	Subcategories	Description
Municipal5 **waste generation**	env_rwas_gen: GEN	Municipal waste generated	It covers the total municipal waste generated

[3] Following the recommendation on food waste allocation by the Platform Food Losses and Food Waste; Subgroup on food waste measurement. See: https://ec.europa.eu/food/sites/food/files/safety/docs/fw_eu-platform_20170925_sub-fwm_pres-03.pdf

[4] Local recollection does not necessarily entail local treatment, nor that a significant recovery of residual materials is performed at all.

5 The term 'municipal' is used in different ways across countries reflecting different waste management practices. The bulk of the waste stream originates from households, similar wastes from sources such as commerce, offices and public institutions are also included. It excludes waste from municipal sewage network and treatment, and municipal construction and demolition waste.

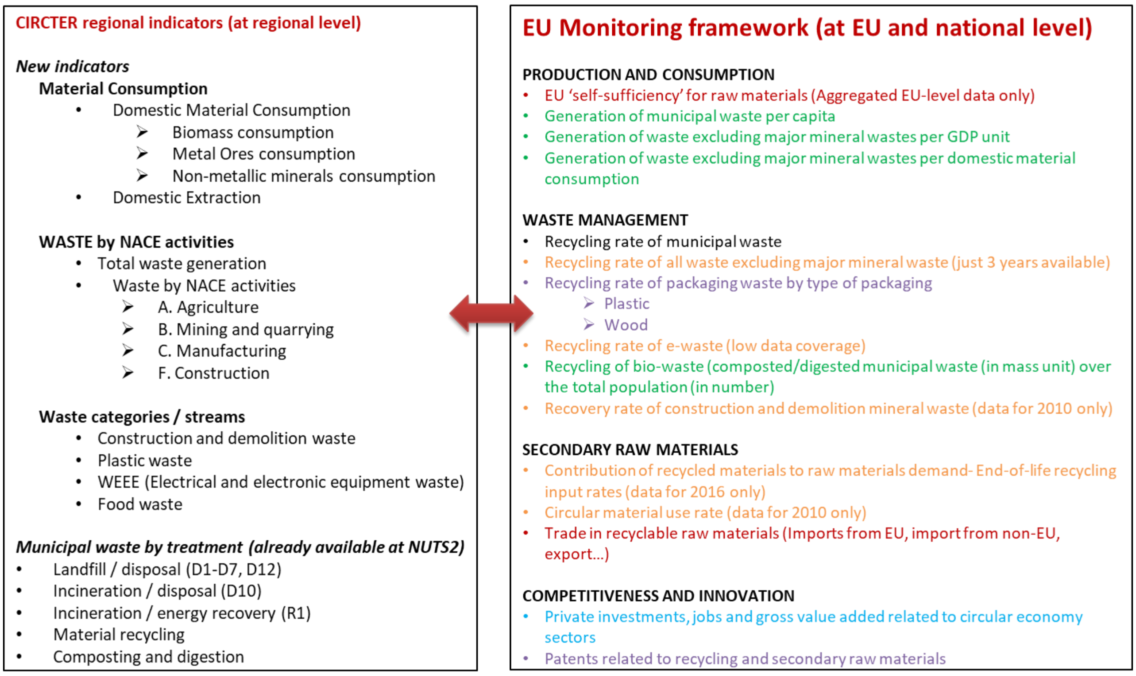
Municipal waste treatment by landfilling	env_rwas_gen: DSP_L	Landfill / Disposal (D1 - D7, D12)	It covers the total municipal waste that is collected locally and sent to landfill; it includes specially engineered landfills and temporary storage of over one year on permanent sites. The definition covers both landfill in internal sites (i.e. where a generator of waste is carrying out its own waste disposal at the place of generation) and in external sites.
Municipal waste treatment by incineration (without energy recovery)	env_rwas_gen: INC	Incineration / Disposal (D10)	It covers the total municipal waste that is collected locally and sent to incineration plants (without energy recovery)
Municipal waste treatment by incineration (with energy recovery)	env_rwas_gen: RCV_E	Incineration / Energy recovery (R1)	It covers the total municipal waste that is collected locally and sent to incineration plants that fulfils the energy efficiency criteria laid down in the Waste Framework Directive (2008/98/EC), Annex II (recovery operation R1)
Municipal waste treatment by recycling	env_rwas_gen: RCY_M	Material Recycling	It covers the total municipal waste that is collected locally and sent to recycling facilities. It includes the reprocessing of organic material but does not include energy recovery and the reprocessing into materials that are to be used as fuels or for backfilling operations
Municipal waste treatment by composting	env_rwas_gen: RCY_OC	Composting and digestion	It covers the total municipal waste that is collected locally and sent to composting and digestion facilities

Source: own elaboration

2 Comparison between the indicators used in CIRCTER and those proposed by the EC Monitoring Framework

Figure 2-1 lists the indicators used in the CIRCTER project, in comparison to those proposed by the EU Monitoring Framework (COM(2018) 29 final).

Figure 2-1: Comparison between the EU Circular Economy Monitoring Framework and CIRCTER indicators



Source: own elaboration

The colour coding on the right side of Figure 2-1 illustrates the situation regarding the specific indicators proposed by the Eurostat Circular Economy Monitoring Framework in relation to those available from the regionalisation process in the CIRCTER project:

- Indicators highlighted in **green** colour are those covered both in CIRCTER (at regional level) and the Eurostat (at national level), using exactly the same definitions.
- Indicators highlighted in **cyan** colour are those covered both in CIRCTER (at regional level) and the Eurostat (at national level), although using different definitions and calculation methodologies.
- Indicators highlighted in **red** colour indicate that indicators are produced at aggregated EU level.
- Indicators highlighted in **orange** colour indicate that Eurostat data is delivered at national level (for some countries) and for one year only.

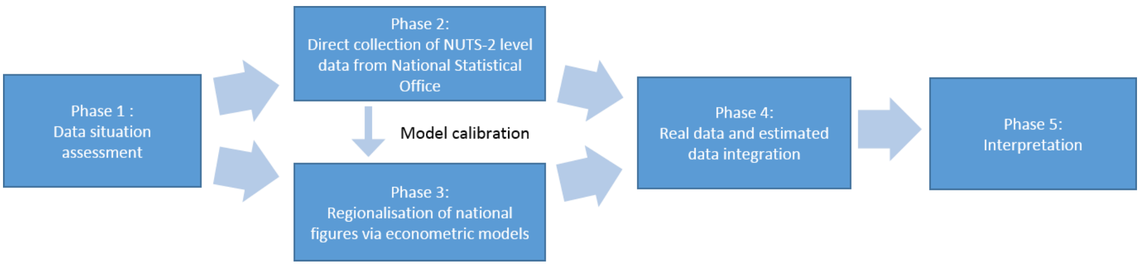
- Indicators highlighted in **purple** colour are those produced by Eurostat based on a number of modelling assumptions. In theory, these could be replicated in CIRCTER.

It should be considered that the CIRCTER project has run in parallel to the work carried out by Eurostat and the EEA in designing the EU Monitoring Framework (EU, 2018). Most of the indicators proposed by the EU Framework were either not defined or not available by the time when the CIRCTER indicators were defined and computed, back in Spring 2018.

3 Overview of datasets construction process

Figure 3-1 shows the main phases the project went through to build the regional material and waste dataset. An initial extensive literature review has been performed in order to understand the-state-of-art of data availability in EU, and consequently decide which indicators to consider depending on geographical and temporal availability. Next steps concerned direct collection of regional data from National Statistical Offices and, together, the regionalisation of national figures for those datasets which direct collection was not possible. Finally, real and estimated data have been integrated in a final database.

Figure 3-1: Overview of datasets construction steps



Source: own elaboration

Each phase will be described in detail in the next chapters.

3.1 Phase 1: Assessment of the data situation

We have performed an extensive review of the data situation across the ESPON Space and the EU Candidate Countries (i.e. The former Yugoslav Republic of Macedonia, Turkey, Montenegro) and/or the other countries of the Western Balkans (i.e. Bosnia and Herzegovina, Serbia, Albania, Kosovo under UN Security Council Resolution 1244). This review relied on the main international databases providing harmonised figures at the regional level (i.e. Eurostat, OECD and the ESPON Database), as well as the National Statistical offices of all countries participating in the ESPON Programme, plus those including in the above list of EU Candidate Countries and/or the Western Balkans.

Overall, our review shows a rather low availability of material and waste data at regional (NUTS-2) and lower levels. Furthermore, the datasets currently available seem to have low consistency in terms of definitions and temporal and spatial coverage. Information on material consumption is virtually absent at regional level. Waste statistics are also rather scarce, while waste classifications in some cases differ greatly among countries6.

3.2 Phase 2: Direct collection of NUTS-2 level data

During Autumn 2017 we performed a comprehensive search of regional data available from the different Statistical Offices of the ESPON area. Regretfully, this search was unsuccessful. Hence, a specific data request was sent to the ESPON and candidate countries. On top of avoiding imputed data whenever possible, these data could also be used to validate our imputation models. The request was sent between April and May 2018. In the case of ESPON countries, the request was channelled through the ESPON EGTC. For the seven candidate countries, the request was directly performed by the project coordinator. The initial appeal was followed by several supplementary exchanges until October 2018 when the data collection process was declared closed.

A total of 13 countries provided information, ranging from actual datasets, to scientific papers, reports and other background documentation. Most of the datasets that were delivered were produced under similar definitions and criteria as those developed by Eurostat for the national classifications. Still, some of the datasets differed to the official Eurostat indicators, making impossible to use the data in this context.

Virtually all the data that has been provided so far refer to waste classifications. In total, we have received tabular data from 11 countries. Of these, we could use the data for 7 of them, namely Belgium (Flanders), Germany, Latvia, the former Yugoslav Republic of Macedonia, Slovakia, and Slovenia and Romania.

Only Germany and the former Yugoslav Republic of Macedonia provided usable data on material flows at regional level. The latter country provided the data at the national level, which in this case is equivalent to the NUTS-2 level. In the German case the data were provided at NUTS-1 level, which implied that we had to aggregate the imputed values at this same level to be able to use the data for model validation.

[6] See for instance “Country specific notes on municipal waste data” (European Commission, 2010)

Table 3-1: Countries delivering data or information following to our request

Countries that provided data	Data provided	Data used in CIRCTER (Y/N)	Notes
Austria	Regional dataset on generation and treatment of Municipal waste at NUTS-2 level	N	The data provided were already available from Eurostat
Belgium	Report including data on material intensity and Waste data by NACE activities and waste categories at NUTS-2 level	Y	Data were provided for Flanders only. Some categories have been computed manually according to the data description. However, since provided data were based on estimations they have been used only for model validation
Croatia	General information and links to online services providing statistical data on waste management at sub-national level	N	The website of the Croatian National Statistical System does not include an English version. We used Google Translate service but failed to find the necessary datasets.
Germany	Material flow data by NUTS-1	Y	Data were provided at NUTS-1. The data were used for model validation by aggregating the predicted NUTS-2 values for material flows up to the NUTS-1 level.
Hungary	Waste data by NACE activities and waste categories at NUTS-2 level	N	Data are calculated according to a different classification criteria and methodological choices differing from those adopted by Eurostat. For example, construction and demolition waste statistics are not registered at the place where waste it is generated, but where the manager of that waste is officially registered (sometimes it can be in a different region).
Latvia	Waste data by NACE activities and waste categories at NUTS-0 level	Y	The data have been mainstreamed to our model since in Latvia NUTS-0 equals NUTS-2
Former Yugoslav Republic of Macedonia	Material flow data and Waste data by NACE activities at NUTS-0	Y	Data refer to 2016 only. Methodological information was not provided. We assume that the definitions are aligned to those provided by Eurostat
Romania	Waste data by NACE activities and waste categories at NUTS-2 level	Y	Data refers to 2008 and 2016
Slovenia	Waste data by NACE activities and waste categories at NUTS-2 level	Y	Data refer to 2005 and 2015. Some waste categories are missing for 2005

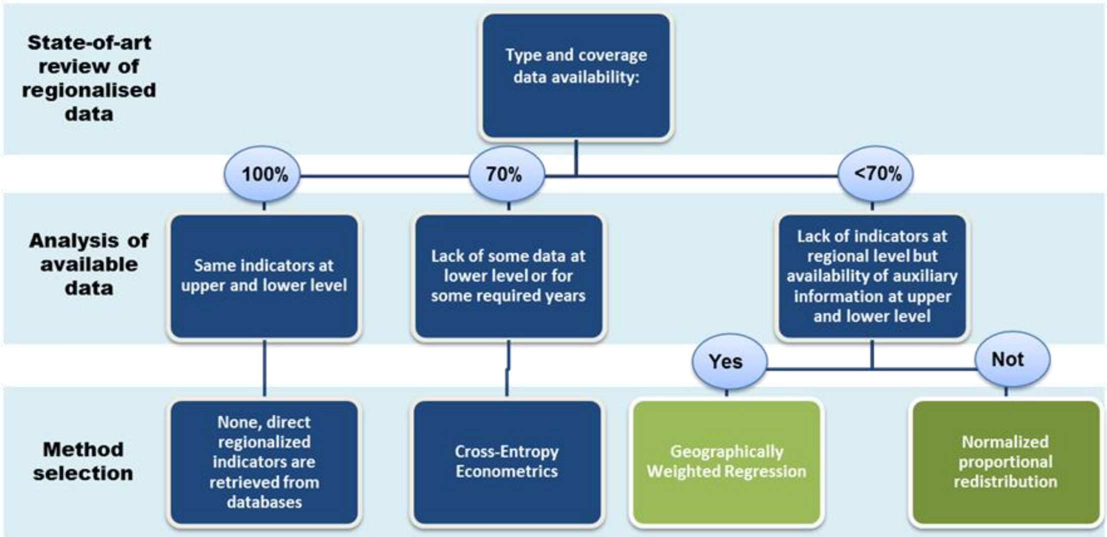
Slovakia	Waste data by NACE activities and waste categories at NUTS-2 level	Y	Data refer to 2005 and 2015. Construction data concern mineral waste from construction and demolition (i.e. Eurostat w121), instead of mineral and solidified wastes (subtotal) by construction (i.e. w12-13 by NACE F, which is the classification used in CIRCTER). Total waste excluded major mineral waste has been computed manually
Serbia	Waste data by NACE activities and waste categories at NUTS-0 level	N	Data refer to 2010 and 2015, with some gaps for specific categories. Data provided are at NUTS0, however cannot be used to generate NUTS2 estimates because of lack of explicative variables at NUTS2 level;
Sweden	Information on recovery and disposal facilities per NUTS-2 regions	N	The provided data were out of scope
Switzerland	Provided background information on different reports and studies including material flow data	N	The data included in the reports were mostly available on graphical format, with limited tabular and numerical information.

3.3 Phase 3: Regionalisation of national figures via econometric models

Since most of datasets are only available at national level (NUTS-0), we developed a regionalisation methodology to disaggregate national figures into regional ones. Among the many statistical downscaling methods suggested in the literature (Horta and Keirstead, 2017), we opted for two approaches, namely a econometric model based on Multiple Linear Regression and extended by Geographically Weighted Regression (GWR), and Normalized Proportional Redistribution. This selection has been driven mostly by the rather scarce data availability at regional level which in turn prevented the application of other approaches (Figure 3-2).

The final choice between econometric or redistribution approach will depend finally on the goodness of fit of econometric models; in other word, when econometric models give evidence to be robust and reliable they will be preferred, otherwise redistribution approach will be applied to simplify interpretation and reduce estimation errors.

Figure 3-2: Decision tree to help select appropriate methods for downscaling[7]



Source: own elaboration

3.3.1 Methodological sequence

The regionalisation method aims to provide regional data for material and waste flows making use of other data typology (e.g. socio-economic, geographic etc.) available at regional level (NUTS-2). The entire dataset of reference is based on Eurostat data for the year 2006 and 2014 (or closest years available) and we accessed and downloaded data using R software. A specific R-library8,9 provides tools to download data from the Eurostat database together with search and manipulation utilities. Bulk data have been downloaded twice, firstly during the Interim Phase (material data in January-February 2018, waste data in May-June 2018 whilst municipal data in July 2018) and secondly during the Final-Phase (September-October 2018). This allowed to (1) fine-tunning the regionalization methodology and (2) collect additional data and supporting information. Figure 3-3 provides an overview of the methodological sequential-flow adopted.

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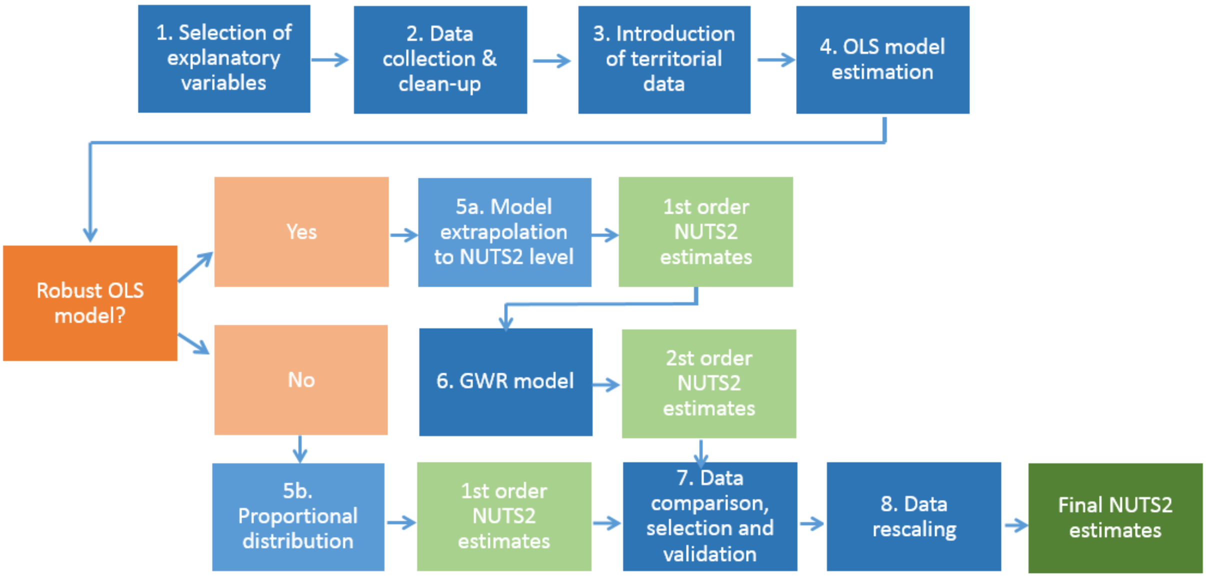
[7] Percentages in this figure refer to data availability, 100% of data availability means no need to regionalise data, high availability of data (>70%) allows for Cross-Entropy Econometrics, low availability (<70%) implies the use of linear regression or proportional redistribution

[8] See "*Retrieval and Analysis of Eurostat Open Data with the Eurostat Package*" Lahti et al., 2017

[9] https://cran.r-project.org/web/packages/eurostat/index.html

Figure 3-3: Methodological sequential flow for regionalisation



Source: own elaboration

Below each step will be described in detail.

Step 1. Selection of explanatory variables

The OLS models are based on a selection of auxiliary data available at NUTS0 and NUTS2. Auxiliary data are meant as the drivers of material and waste flows, namely those socio-economic factors affecting the material consumption and waste generation of MS able to explain observed differences. Differently from other similar research (e.g. Beigl, Wassermann, Schneider, & Salhofer, 2004; Steinberger, Krausmann, & Eisenmenger, 2010; Weisz et al., 2006), we can only select those data available at both level, NUTS-0 and NUTS-2; thus, excluding for example energy consumption or domestic extraction as potential explanatory variables. Beside availability at upper and lower level, the variables selection was based on literature review and explorative data analysis.

Additionally, whereas auxiliary data were not available for the time-period considered (i.e. 2014), we considered the closest years available to fill eventual data gap (up to three years lag); this builds upon the assumption that in general most of the variables do not have disruptive change from one year to another (see following section “data imputation” for further details).

We collected and examined roughly 40 explanatory variables which are presented in the following table.

Table 3-2: Overview of explanatory variable analysed

Socio-economic variables
Population, Gross Domestic Production, Income, Gross Value Added (GVA) (specified for Agriculture, Industrial, Manufacturing, Construction), Gross Fixed Capital Formation (GFCF) (specified for Agriculture, Industrial, Manufacturing, Construction), Employment (specified for Agriculture, Industrial and Construction), Infant mortality rate, Municipal waste;
Territorial variables
Population density, Total Land, Land Cover (specified for Cropland, Forestry, Grassland etc), Location Quotients (for each class of GVA, GFCF and Land Cover), EU geographic regions (Northern, Southern, Eastern, Western).

Source: own elaboration

Step 2. Data collection and clean up

List-wise deletion

The selected datasets present several missing values (NAs) affecting negatively an efficient application of linear regression; Indeed, default statistical program would remove each observation having at least one NA, excluding therefore data potentially informative for the analysis; at the same time imputing in a consistent manner the NA values does not appear feasible given the abundancy of these latter (e.g. some MS do not have any variable at all). As a result, we selected some NA thresholds in order to remove those observations or variables having NAs above a certain threshold. If on one side this prior skimming reduced significantly the number of NA values – minimizing the loss of observations – and thus permitted an efficient use of regression analysis, on the other side, it reduced the size of sample analysis (i.e. number of MS); namely we considered on average 29 observations out of 39 countries.

Data imputation

Remaining NAs have been imputed according to the following approaches:

- Substitution: as mentioned above, we filled NAs figures with values from previous or future years whenever they are available (up to three year lags), behind the assumption that material consumption figures are not characterized by disruptive change from one year to another; though a value from a previous year should be a better proxy than a value imputed according to common imputation criteria (e.g. geometric mean, regression mean etc.).
- Estimation: if there are not values available from closer years, we imputed the NAs according to auxiliary information.

Despite the existence of different imputation methods, we decided to adopt a proportional imputation based on EU and MS average of proxy variables; In this way, we maintain magnitude proportion among countries which would have been lost otherwise simply using EU means.

Data imputation for land cover

Data on land cover have been managed differently given their “uniqueness”. Indeed, they are available only for three years, 2009, 2012 and 2015; additionally, using proportional redistribution approach would have made no sense given their nature. Nevertheless, they are fundamental variables specially to account for physical territorials’ endowments. Therefore, for the 2006 analysis we used 2009 dataset, and missing data have been imputed by using values firstly from 2012 and then 2015. Similarly, for the 2014 analysis we collected the dataset of 2015 and filled gaps with data from 2012 and 2009. Remaining missing variables have been retrieved by Geographic Information System (GIS).

Data transformation

In data analysis, transformation is the replacement of a variable by a function of that variable: for example, replacing a variable “x” by the square root of “x” or the logarithm of “x”. In a certain way, a transformation is a replacement that changes the shape of a distribution or relationship. There are many possible reasons for transforming data. In our case, a logarithmic data transformation has been used to reduce skewness and approximate linear relationships between variables. Regression of the logarithms of selected variables “are preferable to regression of linear quantities, because they comprise non-linear (power law) correlations, and thus are sensitive to a wider range of functional relations” (Steinberger et al., 2010: 1150). We decided to take the logarithms of all socio-economic variables – territorial variables are excluded – and consequently the coefficient values of log variables should be interpreted as elasticities.

Step 3. Introduction of territorial structure data

Analyses of material and waste data are traditionally conducted using socio-economic variables (e.g. population and GDP), which can explain, to some extent, the behaviour of interested data. A strong assumption behind these analyses is that identified explicative variables affect in the same way all the observations considered, neglecting thus any territorial factors affecting the behaviour. Despite country structures could be more or less homogenous across EU (level NUTS-0), when considering NUTS2 regions, the differences become much larger – just consider that regions range in size from 316 km² (Brussels) to 94.226 km² (Castilla y León) and range in population from 128 000 inhabitants (Valle d'Aosta) to 11.8 Million inhabitants (Ile de France). These territorial differences justify the believes that some parameters affect certain regions more than others and vice versa, and that there exist different regimes for each group of selected observations (regions) presenting similar territorial structures. This problem is dealt in general by applying the *switching regimes regression* technique (Alperovich and Deutsch, 2002; Yrigoyen, 2003), which identifies the most likely allocation of n observations into two or more separate regimes, each of them associated with an identified territorial structure (e.g. Chasco identified two regimes based on Income magnitude, while Alperovich used population density).

Despite the technique would have been helpful to identify such territorial structures in our analysis, the restricted sample of observations made inadequate its application. Indeed, the differentiation in regimes would produce a loss in significance of parameters and additionally the increased number of parameters would be too high in comparison to sample size.

Therefore, since the impossibility to account territorial structures through switching regression technique, we decided to include new empirical territorial variables in the model: location quotients and territorial dummies.

Location Quotient

Location quotient (LQ) is a way of quantifying how concentrated an industry, cluster, occupation, or demographic group is in a region as compared to the nation. It can reveal what makes a region "unique" (or "specialised in") in comparison to the national average.

The location quotient is computed as a ratio that compares a region to a larger reference region according to some characteristic or asset. Suppose X is the amount of some asset in a region (e.g., manufacturing jobs), and Y is the total amount of assets of comparable types in the region (e.g., all jobs). X/Y is then the regional "concentration" of that asset in the region. If X' and Y' are similar data points for some larger reference region (like a state or nation), then the LQ or relative concentration of that asset in the region compared to the nation is (X/Y) / (X'/Y').

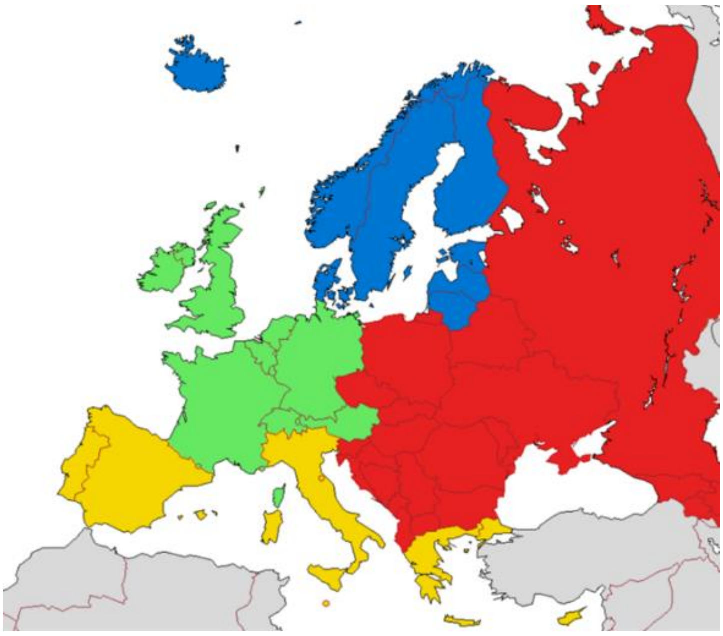
We compute two different level of location quotient, namely national local quotient (LQ-NUTS0) and regional location quotient (LQ-NUTS2); the first measures the concentration of a particular asset in a country with respect to the EU, while the second measures the concentration of a particular asset in a region with respect to the EU. LQ-NUTS0 are used as potential dependent variables during the initial step of model selection. Once identified significant LQ-NUTS0 variables these are then replaced by respective LQ-NUTS2 to generate regional estimates.

LQ provides further insights in addition to the simple number of jobs or the structure of an economy. Industries with high LQ are typically (but not always) export-oriented industries, which are important because they bring money into the region, rather than simply circulating money that is already in the region (as most retail stores and restaurants do). Industries which have both high LQ and relatively high total job numbers typically form a region's economic base. Economic developers and government officials need to pay attention to these industries not only for the jobs they provide, but also for their multiplier effect — the jobs they create in other dependent industries like retail trade and food services.

Territorial Dummies

Following the example of Crescenzi et al. (2007), we also introduced territorial dummies to account for the “national fixed effect”. Namely, we classified MS according to European sub-regions (Figure 3-4), in order to highlight local endowments (if any) specific to the geographical area in which MS are located. The significance and sign of the parameter of the dummy variable indicates, in a synthetic way, all regional specificities not captured in other independent variables (Capello et al., 2007).

Figure 3-4: European Sub-regions



Source: https://en.wikipedia.org/wiki/File:European_subregions_(according_to_EuroVoc,_the_thesaurus_of_the_EU).png

Step 4. OLS model selection

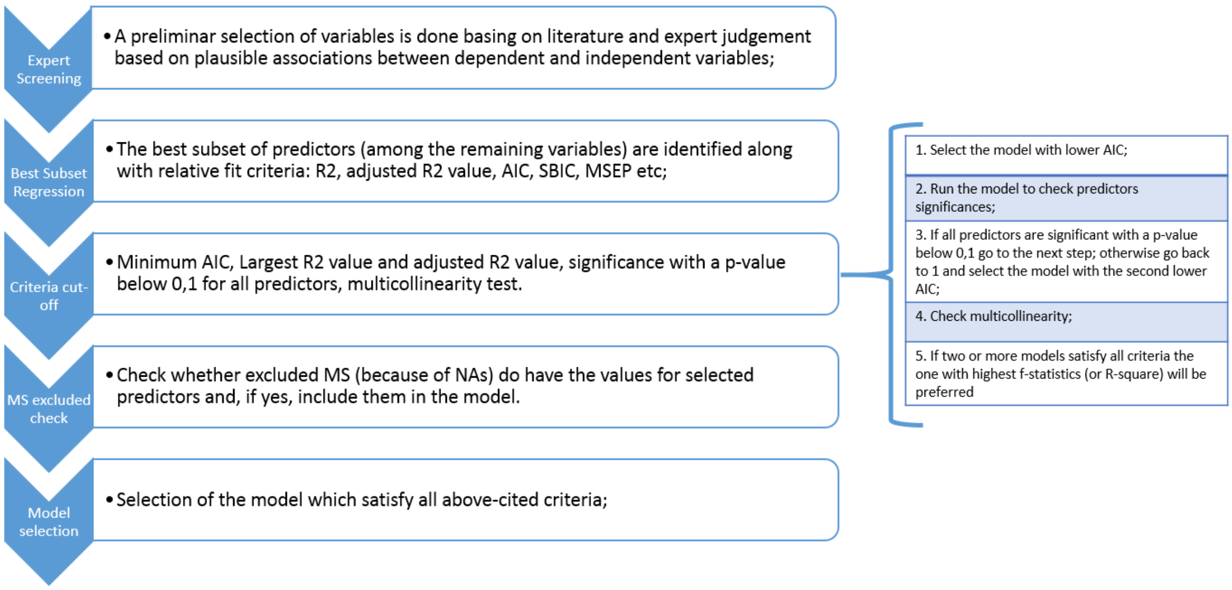
Variables selection in regression – identifying the best subset among many variables to include in a model – is arguably the hardest part of model building. A fundamental problem when having several potential predictors is that some may be largely redundant with others; multicollinearity occurs when some predictors are linear combinations of others (or nearly so), resulting in a covariance matrix of predictors that is singular. One outcome of multicollinearity is that parameter estimates become subject to wild sampling fluctuations.

The single most important tool in selecting a subset of variables is the analyst’s knowledge of the area under study and of each of the variables; however even so, most of the time, researchers need to turn to selection methodologies (namely just to cite some forward selection, backward elimination, stepwise regression and "all possible regressions") which build on a trinity of selection components (Ratner, 2010): (1) statistical tests (e.g. F-statistic, chi-square, and t-test), (2) statistical criteria (R-squared, adjusted R-squared), (3) statistical stopping rule (e.g. P-values thresholds for variable entry/deletion in a model). The goal of variable selection is to divide a set of predictors (our explicative variables) into active and inactive terms depending on a comparison of determined criterion.

To select our models, we combined the trinity criteria in a sequential decision flow, i.e. we first set statistical stopping rules, we then look to statistical criteria and finally we choose the model upon statistical tests.

The following figure summarises the model selection steps.

Figure 3-5: Overview of the Model selection process



Source: own elaboration

In order to facilitate comparability among different time periods (2006-2014), we attempted to identify, for each indicator, equal regression models (i.e. same explicative variables) across the two cross-sections analysed. When this was not possible we sticked to the results of the model selection step (see Table 3-3).

Step 5a. Estimators optimization and model extrapolation to NUTS2 level

In the previous step we identified the regression models for each material and waste category; however, so far estimated parameters are general (or universal) meaning that a parameter's value apply to all countries indifferently, without taking in account any kind of endowments/characteristics specific to the countries. Recalling that our final goal is to estimate regional data, the use of general parameters computed at EU scale would likely generate unrealistic figures since it does not account for spatial heterogeneity. One way to address this issue is the switching regression approach that distinguishes between different groups of observed variables and estimates specific parameters for each group according to specific assets. However, this approach is time consuming since it requires a deep study of endogenous variables to classify them into groups. Additionally, given the reduced set of observations available it would not be feasible. Therefore, in order to address the spatial heterogeneity at national level we introduce a sort of empirical artefact by *optimizing* the parameters values; namely, we allow for the possibility that the parameters in any state may vary within their confidence interval such that the predicted national value match the real known value – this way, national estimators will be *calibrated* to each MS endowment. Mathematically:

$$\text{Minimize} \quad const + \boldsymbol{\beta_1} x1 + \boldsymbol{\beta_2} x2 \qquad \textit{(eq. 3)}$$

such that:

$$\beta_1\text{low} < \boldsymbol{\beta_1} < \beta_1\text{max}$$

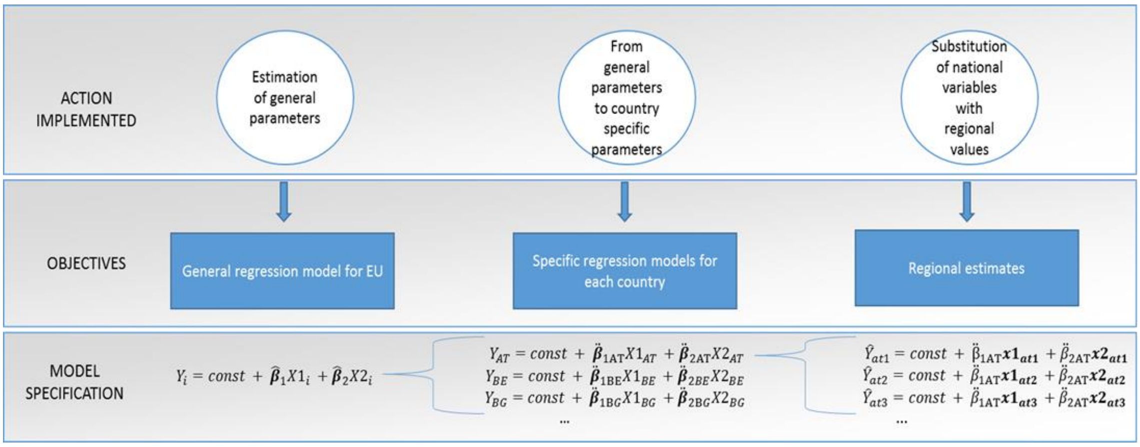
$$\beta_2\text{low} < \boldsymbol{\beta_2} < \beta_2\text{max}$$

$$const + \boldsymbol{\beta_1} x1 + \boldsymbol{\beta_2} x2 = \text{Y (Observed)}$$

Where $\beta_{1,2}$ are the coefficients to be optimized, $X_{1,2}$ are the variable selected for a specific model (e.g. population and GDP), *const* is the constant, and the interval $\beta_{low} \leq \beta \leq \beta_{max}$ is the confidence interval provided by the regression.

Finally, once that a regression model is identified for an indicator and national parameters have been adjusted by optimization we are ready to extrapolate regional estimates by applying the same country-specific regression model wherein we substitute the exogenous variables observed at national level with the same exogenous variable observed at regional level (Figure 3-6).

Figure 3-6: Breakdown of regional extrapolation



Note: (β are the parameters estimated associated to explicative variables; X (upper case) is the variable measured at national level; x (lower case) is the variable measured at regional level; i is the n country; Source: own elaboration

Step 5b. Proportional distribution

For some indicators we were not able to fit robust OLS models, i.e. we could not find any combination of explicative variables capable of explaining data variability with enough statistical significance. In these cases, we were constrained to downscale the data by simply redistributing national values according to a set of socio-economic factors, namely variables related to economic size (total population and GDP) and/or variables related to final consumption (GVA and employment).

All the indicators for which robust OLS models could not be estimated were disaggregated by applying the same methodology: we first selected the socio-economic variables to be used as redistribution factors depending on the specific indicator to be regionalised. Section 3.3.3 below provides a detailed description of the redistribution factors used in each case. Secondly, we standardized all the variables by using the unit vector methodology, making them dimensionless but keeping proportions among them. Thirdly, we aggregated the standardized variables in a regional index and finally we estimated regional values by a weighted distribution of the national value, according to the regional indexes produced on previous step.

Step 6. Correction for spatial effects via Geographically Weighted Regressions (GWR)

We finally tested regional estimates to spatial dependence by computing Moran's Index test (Viton, 2010); we checked both error autocorrelation and dependent variable autocorrelation using a contiguity matrix where the coefficients is 1 if two regions share boundary and 0 otherwise. The theoretical purpose behind this approach is to add interregional interdependence to the measurement of material and waste flows; in fact in a concentrated location, the beneficial effect of a firm's research and development activities are not confined within the boundary of the firms, but they "spill-over" into the surrounding environment, to the advantage of innovative activity by other firms (Capello et al., 2007). In those cases where spatial autocorrelation is detected, we recalculate regional estimates by including such spill-overs effect.

Step 7. Consistency and validation analysis

The next methodological step concerned consistency and reliability analysis. First, we tested consistency by comparing the real national values with the sum of respective regional estimates. This measure should give us a general overview of whether regional estimates magnitude reflects reality at aggregated level; namely if the sum of regional values is close to the real national value it implies that differences between countries have been correctly accounted. Results close to 1 imply a good approximation of reality, while results deviating from 1 suggest an inappropriate estimation (equation below).

$$\left(\frac{\sum_{i=1}^{S}\widehat{dmc_i} \quad -DMC_S}{DMC_S}\right) \cong 0 \qquad \textit{(eq. 4)}$$

Where $\widehat{dmc_i}$ is the predicted domestic material consumption for each region "i" of a specific MS "S", while DMC_s is the observed total domestic material consumption of the same MS "S".

We tested consistency for both regional estimates typologies, OLS and OLS+GWR, and finally we selected the regional estimates – for each MS – having smaller deviation. We assume that spill-overs does not occur in all nations regularly, therefore where we detected an increase in deviation (i.e. values departing from 0) when accounting for spatial autocorrelation we preferred to stick up to OLS estimates.

Finally, we validate estimates by comparing these latter with real values retrieved directly from National Statistical Database (for those MS available). The validation purpose, rather than corroborate regional estimates (which remain a far proxy of reality) served to identify potential weaknesses of estimation models, therefore to better understand results and help in their interpretation.

For instance, we improved the prediction model for DMC in Germany by introducing spatial effect correlation since this gave evidence of better results in term of overall deviation (i.e. the overall deviation decreased from 20% to 9% in 2006, while in 2014 from 19% to 4%). It is not a case that Germany presented significant spatial spill-overs among regions, in fact it represents the EU country with the biggest share of trade flows in EU (Source: Eurostat).

This result is further strengthened when we look to the specific regional estimates; Fortunately, Germany was among those countries having disaggregated data (in this case at NUTS-1 level), therefore we could have verified that, overall, regional figures estimated accounting for spatial spill-overs showed a reduced variance.

Another improvement occurred through the validation process was to set to zero domestic extraction for those metropolitan regions characterised by high population density and low surface. This came across after viewing that the real German Länder values (i.e. regions) did not register extraction activity for capital regions (Berlin, Bremen and Hamburg). As threshold to define metropolitan/capital regions we adopted population density greater than 1000 habitant per km2 and surface land less than 1000 km2.

Step 8. Data Rescaling

The final of the regionalisation methodology was the rescaling of the estimated regional value according to real national value observed. We do so by weighted distribution of the real national value to regions whereas estimated regional values represent the *weight* of distribution.

In this way, behind the assumption that difference between regions have been rightly captured by the estimation model, we ensure a perfect match the sum of regional estimates and their corresponding national value, and also we limit the impact of outliers.

3.3.2 Models used and discussion

Following tables provide an overview of regionalisation results, Table 3-3 presents the approaches (regression, spatial regression, distribution) applied to each indicator; we also show the countries (Member States) which presents deviation greater than 20%, with respect to the real national value.

In some cases, the larger deviation could be due to a scarce correspondence between the explicative variables used in the regression model and the real economic structure of a country; this can be particularly true for countries which depart greatly from EU averages across considered variables. In other cases, the deviation can also be due to exceptional cases (e.g. construction of port areas, airports, industrial park etc); this is more likely to produce disruptive changes from a time-period to another that the model is unable to capture.

Table 3-3: Regionalisation approaches and deviation overview.

Indicators	**Years**	**OLS**	**GWR**	**Distribution**	**MS with Deviation >20%**
DMC	2006	√	√		CH;
	2014	√	√		ES, IT, NL;
Biomass	2006	√	√		-
	2014	√	√		NL;
Metal ores	2006	√	√		AT, CH, CZ, DE, EL, FR, HU, NL, RO, UK;
	2014	√	√		AT, BG, CH, CZ, DE, ES, FI, FR, HR, IE, IT, NO, PL, PT, RO, UK;
Construction (Non-metalic minerals)	2006	√	√		EL, NL, UK;
	2014	√	√		IT;
DE	2006	√	x		CH;
	2014	√	x		NO;
Total Waste (excluding major mineral waste)	2006	√	x		CZ, DE, NO, RO;
	2014	√	x		BE, PL;
Household waste	2006	√	x		-
	2014	√	x		HR;
Food waste	2006	√	√		-
	2014	√	x		BE, NL;
WEEE	2006	√	x		NO,
	2014	√	√		NO, UK;

Construction waste	NA	NA	√	N/A
Plastic waste	NA	NA	√	N/A
Waste by agriculture	NA	NA	√	N/A
Waste by mining and quarrying	NA	NA	√	N/A
Waste by manufacturing	NA	NA	√	N/A

Note: OLS: ordinary least square (linear regression); GWR: geographically weighted regression (linear regression with spatial correlation included); Distribution: regionalisation based on distribution by standardized factors; MS with deviation >20%: countries having deviation greater than 20%

Source: own elaboration

Things differ for estimates based on distribution approach. In fact, these are computed on the strong assumption that national values are equally distributed across regions depending on a factor; therefore, we cannot apply statistical test to check estimates robustness, nor we can validate the approach because first, no regional data are (so far) available for these categories and, second, deviation is null by-construction (i.e. we do not estimate regional figures, rather we only distribute national value across regions).

Table 3-4, Table 3-5 and Table 3-6 show regression models applied for material and waste indicators respectively, along with main statistical results; it follows a brief discussion on best regression models, while a deeper discussion for each model is provided below.

Table 3-4: OLS estimations for material consumption indicators

	DMC 2006	**DMC 2014**	**Biomass 2006**	**Biomass 2014**	**Metal ores 2006**	**Metal ores 2014**	**Construction 2006**	**Construc-tion 2014**	**DE 2006**	**DE 2014**
Constant	5.064*** *(0.327)*	5.233*** *(0.334)*	-1.353 *(1.330)*	-1.240 *(1.364)*	-0.470 (1.143)	-5.680** *(1.912)*	4.977*** *(0.971)*	3.990** *(1.166)*	7.982*** *(0.903)*	6.820*** *(1.141)*
GDP							0.289. *(0.145)*	0.439* *(0.169)*		
Population			0.441* *(0.163)*	0.413* *(0.163)*						
Pop. density	-0.139** *(0.050)*	-0.174** *(0.051)*				-1.031** *(0.280)*	-0.194* *(0.076)*	-0.272** *(0.086)*	-0.918*** *(0.155)*	-0.780*** *(0.191)*
Tot. employment	0.787*** *(0.065)*	0.755*** *(0.091)*							1.390*** (0.114)	1.241*** (0.137)
Construction employ-ment							0.641*** *(0.153)*	0.509** *(0.173)*		
GFCF agriculture	0.155* *(0.059)*	0.165* *(0.077)*								
LQ GFCF industry						2.280. *(1.185)*				
Industrial GVA					0.384* *(0.156)*	0.888*** *(0.123)*				
LQ GVA industry						-2.542* *(1.110)*			0.353** (0.118)	0.536** (0.179)
Total landuse					0.470** *(0.161)*					
Artificial land cover			0.581** *(0.0.171)*	0.627*** *(0.0.165)*						
Woodland cover									-0.380** (0.106)	-0.231 (0.128)

Northern EU countries					-.072* *(0.430)*	-2.260*** *(0.579)*				
Southern EU countries			-0.417** *(0.158)*	-0.559** *(0.159)*						
Observations	29	30	29	30	28	30	29	30	29	30
R-squared	0.97	0.97	0.95	0.95	0.74	0.74	0.93	0.92	0.98	0.97
F- statistic	29.6	285.4	159.6	170.9	23.99	14.28	110.6	97.42	258.1	209.9

*Note: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1; LQ: location quotient; GFCF: gross fixed capital formation; GVA: gross value added; GDP: gross domestic production.*

Source: own elaboration

Table 3-5: OLS estimations for waste indicators

	Tot. waste 2006	**Tot. waste 2014**	**Households waste 2006**	**Households waste 2014**	**Food waste 2006**	**Food waste 2014**	**WEEE 2006**	**WEEE 2014**
Constant	0.197 (1.254)	1.883* (0.772)	2.662. (1.325)	3.690** (1.102)	-2.098* (0.883)	-1.940. (1.047)	0.554 (0.434)	-1.510* (0.721)
Population	0.788*** (0.126)	0.680*** (0.088)	0.494** (0.168)	0.363* (0.139)				0.374*** (0.088)
Pop. density					1.077*** (0.088)	1.066*** (0.106)		
Municipal waste			0.537** (0.168)	0.669*** (0.140)				
Tot. GFCF							0.288 (0.179)	
Industrial GFCF		-0.569. (0.276)						
Manufacturing GFCF	-0.827* (0.392)	0.309* (0.124)						
LQ GFCF industry	0.363.							

	(0.238)							
LQ GFCF manufacturing								0.769*** (0.201)
Industrial GVA	1.021* (0.383)	0.621* (0.267)					0.685*** (0.164)	0.662*** (0.074)
LQ GVA agriculture					-0.098 (0.064)	-0.540*** (0.064)		
LQ GVA manufacturing		-0.305* (0.144)						-1.178*** (0.239)
Land					1.045*** (0.050)	1.068*** (0.060)		
Northern EU countries							0.335* (0.127)	
Southern EU countries								-0.349* (0.132)
Observations	27	27	27	27	27	29	26	27
R-squared	0.95	0.98	0.98	0.98	0.95	0.95	0.97	0.98
F- statistic	111.1	233.6	511.2	746.1	151.2	152.3	279.5	246.2

*Note: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1; LQ: location quotient; GFCF: gross fixed capital formation; GVA: gross value added; GDP: gross domestic production.*

Source: own elaboration

The best regression models for material consumption are those related with Domestic Material Consumption and Domestic Extraction. Comparison of regional estimates and real regional values also confirm the goodness of the models. The validation process (with Germany) also helped us to improve Domestic Extraction estimates; we delete extraction figures for those regions characterised by large metropolitan areas which theoretically do not have available land for natural resource extraction activities (evidence by Berlin, Hamburg and Bremen cases). We considered as metropolitan cities all those regions having population density greater than 1000hab/km^2 and surface less than 1000km^2. For these regions, DE was set to zero.

Metal ores consumption on the other hand is the worst model, probably also due to the reliability and consistency of real national data (some countries present disruptive changes of metal consumption from 2006 to 2014).

With respect to waste indicators, best models are total waste generation and household waste; the first because of its aggregated nature (better explained by macroeconomic variables), and the second because of municipal waste predictor (available at NUTS2) for which household waste represents the main component. Validation (with Slovakia and Flanders Belgium region) to large extent validates the two models (some incongruences for 2006 in total waste generation), while estimated households waste fits very well real data.

On the other side, WEEE estimates contrast with real figures for Slovakia (despite the theoretically good regression model), so here again, it is likely that issues related with measurability and differences in methodological approaches for data collection among MS, could hinder the WEEE figures (not only the regional estimates, but also real national values published in Eurostat).

For what concern waste generated by economic NACE activity and plastic waste we did not find any regression model good enough to predict regional values. Therefore, for these categories we adopted the distribution approach (see following chapter).

3.3.3 Alternative regionalization via Normalized Proportional Redistribution (Step 5b)

When analysed waste generated by specific economic activity (namely: waste by agriculture, waste by mining and quarrying, waste by manufacturing and mineral waste by construction waste) we did not find any combination of explicative variables capable to thoroughly explain the waste generated. The same applies to plastic waste. In these cases, we decided to adopt the easier approach based on normalised redistribution of national values according to socio-economic factors (e.g. population, GDP, GVA etc.), as explained on the methodological section above.

For plastic waste, since it concerns not only waste generated by economic activity but also waste generated by households (i.e. consumption), we chose two consumption-related variables, (i.e. GDP and population), and two variables related to the economic activity (i.e. GVA and employment). On the other hand, since in waste generated by economic activity we are interested in waste generated solely by the production side, we only used variables related to economic activities (e.g. employment and gross value added; population size in this case would bias the results since it relates mostly to consumption rather than production). Table Table 3-4 shows in detail variables adopted for each indicator.

Table 3-6: Waste data regionalised through redistribution approach

Indicator	**Socio-Economic factors applied**	**Eurostat database of reference**	**Estimates con-sistency**
Total Waste gen-erated by agricul-ture, forestry and fishing	Agricultural employment, and Agri-cultural gross value added;	lfst_r_lfe2en2 nama_10r_3gva	Low
Total Waste gen-erated by mining and quarrying10	Local unit number, mining and quar-rying employment	sbs_r_nuts06_r2	Low
Total Waste gen-erated by manu-facturing	Industrial employment, Industrial + Manufacturing gross value added;	lfst_r_lfe2en2 nama_10r_3gva	Low
Construction and demolition waste	Construction employment, Construc-tion gross value added;	lfst_r_lfe2en2 nama_10r_3gva	Low
Plastic Waste	Population, Income, Total employ-ment, Total gross value added;	lfst_r_lfe2en2 nama_10r_3gva	Low

Source: own elaboration

3.3.4 Special note on missing values

Albeit all the efforts made to collect data, including direct request to interested countries via the MC representatives (phase 2) and data imputation via econometric and redistributive ap-proaches (phase 3), in some cases data availability did not allow to produce reliable estimates. This was the situation in Albania (AL), Bosnia-Herzegovina (BA), Liechtenstein (LI), , Turkey (TR) and Kosovo under UN Security Council Resolution 1244 (XK) and to some extent Monte-negro (ME)11.

In the case of Iceland (IS) and Switzerland (CH) the regional estimates have been generated with a slight different approach due to a singular data situation in those areas. In the case of Iceland material data are not available at any level, while for Switzerland the same is true for selected waste data. Still, we managed to collect enough explanatory data at regional level as

10 Waste generated by mining and quarrying activities refers to a different database (sbs_r_nuts06_r2) due to unavailability of data in lfst_r_lfe2en2 & nama_10r_3gva for specific mining NACE activity.

11 Montenegro (ME) presents some waste data available for 2014.

to allow the application of the model parameters developed for the remaining countries. However, the lack of data for these countries at NUTS 0 level prevent us not only to optimize the respective parameters, but also to apply the rescaling step. Therefore, it is likely that material data for Iceland and waste data for Switzerland present lower accuracy with respect to the other countries.

4 Datasets already available at regional level: Municipal Waste generation and treatment

Municipal waste generation and treatment is already available at regional (NUTS-2) level in Eurostat database (i.e. Municipal waste by NUTS 2 regions – pilot project data (env_rwas_gen)). The statistical unit for municipal waste generation and municipal waste treatment differ; while the first refers to waste generated by small businesses and households, the second refer to the waste treated by the plants. Due to the voluntary nature of reporting for these indicators there are many gaps in the data, which prevented, consequently, the estimation of EU totals or EU averages (Source: Eurostat).

According to Eurostat, France and Germany have reported data that deviate considerably from the coverage of the municipal waste definition and are in principle not comparable to other countries. In general, for Germany, only pure household waste collected by or on behalf of the municipality is reported. Therefore, the sum of all NUTS-2 regions of Germany is lower than in Municipal waste by waste operations (env_wasmun). On the other hand, French data do not comply with the definition of municipal waste and are thus not comparable to data from other country. Furthermore, the data on Municipal Waste generation do not reflect the regional Municipal Waste generation but the sum of the waste treated in the region (source Eurostat).

Given the low geographical coverage and the problematic consistency of these data, we tried to, at least, address the first shortcoming by filling the gaps considering the whole-time series of municipal data available. Basically, starting from year 2006 we filled missing values with figures from 2007, 2008 and 2009. Similarly, for 2014 dataset, we started from 2013 (first year available), and we filled missing values by means of 2012, 2011 and 2010 data.

5 Shortcomings and limitations

5.1 Input data limitations

The assessment and interpretation of the indicators and overviews developed in this project has to take into account specific challenges linked to the systematic of European waste and

MFA statistics. The statistical compilation of material consumption, measured at the DMC, is methodically established and meanwhile standardized and internationally comparable on the basis of corresponding manuals for compiling resource flows. Nevertheless, there are two serious methodological problems with DMC data and its regionalization. The fundamental problem with the two indicators DMI and DMC is that imports and exports of intermediate and end products are measured by their own weight and the resources that was necessary to produce these goods are no longer included in the calculation of the DMC and DMI, especially for countries/regions in which the first processing stages for intermediate and end products take place. This is particularly fatal for consumption indicators such as the DMC. Therefore, the indicators RMI (Raw Material Input) or RMC (Raw Material Consumption) are increasingly used to measure the resource consumption of national economies. However, the effort to calculate these indicators is enormous and accordingly few RMI or RMC data are available at present.

The second methodical problem addresses the difficulty of measuring material consumption at a sub-national level. The quantities of national imports and exports can be determined without difficulty via the foreign trade statistics. It is very likely that these data are also available for sub-national areas, whether NUTS 1, NUTS 2 or even NUTS 3 regions, as in most European countries the statistics are compiled locally and collected at the next highest level. However, imports and exports to other countries at the regional level are only one part of the exchange of goods. The probably larger part are domestic goods transports between regions, e.g. between city and surrounding countryside, which are statistically recorded only little or not at all. As a result, it is difficult to produce reliable data for the material consumption of regions.

Regular statistics on the production and management of waste from businesses and private households are collected from Member States and published every two years following common methodological recommendations. With the growing experience some shortcomings of the original legislation and the methodological manual have become apparent. As a consequence, Commission Regulation 849/2010, which took effect from reference year 2010 onwards, brought about various simplifications and improvements to the legal framework.

Nevertheless, municipal waste management in Europe has become more and more complex in the last decade. This complexity is due to some extent to the introduction of additional facilities for pre-treatment of waste, mainly mechanical biological treatment and sorting for recovery. In addition, there are legal requirements for increasing recovery of certain waste streams, resulting also in increasing cross-boundary transports of waste for recovery. Depending on national waste management and waste data collection systems, the approaches for municipal waste data collection established in the Member States vary to a large extent, thus hampering data comparability across countries. The following outlines key challenges that need to be considered based on an assessment of Eurostat department on environmental statistics and accounts (Eurostat, 2010).

5.1.1 Collection and scope of municipal waste

The Eurostat approach for the classification of household waste is based on the principle that the scope of municipal waste includes household waste and similar waste types generated by other sources than households, regardless of whether municipalities or private actors are responsible for the collection. This is often interpreted differently in the Member States, leading to difficulties for the assessment of waste generation figures. It has been argued that the overall target is to reduce the unsorted, mixed municipal waste regardless of the origin. If this should be done, it is consistent to cover the separately collected fractions from all origins as well. Therefore, the starting point for the waste types to be included are the waste codes listed in chapter 20 of the European List of Waste (LoW) with some additions from sub-chapter 15 01. Recent experience nevertheless demonstrates that a relevant number of countries include amounts of mixed municipal waste from all NACE activities in the municipal waste data.

5.1.2 Pre-treatment/ secondary waste

Where the pre-treatment operations Mechanical-Biological Treatment (MBT) or sorting occurs, their outputs have to be allocated to either of the four defined treatment operations: incineration, landfill, recycling and composting. The amounts of these outputs may be based on estimation and / or modelling, but should not contain process and water losses from pre-treatment, but only the secondary waste actually managed. The secondary waste amounts from pre-treatment shall be reported regardless of their codes and linked back to the input of municipal waste in the overall input of the operations. Secondary wastes from the four treatment operations (incineration, landfill, composting and recycling) should not be reported. Nevertheless these procedures are often handled differently in the Member States and lead to relevant over- or underestimations of recycling rates. Such deviations are transferred to the regionalised figures produced in this project.

5.1.3 Recycling operations

According to the official Waste Framework Directive, recycling includes “any recovery operation by which waste materials are reprocessed into products, materials or substances whether for the original or other purposes” (Directive 2008/98/EC, Art. 17). Albeit recycling seems to be clearly defined, in practice, however, several obstacles exist:

- Firstly, the input to the “final” (composting/digestion- or recycling-) processes is often not known. Instead the data collection covers, at least partly, only the inputs and/or outputs of the preparation processes that divert non-recyclable or non-compostable residues from the main stream to be recycled or composted/digested. In composting/digestion facilities, a major sorting or screening step is typically integrated so that it is difficult to directly monitor the amounts actually treated biologically.

- Secondly, when the data collection on waste treatment is classified based on the R-codes, this may lead to an over-estimation as these concepts are broader than the definition of recycling and composting cited above. Thus, in practice, facilities may be classified as recycling (R2 to R11) or composting (R3) facilities, although they constitute or contain a major sorting / screening step that may generate significant amounts of residues not suitable for material recovery. Moreover, sorting for recycling is, in some countries, performed at landfills or at composting plants, resulting in overestimated amounts allocated to these operations while those for recycling are underestimated.

These outlined uncertainties and statistical challenges especially require a higher level of mindfulness when comparing indicators between regions in different countries. Also over time changed procedures for the collection of data might cause inconsistencies that are reflected in the data.

5.2 Methodological limitations

The regionalisation method applied is based on an econometric approach which identifies and estimates the best predictive parameters for each selected indicator. The main drawback from this top-down approach is the impossibility to define a set of estimated parameters which soundly represent the economic structure of all the 331 EU regions considered; consequently, for those regions presenting atypical figures with respect to EU averages, some outliers' estimates, which do not necessarily reflect the reality, could be generated.

Quality of regional estimates do not depend solely on the regionalisation model itself but also (and above all) on quality of input data collected. Despite the accurate guidelines the EC provide with MS to build a harmonized database, it is likely that approaches and methodology accurateness differ between MS; it can also be the case that it differs for a single MS across the time-period analysed (e.g. improvement of collection process and/or collection rather than estimation, change in EC collection guidelines etc.). Indeed, we noted many cases where unlikely "jumps" occurred across time for a single MS, or a doubtful magnitude scale of certain MS indicators when compared to similar MS.

Since the econometric approach is top-down (i.e. it starts from national values) the materials and wastes interflows occurring among regions within a single country is likely that go undetected; consequently, even though we addressed this shortcoming by introducing spatial effects, those MS characterised by high trade levels (e.g. Germany) are more subject to a regional estimates distribution which might differ from reality.

Furthermore, in order to facilitate interpretation we made an additional effort to identify a potential set of variables common to both years. We did this by trying, at the same time, not to hinder estimates robustness, but this was not always possible. In fact, due to potential structural changes (but also changes in accounting methods), some indicators presented highly significant variables in 2006 which were not anymore in 2014 and *vice versa.* In this cases, different models apply[12] and therefore comparison over time of indicators must be done cautiously.

From an econometric point of view, the basic assumption underlying all the regression approaches is that models are responsive to the respective variables selected. In this sense, we tried to identify (through literature review and explorative data analysis) those variables strongly linked with indicators and therefore able to explain to large extent how indicators could vary in the EU. However, this approach carries on different issues:

1. We cannot exclude the existence of better or other variables able to explain indicator's behaviour; e.g. waste generation is not just a function of population size and economy structure, but it can also be affected by other factors not considered in this analysis (e.g. environmental awareness, taxes etc.). Therefore, for what concerns policy insights it is important to keep in mind that we considered just a part of macroeconomic variables influencing material or waste flow, but these are by no way the only ones;
2. All parameters values are valid *ceteris paribus*; this means that the comparison between the model parameters can be done only under certain conditions, i.e. only when the model does not change across years or across indicators, i.e. models must include the same explicative variables to be entirely comparable. This implies that if, for example, the elasticity of population with respect of total waste generation is 0.8% in one model, this relation holds only for that specific model and cannot be compared with the population elasticity of a different model unless this second model is identical to the first one. If the same variables have been used to estimate waste generation in 2006 and 2014 then variables' elasticity can be compared. Different models for the same indicator could suggest a structural change in the economy; for example, the inclusion of a further significant explicative variable could denote a relevant change in the behaviour of the indicator linked with that variable.
3. For the sake of simplicity and interpretability, we did not consider interaction terms; the high number of variables and low number of observations as well as the many regression models to be generated prevented us from exploring comprehensively the use of interaction terms as potential independent variables. In fact, considering that our dataset counts already up to 50 variables, the inclusion of interactions term would increase the number of regression model possibilities up to being out of reach. Nevertheless, we cannot exclude that interaction terms could improve the goodness of fit of regression models.

Overall the estimates are built on key-variables common to all countries and which best describe the pattern of material and waste flow from a top-down approach. We are aware that

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12 This is the case for Metal ores consumption, total waste generation (excluding major mineral waste) and WEEE.

specific circumstances often play a key role in explaining material and waste patterns (especially trade between and within countries), however these would vary from region to region (therefore immeasurable from a top-down approach); though we are confident that regional estimates still represent a good proxy of reality.

5.3 Qualitative assessment of regional estimates

Given the above-discussed limitations related to data quality and/or methodological shortcomings we decided to classify qualitatively each regionalisation model, and thus regional estimates, according to following criteria: (i) the quality of input data, (ii) the model robustness, and (iii) the regional estimates consistency; each criterion is assessed on a high/low basis and Table 5-1 provides a description of these criteria.

Table 5-1: Qualitative criteria assessment for regional estimates

Criterion	Low	High
Quality of Input Data	Low geographical coverage, weak reliability of EU statistics due to accounting/collection differences and indicator nature issues;	High geographical coverage, good EU statistics reliability;
Model robustness	Distribution models, regression models with low predictive power (R<0.9), low parameters significance;	Regression models with high predictive power (R>0.9), high parameters significance;
Consistency of estimates	High cumulative deviation (ref. Equation 1)	Low cumulative deviation (ref. Equation 1)

Source: own elaboration

After assessing regionalisation models according to each criterion, we averaged the results and assigned a qualitative score to regional estimates; namely, if the regionalisation model scores *high* across all criteria we assigned a *high-quality* estimate, if criteria results are mixed then we assigned *a medium* quality, while if model scores *low* across all criteria, then the regional estimates as well will score *low-quality* (Table 5-2).

Table 5-2: Regional estimates: qualitative assessment

Indicator	Quality of input data	Model robustness	Consistency of estimates	Expected accuracy of estimates
Domestic Material Consumption	High	High	High	High
Biomass	High	Low	High	Medium
Metal Ores	Low	Low	Low	Low
Non-metallic minerals	High	Low	Low	Medium
Domestic extraction (DE)	High	High	High	High

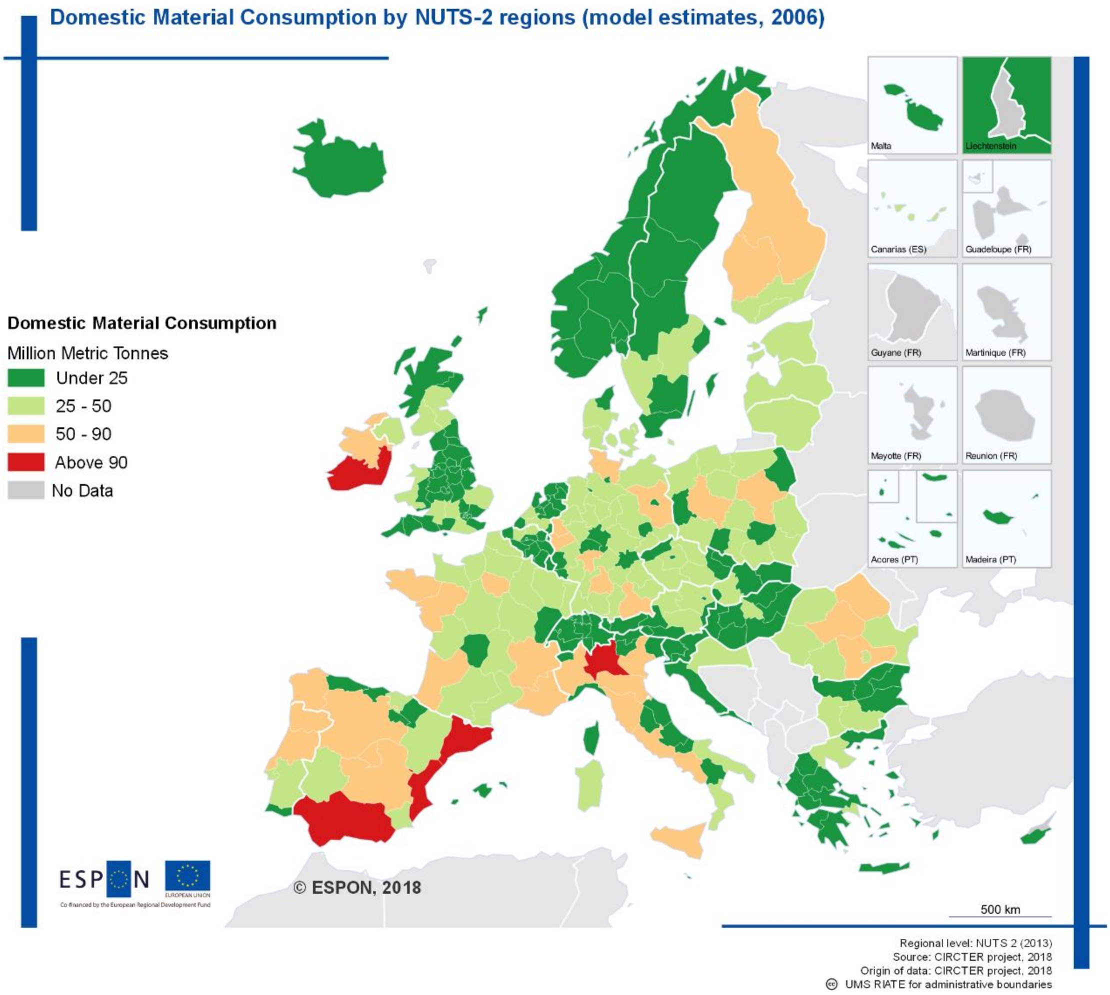
Total waste generation, excluding major mineral wastes	Low	High	High	Low
Total Waste generated by Households	Low	High	High	Low
Food Waste	Low	High	High	Low
Total Waste generated by agriculture, forestry and fishing (NACE A)	Low	Low	Low	Low
Total Waste generated by mining and quarrying (NACE B)	Low	Low	Low	Low
Total Waste generated by manufacturing (NACE C)	Low	Low	Low	Low
Construction and demolition waste generated by the construction sector (NACE F)	Low	Low	Low	Low
Plastic Waste	Low	Low	Low	Low
Electric and Electronical Waste (WEEE)	Low	Low	Low	Low

Source: own elaboration

6 Results

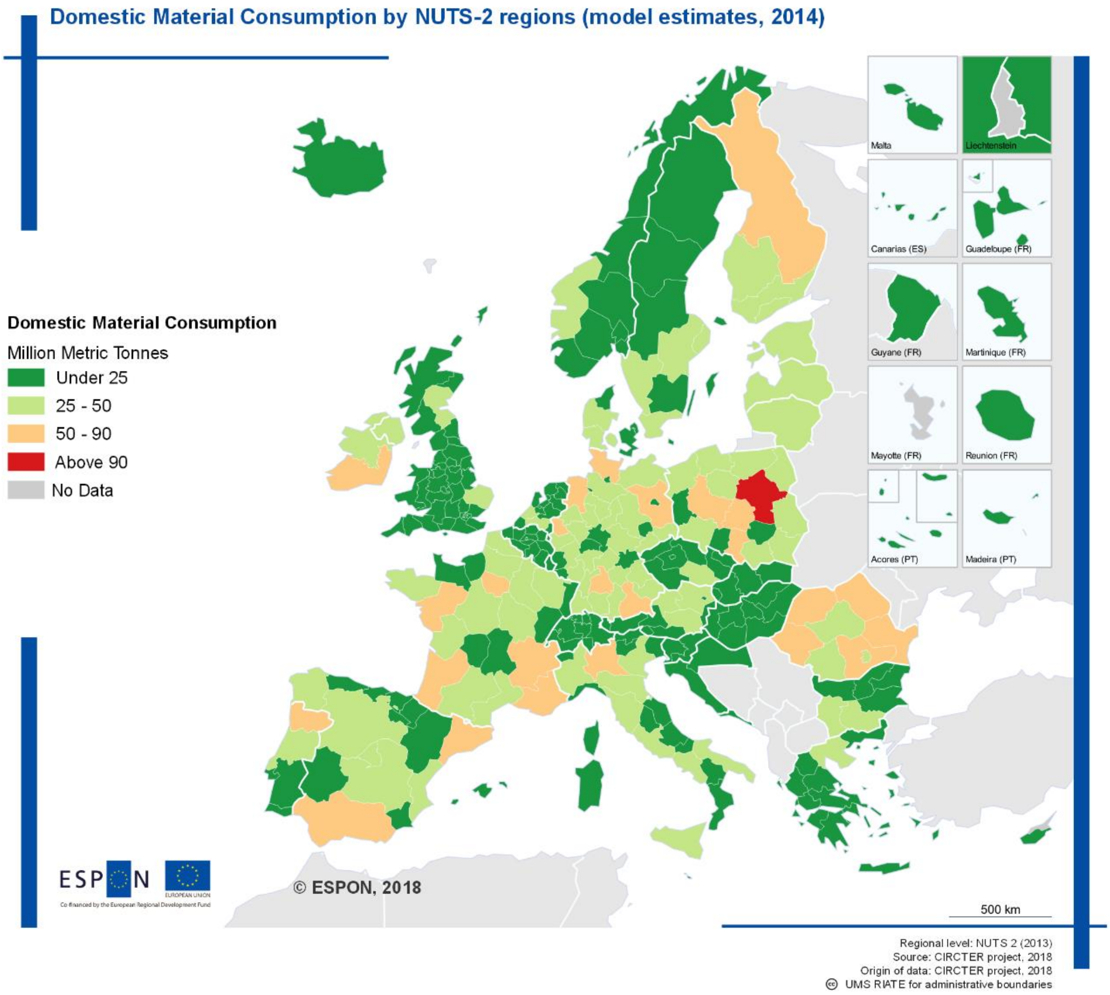
6.1 Domestic Material Consumption

Map 6-1 Regional Estimates Domestic Material Consumption (2006) absolute values



Expected accuracy of estimates: high (see Section 5.3 for further details)

Map 6-2: Regional Estimates Domestic Material Consumption (2014) absolute values

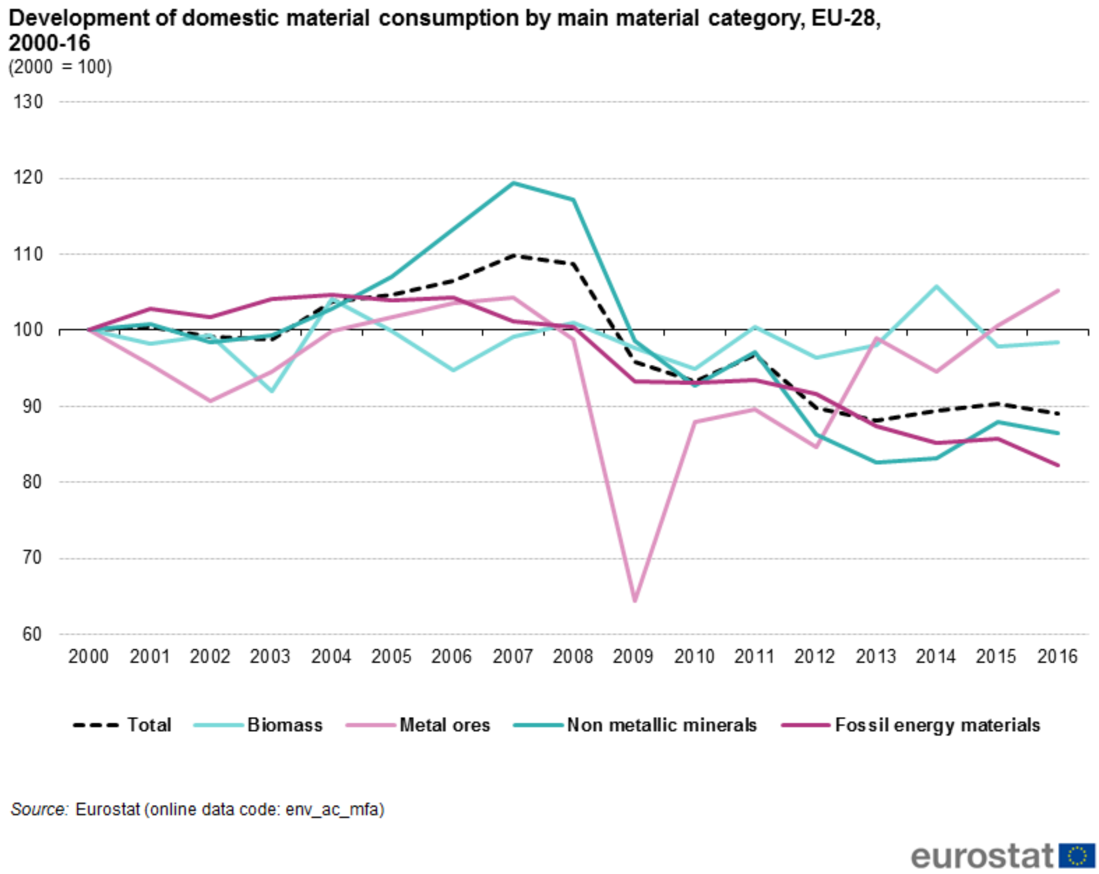


Expected accuracy of estimates: high (see section 5.3 for further details)

The DMC indicator showed in Map 6-1 provides an overview of the absolute level of the use of the resource directly used by an economy. It is important to note that the term "consumption" as used in DMC denotes apparent consumption and not final consumption; in fact, DMC does not include upstream "hidden" flows related to imports and exports of raw materials and products. This drawback favour countries whose consumption is based mostly on imported goods since loss of raw materials occurring during the production processes is allocated to the producer regions even though these latter, actually, do not consume final goods.

Overall regional estimates seem coherent with EU published data; in fact, Map 6-2 reflects a general decrease in domestic material consumption in line with Eurostat statistics for 2000-16 years (Figure 6-1).

Figure 6-1: Evolution patterns of EU material flows (2000-2016)

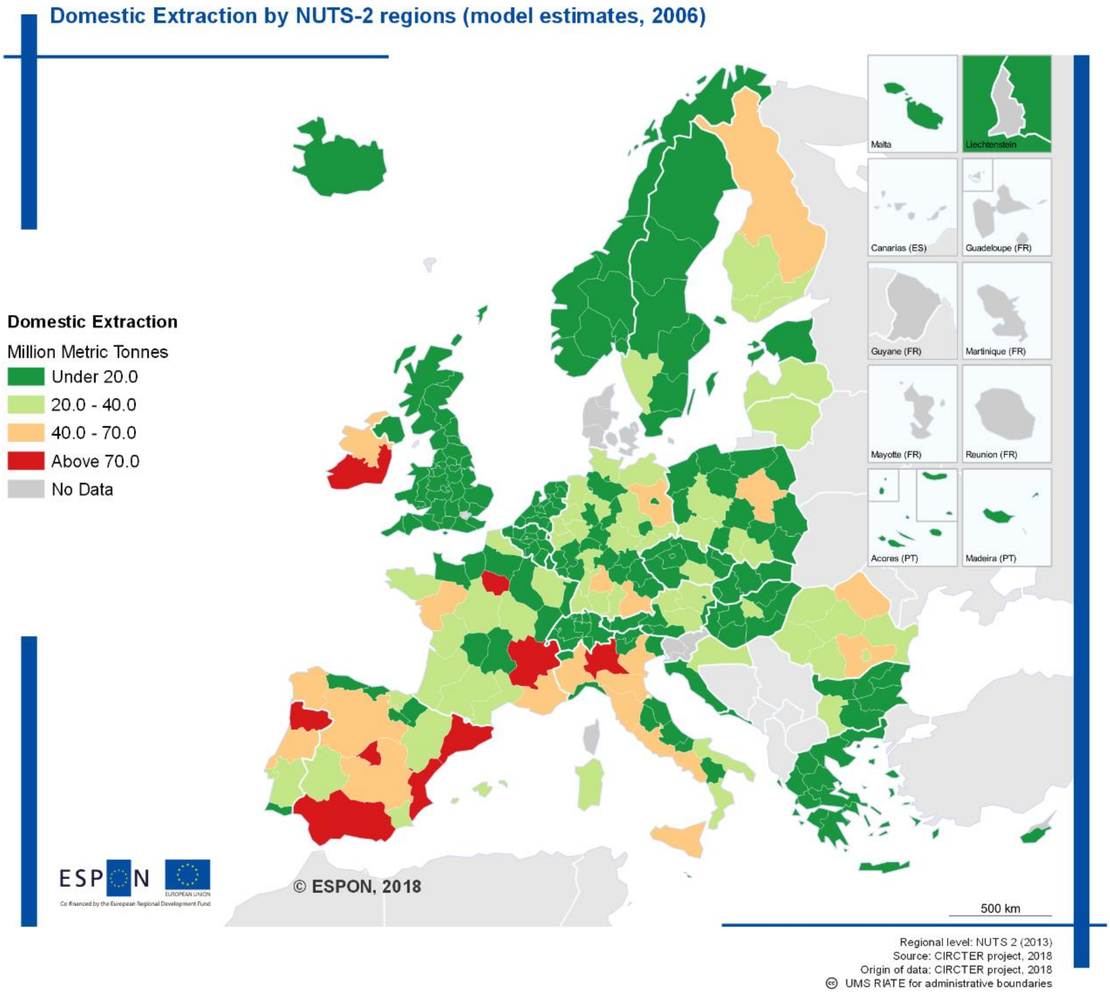


The parameters applied to estimate regional values (see Table 3-4) are also in line with theoretical frameworks; namely, population density is a territorial factor that potentially decrease DMC thanks to synergies an economies of scale exploited (Weisz et al. 2006, Steinberger J. K., et al. 2010); additionally, population also is a common predictor adopted in the literature positively correlated with consumption (and thus DMC), however we found that total employment may be possibly superior since it better address population most active in an economy (on one side more employees means more production, on the other side employees do have more purchasing power capacity than unemployed). Finally, we used also Gross Fixed Capital Formation (GFCF) as a factor positively linked with the physical (production) aspect of an economy since it refers to the net increase of physical assets (asset investments).

In view of the above parameters, it is not surprising therefore that regions with the highest level of absolute employment and, to lower extent, high capital investments (i.e. Ile de France, Lombardy, Cataluña etc) figure among regions with highest DMC.

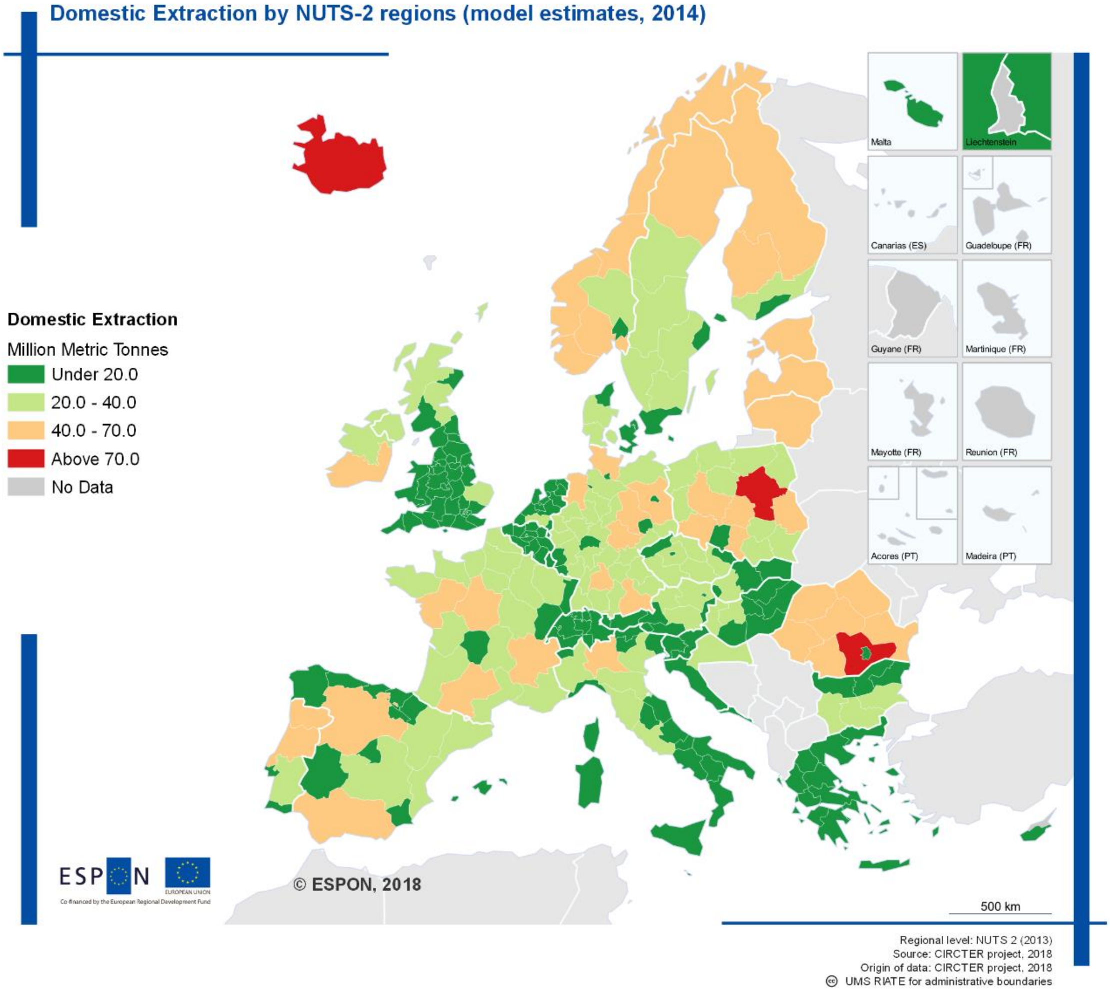
6.2 Domestic Extraction

Map 6-3: Regional Estimates Domestic Extraction (2006), absolute values



Expected accuracy of estimates: high (see Section 5.3 for further details)

Map 6-4: Regional Estimates Domestic Extraction (2014), absolute values

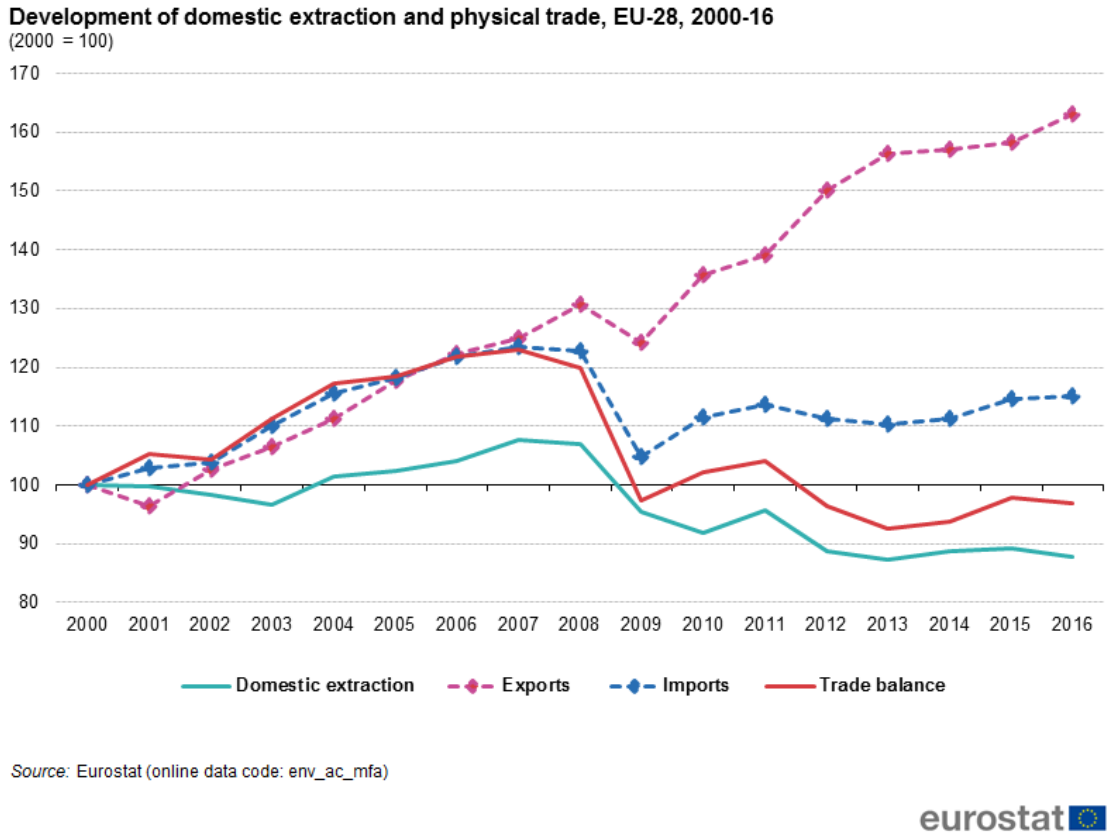


Expected accuracy of estimates: high (see Section 5.3 for further details)

Domestic extraction figures reflect largely the regional availability of vacant land (i.e. captured through population density), as it is the indicator mostly tied with the availability of regional natural capital; consequently, the regions more densely populated will feature reduced extraction – metropolitan regions with population density greater than 1000hab per km2 and reduced surface (e.g. Hamburg, Berlin, Brussels etc.) will not have domestic extraction at all due to lack of available land.

As it was for material consumption, Map 6-3and Map 6-4 show a decreasing regional pattern for material extraction across European Union. Such downturn came together with a constant increase in EU physical exports – 63% increase through the period 2000-2016 – and a rather stable physical import across the same period (see Figure 6-2). These trends suggest at least two important key facts, first that the EU has moved towards a more exported-oriented economy, and second it has improved its resource productivity since it is producing more with less resources.

Figure 6-2: Pattern evolution of domestic extraction and physical trade (2008- 2016)

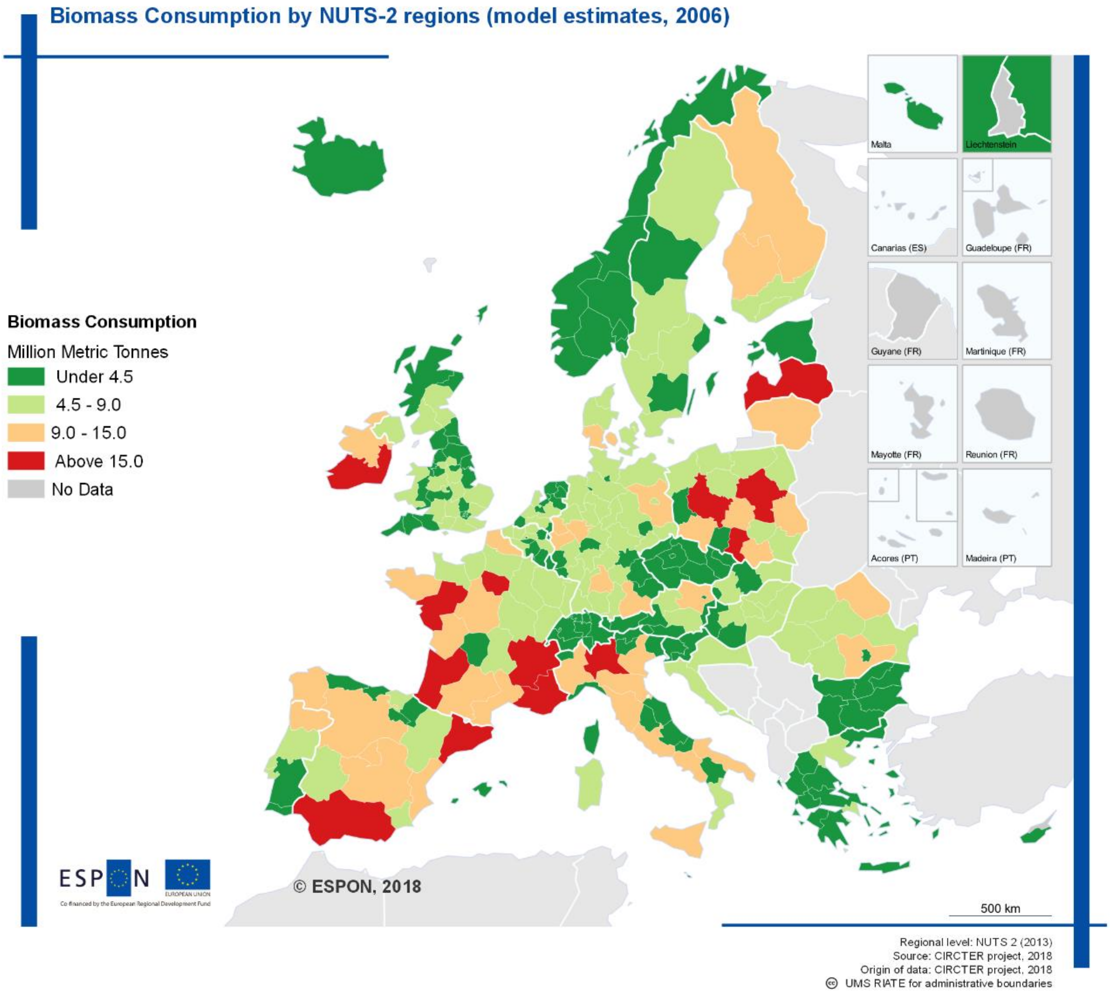


Similarly to DMC, we can observe a general reduction in western and southern EU regions; Italy's regions are among those that most experienced domestic material extraction reduction (Campania, Sardinia, and Sicily almost by a factor of three, probably favoured by a shrinking economy); the northern countries, with stronger economies based on the extraction of mineral, metallic and biomass resources, remained constant across time, with the exception of Sweden that slightly increased its material extraction (probably due to increased mining activities, consumption of metal ores in Finland and Sweden is by far among the highest figures in EU 5.5 tonnes per capita and 5.2 tonnes per capita in 2016 respectively; source Eurostat). Finally, Eastern regions are those that seems to have experienced upward trends; North-Western and Southern-Central regions of Bulgaria almost doubled domestic extraction, while Nord-Vest and Nord-Est regions of Romania also featured significant increase in resource extraction likely driven by biomass consumption.

With respect to model's parameters, we can observe how land availability, employment and total gross fixed capital formation are all positively correlated with DE and in line with other scientific findings (Steinberger et al., 2010); in addition, we also detected a negative correlation with Gross Domestic Consumption (GDP). This can be explained by the fact that wealthier economies tend to import rather than extract (or produce) primary goods and/or raw materials.

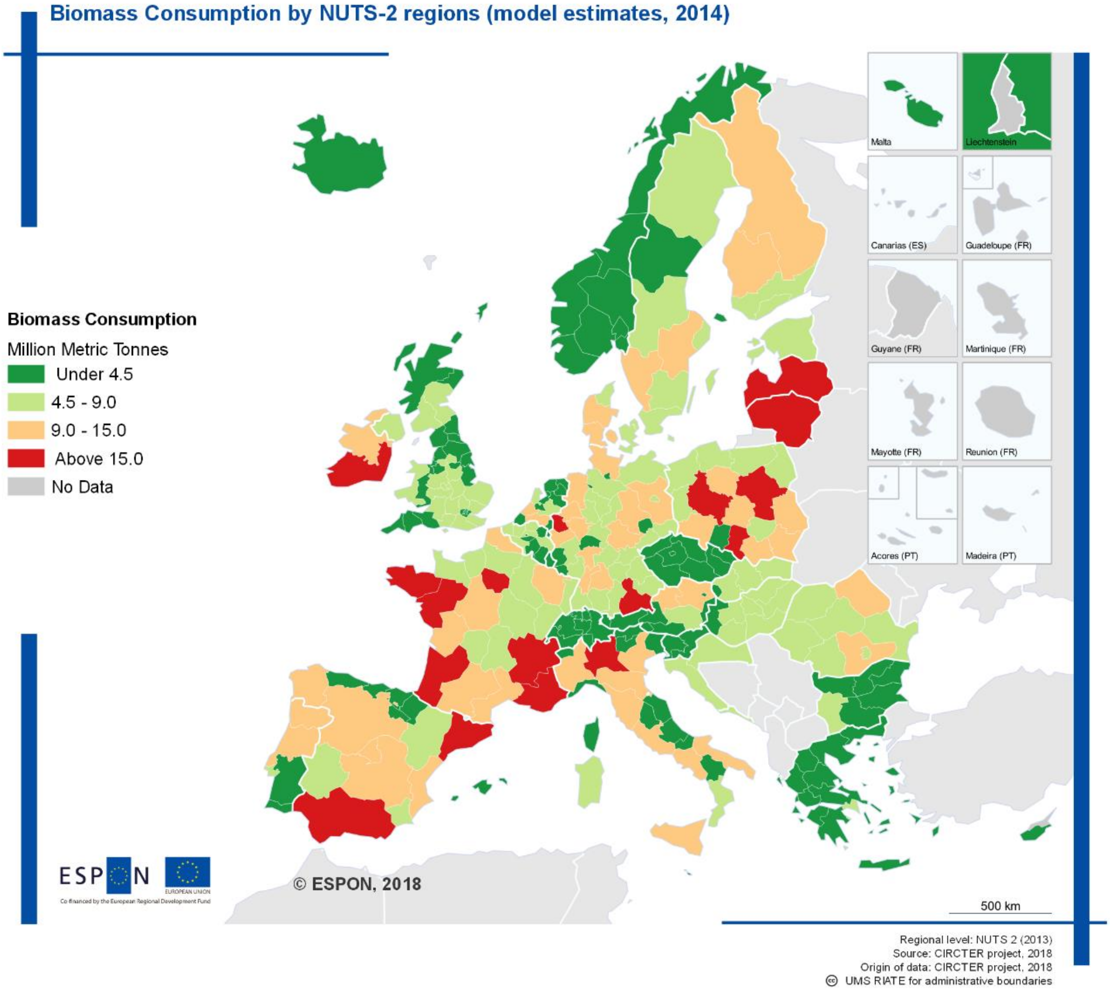
6.3 Biomass consumption

Map 6-5: Regional Estimates Biomass consumption (2006), absolute values



Expected accuracy of estimates: medium (see Section 5.3 for further details)

Map 6-6: Regional Estimates Biomass consumption (2014), absolute values



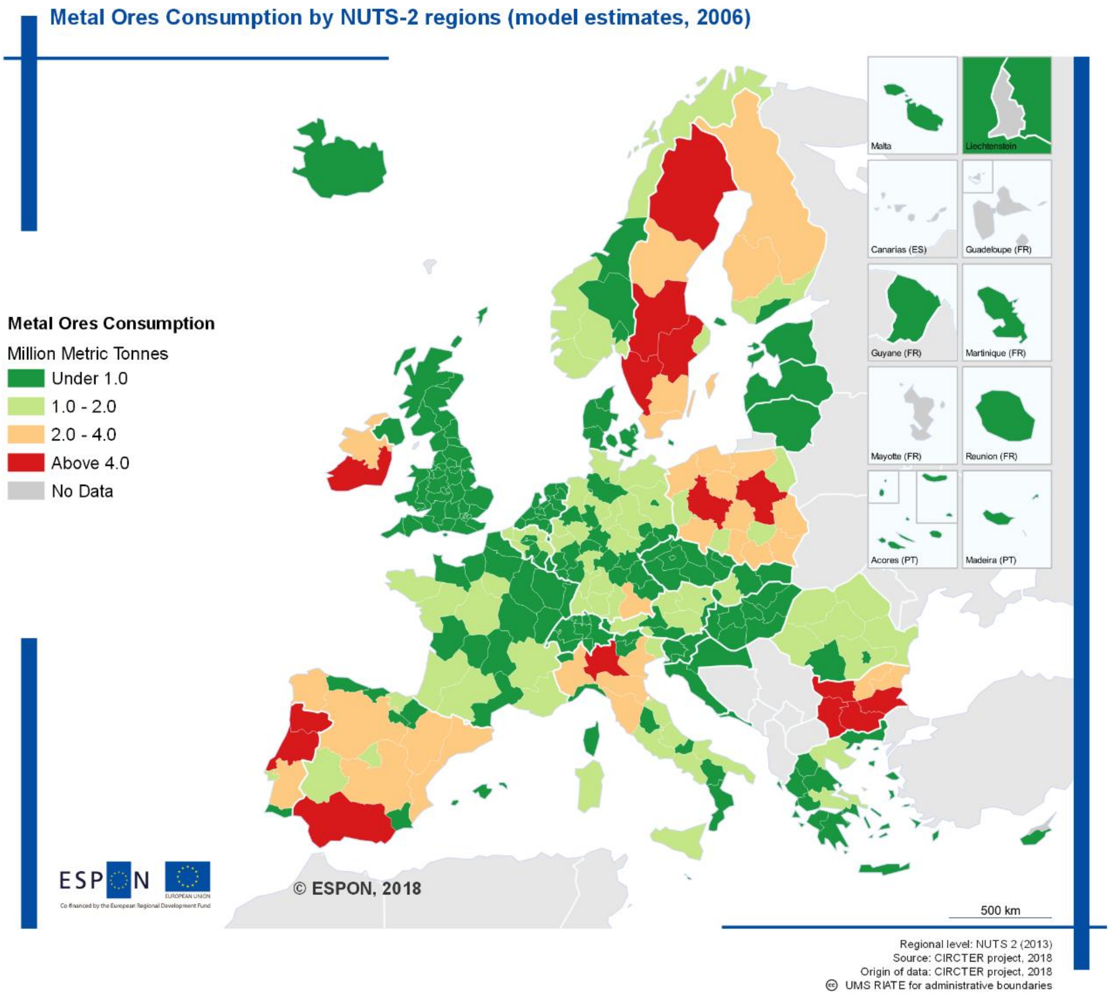
Expected accuracy of estimates: medium (see Section 5.3 for further details)

Biomass consumption varies a lot across countries ranging between 2 and more than 10 tonnes per capita, and it represents the only material flow that has been on a rather stable level over the long term (Figure 6-1). Economies with high biomass consumption are specialised on timber production (e.g. Latvia and Finland) or certain livestock production (Ireland, Denmark, Germany and France). In Ireland for instance, fodder crops and grazed biomass made up the biggest share of this category, while in Eastern and Northern EU regions (e.g. Finland, Latvia, Sweden) forestry played a major role in the economy. Among the Member States, consumption per capita of biomass was lowest in Estonia (0.09 tonnes per habitant), and metropolitan regions such as Praha, London, Berlin and Brussels (all below one tonne per capita consumption).

The parameters applied are all strictly tied with the natural endowment of regions and/or the primary sector; indeed, if on one hand we find land availability, agricultural and forestry landuse that confirm the close link of biomass with availability of natural capital, on the other hand we have investments and value generated (GFCF and GVA) in agriculture. As expected, these predictors impact positively the domestic consumption of biomass (regions which do have more land addressed to agriculture and forestry do also have more biomass consumption). Finally, also the magnitude of population could play a key role in explaining biomass consumption figures as highlighted elsewhere (Steinberger et al., 2010).

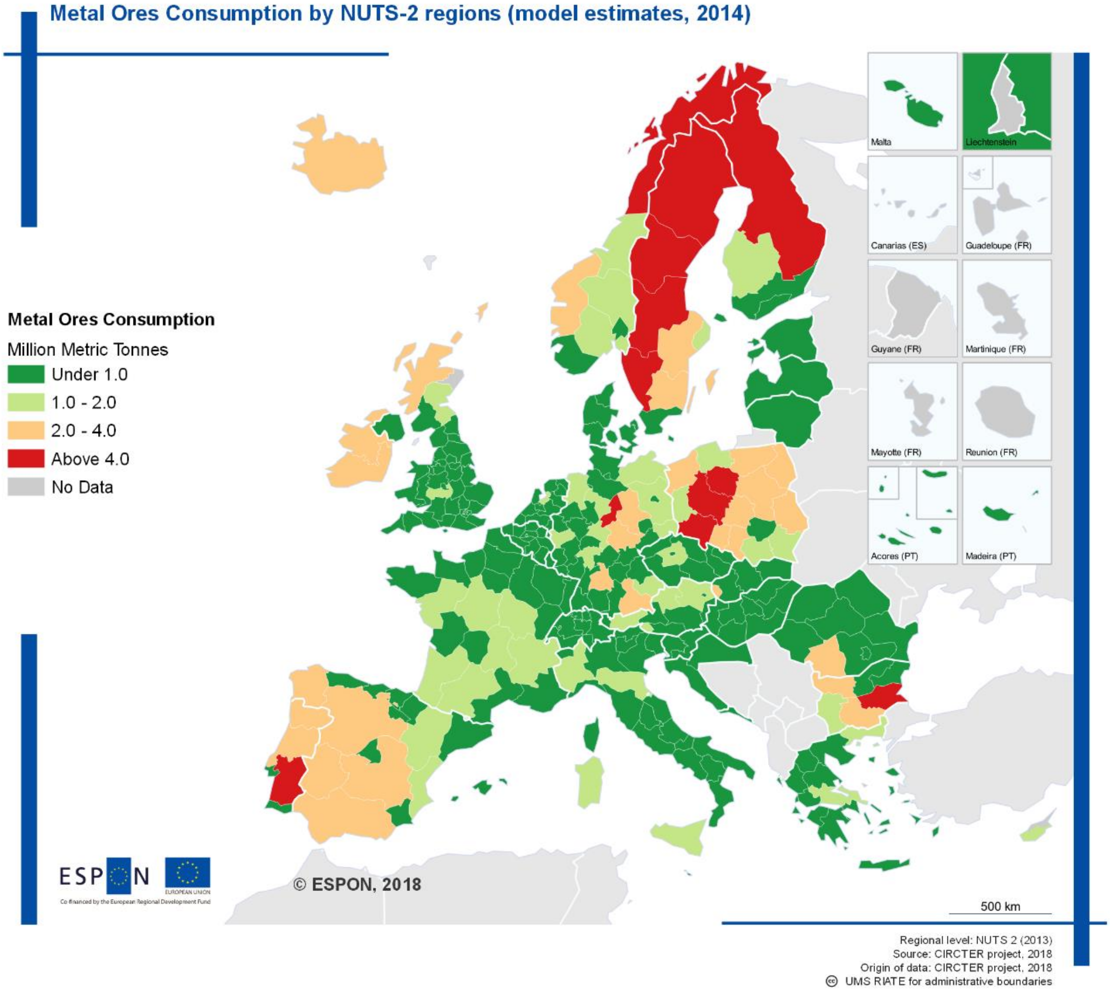
6.4 Metal ores consumption

Map 6-7: Regional Estimates Metal ores consumption (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Map 6-8: Regional Estimates Metal ores consumption (2014), absolute values



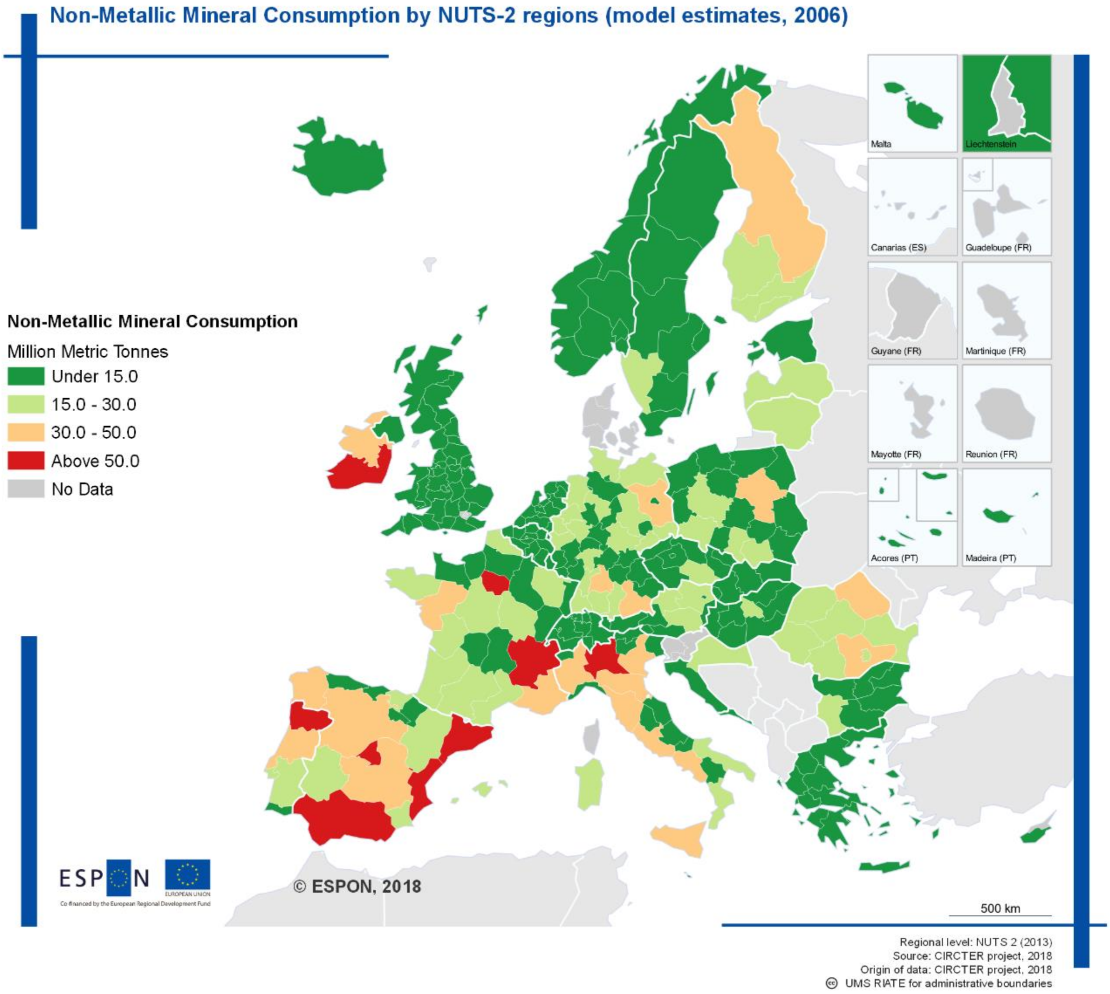
Expected accuracy of estimates: low (see Section 5.3 for further details)

Consumption of metal ores is highest in extracting countries (Finland, Sweden and Bulgaria) having greater availability of land per capita. However, this is also due to the large apparent consumption of metal ores for export. In fact, since the complex elaboration and processing steps that metals ores require to achieve final products, the quantities that are traded or consumed are typically much smaller than the quantities originally extracted, leading to a discrepancy between apparent and final consumption. Countries with uninhabited areas tend to have more mineral extraction per capita, and be net exporters; consequently, since exported minerals are a small fraction of the extracted materials, these countries have larger apparent consumption in comparison to their costumers (Steinberger et al., 2010). This also explains why consumption of metal ores in EU is higher than domestic extraction of metal ores (Weisz et al., 2006); extraction and to some degree also the related heavy industries, which further process the commodities, increasingly are being re-allocated to countries outside the European Union.

The high level of trade characterising this material flow, together with the difference between apparent and final consumption, clearly hindered a correct measurement and estimation of the indicator; many Eurostat figures are based on estimation, and different MS present doubtful changes in metal ores consumption figures across the two-year considered. Consequently, also our estimation model did not produce satisfying results in term of reliable regional estimates, despite parameters applied are significant and coherent with theory (i.e. land availability, industrial investment, and industrial value added all as a potential drivers of metal ores consumption).

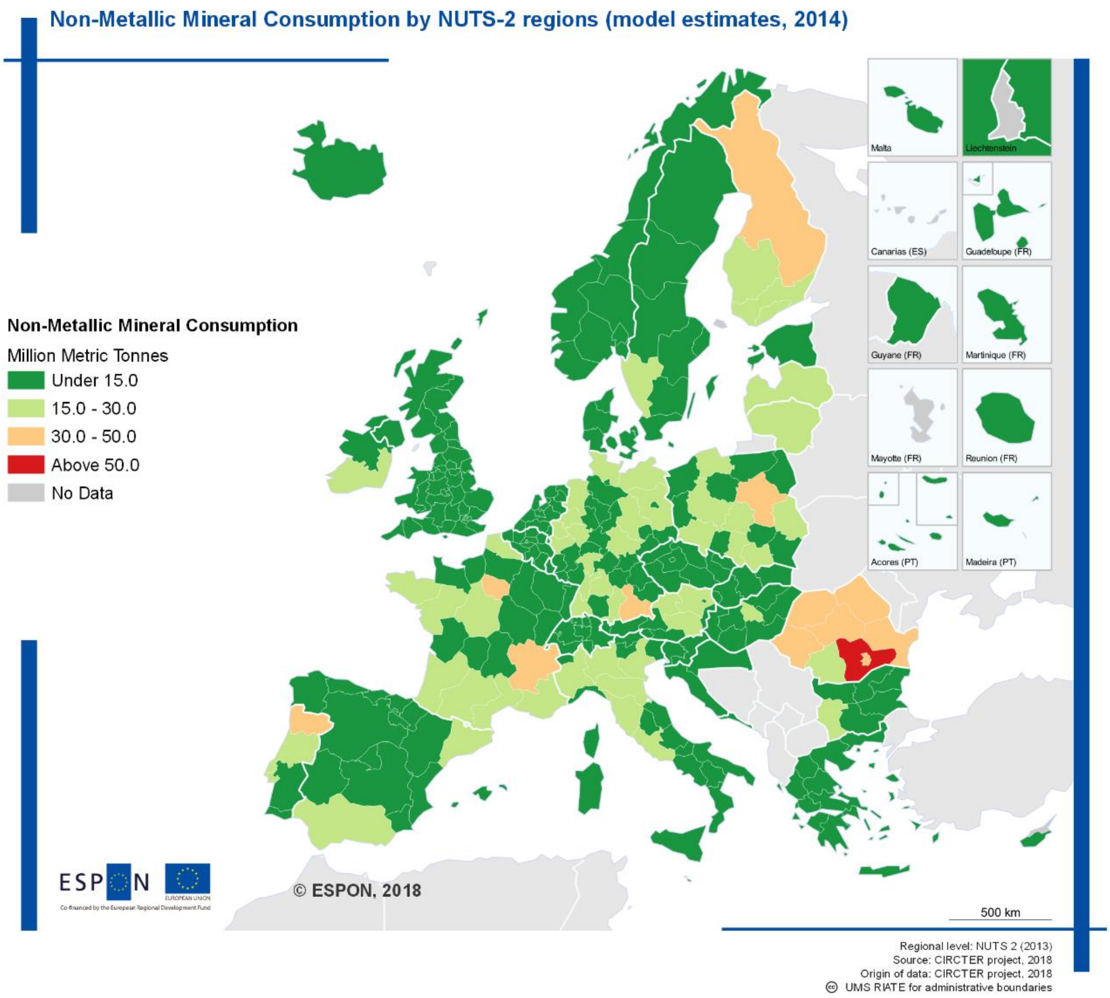
6.5 Non-metallic mineral consumption (Construction)

Map 6-9: Regional Estimates Non-metallic mineral consumption (2006), absolute values



Expected accuracy of estimates: medium (see Section 5.3 for further details)

Map 6-10: Regional Estimates Non-metallic mineral consumption (2014), absolute values



Expected accuracy of estimates: medium (see Section 5.3 for further details)

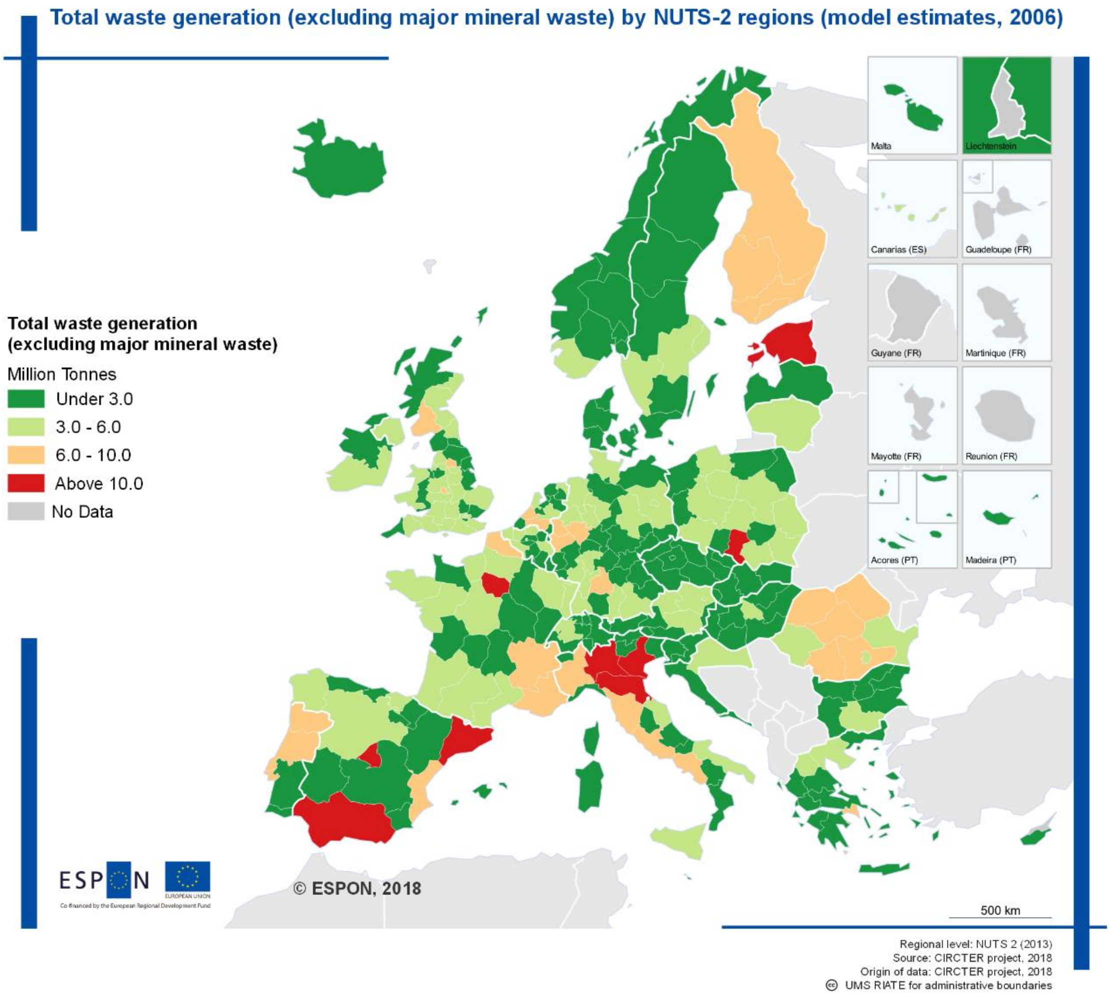
The differences between countries in non-metallic mineral consumption are influenced amongst others by levels of construction activities (investments), population densities, and size of infrastructures such as e.g. road networks (source: Eurostat); consequently, we included parameters strictly linked with these factors, and results strongly agree with past findings confirming thus the model goodness.

Non-metallic mineral construction is the indicator most correlated with GDP, highlighting the close link between economic growth (and thus investment) and the consumption of construction minerals. This evidence is further reinforced by looking to positive relationship with the other economic parameter, the location quotient for construction investment (GFCF). Periods of greater economic growth in fact often result in enhanced construction activities. During these periods high amounts of construction minerals are used to build up stocks while during periods of "average" growth or in recession phases, investment in physical infrastructures and thus the use of construction minerals usually declines (Weisz et al 2006). Romania, which figures among the countries that experienced highest economic growth between 2006-14, ranks among the first countries in construction mineral consumption per capita – București-Ilfov, Nord-Vest and Nord-Est regions (all above 17 tonnes per capita). Also, Polonia (even if at lower magnitude) undergone a similar pattern with an increased welfare and consequently expanding construction activities.

Likewise, Southern regions (Greece, Portugal, Spain, and Italy) that went through an economic recession phase (e.g. many Greece regions experienced more than 20% GDP per capita reduction) strongly reduced construction mineral consumption. Andalucía and Cataluña for Spain and Lazio and Veneto in Italy are the southern regions most affected in amount reduction terms. The same pattern can be observed also for some western regions, namely Ireland regions also affected by economic growth stagnation and/or recession.

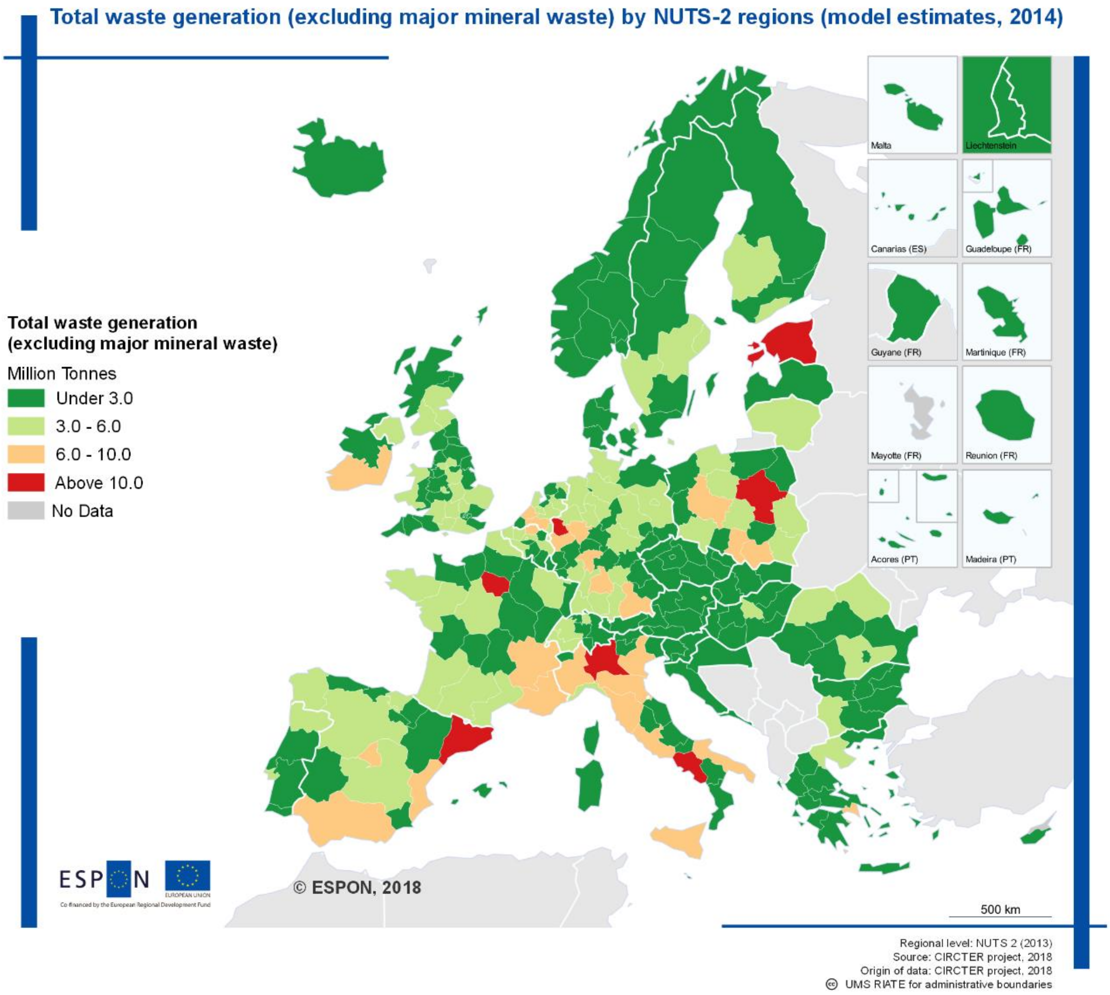
6.6 Total waste generation (excluding major mineral wastes)

Map 6-11: Regional estimates Total waste generation (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Map 6-12: Regional estimates Total waste generation (2014), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

As it might be expected, the overall amount of waste generated is related to some extent to the population and economic size of a country. This explain the highest figures of waste generation estimated for Lombardy and Emilia Romagna (Italy), Ile de France (France) and Dusseldorf (Germany). The smallest EU economies, together with islands and scarcely populated regions on the other hand generally produce the lowest levels of waste generation (e.g. Valle d'Aosta, Azores island and Madeira).

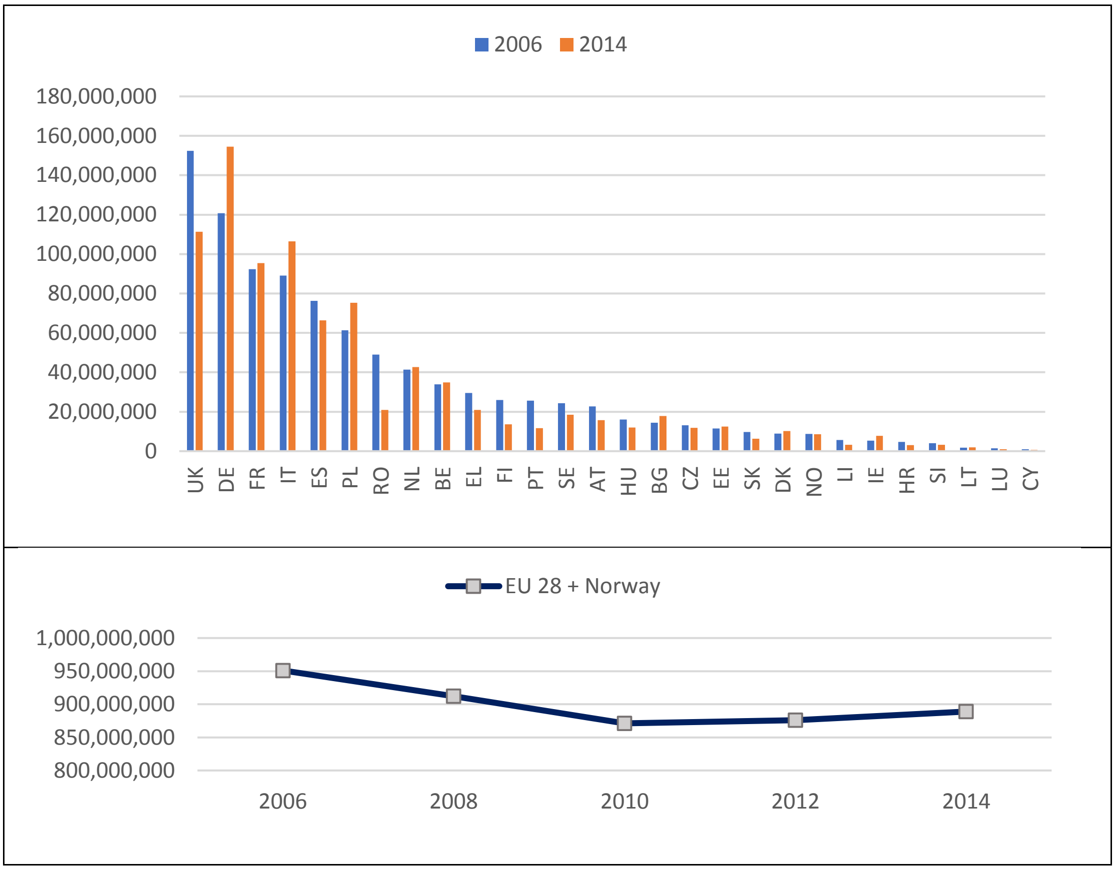
An exception is constituted by Estonia which, in 2014, produced relatively high quantities of waste (9.5 tonnes per inhabitants) due to its localised economy on energy production based on oil shale. This material still provides around 70% of the energy supply in the country[13]. Albeit of mineral origin, around a half of the waste produced on annual basis by oil shale processing in

13 http://www.oecd.org/environment/estonia-should-reduce-its-oil-shale-reliance-for-greener-growth.htm

Estonia is not classified as mining waste but as combustion waste (combustion ashes) and other wastes[14]. This is due to the technical processes involved in its extraction and transformation, that rely on a combination of chemical and thermal trearment steps (and not simply extractive). For details the reader may check Gavrilova et al. (2005).

In general, we can observe an overall reduction across EU regions in line with Eurostat statistics (Figure 6-3); in fact, waste excluding major mineral wastes fell 5.3 % between 2004 and 2014 while the quantity per inhabitant fell by 8.0 % (as the EU's population also grew over this period).

Figure 6-3: Total waste generation (excluding major mineral waste), national and EU aggregated statistics

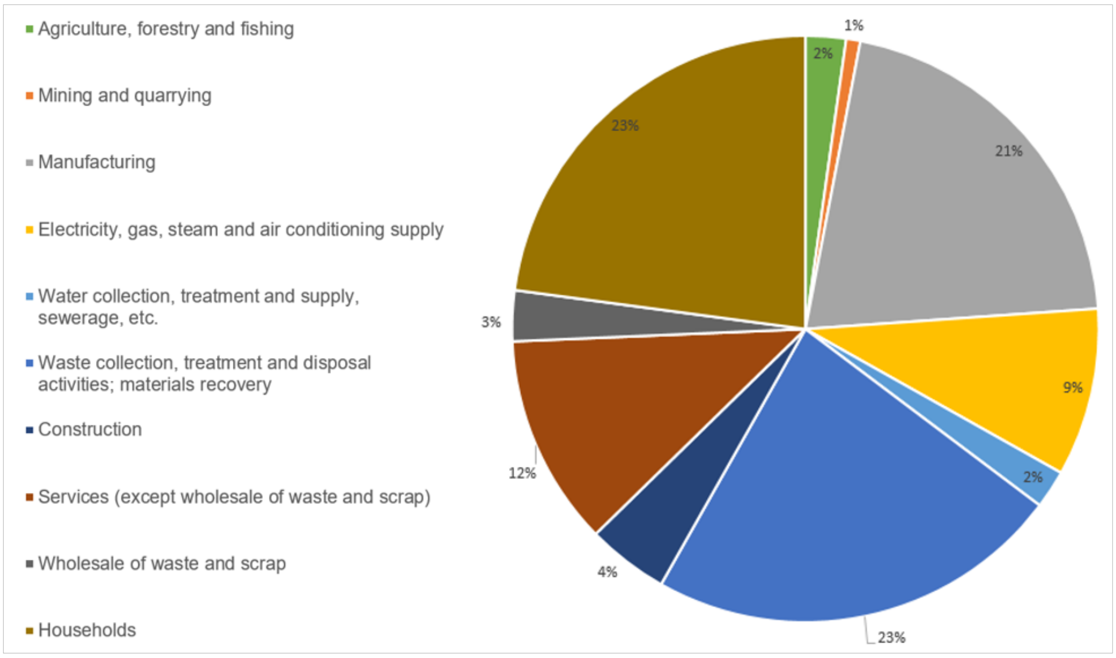


Source: own elaboration based on Eurostat data

Looking at the waste categories that determine total waste, the composition is mainly driven by household waste, manufacturing waste and waste collection and treatment (Figure 6-4). Hence, it is not surprising that population is the main driver among our model's parameters. This indicator is followed by economic indicators such as industrial and manufacturing investment and/or industrial and manufacturing value added.

[14] https://ec.europa.eu/eurostat/statistics-explained/index.php/Waste_statistics

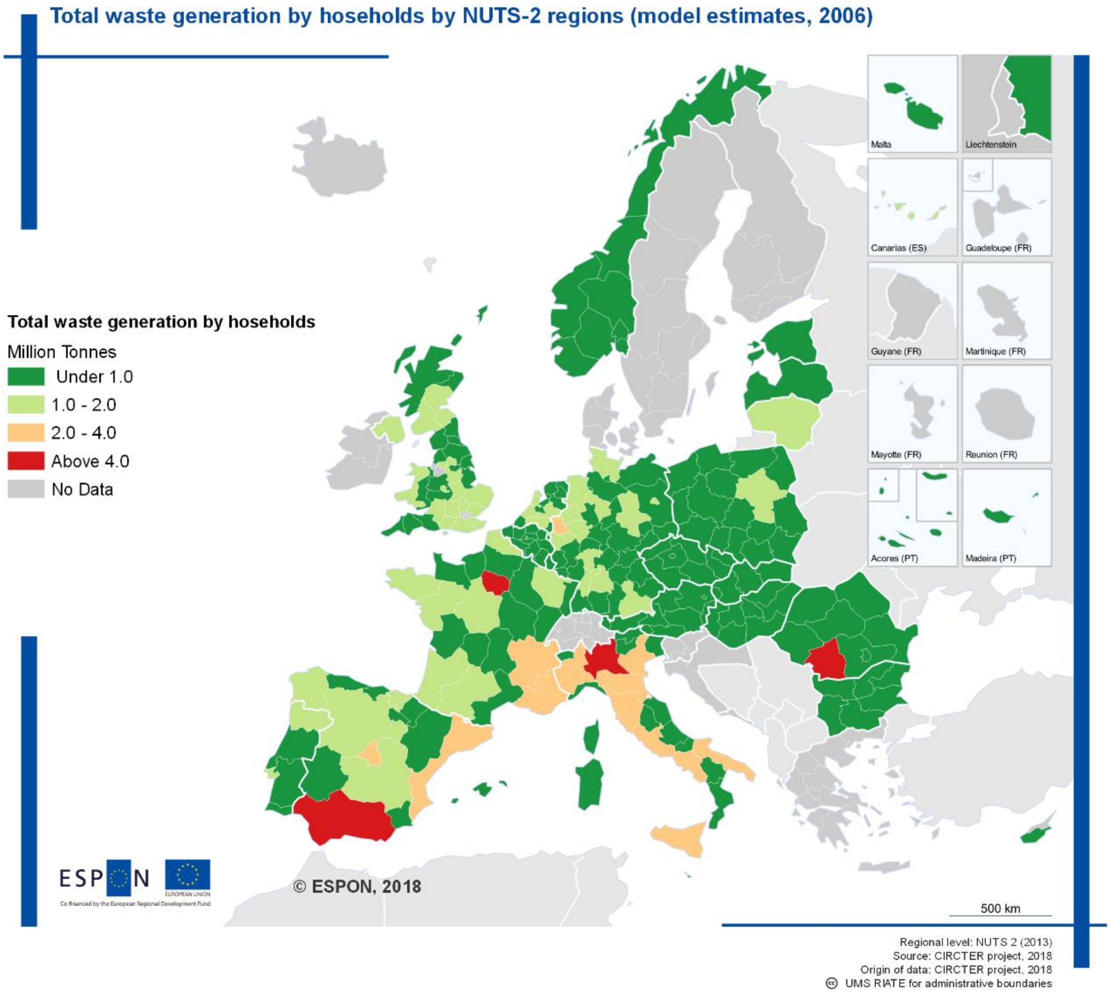
Figure 6-4: Generation of waste by waste category as a share of total waste, excluding major mineral waste. Data for EU28 (2016)



Source: Eurostat (env_wasgen)

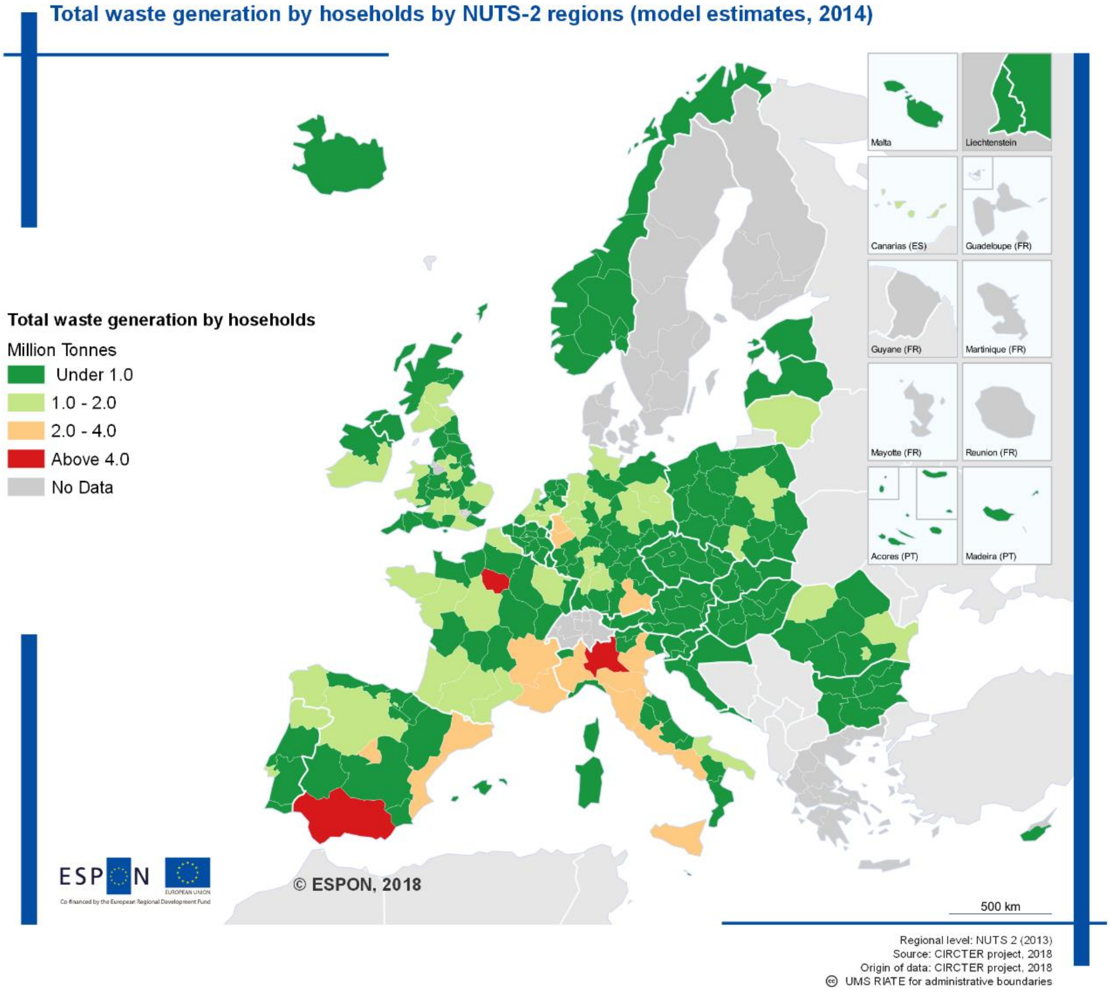
6.7 Total waste generated by households

Map 6-13: Regional Estimates Total waste by households (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Map 6-14: Regional Estimates Total waste by households (2014), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

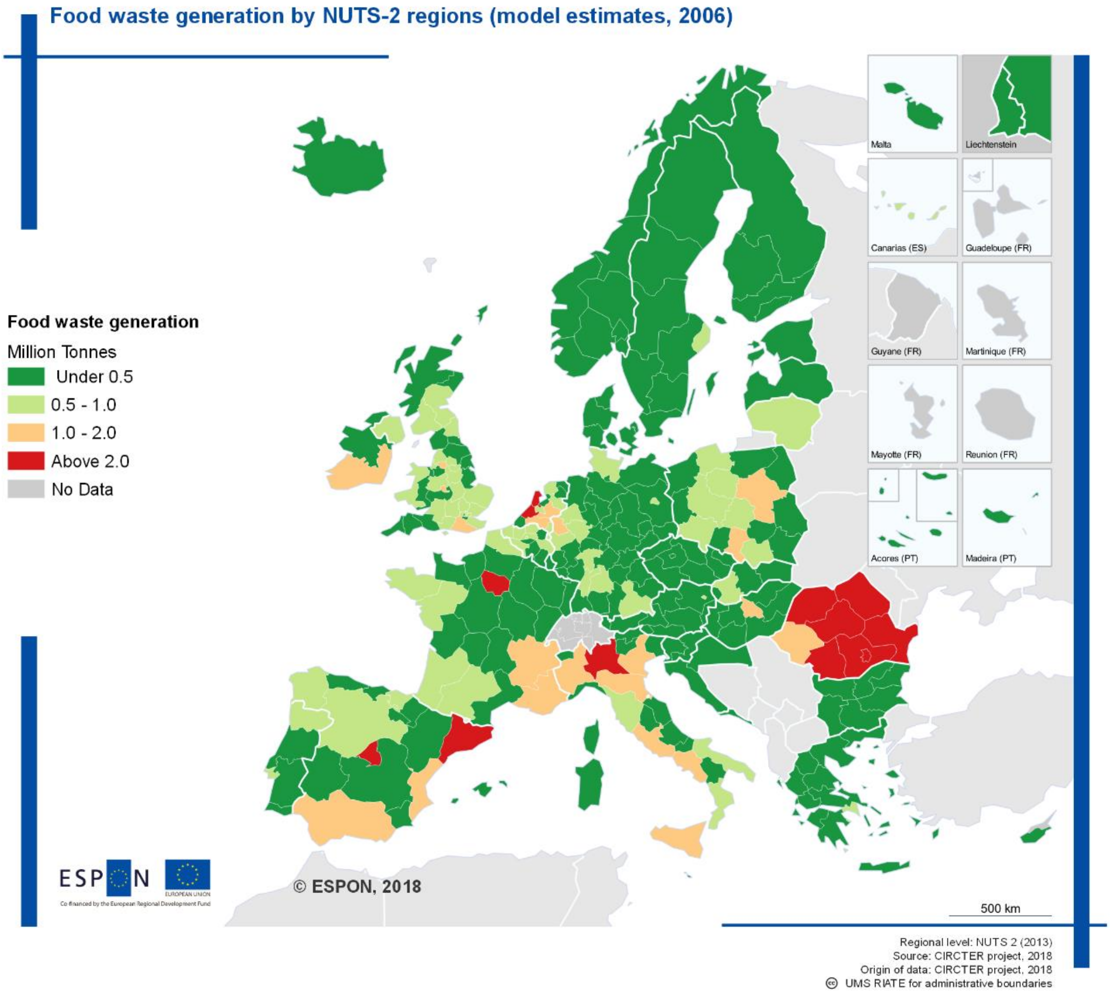
Total waste generated by household vary considerably, ranging from almost 600 kg per capita in Belgium's regions to less than 200 kg per capita in some eastern regions of Romania and Poland. The variations reflect differences in consumption patterns and economic wealth, but also depend on how municipal, and thus household waste is collected and managed. There are differences between countries regarding the degree to which waste from commerce, trade and administration is collected and managed together with waste from households so that comparison among countries have to made cautiously. In particular, depending on national waste management and collection system, the approaches for municipal waste data collection established in the Member States might vary significantly, thus limiting data comparability across countries (see also 5.1 on input data limitation).

If we focus on Map 6-13 and Map 6-14 we can see that EU household waste generation has been on a rather stable level over the time-period analysed. In fact, regional estimates (and Eurostat statistics) confirm a 3% decrease in household waste from 2006 to 2014. According to estimated figures, this downturn seems to be particularly evident for many regions of Spain which decreased household waste by 20%, as well as southern UK regions (10%) and some Italian regions (Abruzzo, Piemonte and Campania among others).

For what concern the regionalisation model, the parameters which best explained household waste generation are population and municipal waste, both positively correlated. The first is clearly linked with the overall amount of household consumption (and thus waste) of a region; whilst the second refers to the municipal waste collected within a region, where household waste accounts for the most part.

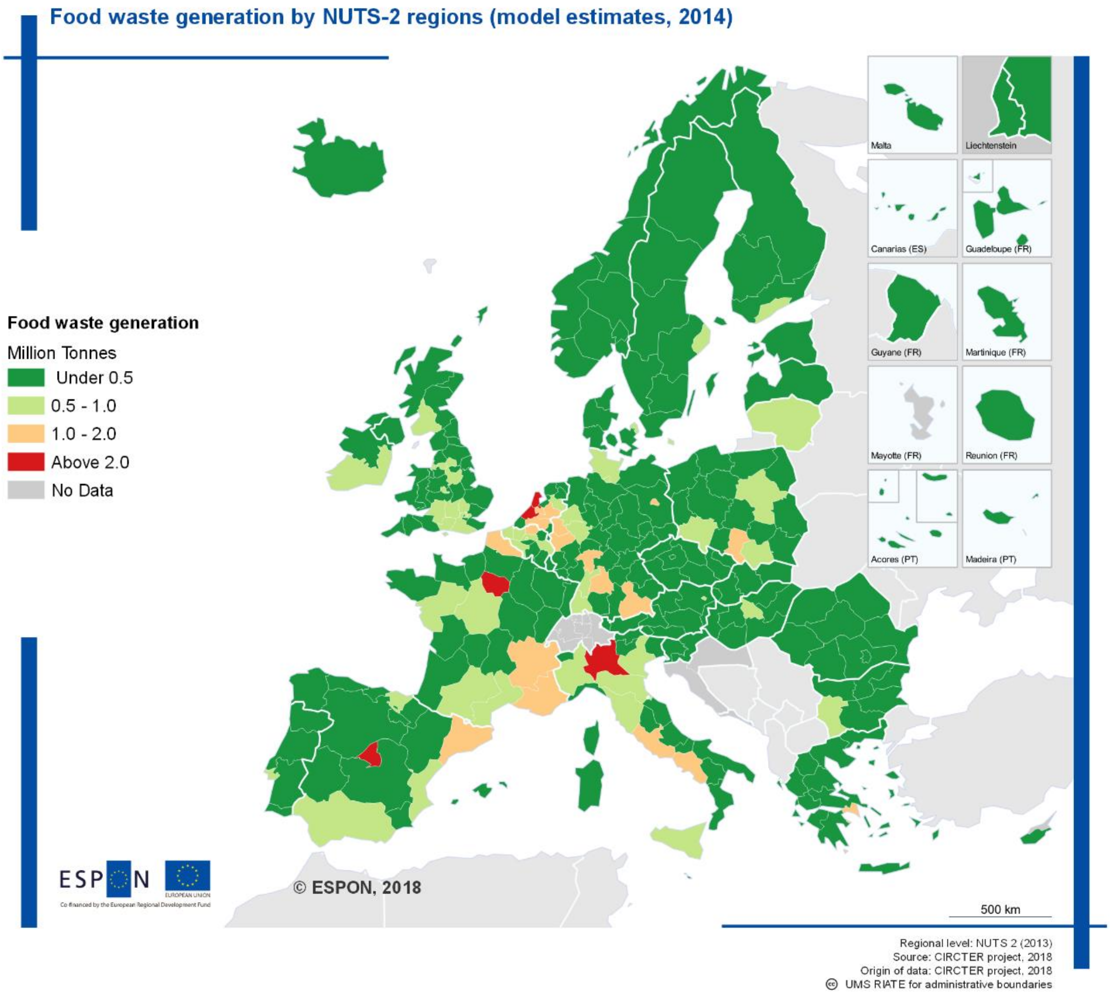
6.8 Food waste generated

Map 6-15: Regional Estimates: Food waste generation (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Map 6-16: Regional Estimates: Food waste generation (2014), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

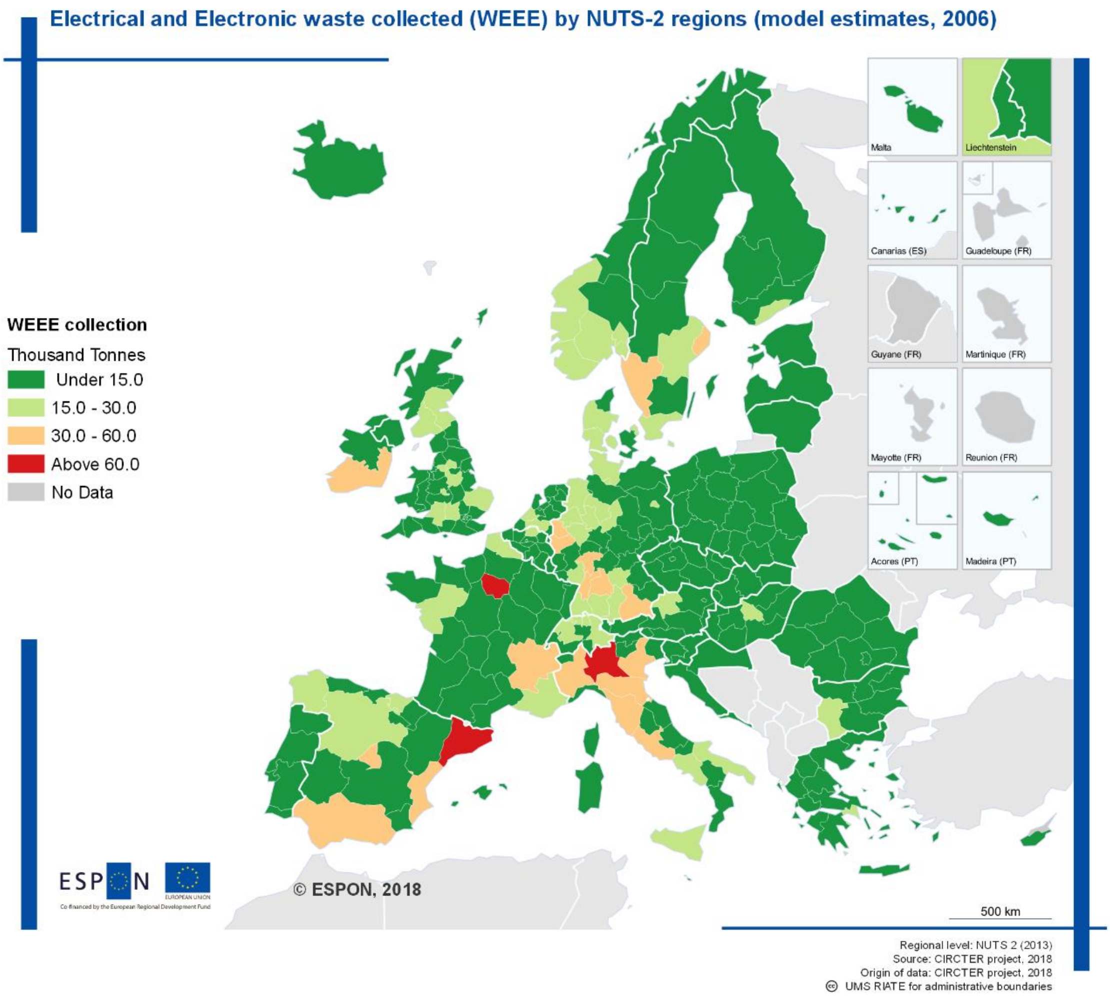
In general, Europe average experienced a downturn trend in food waste generation (-12%), going from 250 kg per inhabitant in 2006 to 190 kg in 2014. In general, the highest figures correspond to highly populated regions. In fact, according to the estimates, many western and southern metropolitan regions (e.g. Ile de France) undergone above 20% increase in food waste generation. This could suggest that economies of scale for food consumption does not work as for other consumption utilities (i.e. transport, housing, employment etc.) where synergies deployed decrease the consumption of material per capita; rather the food consumption seems to behave like a fixed good demand directly proportional to the magnitude of agglomeration, in other words food waste keeps pace with the growth of the cities. On the other hand, less populated regions seem to have reduced food waste, reflecting the depopulation process that many peripheral regions are experiencing.

Romania in particular stands out from the rest of Europe in terms of food waste generation. According to Eurostat data this country has significantly decreased the generation of food waste, from 21.5 million tonnes in 2006 to 2.3 million tonnes in 2014. Despite a decreasing trend might be expected due to the adhesion of Romania to the EU in 2007 – as an outcome of the the efforts to reach the targets imposed by European legislation regarding overall municipal waste reduction and landfill –, it is unlikely that such decrease could be verified in just two years (animal and vegetal wastes went from 19.8 thousand tonnes in 2008 to 1.1 thousand tonnes in 2009). A more reasonable explanation might be given by a change in methodological data accounting.

With respect to the parameters applied to regionalise food waste, we find population density, clearly linked with the consumption stage of food waste, and land surface, linked on the other hand to the production stage (i.e. larger regions are more likely to have surface areas for agricultural and/or livestock activities).

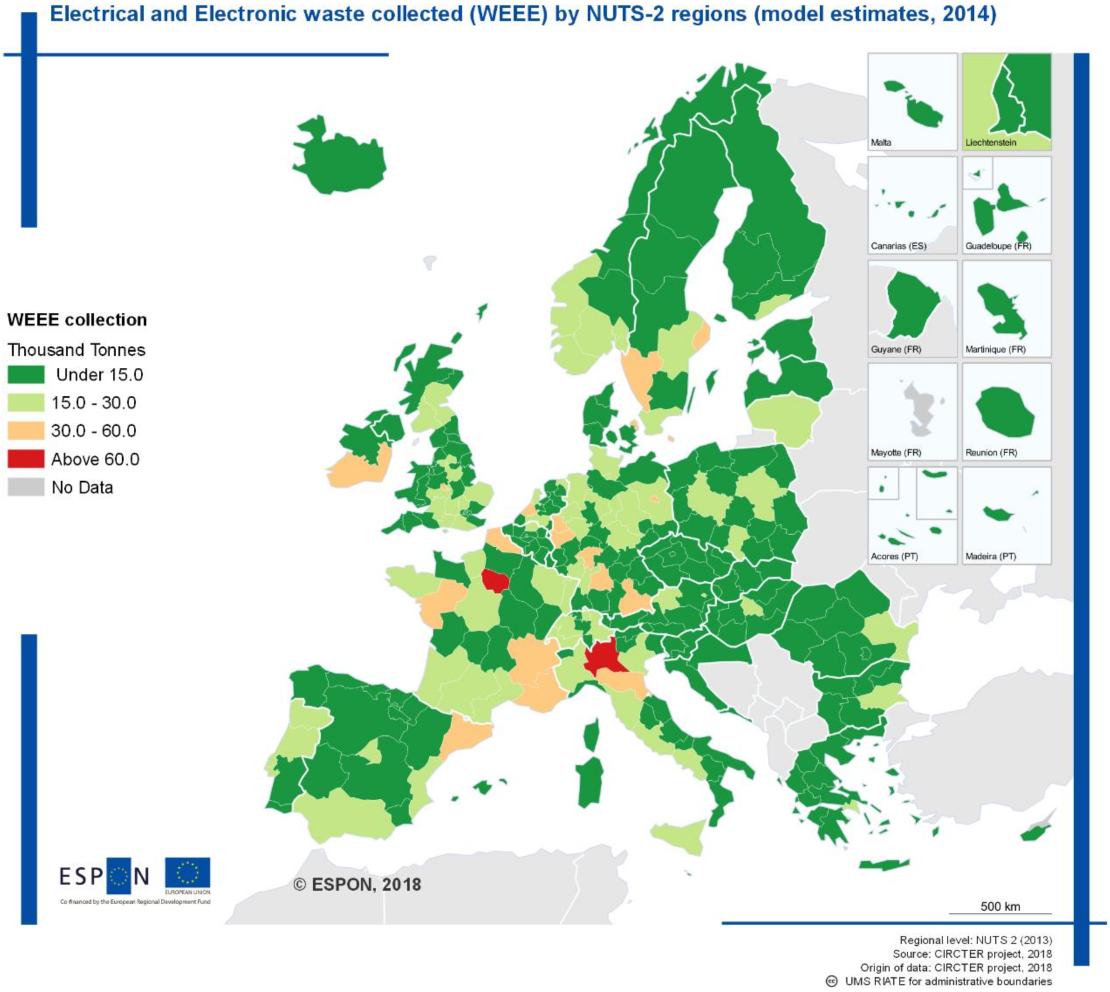
6.9 Electrical and electronic waste (WEEE) collected

Map 6-17: Regional Estimates Electrical and electronic waste collected (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

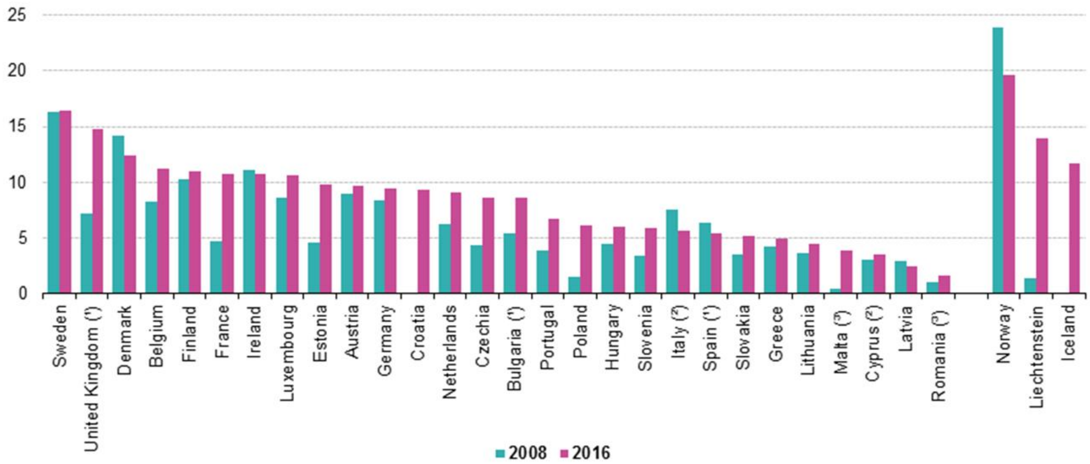
Map 6-18: Regional Estimates Electrical and electronic waste collected (2014), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Differently from other waste categories characterised by downturn trends, electrical and electronic equipment (WEEE) is currently considered to be one of the fastest growing waste streams in the EU, growing at 3-5 % per year. Indeed, according with Eurostat database, EU average across 2006-14 years is increased by 10% (from 6.3 Kg per capita to 7.0 Kg per capita).

Figure 6-5: Waste electrical and electronic equipment, total collected, 2008 and 2016 (kg per inhabitant)



Note: Ranked by 2016 data.
(¹) 2008: Eurostat estimate.
(²) 2016: 2015 data instead.
(³) 2016: 2014 data instead.

Source: Eurostat (env_waselee)

Similarly to the municipal waste, WEEE measurement is often biased by different definitions of electronical waste collection and different statistical units across reporting countries; these shortcomings, together with the high level of trade characterising WEEE (it is among the waste streams with the highest economic value since the large content of critic raw material), may explain the rather low goodness of regionalisation models.

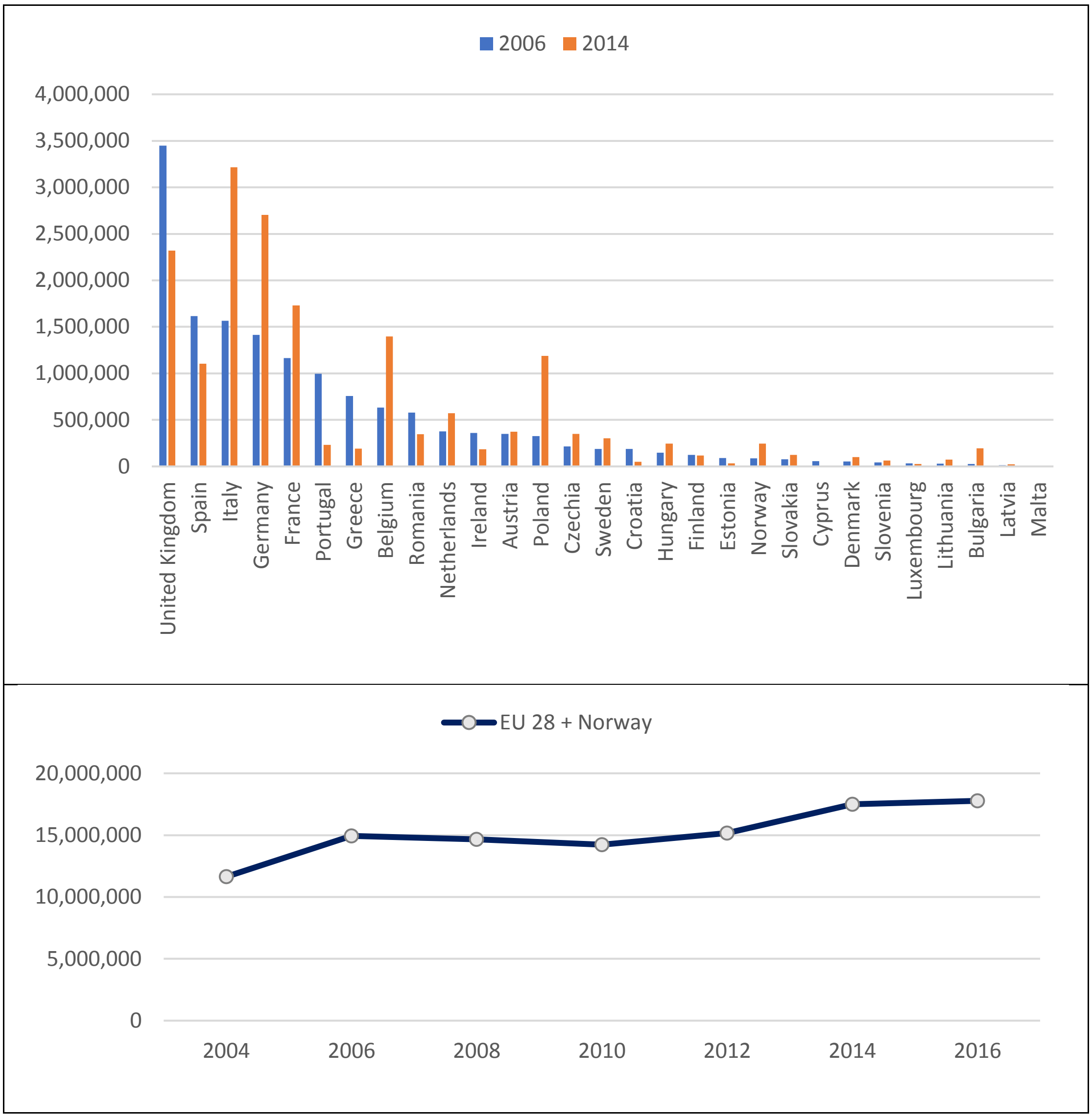
Our regionalization models strongly differ between 2006 and 2014 with some parameters of doubtful sign (i.e. high specialisation in manufacturing seems to be negatively correlated). This low reliability might be explained by the instability of input data – similarly to municipal waste, different national legislations and collection systems can bias the WEEE data collection – , but also by the nature of the waste typology itself. Indeed, the complex mixture of materials and components charactering WEEE makes arduous the identification of consistent and significative parameters. As a result, data interpretability is strongly hampered by the instability of- national statistics.

This said, according to our correlation analysis, it seems that industrial gross value added is the main driver for WEEE collection and, consequently, regions with the highest industrial activity (e.g. Ile de France and Lombardy) are also those collecting highest amount of WEEE.

6.10 Plastic waste generated

Regional estimates for plastic waste suggest a clear upward trend across EU regions. This is entirely compatible with aggregated statistics. According to official Eurostat data, EU increased plastic waste generation by 17%, from almost 15 million tonnes in 2006 to over 17 million tonnes in 2014 (Figure 6-6).

Figure 6-6: Plastic waste generation, national and EU aggregated statistics (tonnes)



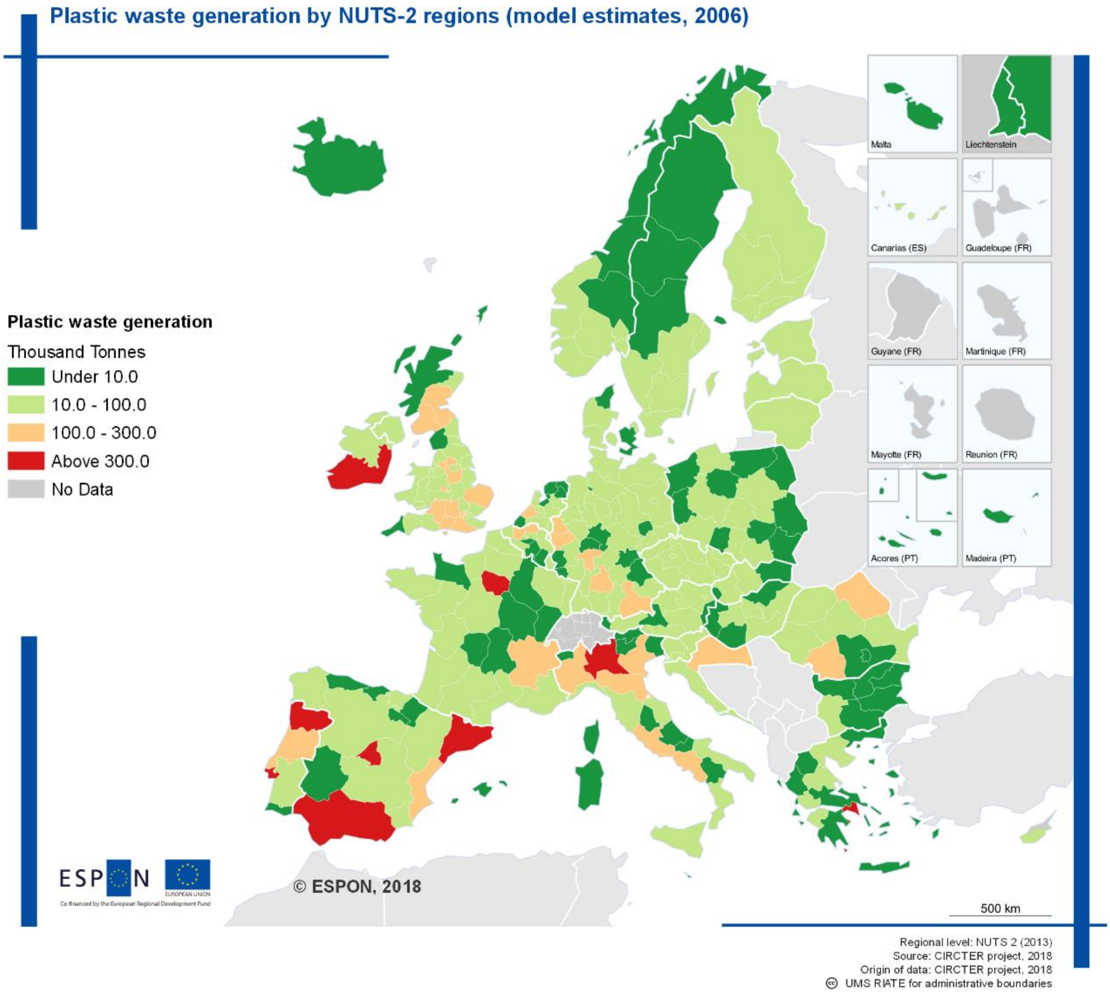
Source: own elaboration based on Eurostat data (env_wasgen)

Due to data and methodological shortcomings, plastic waste could not be regionalised by applying our econometric regionalisation method. In this case, regional figures have been estimated by *normalized proportional redistribution* (see Paragraph 3.3.3). We assumed that plastic waste generation is potentially driven by population size and the size of regional economies. Accordingly, national data have been proportionally distributed among the respective regions based on population, income and total gross value added.

This approach strongly limits the reliability, and thus the interpretability, of estimated data since it is not based on robust statistical tests

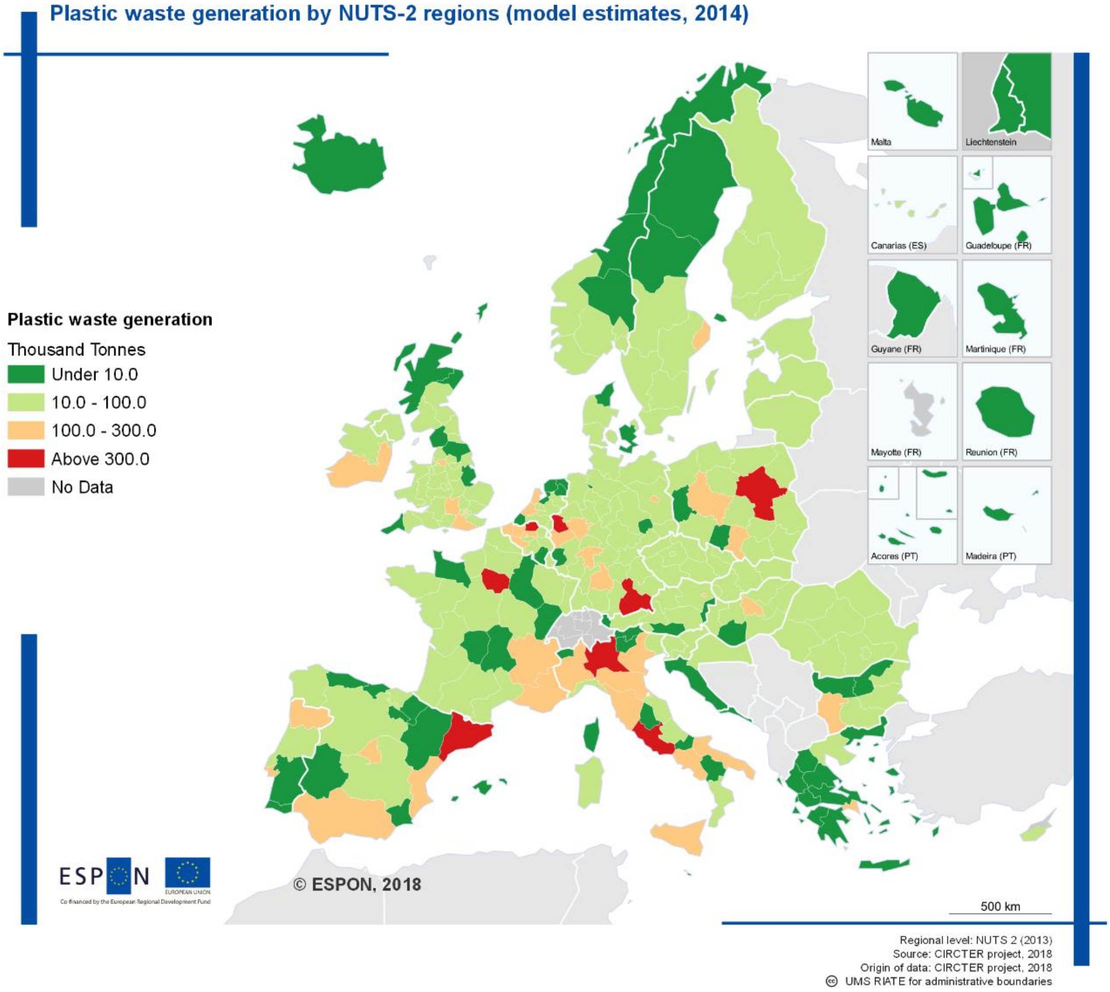
This said, according to our estimates Lombardy (Italy), Ile de France (France), and Mazowieckie (Poland) seem the regions that recorded the highest increase (in absolute terms) of plastic generation (more than 0.3 million tonnes). While Athene (Greece), Lisbon and Norte (Portugal) and Cataluña (Spain) are the regions that reduced the most waste plastic generation. These trends are mostly driven by divergent economic and demographic trajectories in such areas.

Map 6-19: Regional Estimates Plastic waste generation (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Map 6-20: Regional Estimates Plastic waste generation (2014), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

6.11 Total waste generated by NACE activities

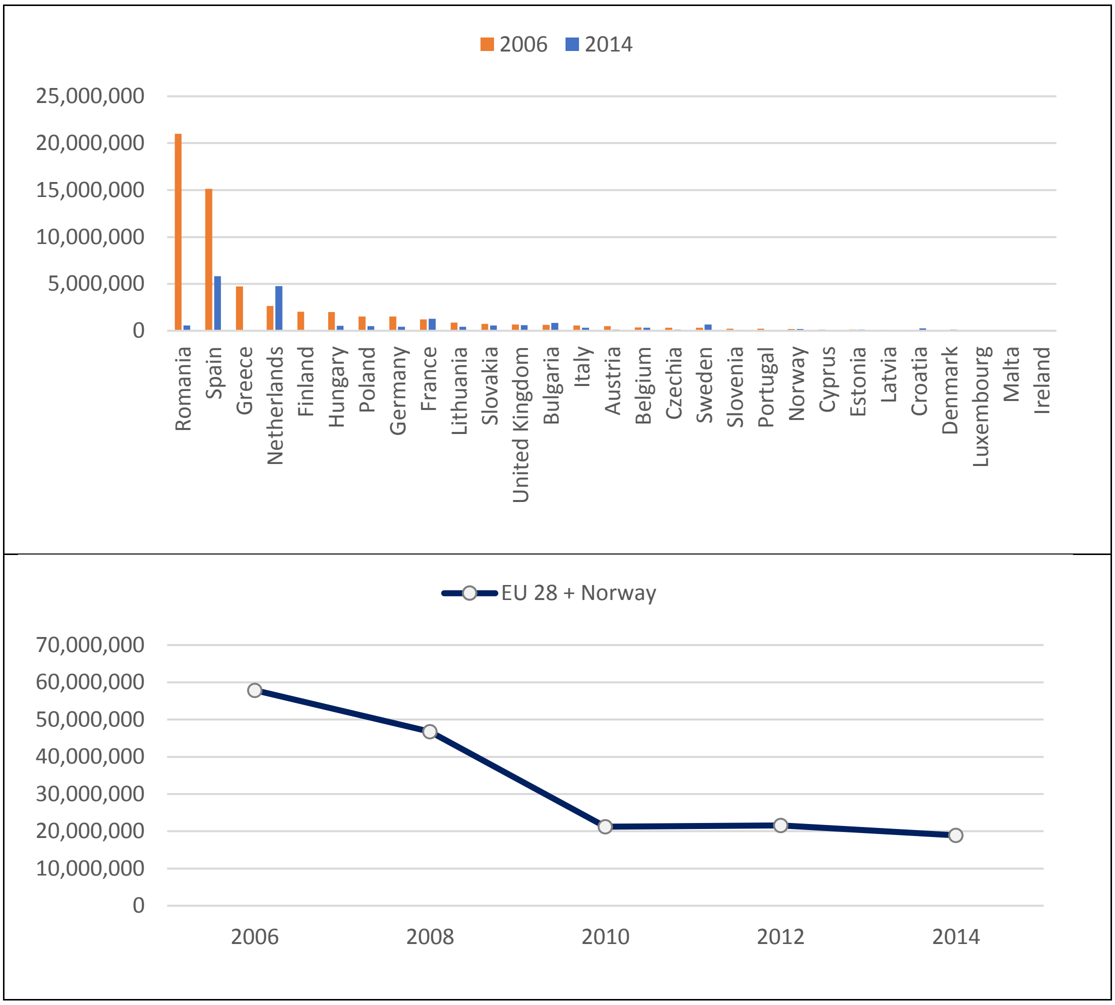
As for plastic waste, the estimates for total waste presented below are estimated by *proportial allocation* of national values to respective regions according to a consistent set of socio-economic variables (see Section 3.3.3 in methodology description).

This is motivated by the lack of staibility and poor quality of national waste statistics, which make impossible to develop and apply robust OLS models for data disaggregation. As mentioned, this state of affairs strongly limits the reliability of the regional estimates, and thus the interpretability of the resulting indiactors (EC, 2011). This makes arduous to derive relevant conclusions leading to strong policy messages. Therefore, the following paragraphs provide a limited explanation on the observed waste generation patterns, mostly based on national data.

6.11.1 Waste by agriculture

Among all categories of waste by NACE classification, waste by agriculture presents the stronger downturn in the observed period (-205%). According to the official statistics, at aggereated EU level this sub-category of waste curbed from 57.9 million tonnes in 2006 to 19 million tonnes in 2014 (Figure 6-7).

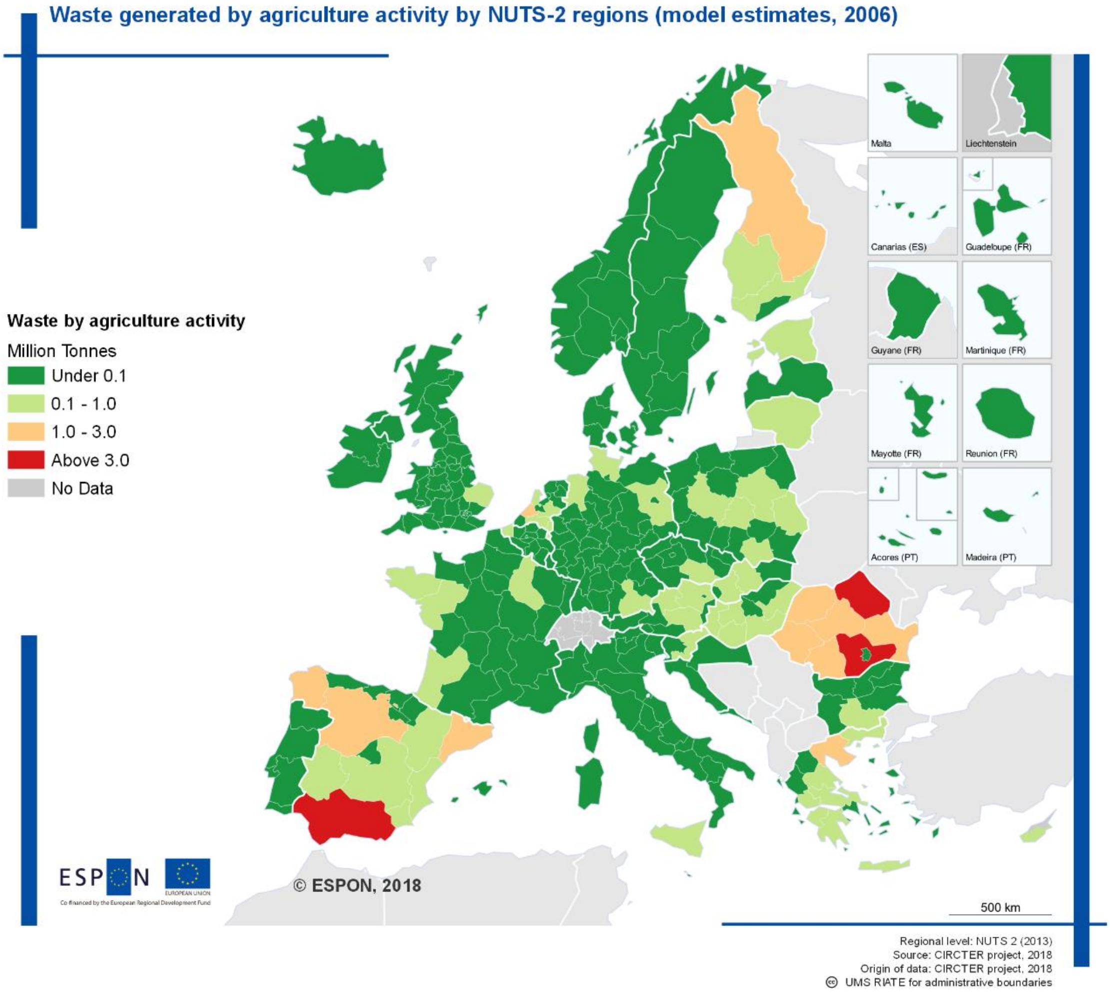
Figure 6-7: Waste generation by agriculture, national and EU aggregated statistics (tonnes)



Source: own elaboration based on Eurostat data (env_wasgen)

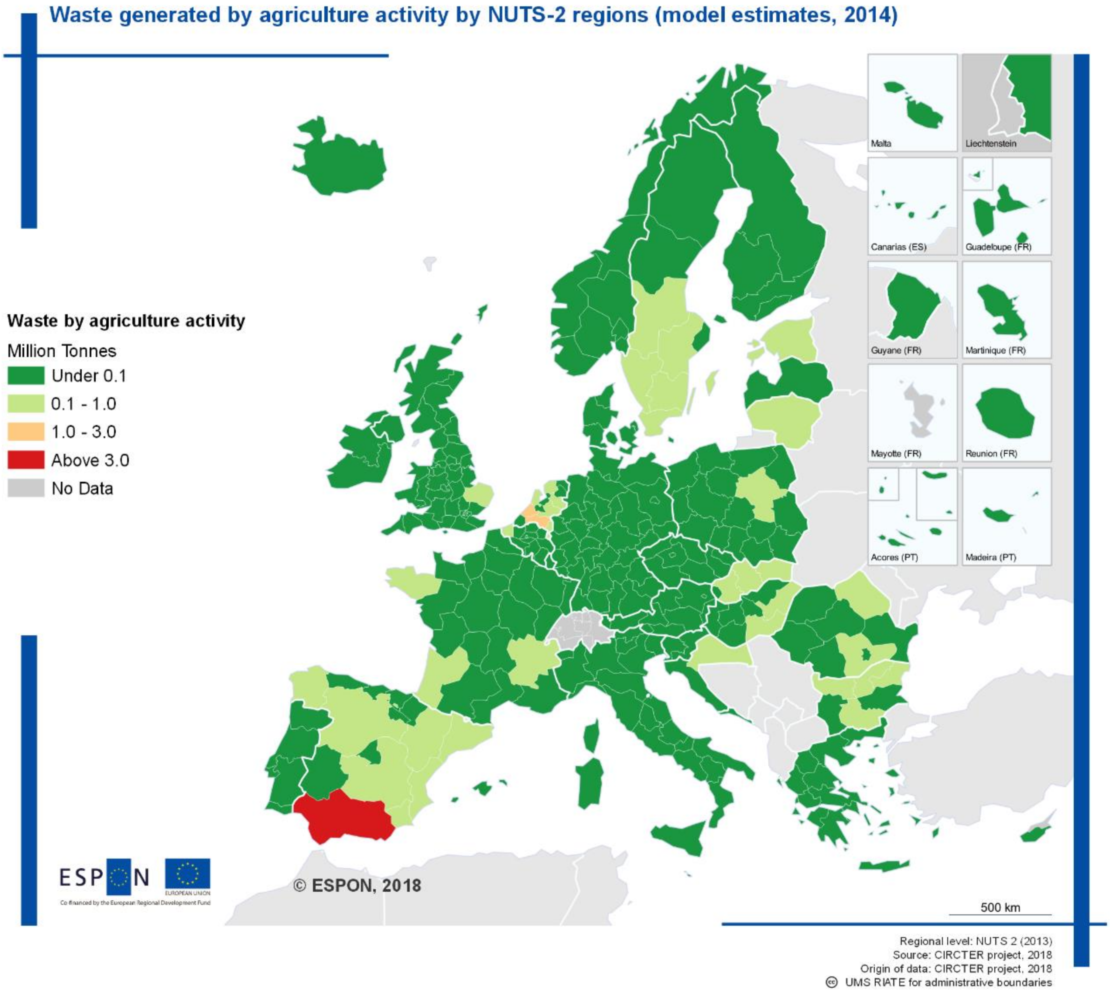
While in 2006 the generation of waste by agricultural activities was mostly driven by EU Eastern and Southern regions like Andalucía in Spain, Nord-Est, Sud-Muntenia, Sud-Est and Nord-Vest in Romania (Map 6-21), a more homogenous distribution of this type of waste across EU regions can be evinced when looking at 2014 data (Map 6-22).

Map 6-21: Regional Estimates Waste by agriculture, forestry and fishing activities (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Map 6-22: Regional Estimates Waste by agriculture, forestry and fishing activities (2014), absolute values

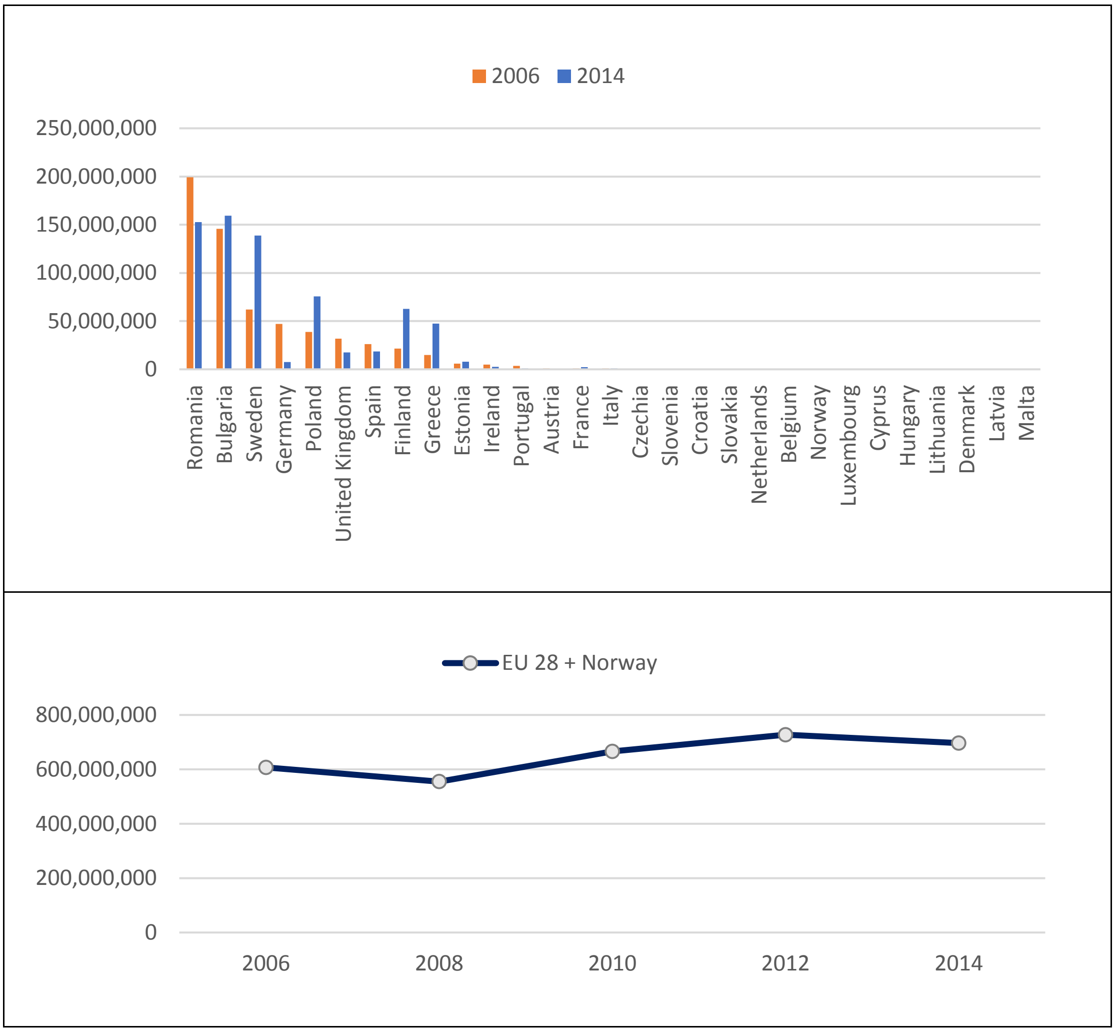


Expected accuracy of estimates: low (see Section 5.3 for further details)

6.11.2 Waste by mining and quarrying activities

Waste by mining and quarrying activities increased by 90 million tonnes (15%) during the reference period (2006-2014). This was the waste by NACE sub-category with the highest upward trend.

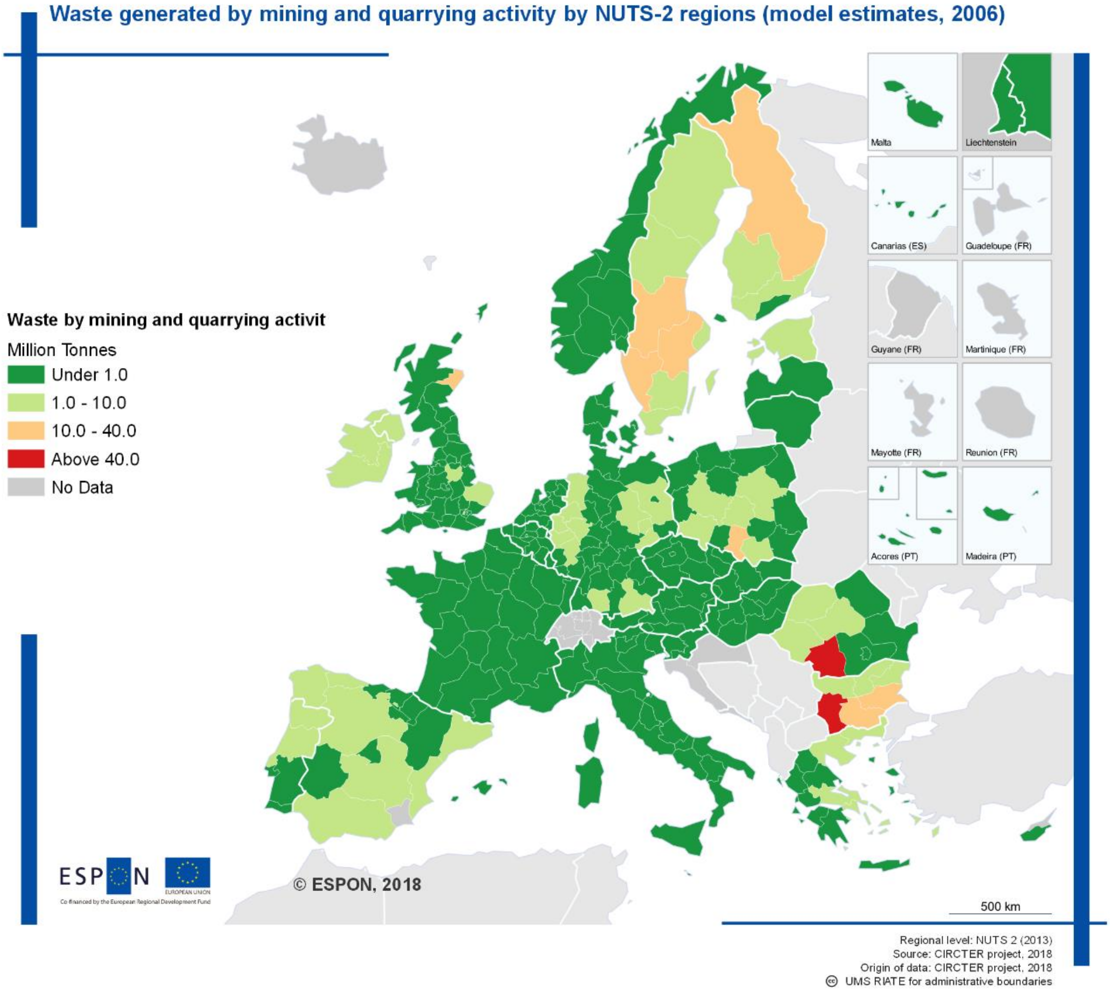
Figure 6-8: Waste generation by mining and quarrying activities, national and EU aggregated statistics (tonnes)



Source: own elaboration based on Eurostat data (env_wasgen)

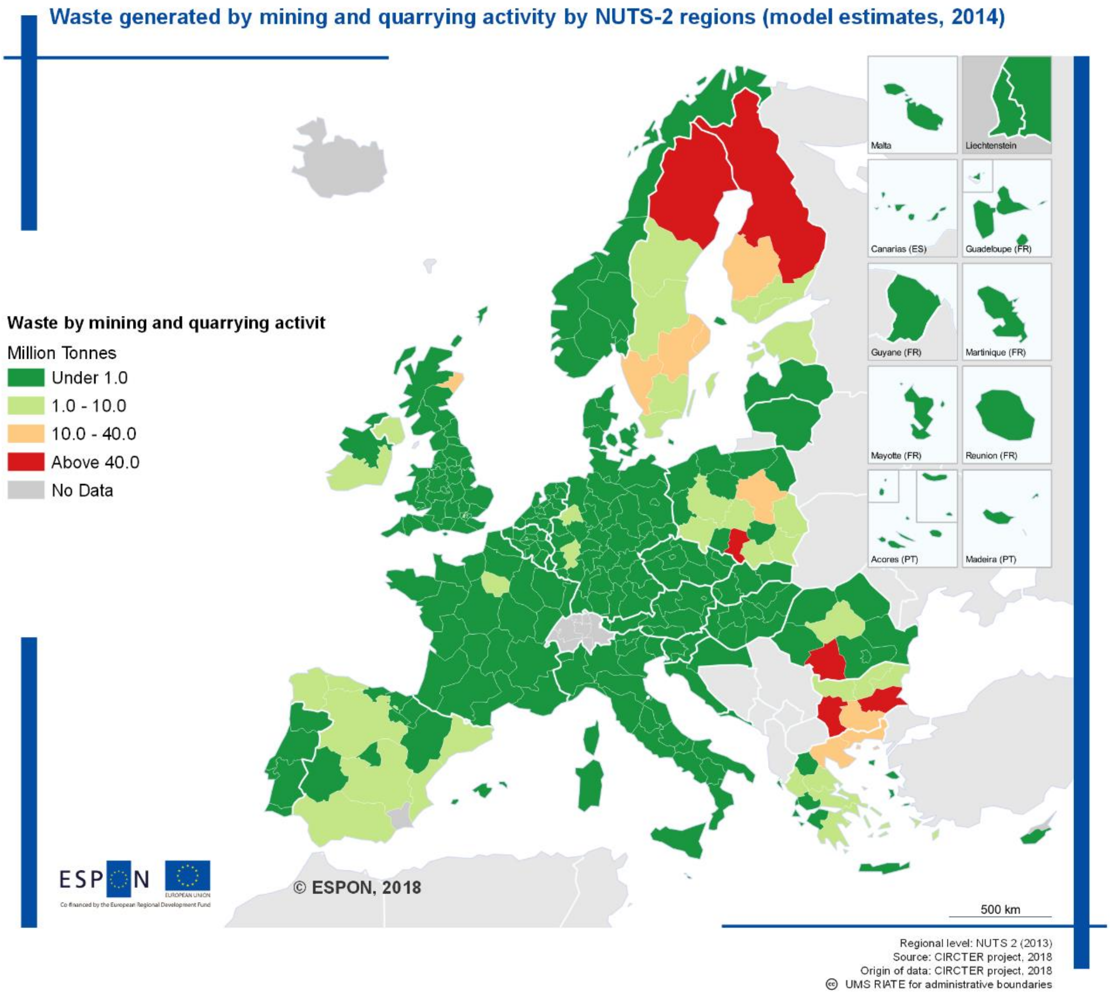
According to regional estimates, the Northern and Eastern EU regions (e.g. Romania, Bulgaria and Sweden regions) are those presenting highest amounts of waste by mining, reflecting to large extent the local economies highly specialised in mining and quarrying activities. In particular, regional estimates suggest an increase by over 20 million tonnes for Upper Norrland (Sweden), North & East Finland and Śląskie (Poland). This might be justified by – and reflects –a huge employment growth in the mining sector experienced in these areas.

Map 6-23: Regional Estimates Waste by mining and quarrying activities (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Map 6-24 Regional Estimates Waste by mining and quarrying activities (2014), absolute values

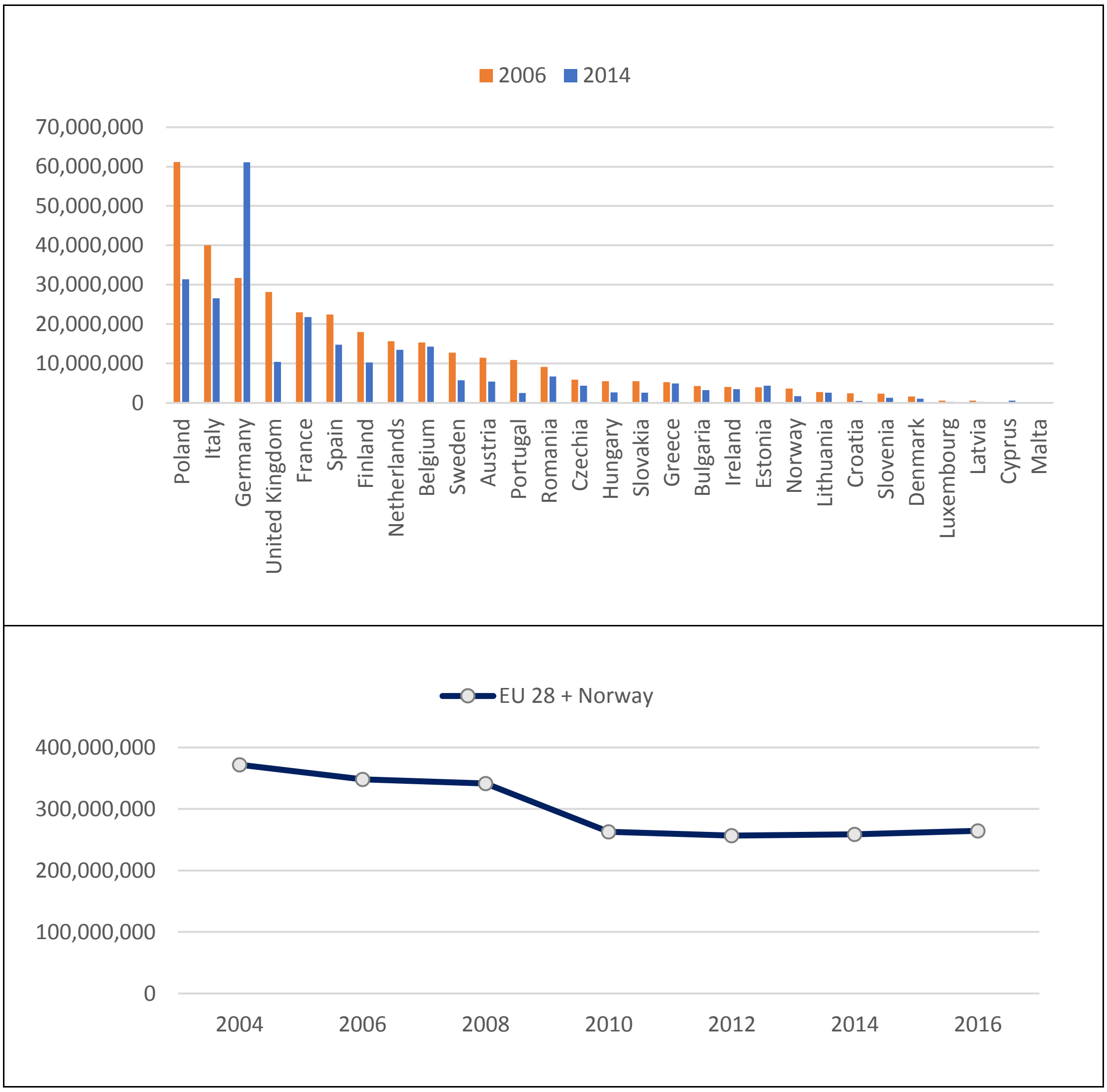


Expected accuracy of estimates: low (see Section 5.3 for further details)

6.11.3 Waste manufacturing activities

At aggregated EU level, waste by manufacturing decreased by 35% during the reference period (from 348 to 258 million tonnes). Poland undergone the bigger decrease in absolute term of waste by manufacturing activities, from 61 million in 2006 to 31 million in 2014 (almost halved its waste by manufacturing). On the other hand, Germany and Estonia are the only countries that experienced a net increase in waste generation by manufacturing activities. These trends may suggest a structural transformation of tradidional industrial and manufacturing activities in countries under rapid economic transformation, such as Poland, Slovakia or Romania, coupled with a more cojunctural shifts in industrial production in countries such as Germany or Italy.

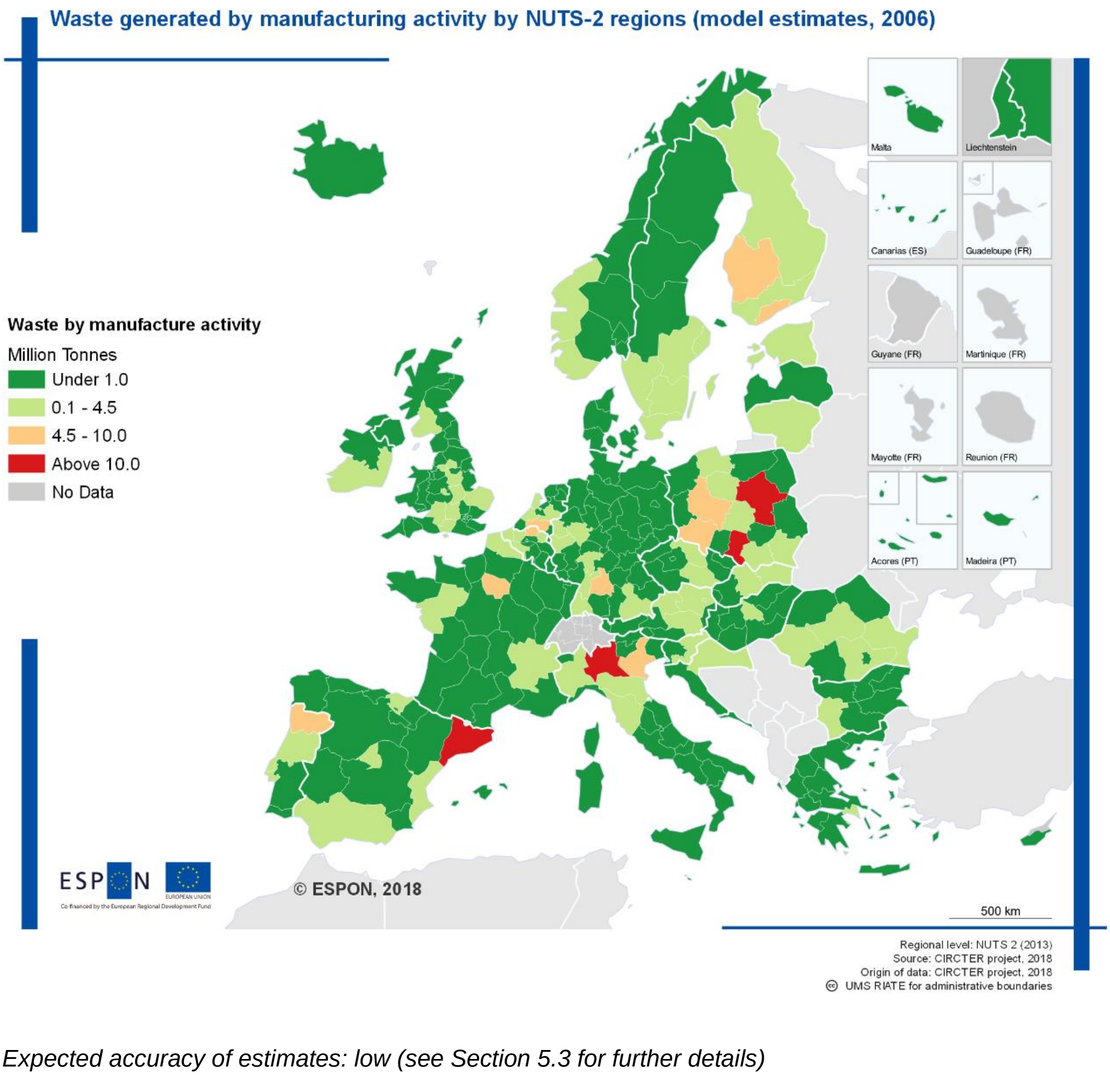
Figure 6-9: Waste generation by manufacturing, national and EU aggregated statistics (tonnes)



Source: own elaboration based on Eurostat data (env_wasgen)

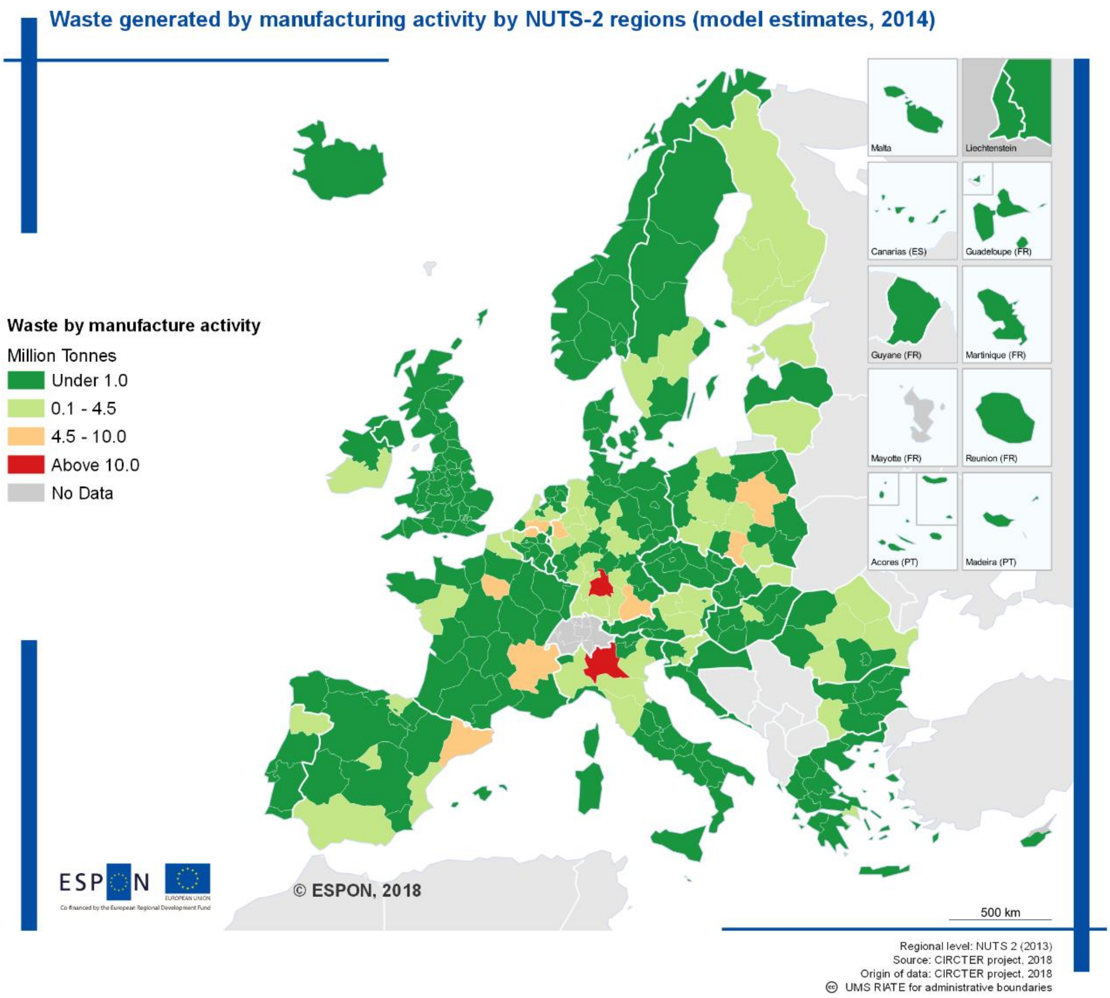
Regional estimates, Lombardy (Italy) and Stuttgart (Germany) recorded the highest volumes in 2014 (14 and 12 million respectively) reflecting the magnitude of local manufacturing and industrial economies with respect to other areas (Map 6-26). Interestingly, these two regions experienced an opposite trend for 2006-14 years: while in Lombardy projected waste generation by manufacturing decreased by roughly 50%, in Stuttgart it increased by a similar share. This is potentially explained by divergent industrial production trends. For example, while in Stuttgart gross investment in manufacturing expanded by 30% circa from 2006 to 2017 (98 million to 126 million), in Lombardy the indicator remained on a similar order of magnitude over that same period (132 and 138 million respectively).

Map 6-25: Regional Estimates Waste manufacturing activities (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Map 6-26: Regional Estimates Waste manufacturing activities (2014), absolute values

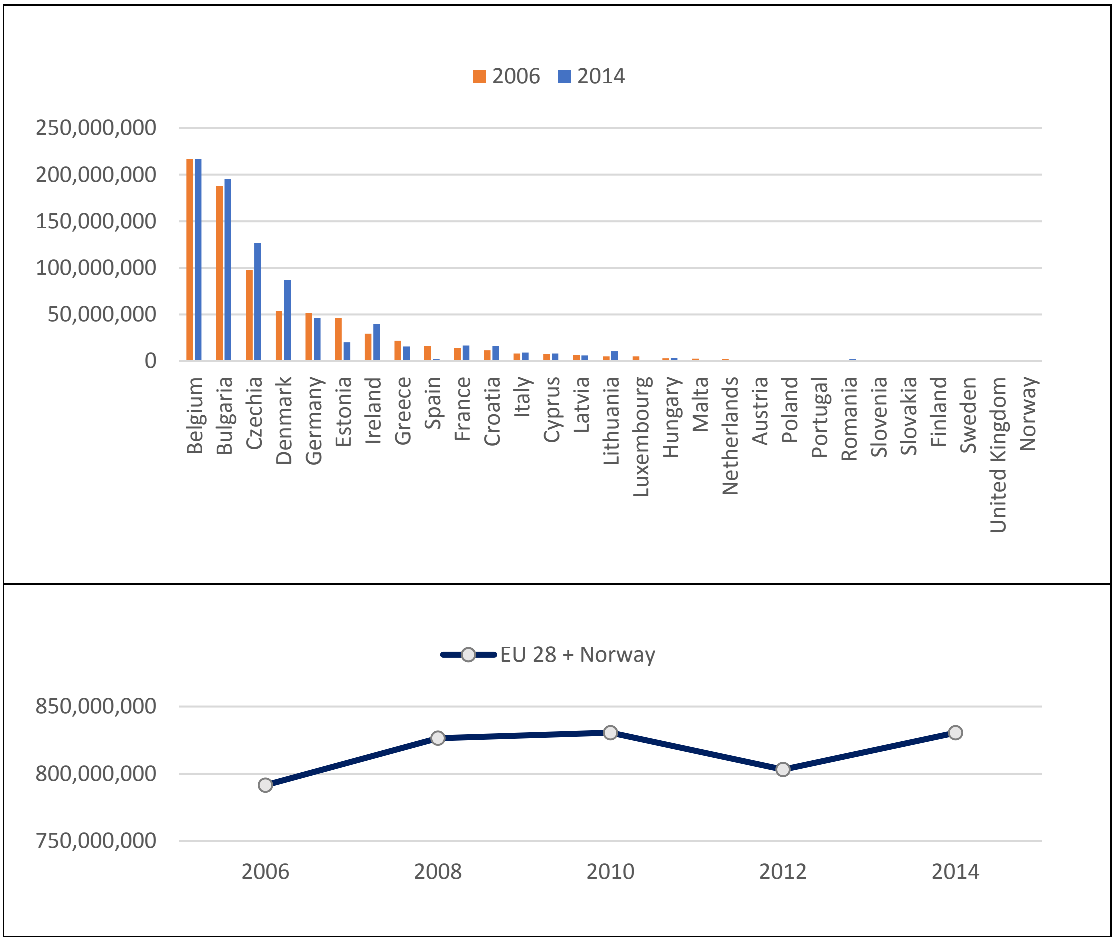


Expected accuracy of estimates: low (see Section 5.3 for further details)

6.11.4 Waste by construction activities

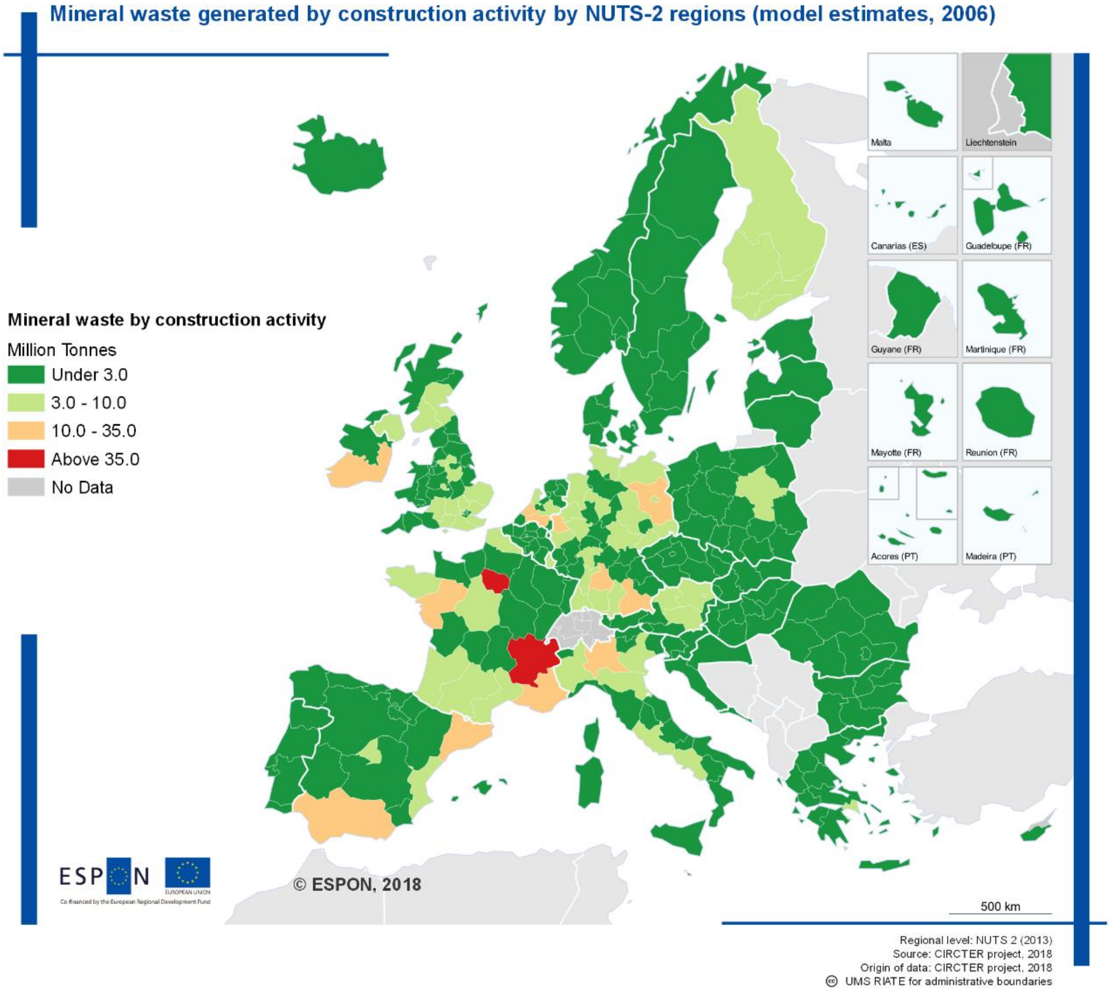
Mineral waste by construction activities shows a rather stable trend over the analysed period. In absolute terms, this waste sub-category increased by 5% between 2006-2014 (Figure 6-10). In 2014, the highest rate was estimated for Ile de France (100 million tonnes) followed by Zuid-Holland and Rhône-Alpes. Some highly urbanised countries such as United Kingdom and Netherlands show lower-than-average estimates. This can also be linked to the different collection and data accounting systems, which as said limit data comparability accross countries.

Figure 6-10: Mineral waste generation by construction activities, national and EU aggregated statistics (tonnes)



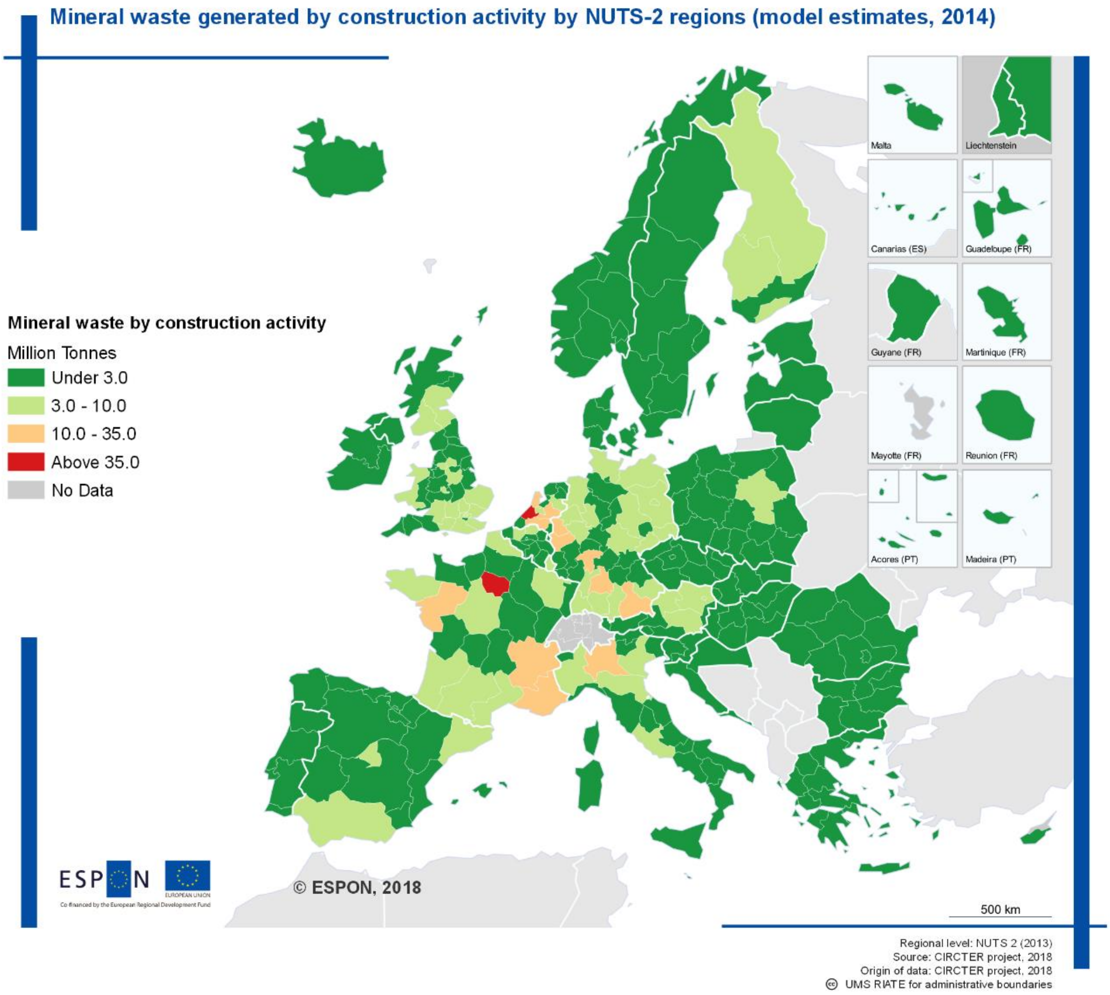
Source: own elaboration based on Eurostat data (env_wasgen)

Map 6-27: Regional Estimates Mineral waste by construction activities (2006), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

Map 6-28: Regional Estimates Mineral waste by construction activities (2014), absolute values



Expected accuracy of estimates: low (see Section 5.3 for further details)

6.12 Municipal waste

The following maps show trends in the amounts of municipal waste generated and treated at regional level. The maps represent data on regional municipal waste collection and treatment. These data are directly available from Eurostat at NUTS-2 level (env_rwas_gen). Data are collected as part of a pilot project by means of an environmental questionnaire distributed among Member States. Data classification is based on the different disposal and recovery operations listed in the Waste Framework Directive (2008/98/EC, Annexes 2 and 3).

Treatment options are:

- landfill
- incineration (with and without energy recovery)
- recycling & composting.

Municipal waste constitutes only around 10 % of total waste generated, but because of its heterogeneous composition the environmentally sound management is challenging. The way municipal waste is managed thus gives a good indication of the quality of the overall waste management system in each region. However, as it is the case for all types of waste statistics, figures for municipal waste are also challenged by very different waste collection systems and interpretation issues (EC, 2011).

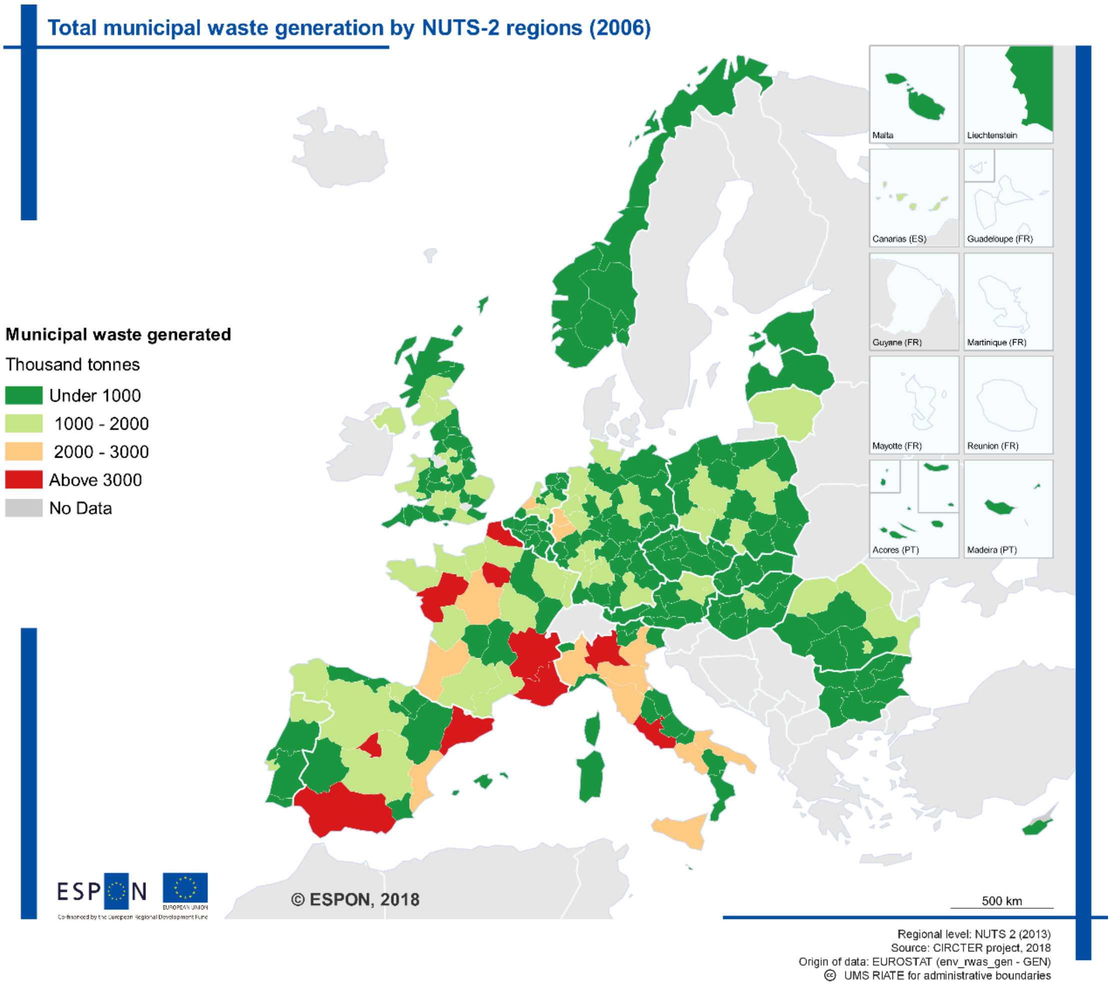
6.12.1 Total municipal waste generated

For 2014, municipal waste generation totals vary considerably, ranging from 5 534 thousand tonnes in Ile de France to 72.59 thousand tonnes in Valle d'Aosta (Italy). The variations reflect differences in consumption patterns and economic wealth, but also depend on how municipal waste is collected and managed, as well as on how waste statistics are collected.

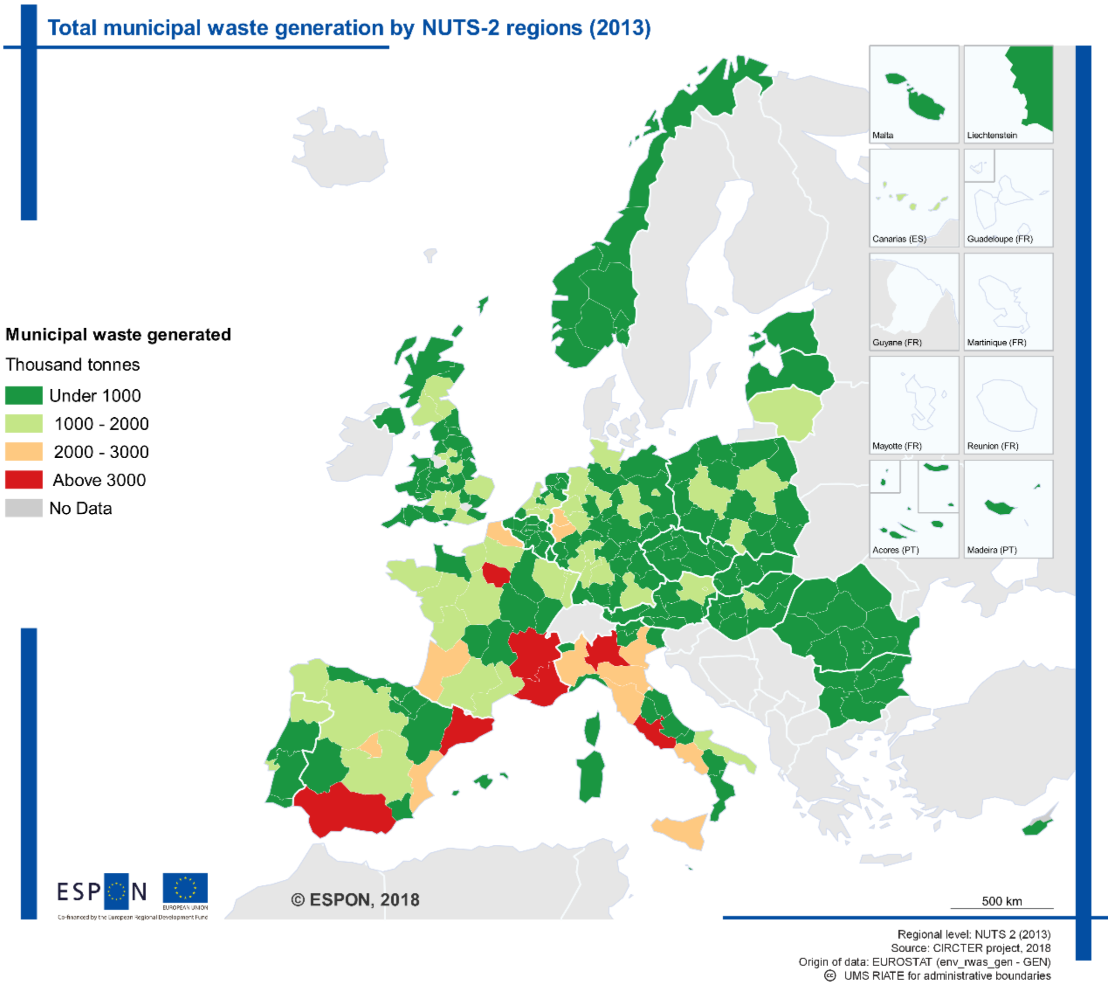
There are differences between countries regarding the degree to which waste from commerce, trade and administration is collected and managed together with waste from households. Additionally, further differences can be due to changes in methodology over time of calculation for municipal waste generated and treated, as well as in waste classifications (EC, 2011).

Based on the regional figures collected, EU municipal waste generation decreased by 9% from 2006 to 2014. Nord-Vest and Nord-Est Romania's regions showed the largest reduction (131% & 84%), whilst France Mediterranean's regions (Languedoc-Roussillon & Provence-Alpes-Côte d'Azur) the biggest increase (86% & 41%).

Map 6-29: Regional municipal waste generation (2006), absolute values



Map 6-30: Regional municipal waste generation (2013), absolute values



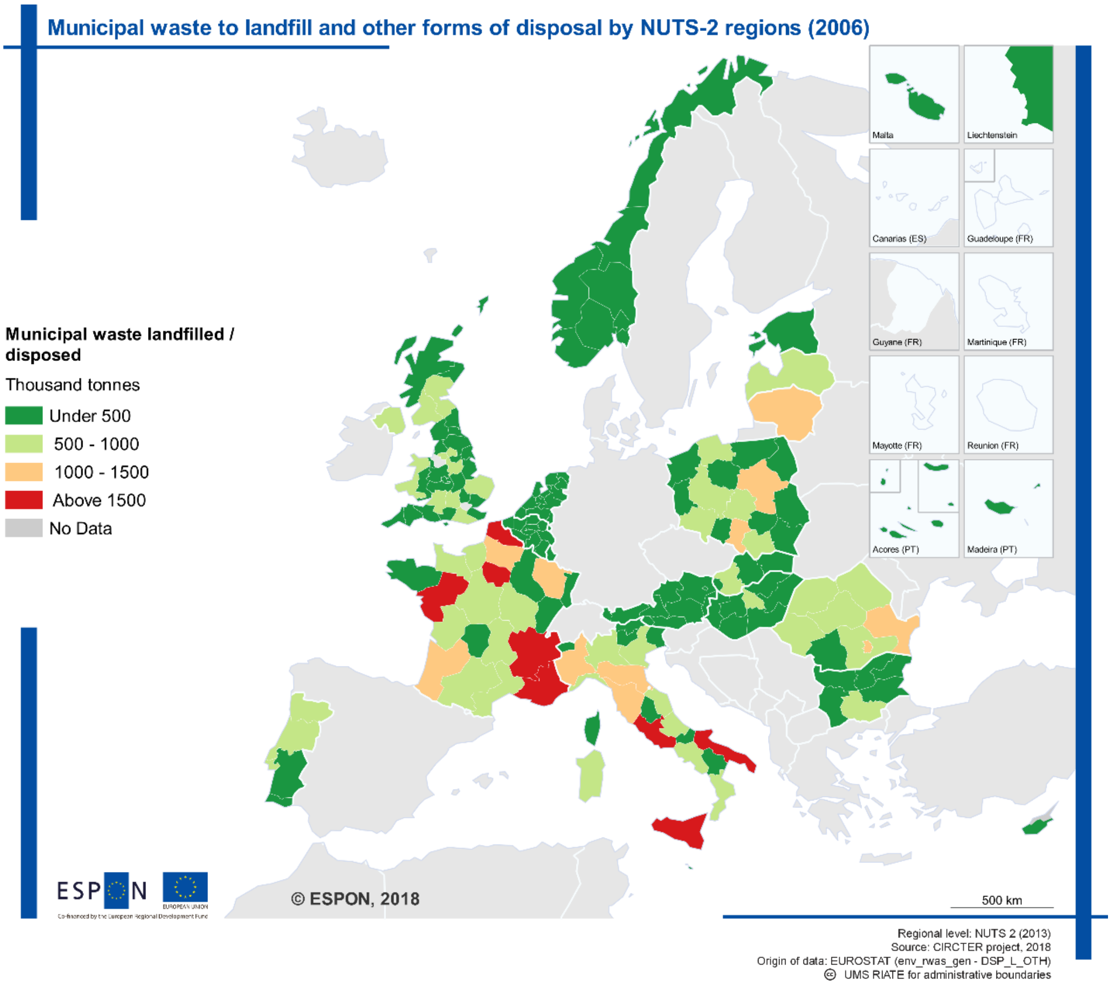
6.12.2 Municipal waste to landfilling

Map 6-31 and Map 6-32 show a clear trend towards less landfilling, as countries move towards alternative waste treatment paradigms. In the reference period, the total municipal waste landfilled, stocked or disposed on the oceans fell by 34 million tonnes, or 38%, from 122 million tonnes in 2006 to 88 million tonnes in 2013.

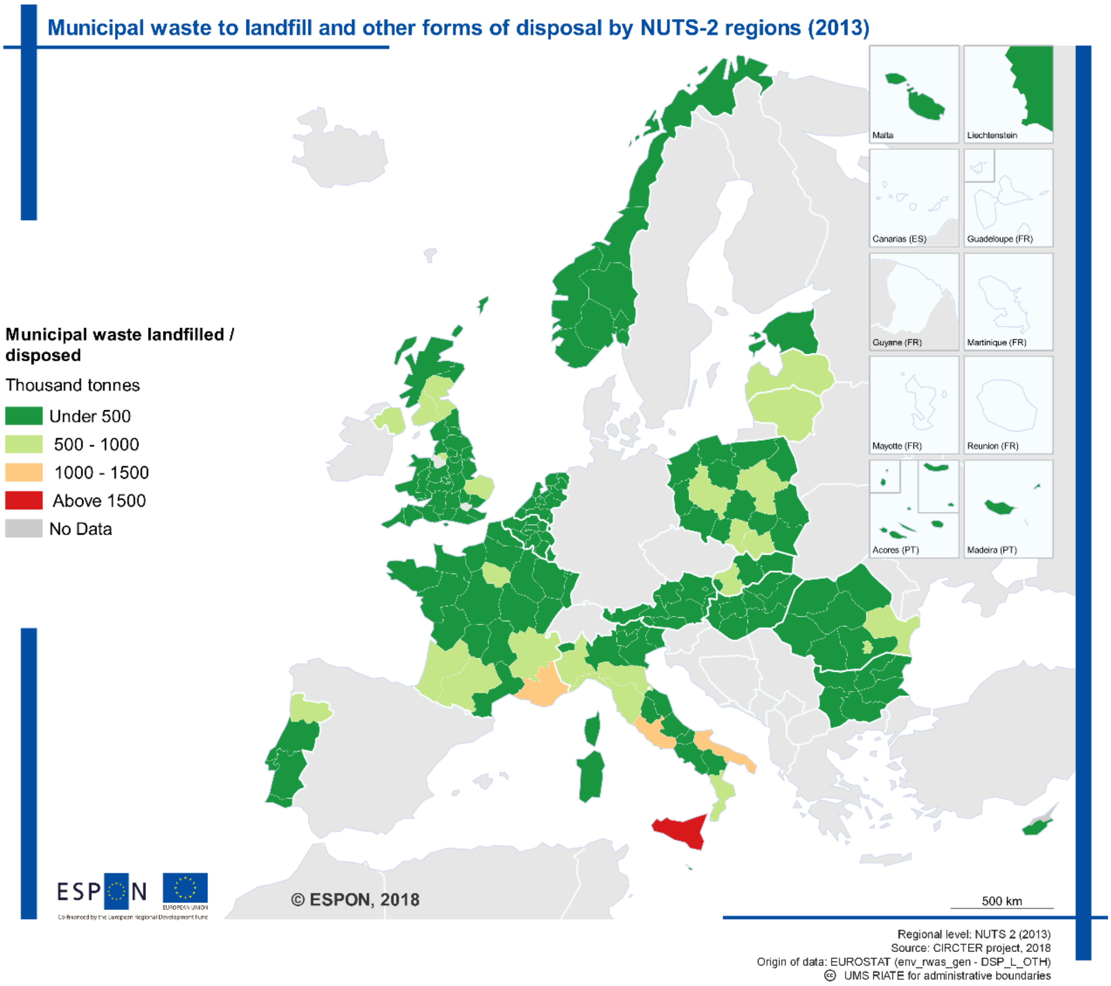
Sicily and Lazio reported the highest figures for municipal waste landfilled in 2013, while regions in Belgium reported close to zero waste to landfil. Some regions in Belgium also registered the sharper decrease in municipal waste landfilling (up to 33% in the 2006-2014 timeframe). These were followed by Madeira (Portugal), Vestlandet (Norway) and Tirol (Austria).

The overall reduction can partly be attributed to the implementation of European legislation, i.e. Directive 62/1994 on packaging and packaging waste, and Directive 31/1999 on landfill. According to these Member States were obliged to reduce the amount of biodegradable municipal waste going to landfills down to less than 75% by 16 July 2006, to less than 50% by 16 July 2009 and to less than 35 % by 2016. The Directive has led to countries adopting different strategies to avoid sending the organic fraction of municipal waste to landfill, namely composting (including fermentation), incineration (including energy recovery) and recycling. These are analysed in the following sections.

Map 6-31: Regional waste to landfilling (2006), absolute values



Map 6-32: Regional waste to landfilling (2013), absolute values



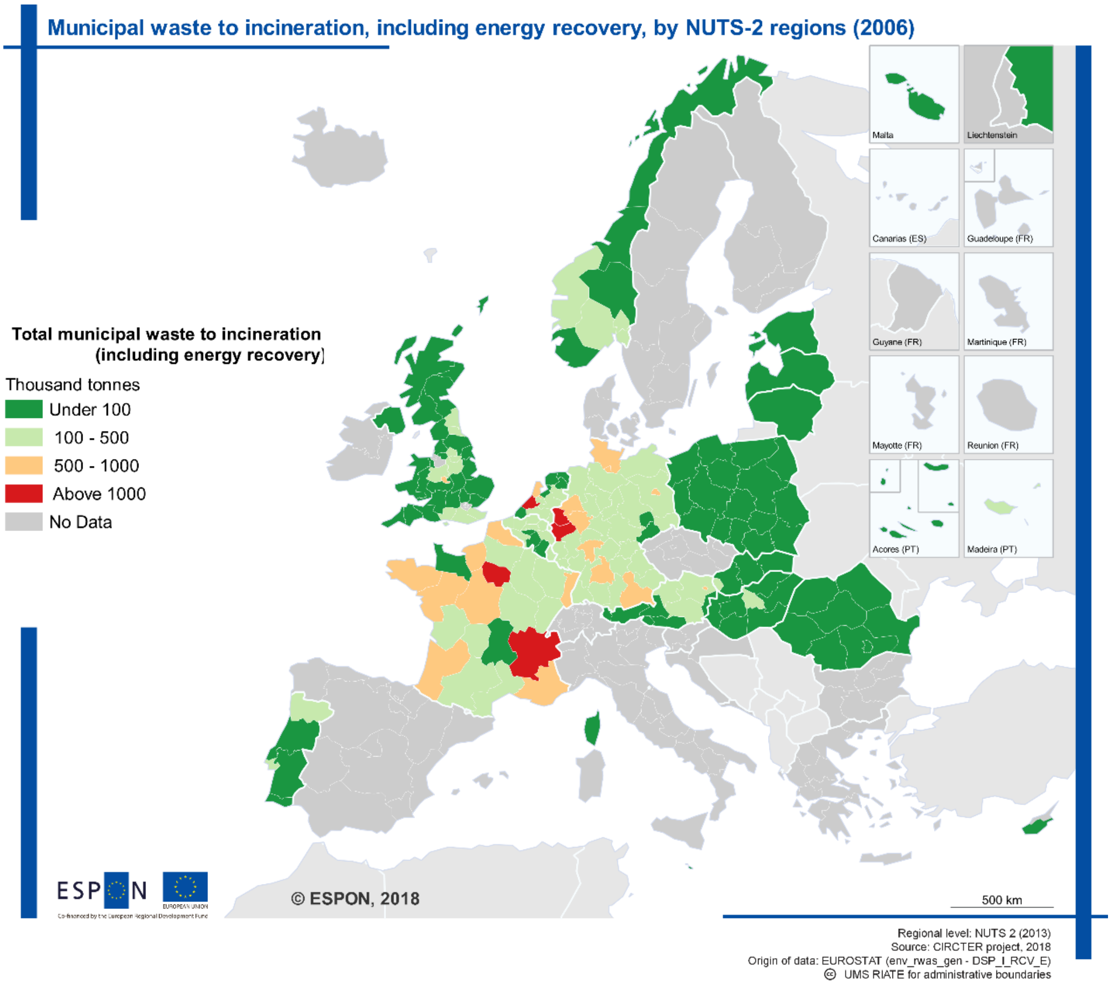
6.12.3 Municipal waste to incineration

Waste incineration has also grown steadily in the reference period; between 2007 and 2013, nearly 300 new incineration plants were constructed and technical capacities have increased by 25% up to more than 250 Mt per year (Wilts and von Gries, 2015). According to regional collected data, the amount of municipal waste incinerated has risen by 4 million tonnes or 9% and accounted for 53 million tonnes in 2016.

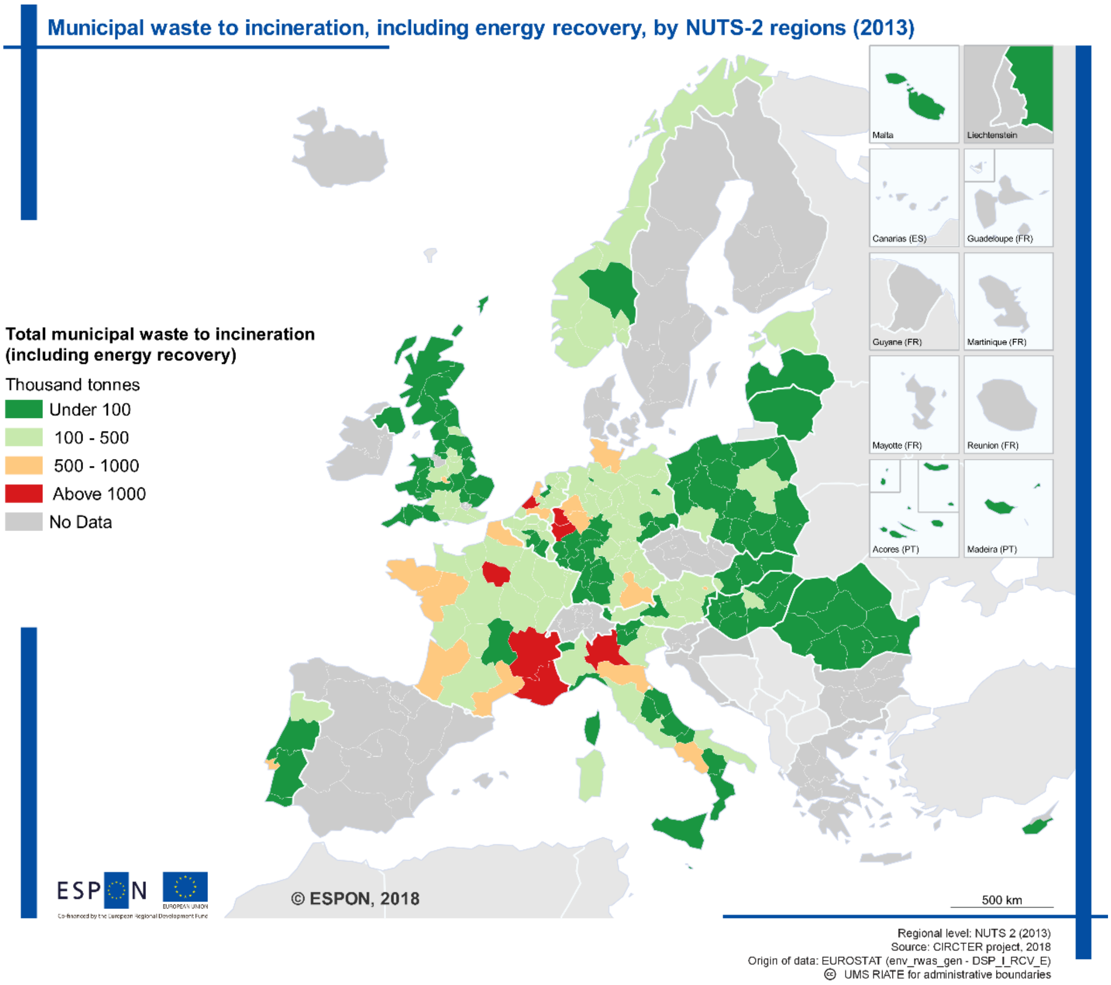
Dedicated incineration capacity for municipal waste is unevenly spread in the EU. Germany, France, the Netherlands, Italy and the UK account for three quarters of the EU's incinerators. Ile de France and Lombardy reported the highest figures in 2013 for municipal waste incineration with 3.4 and 2.2 million tonnes, respectively. In contrast, the southern and eastern regions of the EU are practically devoid of dedicated incineration capacity and are still highly reliant on landfill.

Comparing maps covering total incineration, with and without energy recovery (Map 6-33 and Map 6-34), with those showing only incineration with energy recovery (Map 6-35 and Map 6-36), it is possible to identify how regions are progressively increasing the share of waste-to-energy processes over plain incineration. Regions in Austria, Belgium, the UK, and France seem to be those that make most use of energy-efficient waste-to-energy techniques. In some of these regions all the incinerated municipal waste undergoes some kind of energy recovery process.

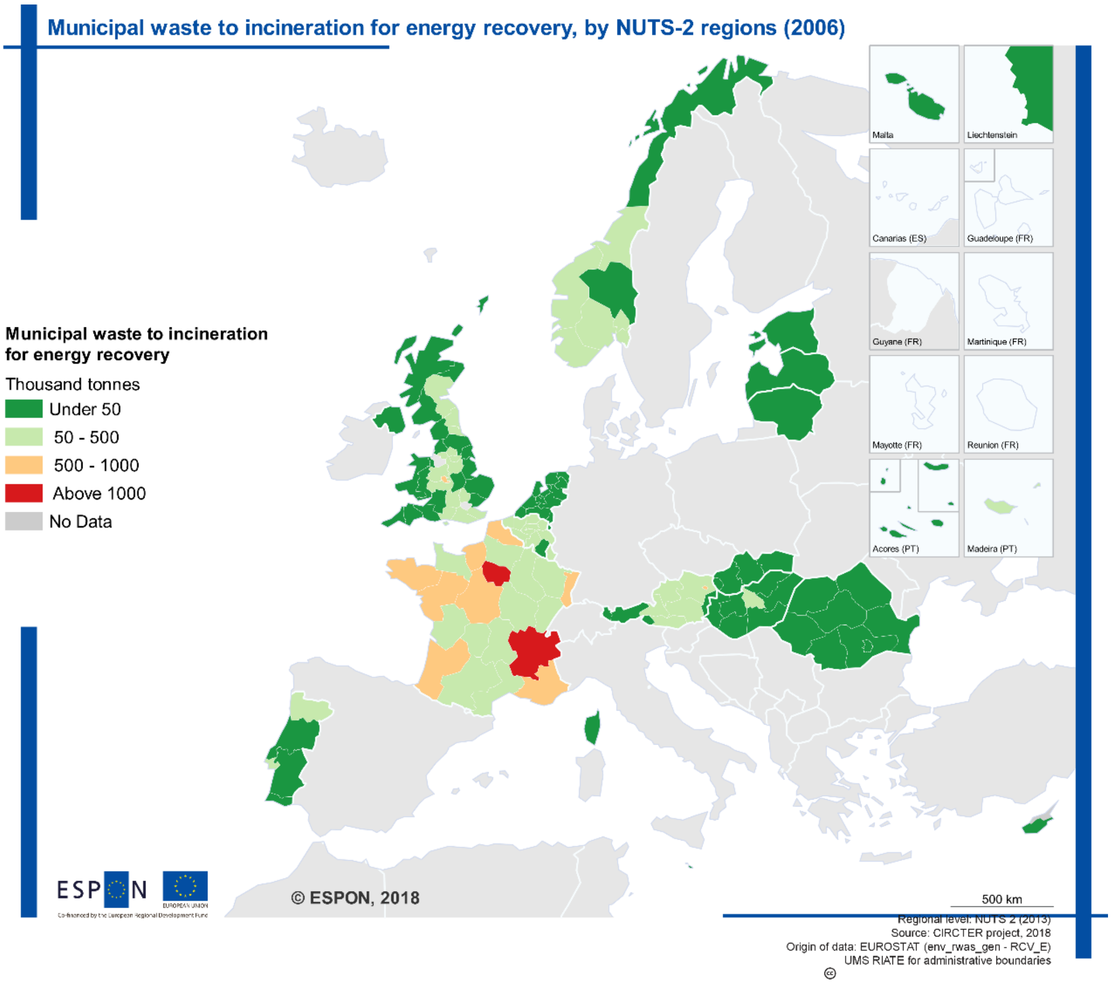
Map 6-33: Total municipal waste to incineration (2006), absolute values



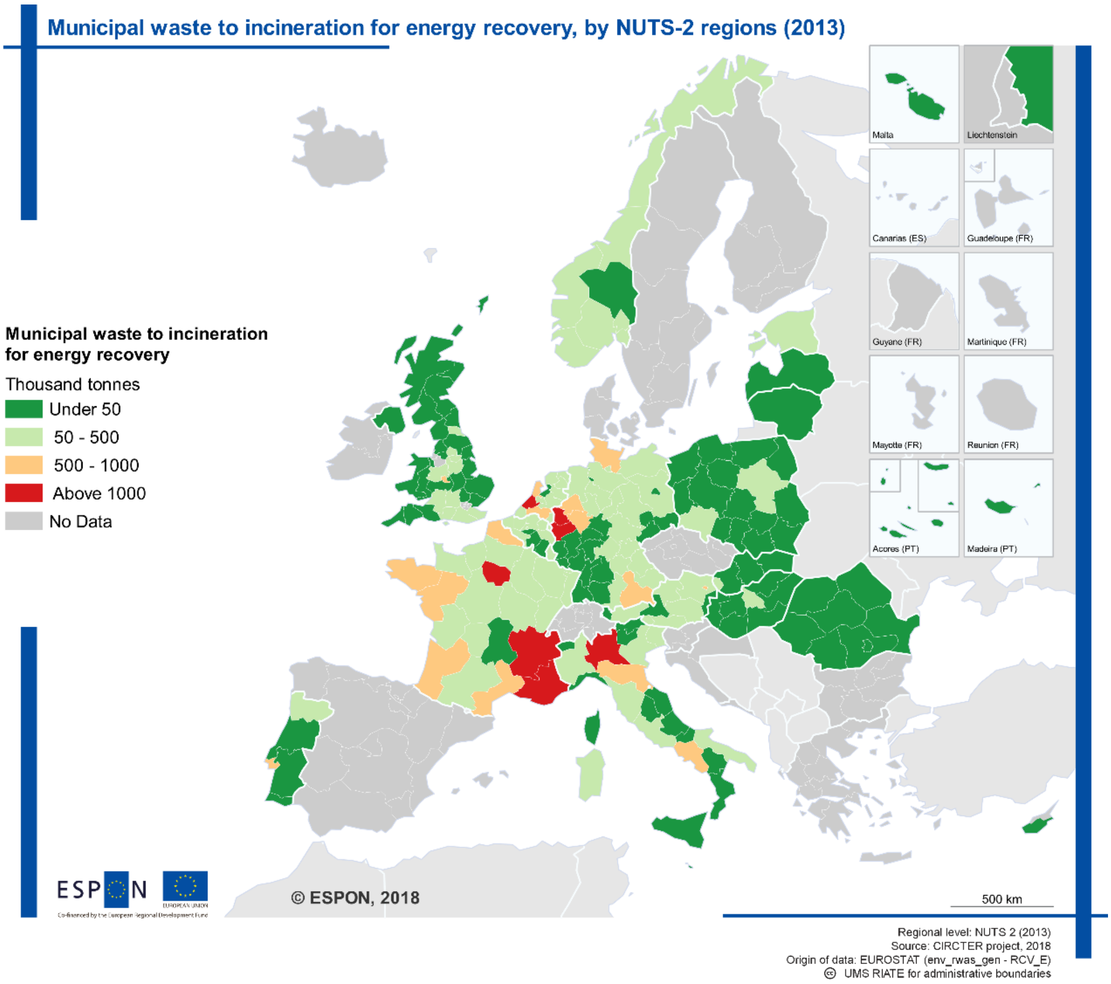
Map 6-34: Total municipal waste to incineration (2013), absolute values



Map 6-35: Municipal waste to incineration for energy recovery (2006), absolute values



Map 6-36: Municipal waste to incineration for energy recovery (2013), absolute values



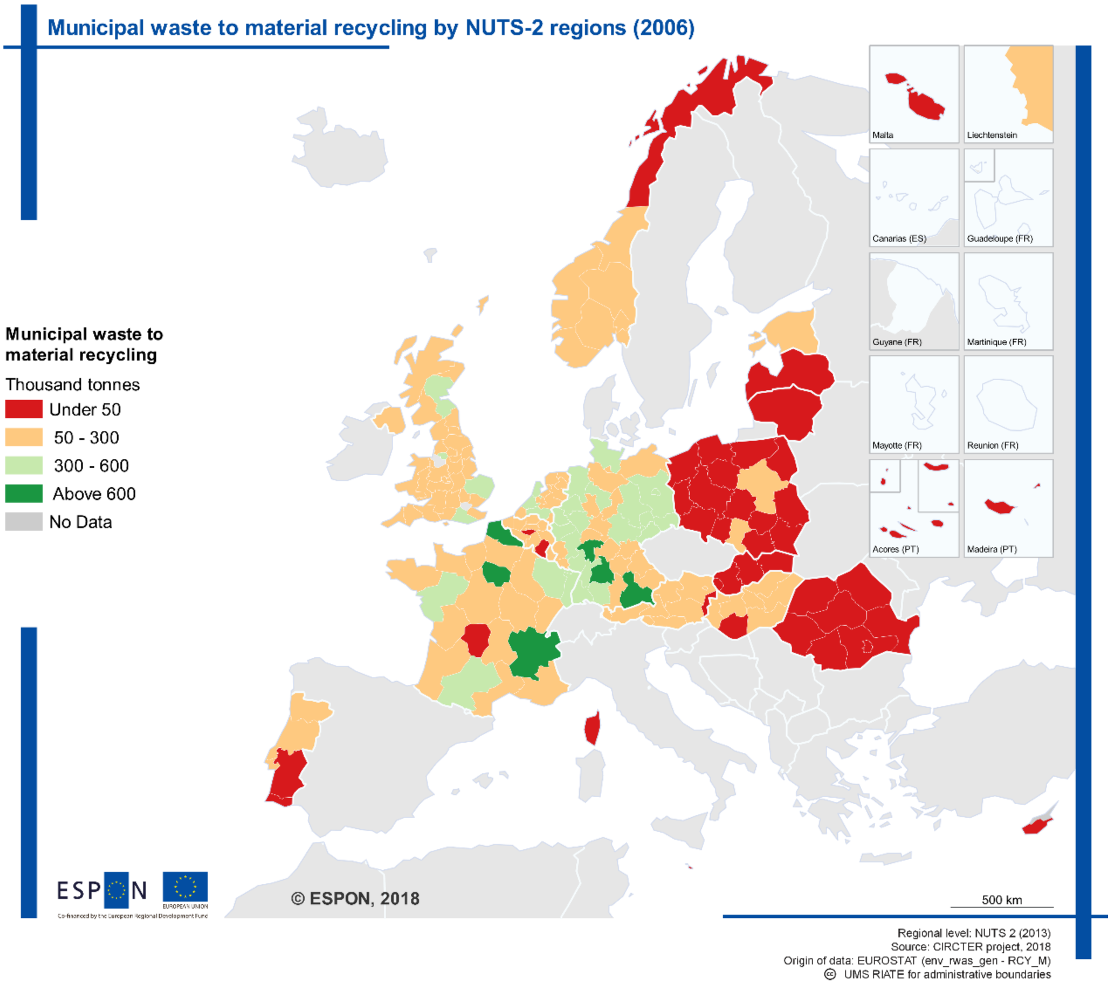
6.12.4 Municipal waste to recycling and composting

As a response to the stimulus coming from the EU waste legislation, material recycling and composting are the two waste treatment operations that increased the most in the considered period. Between 2006 and 2014 the amount of municipal waste recycled and composted increased by 17.6 million tonnes (a 20% of the total waste treated by municipalities), already accounting for 53 million tonnes in 2016. In this year, recycling and composting combined accounted in 2014 for nearly two-thirds (64%) of waste treatment in Germany, followed by Slovenia (61%), Austria (58%), Belgium (55%) and the Netherlands (51%) (Eurostat Press, 2015).

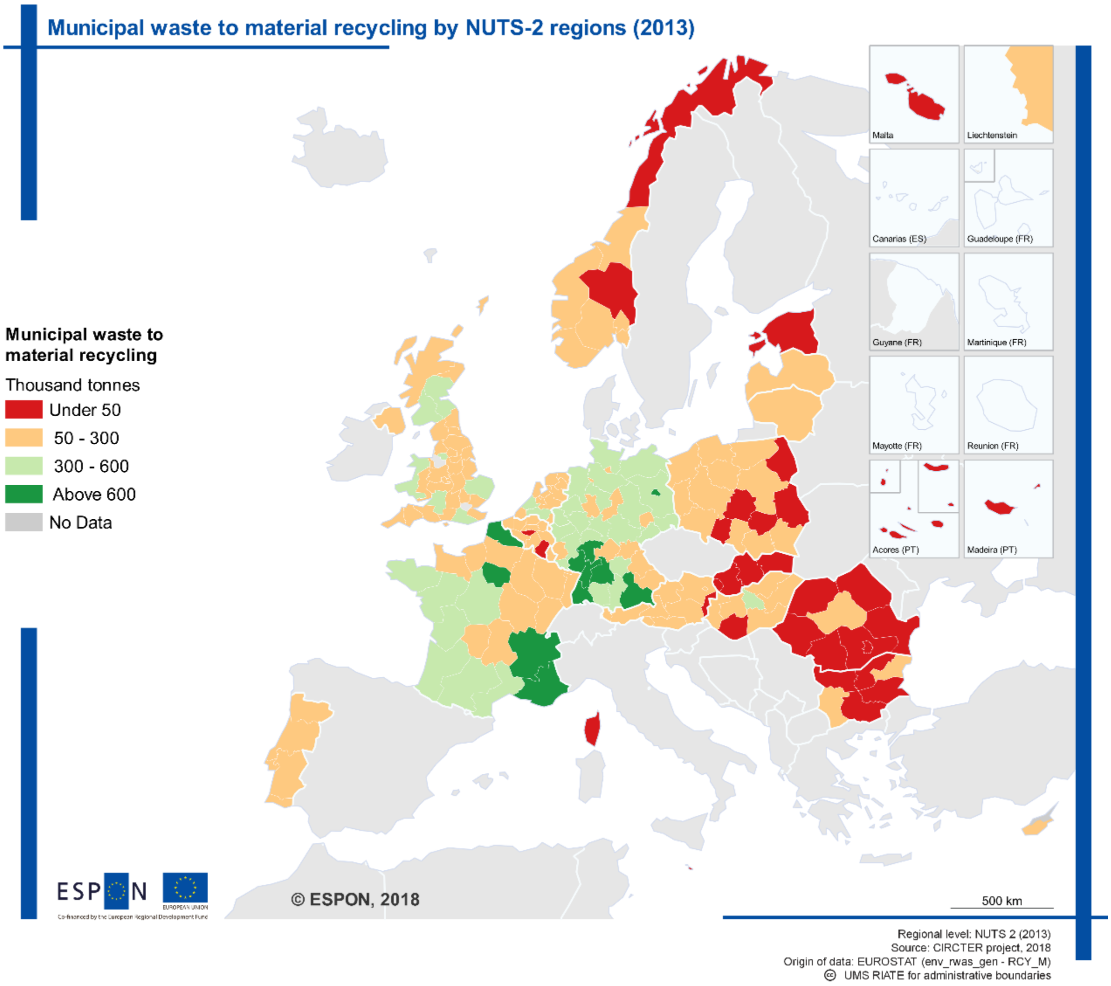
In terms of material recycling, Darmstadt, Berlin and Stuttgart (Germany) reported the highest amount of municipal waste recycled among EU regions. All these regions report more than one million tonnes of recovered materials, on annual basis. On the other hand, Eastern regions seem to have lagged behind in terms of recycling and composting capacity. However, according to the official statistics by Eurostat, these areas seem to be catching-up quickly. In fact, Romania and Polonia regions are among those that reported highest increase in municipal waste recycled across 2006-14 period (over 80%).

Similarly to material recycling, composting also presents a scattered trend across EU regions. Regional data confirms an upward trend from 2006 to 2014 (20%), with the pentagon regions outperforming EU average. Lombardy and Veneto (Italy) lead the EU rankings in municipal waste composting and digestion with 948 and 717 thousand tonnes, followed by Bretagne (France) and Stuttgart (Germany).

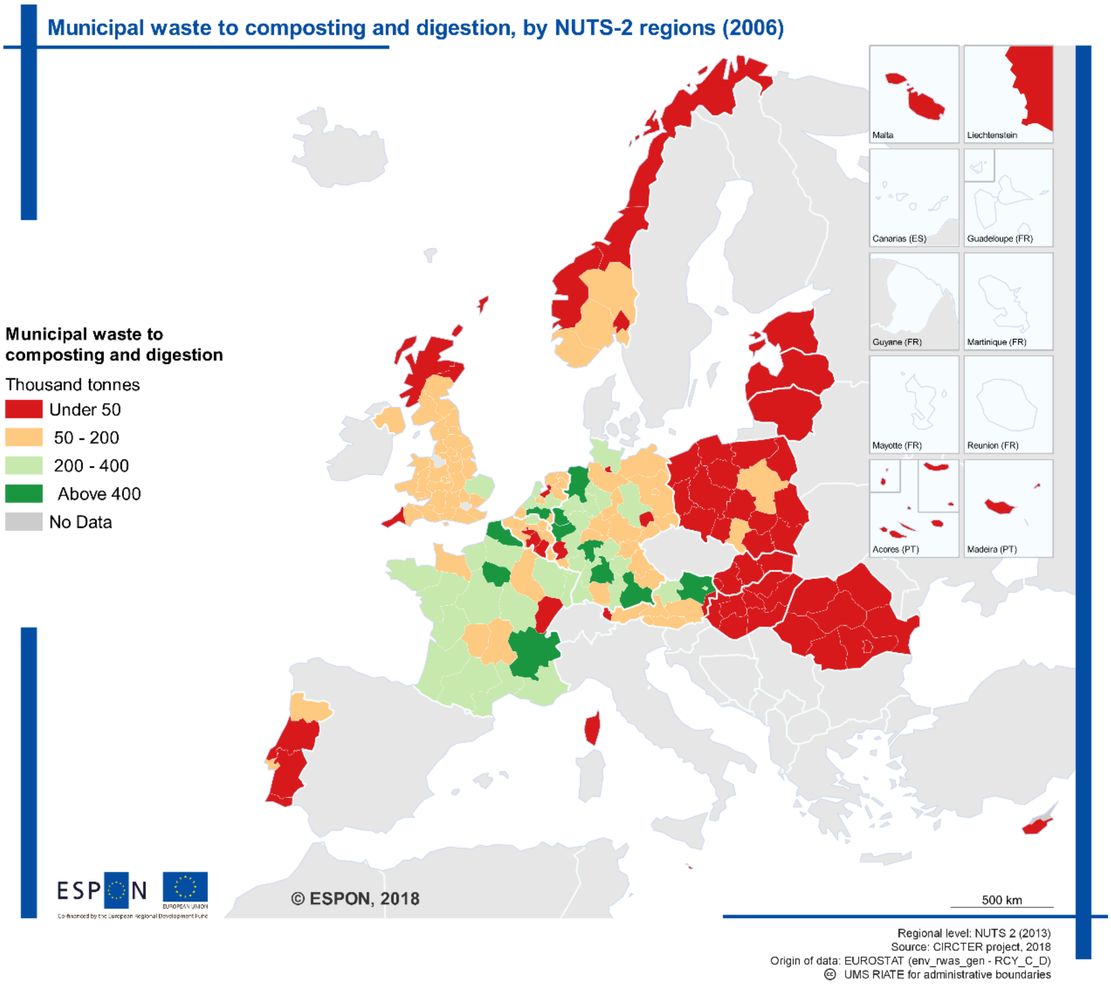
Map 6-37: Municipal waste to material recycling (2006), absolute values



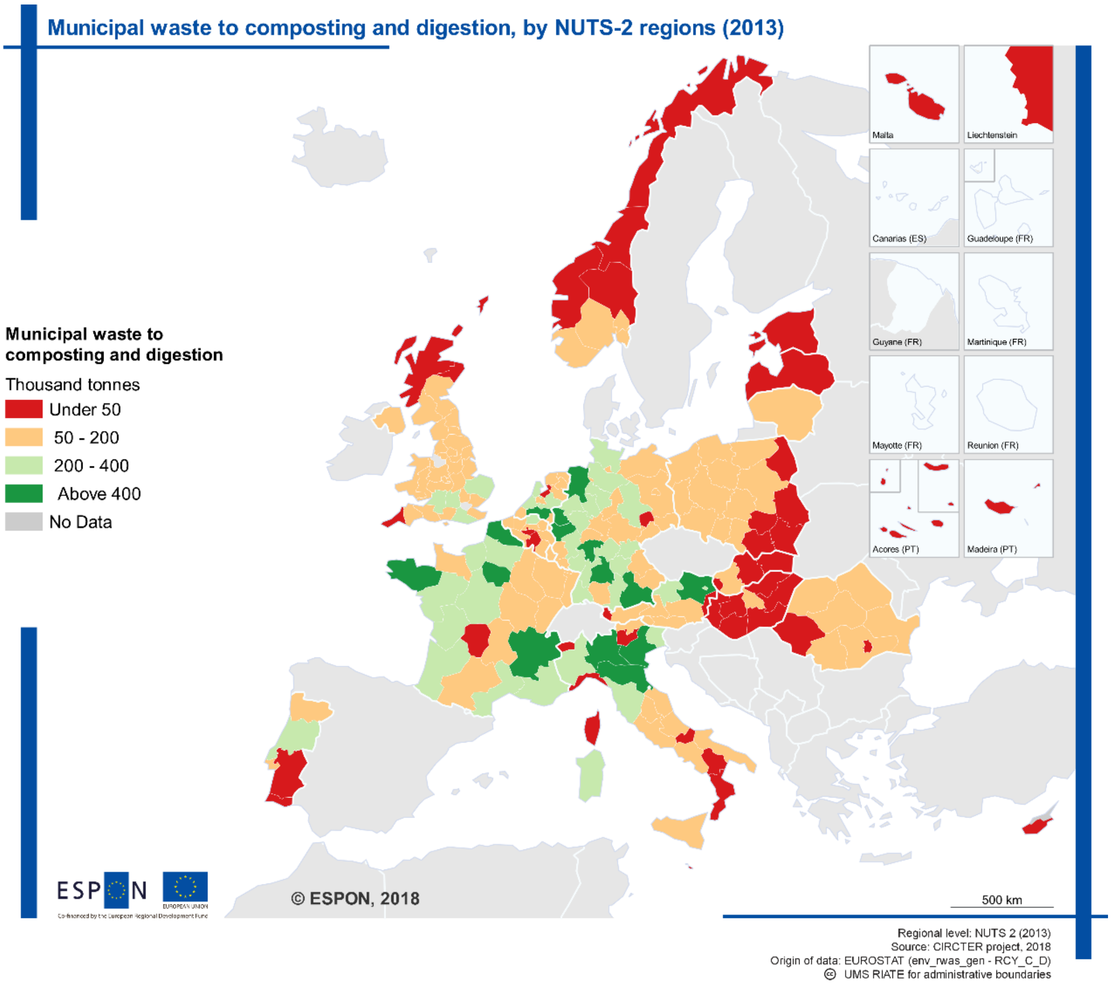
Map 6-38: Municipal waste to material recycling (2013), absolute values



Map 6-39: Municipal waste to composting and digestion (2006), absolute values



Map 6-40: Municipal waste to composting and digestion (2013), absolute values



7 Suggestions for future research

In this section we propose a number of suggestions to improve the regionalisation methodology and to simplify the interpretation of results. These could not be already considered in our own research due to lack of resources, including data and/or time constraints.

From a methodological point of view, both regional estimates and interpretation might be enhanced by exploring the use of **time-series** instead of cross-section data. The use of time-series would for instance better spot the presence of outliers in specific years, and also allow a more accurate analysis of consumption and/or waste generation estimates over time. However, there is a trade-off between approach complexity and the scope (breath) of the analysis. Given the resources requested to perform time-series analyses, the scope of such analysis in terms of indicators would necessarily be significantly narrower than the one proposed in CIRCTER.

Another aspect that could improve interpretation is the selection of **progress variables instead of static snapshot**s. For instance, in this study we considered static indicators and annual exaplanatory variables (e.g. GDP and/or population in a specific year) to build our models. While these static variables are the best alternative to regionalise one given indicator at some point in time, such variables say little about the dynamics of change of the regionalised indicators. In this sense, it would be **helpful to consider progress variables and indicators** (e.g. a material consumption rate or the change in waste generation in a given period) This dynamic approach would allow to e.g. gauge the impact of specific drivers on material efficiency and better understand the impact of policies on waste management.

In any case, the quality of the regional estimates does not solely depend on the regionalisation approach per-se but also (and above all) on the quality of the input data that has been regionalised. As commented previously, the data collection approaches and methodological assumptions differ between countries and/or periods (e.g. due to changes in terminology and definitions), especially for waste indicators. Hence, further efforst need to be allocated to the development of a harmonised and stable accounting system for waste statistics, as well as to the construction of a more ambitious set of indicators on material consumption that adopts a footprint approach. Remarkably, the available statistics do not allow to capture material/waste shipments across regions.

However, improvements in official statistics will take time to be implemented. In the meanwhile, it would be very helpful to **compare our regional estimates with freight transport data** to determine whether regions are really decreasing their material and waste footprint. This would allow to understand if territories are really decreasing their material consumption or simply “shifting the burden” to other areas (e.g. if they are actually increasing the import of goods instead of producing them locally, of expanding their waste shipments instead of treating waste witin their own territories).

8 References

Alperovich G and Deutsch J (2002) An application of a switching regimes regression to the study of urban structure. Papers in Regional Science 81(1): 83–98. DOI: 10.1007/s101100100079.

Beigl P, Wassermann G, Schneider F, et al. (2004) Forecasting Municipal Solid Waste Generation in Major European Cities. Internation Congress: Complexity and Integrated Resources Management: 1–6.

Capello R, Camagni R, Chizzolini B, et al. (2007) Modelling Regional Scenarios for the Enlarged Europe: European Competiveness and Global Strategies. Springer Science & Business Media. DOI: 10.1007/978-3-642-17940-2.

Commission E (2010) Country specific notes on municipal waste Data 2010 Country specific notes on municipal waste Data 2010. (November): 1–7.

Crescenzi R, Rodríguez-Pose A and Storper M (2007) The territorial dynamics of innovation: A Europe-United States comparative analysis. Journal of Economic Geography 7(6): 673–709. DOI: 10.1093/jeg/lbm030.

EC (2008) Directive 2008/98/EC on Waste (Waste Framework Directive).

EC (2011) COM/2011/0131 final - Report from the Commission to the European Parliament and the Council on statistics compiled pursuant to Regulation (EC) No 2150/2002 on waste statistics and their quality. European Commission.

EC (2018) COM/2018/29 final - A Monitoring Framework for the Circular Economy. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions (pp. 1–11).

ESPON (2011) Guidance to ESPON Lead Partners for P1 Projects on the use of Regional Typologies within the ESPON 2013 Programme. ESPON.

European Commission (2018) A monitoring framework for the circular economy. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committe of the Regions: 1–11. DOI: COM/2018/029 final.

Eurostat (2001): Economy-wide Material Flow Accounts and Derived Indicators. A methodological guide. Eurostat, European Commission

Eurostat (2010) Environmental statistics and accounts in Europe: 2010 Edition. DOI: 10.2785/48676. Eurostat, European Commission

Eurostat (2013a): Economy-wide Material Flow Accounts and Derived Indicators. A compilation guide. Eurostat, European Commission

Eurostat (2013b) Manual on waste statistics: A handbook for data collection on waste generation and treatment. Theme: Environment and energy Collection, Methodologies & Working papers, Eurostat, European Commission. Available from: http://bookshop.europa.eu.

Eurostat Press (2015) Environment in the EU Each person in the EU generated 475 kg of municipal waste in 2014. Eurostat Press Office (March): 54–56. Available at: http://ec.europa.eu/eurostat/documents/2995521/7214320/8-22032016-AP-EN.pdf/eea3c8df-ce89-41e0-a958-5cc7290825c3.

Gavrilova O, Randla T, Vallner L, et al. (2005) Life Cycle and Analysis of the Estonian and Oil Shale and Industry. Tallinn University of Technology.

Horta IM and Keirstead J (2017) Downscaling Aggregate Urban Metabolism Accounts to Local Districts. Journal of Industrial Ecology 21(2): 294–306. DOI: 10.1111/jiec.12428.

Lahti L, Huovari J, Kainu M, et al. (2017) Retrieval and Analysis of Eurostat Open Data with the eurostat Package. The R Journal 9(1): 385–392. Available at: https://journal.r-project.org/archive/2017/RJ-2017-019/index.html.

Ratner B (2010) Variable selection methods in regression: Ignorable problem, outing notable solution. Journal of Targeting, Measurement and Analysis for Marketing 18(1): 65–75. DOI: 10.1057/jt.2009.26.

Steger S, Ritthoff M, Bulach W, et al. (2018) Material flow based determination of the contribution of the waste management industry for conserving primary raw materials and increasing resource productivity. German Environment Agency (UBA). Publication in preparation.

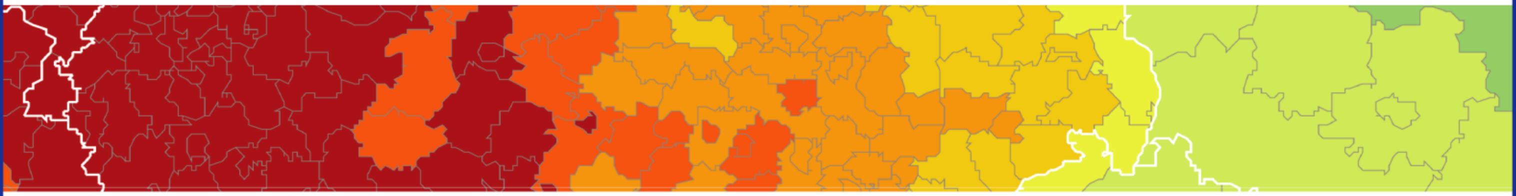
Steinberger JK, Krausmann F and Eisenmenger N (2010) Global patterns of materials use: A socioeconomic and geophysical analysis. Ecological Economics 69(5). Elsevier B.V.: 1148–1158. DOI: 10.1016/j.ecolecon.2009.12.009.

Viton P a. (2010) Notes on Spatial Econometric Models. City and regional planning 870(3): 1–21. Available at: http://facweb.knowlton.ohio-state.edu/pviton/courses2/crp8703/spatial.pdf.

Weisz H, Krausmann F, Amann C, et al. (2006) The physical economy of the European Union: Cross-country comparison and determinants of material consumption. Ecological Economics 58(4): 676–698. DOI: 10.1016/j.ecolecon.2005.08.016.

Wilts H and von Gries N (2015) Europe's waste incineration capacities in a circular economy. Proceedings of the Institution of Civil Engineers - Waste and Resource Management 168(4): 166–176. DOI: 10.1680/warm.14.00009.

Yrigoyen CC (2003) Econometría espacial aplicada a La Predicción-Extrapolación De Datos Microterritoriales.



ESPON 2020 – More information

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