Paving the way to Circular Economy monitoring: regionalising official European statistics of Domestic Material Consumption

1. Introduction

The Circular Economy (CE) is the far-reaching strategy adopted by the European Commission and other actors across the Globe to set European economy on the path to sustainability (European Commision, 2015; Macarthur, 2015). By enabling closed-loops product systems, the CE advocates for a paradigm shift in the way we produce, distribute and consume goods and services, while, at the same time, creating new opportunities for economic growth and social prosperity (Bourguignon, 2016; Ghisellini et al., 2016; Kalmykova et al., 2018). Understanding how these systemic transformations could impact regional economies and how different areas will evolve towards circular trajectories is one of the major challenges that policy-makers dealing with cohesion policies are currently faced with (Fratini et al., 2019).

Monitoring and assessing such structural changes is critical, both from a macroeconomic perspective – to assess whether sufficient action has been taken, as well as from a local perspective – to support local decision-makers in setting new priorities towards the long-term objectives of a circular economy (Corvellec et al., 2013; van Buren et al., 2016). Within the circular economy action plan, the European Commission has implemented a monitoring framework composed of a set of key indicators that capture the main underlying elements of the CE. These are grouped into four stages and aspects including: production and consumption, waste management, secondary raw materials and competitiveness and innovation (European Commission, 2018). However, these indicators fail short in providing territorial evidence at sub-national levels: all the indicators are provided at National or aggregated pan-European levels. Hence, additional efforts are needed to calculate, derive or estimate circular economy indicators at sub-national levels.

In this paper we will focus on Domestic Material Consumption (DMC), by far the most used and relevant indicator informing on material use by a given economy (Steinberger et al., 2010; Weisz et al., 2006). The DMC and its fours subcategories (i.e. biomass, mineral ores, fossil fuels and construction materials), is one of the key indicators included in most circular economy monitoring frameworks, including the one in the EU (see e.g. European Commission, 2018; PBL, 2018), and environmental reporting systems (EUROSTAT, 2018).

The DMC indicator is defined as the sum of domestic material extraction and importations, minus exportations (EUROSTAT, 2018). It is calculated according to the Economic-Wide Material Flow Accounting (EW-MFA), which is the most wide-spread and standardized methodology to account material flows on a national or global scale (Fischer-Kowalski et al., 2011). DMC measures the quantity of resources consumed by a given spatial unit and, despite it presents some shortcomings (Giljum et al., 2014; Wiedmann et al., 2015), it is often used to conduct quantitative analyses on the circulartity and efficiency of economies (Haas et al., 2015; Talmon-Gros, 2014). Its combination with population, surface area and/or GDP variables permits to delineate socio-metabolic profiles of territories providing important information in understanding future territorial trajectories (Baynes and Musango, 2018; Krausmann et al., 2009; Steinberger et al., 2013). As an example, material productivity (i.e. GDP/DMC) is the indicator of reference used at the national policy level to measure the relative dematerialization of an economy (UNEP, 2016; Wiedmann et al., 2015).

Thanks to the high degree of methodological standardization and the quality of the underlying primary data, the comparability of DMC indicators across countries and over time is high (Fischer-Kowalski et al., 2011). Given that the EW-MFA methodology has been primarily developed to assess material flows of national and/or global economies (Schandl and West, 2010; Steinberger et al., 2010; Weisz et al., 2006), in general, harmonised data on material flows and associated indicators are only available at aggregated national level (EUROSTAT, 2018; Gierlinger and Krausmann, 2012; Krausmann et al., 2011). By contrast, local/regional implementations exhibit a great variability in terms of methods and approaches. Scholars have been proposing methods and estimating material flows at sub-national levels for many years (see e.g. Wolman (1965) for an early example of MFA in the city of New York). More recently, studies have been conducted, among others, on Paris and its region (Barles, 2009), Czech regions (Kovanda et al., 2009), Lisbon (Niza et al., 2009; Rosado et al., 2014), Amsterdam (Voskamp et al., 2017) and Spanish regions (Sastre et al., 2015), to cite only a few recent examples. These studies defined a solid knowledge base on the regional and urban metabolism in the EU. However these works embrace a large spectrum of approaches and scopes (see e.g. Horta and Keirstead, 2017) that makes inter-regional comparison biased (Kovanda et al., 2009; Rosado et al., 2014). In addition, these approaches generally did not attempt to explain the relation between material consumption and their potential drivers, even if some studies present interesting findings in this respect (see e.g. Courtonne et al., 2015; Steinberger et al., 2010).

To a large extent, this diversity of approaches is explained and driven by data availability in each setting. One of the main limitations for the application of the EW-MFA approach at local and regional levels is the lack of statistical information on material flows at these levels (Hammer et al., 2003; Sastre et al., 2015; Voskamp et al., 2017). The high costs associated with data collection at lower territorial levels, alongside the limited capacity of intervention and incentives offered to regional and local governments to monitor and minimize material consumption in their own jurisdictions, make official statistics on material flows at sub-national levels a rare exception. Besides, the small number of datasets available at these levels are not collected in a harmonised way, undermining comparability. This represents an important limitation for the characterisation of the metabolic profiles of territories under a consistent approach and, therefore, it hinders the design of place-based policies targeting socio-metabolic processes (Binder et al., 2009; Kennedy et al., 2015; Ten Brink et al., 2017).

This study proposes a method to estimate the DMC in the EU and EFTA countries at regional level[1]. Our goal was to develop and apply a methodology to estimate regional data that: (1) uses a consistent approach that recognises territorial heterogeneity but at the same time permits comparability across different years and between regions, (2) accounts for multiple correlation between materials consumption and its key drivers, (3) allows a certain degree of automatization and thus the estimation of larger datasets at once and the application to other indicators. Based on the STIRPAT approach, which seeks to explain resource consumption in terms of population, affluence and technology (Dietz et al., 2007; York et al., 2003), we estimate DMC figures at regional scale (NUTS 2 level)[2] for two time periods (2006 and 2014). Our study differs from past studies in terms of coverage and exhaustiveness (data for all EU regions plus Norway and Switzerland regions), and also consistency (figures are estimated through a single and stable approach that allows inter-regional comparisons). In addition, the high systematisation level of the methodology permits its application to other fields and/or indicators, paving the way for further comparative analyses and therefore advancing the general knowledge based so far on city-specific case studies.

The article is structured as follows. In the next section, we present the data sources and methods applied. In particular, we first provide an overview of data sources at both, national (NUTS 0) and regional (NUTS 2) levels, and then, we describe the three-steps methodological approach based on (1) model specification, (2) parameters optimization and (3) regional data extrapolation. In Section 3 we present our DMC regional estimates for 280 European regions, including a comparison with DMC figures provided by other peer-reviewed studies. Finally, in Section 4 we summarise the main conclusions about the contributions of our method to the estimation of DMC at sub-national levels and conclude with some perspectives for future research needs.

[1] Hereafter the terms “regions” and/or “regional level” will refer specifically to the NUTS-2 level.

[2] The Nomenclature of Territorial Units for Statistics (NUTS) is a geocode standard for referencing the subdivisions of countries for statistical purposes. The standard is developed and regulated by the European Union, and thus only covers the member states of the EU in detail.

2. Materials and methods

2.1. Data

For the purpose of this paper we built a dataset that includes DMC, Gross Domestic Product (GDP) – measured in purchasing power standard (PPS) –, population (Pop), and surface area (Area). From these variables we computed the GDP per capita (GDP/Pop), population density (Pop/Area), DMC per capita (DMC/Pop) and DMC intensity (DMC/GDP). Data were downloaded from the Eurostat "nama_10r_2gdp", "demo_r_d3dens", and "env_ac_mfa" databases. Missing data have been retrieved from OECD and/or national statistical databases. We accessed data on March 2019 and downloaded data using the R package "Eurostat" v.3.3.5 (Lahti et al., 2019). We downloaded data for 2006 and 2014 at both, national (NUTS 0) and regional (NUTS 2) levels. We selected 2006 and 2014 as reference for two reasons. Firstly, because it covers a significant time-span, allowing to better capture potential structural changes across countries. Secondly, because data availability is acceptable: 2006 and 2014 are the oldest and the most recent year where reasonably complete data sets were available[3].

Table 1 presents an overview of selected variables across EU countries. As it can be seen, countries exhibit a large heterogeneity in term of both socio-economic and physical factors. For example, Germany recorded the highest values for GDP and population. These are 265 and 188 times bigger than those recorded for the smaller country in our dataset, Malta. On the other hand, this country shows the highest population density across EU countries (1.375 hab/km2). This is a clear example of how geographical features may contribute to define the socio-economic structure of territories and it also explains why scholars often distinguish between extensive variables (e.g. area, population and GDP) and intensive variables (e.g. income per capita and population density), when describing territorial patterns of material use (Steinberger et al., 2010; Weisz et al., 2006).

Table 1: Overview of selected data for EU Countries (2014)

Country code	Country name	GDP	Pop	Area	DMC	GDP/Pop	Pop/Area	DMC/Pop	DMC/GDP
AT	Austria	307299	8508	83878	176002	36120	104	20.69	0.57
BE	Belgium	368671	11181	30666	147283	32973	370	13.17	0.40
BG	Bulgaria	93219	7246	110996	135627	12865	66	18.72	1.45
CH	Switzerland	373646	8140	41287	99293	45905	205	12.20	**0.27**
CY	Cyprus	19090	858	9253	11928	22249	93	13.90	0.62
CZ	Czechia	250275	10512	78871	160384	23808	136	15.26	0.64
DE	Germany	**2810712**	**80767**	357569	**1362428**	34800	227	16.87	0.48
DK	Denmark	199236	5627	42925	123755	35406	132	21.99	0.62
EE	Estonia	27649	1316	45336	37173	21013	30	28.25	1.34
EL	Greece	215454	10927	131694	138772	19718	83	12.70	0.64
ES	Spain	1154784	46512	505983	391232	24828	93	8.41	0.34
FI	Finland	166925	5451	338411	169434	30621	18	**31.08**	1.02
FR	France	1959963	65942	**638475**	777286	29722	104	11.79	0.40
HR	Croatia	68900	4247	56594	38582	16224	75	9.08	0.56
HU	Hungary	185607	9877	93012	127209	18791	106	12.88	0.69
IE	Ireland	175052	4638	69947	96844	37744	68	20.88	0.55
IT	Italy	1616043	60783	302073	474853	26587	201	**7.81**	0.29
LT	Lithuania	60890	2943	65284	43503	20686	47	14.78	0.71
LU	Luxembourg	41674	550	2595	11914	**75815**	215	21.67	0.29
LV	Latvia	35078	2001	64586	41415	17526	32	20.69	1.18
MK	North Macedonia	20598	2066	25434	19189	**9971**	83	9.29	0.93

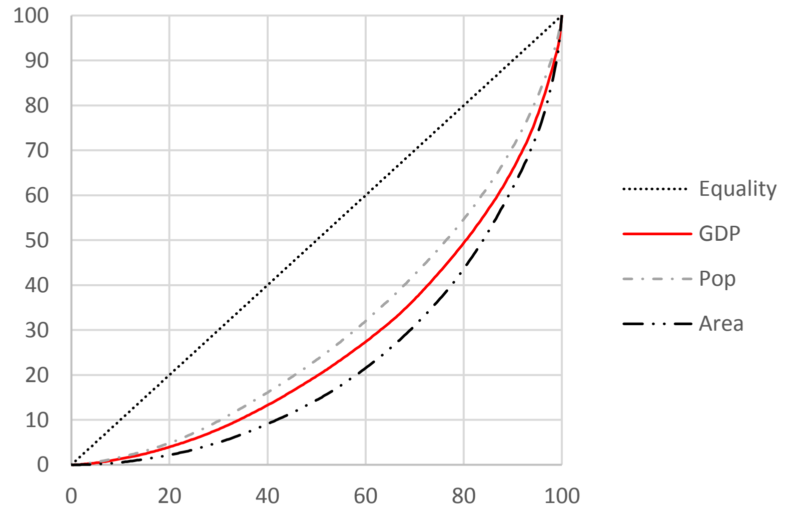
[3] 2006 is the first year in which Norway reports on DMC, while the years after 2014 present many *estimated* DMC figures.

MT	Malta	**10620**	**429**	**316**	**5246**	24731	**1375**	12.22	0.49
NL	Netherland	604157	16829	37378	174377	35899	501	10.36	0.29
NO	Norway	248133	5108	323381	146596	48578	**17**	28.70	0.59
PL	Poland	717249	38018	311928	654385	18866	124	17.21	0.91
PT	Portugal	220362	10427	92227	154435	21133	113	14.81	0.70
RO	Romania	302406	19947	238398	450860	15160	87	22.60	**1.49**
SE	Sweden	332467	9645	447424	221699	34471	24	22.99	0.67
SI	Slovenia	46889	2061	20273	26989	22750	102	13.09	0.58
SK	Slovakia	115525	5416	49035	68069	21331	111	12.57	0.59
UK	United Kingdom	1938495	64351	244381	589558	30124	266	9.16	0.30

Note: Bold figures represent max and min values. Gross Domestic Product (GDP) is measured in purchasing power standard (PPS); population is measured in 1000 inhabitants; area is measured in square kilometres; Domestic Material Consumption (DMC) is measured in 1000 tonnes; income (GDP/Pop) is measured in GDP PPS per capita; population density (Pop/Area) is measured in inhabitants per square kilometres; DMC per capita (DMC/Pop) is measured in tonnes per capita; DMC intensity (DMC/GDP) is measured in tonnes per 1000 GDP PPS.
Source: own elaboration based on Eurostat.

The heterogeneity observed at national level increases when we move the focus to the regional scale. Figure 1 illustrates the Lorenz curve of GDP, Pop and Area observed at regional level, while Table 2 provides some summary statistics, including mean, coefficient of variation and the variation factor, on the same data. According to the figures, both GDP and Pop showed very skewed distribution. Around 20% of EU regions produce almost 50% of total GDP. Similar percentages hold for population data. Regions with the highest GDP per capita, such as Inner London-West (UK), show values that are 21 times higher than those of the regions situated in the lower rank (e.g. Bulgarian and Romanian regions). However, absolute surface area is the variable more unevenly distributed, with only four regions (Nordic regions of Scandinavia plus Castilla y Leon (ES)) covering around 10% of total European surface. In terms of population density, greater agglomerations such as Inner London and Brussels regions, with more than 7000 inhabitants per square kilometres, contrast with very low-density regions, such as Upper Norrland (SE) and Nord-Norge (NO), with only 3 and 5 inhabitants per square kilometres, respectively.

Figure 1: Lorenz curves of GDP, population, and surface



Source: own elaboration.

Table 2: Comparative statistics for EU regions

Concept	Level of analysis	GDP/Pop	Pop/Area	DMC/Pop	DMC/GDP
Mean	Countries	27949	168	16.32	0.67

	Regions	27462	452	n.a.	n.a.
CV	Countries	0.46	1.47	0.38	0.50
	Regions	0.48	2.68	n.a.	n.a.
VF	Countries	8	81	3.98	5.61
	Regions	21	3478	n.a.	n.a.

Variables	Selected outliers			
	Maximum		Minimum	
GDP/Pop	Inner London - West (UK)	173032	North-western (BG)	8214
	Luxembourg (LU)	75571	Southern Central (BG)	8802
	Hamburg (DE)	57608	Nord-Est (RO)	9290
Pop/Area	Inner London - East (UK)	10780	Upper Norrland (SE)	3
	Inner London - West (UK)	10283	Nord-Norge (NO)	5
	Brussels (BE)	7393	Middle Norrland (SE)	5

Note: GDP/Pop is measured in GDP PPS per capita; Pop/Area is measured in inhabitants per square kilometres; DMC/Pop is measured in tonnes per capita; DMC/GDP is measured in tonnes per 1000 GDP PPS. The mean refers to the mathematical average of the sample; The coefficient of variation (CV) = sd/mean. The variation factor (VF) = Max/Min.
Source: own elaboration.

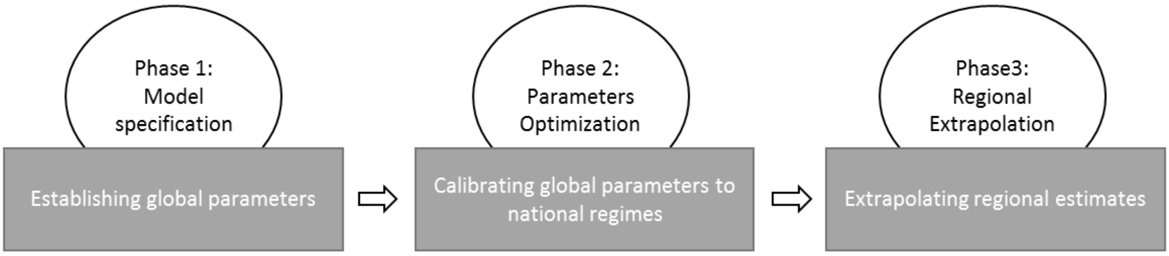
Attention should also be paid on the selection of Pop/Area and GDP/Pop to analyse DMC patterns, which is not random. In fact, both variables are acknowledged as synthetic indicators that embody historical socio-metabolic characteristics of territories (Fischer-Kowalski et al., 2013). The former is a key variable in explaining various aspects related to socio-metabolic regimes and their transition: a high population density across larger territory presupposes a long history of intensive agricultural colonization (Krausmann et al., 2008). Notice that it takes many centuries of an agrarian regime to bring about a high population density, and there is no densely populated country without such a long agrarian history (Krausmann et al., 2008). On the other hand, if population density is low, this might be due to either historical reasons (i.e., no long, uninterrupted history of agrarian colonization), or geophysical reasons (such as adverse natural conditions, e.g., aridity, cold climate, or adverse terrain). Population density not only reflects geophysical conditions and agricultural history, it also systematically differentiates between areas of high and low per capita availability of natural resources (Weisz et al., 2006). The per capita endowment of natural resources, being these mineral resources, biomass, or livestock farming, is higher in sparsely populated regions than in regions with high population density. This is further enhanced by the historical argument outlined above. Countries with a high population density usually have a longer history of resource exploitation and hence have often exhausted their domestic resource base (Krausmann et al., 2008). Finally, sparsely populated countries require a higher input of energy and materials for the same level of supply of services per person compared to densely populated countries, therefore population density can be expected to have a significant impact on metabolic profiles (Weisz et al., 2006).

GDP/Pop, on the other hand, is a proxy of the productive structure of a region. In general, economic activities belonging to the tertiary sector are the most productive ones, and these can generate up to 86% of the total gross value added of metropolitan areas (Duarte, 2016). Therefore, we expect that regions with above-average income level represent economies specialised in tertiary sector, while lower income level would suggest economy mainly oriented to agricultural and/or industrial sectors. However, we also need to keep in mind some limitations when linking economic development and resource consumption. In fact, there is evidence that highly developed economies outsource material-intensive products to other countries (Giljum et al., 2014). Roughly speaking, richer regions (i.e. metropolitan and capital regions) might be better-off when looking to material consumption figures since it is likely that they import material-intensive products and/or semi-finite products instead of producing them in-site.

2.2. Methods

As shown graphically in Figure 2, our methodology proposal is a three-steps econometric approach based on: (1) global model specification, (2) national level parameter optimization and (3) regional extrapolation. The model specification step (1) focuses on the identification of the best regression model to describe DMC figures at country or national level. This phase goes from the very early phases of model building, which includes variables selection and theoretical foundations, to spatial data analyses aiming to detect potential spatial correlations. The main output of this first task is the estimation of the global parameters (β_g) (i.e. the regression coefficients observed between DMC and drivers at European level). Once the β_g have been identified, in step 2 we calibrate them in order to reflect the specific "metabolic-regimes" of the different countries. This calibration is implemented by an optimization algorithm that automatically adjusts the estimated parameters for each country. This generates a set of *country-specific* parameters (β_{cs}). Finally, in phase (3) we extrapolate the regional figures for DMC by applying β_{cs} on the selected explicative variables, which are now measured at the regional level.

Figure 2: Methodological approach to estimate regional figures



$Y_i = const \ + \boldsymbol{\beta}_{\mathbf{g1}} X1_i + \boldsymbol{\beta}_{\mathbf{g2}} X2_i + e$

$Country: i = 1,2,3 \ldots 31$

$Y_i = const \ + (\boldsymbol{\beta}_{\mathbf{cs1}})_{\boldsymbol{i}} X1_i + (\boldsymbol{\beta}_{\mathbf{cs2}})_{\boldsymbol{i}} X2_i$

$Country: i = 1,2,3 \ldots 31$

$\hat{\boldsymbol{y}}_{\boldsymbol{j}} = const \ + (\beta_{\mathrm{cs1}})_i \, x1_j + (\beta_{\mathrm{cs2}})_i \, x2_j$

$Country: i = 1,2,3 \ldots \ 31$

$Region: j = 1,2,3 \ldots \ 280$

Note: bold terms refer to the output of each phase; upper case letters (Y-X) refer to variables measured at national level (NUTS 0); lower case letters (y-x) refer to variables measured at regional level (NUTS 2).
Source: own elaboration.

Our proposal differs from similar data regionalization studies based on econometric approaches in the fact that we are here applying an optimization algorithm that accounts for territorial heterogeneity within the sample. While previous studies often addressed the different territorial regimes by using a switching regression approach (see e.g. Chasco (2003)), we implemented an algorithm that automatically adjusts global estimated parameters to the "metabolic-profile" of each country. Our approach not only overcomes the limited accessibility to data that often limits the application of traditional EW-MFA metabolism studies at regional and local level, but it also addresses two issues that most of the existing studies have so far ignored, namely: (1) the issue of national regimes dependency and (2) the multiple correlation accounting problem.

When it comes to item (1), it should be considered that correlations between drivers and response variable might not only vary across scales, but also across observations belonging to different "spatial regimes". In particular, when considering the nations-to-regions extrapolation, it is likely that regional drivers are also influenced by their own national regimes and not only by highly-aggregated supra-national structures. For instance, softer territorial factors (e.g. governance and administrative traditions, milieus, etc.) operating in nation A, which frequently are not directly captured by the explanatory drivers in regression equations, could expectedly affect the respective regions in a different way from how these same factors affect regions in nation B. In practice, this means that similar underlying drivers can affect regions in different and diverse ways, depending on the specific socio-metabolic conditions defined by the upper governance structures.

Regarding item (2), most local metabolism studies use a single proxy factor (or driver) to estimate missing data (Barles, 2009; Courtonne et al., 2015,). These decisions are often based on bold hypothesis like the assumption that "consumption is almost proportional to population". However, a number of correlation studies (Baynes and Musango, 2018; Steinberger et al., 2010) assert that this statement only holds for material consumption flows, since other material flows such as e.g. material extraction can also (and above all) depend on the geophysical characteristics of regions (Weisz et al., 2006).

Step 1: Model specification

The theoretical foundation of our empirical model is based on the STIRPAT analysis (STochastic Impacts by Regression on Population, Affluence and Technology) conducted on carbon emissions and the ecological footprint (York et al., 2003) and adopted later by, inter alia, Steinberger et al. (2010) to understand and quantify the relations between material consumption flows, socioeconomic drivers and geophysical factors, and Baynes and Musango (2018) to predict global material consumption in 2050 (see also Dietz et al., 2007). The STIRPAT approach seeks to explain environmental impact (I) of a given socio-economic system in terms of population (Pop), affluence (A) and available technology (T). Affluence stands for the level of consumption and it is generally approximated by GDP per capita (GDP/pop). Technology, in turn, can be interpreted as the materiality of affluence in lifestyle, ownership of durable goods and access to infrastructure and services such as buildings, roads, water and electricity supply (Baynes and Musango, 2018). In some studies, (see e.g. Dong et al., 2017), Technology is approximated by material intensity (i.e. DMC/GDP). However, given the uncertainty surrounding the identification of an efficient proxy for T, this component is commonly omitted in most modes. Its effects is captured, by default, in the error term (*e)* (Dietz et al., 2007).

The STIRPAT model has been applied in the past using both total DMC or its intensive expressions, i.e. DMC/Pop and DMC/GDP (Baynes and Musango, 2018; Dietz et al., 2007). Although we expected that the intensive form is more appropriate since it allows to better capture the relationship between DMC and its drivers, avoiding the bias produced by the absolute size of each country, we first conducted an analysis on both specifications. These are: (a) $Log\left(\frac{DMC}{GDP}\right) = const + \beta_1 Log\ \left(\frac{Pop}{Area}\right) + \beta_2 Log\ \left(\frac{GDP}{Pop}\right) + e$ for the intensive mode and (b) $Log(DMC) = const + \beta_1 Log\ \left(\frac{Pop}{Area}\right) + \beta_2 Log\ \left(\frac{GDP}{Pop}\right) + \beta_3 Log\ (Pop) + e$ for the extensive mode. Where $\beta_{1,2,3}$ are the parameters to be estimated respectively for population density $\left(\frac{Pop}{Area}\right)$, GDP per capita $\left(\frac{GDP}{Pop}\right)$,and population (Pop), while *e* is the error term. Logarithmic forms were used to reduce skewness and approximate linear relationships between variables (Steinberger et al., 2010). Notice also that logarithmic forms also allow to interpret parameters' coefficient (β) as "ecological elasticities" (York et al., 2003). Then, if $|\beta|$ >1 the relationship is elastic, meaning that as the predictor X increases, Y increases, and it does so at a faster rate than X. If $|\beta|$ <1, the relation is inelastic, i.e. as X increases, the response Y increases as well, but a slower rate than X. When $|\beta|$ =1, the relation is proportional.

Table 3 shows the regression results for both, (a) and (b) models for years 2006 and 2014. Overall, the STIRPAT approach is quite successful at explaining cross-country differences in material consumption for both models, and results are in line with past studies (Dietz et al., 2007; Steinberger et al., 2010). As expected, with a coefficient close to 1, the most significant explanatory variable is total population, indicating that DMC is almost exactly proportional to population size. Pop/Area on the other hand is inversely correlated with material consumption in both models. To a certain extent, this can be explained by assuming that denser areas optimize material consumption (think for example on how the construction of transport infrastructures may have a greater impact on per capita values when built in low-density areas). Besides, denser regions are typically regions where material intensive activities such as primary and secondary transformations of raw materials are rarely conducted (Weisz et al., 2006). However, the fact that the coefficient is almost inelastic suggests that the mitigation effect of agglomeration economies on DMC remains, in any case, limited. Quite interestingly, GDP/Pop assumes opposite signs depending on the model, clearly suggesting income elasticity. If we first analyse the relationship between GDP/Pop and DMC, we observe that richer countries tend to consume more resources than the poorer ones. However, a deeper analysis showed that this connection has been losing strength in Europe during the last 15 years[4], probably linked to underlying income convergence processes across European countries. On the other hand, as initially expected, the GDP/Pop parameter is significant and inversely correlated with the DMC/GDP. In fact, the decrease in material intensity in recent decades is largely explained by the steady growth of GDP, as the DMC has decreased at a much lower pace.

Residuals generated from both models respect normality condition (Jarque-Bera test and Shapiro-Wilk test not significant at 1%), however we noted that model (a) seems to suffer residual heteroskedasticity for 2006, while model (b) seems to suffer heteroskedasticity for 2014 (see Breusch-Pagan Koenker's version statistics in Table 3). Even if we could easily overcome the heteroskedasticity problem by applying robust errors, this would have important implications in the next step. In fact, a critical factor in the following optimization phase are the standard errors that define the confidence intervals. Since the optimization phase depends on the confidence intervals of estimated parameters, it is only reliable in presence of tied intervals, or in other words, with highly significant parameters. The use of robust errors would increase the intervals used as a boundary during optimization. We also tested for non-linear combinations of drivers by the RESET test. Results seems to suggest that the models are correctly specified. Finally, although we initially considered to pool the two cross-sections in a unique sample, according to the similarity of figures for 2006 and 2014, the Chow test suggested a structural change between the two periods. We hence decided to keep the two cross-sections as separated analyses.

Table 3: OLS regressions results of model (a) and (b)

	(a) DMC/GDP		(b) DMC	
	2006	**2014**	**2006**	**2014**
Constant	7.73***	7.374***	-5.097***	-5.415***
	(1.052)	*(1.289)*	*(1.157)*	*(1.350)*
Pop/Area	-0.225***	-0.251***	-0.216***	-0.241***
	(0.051)	*(0.057)*	*(0.049)*	*(0.055)*
GDP/Pop	-0.688***	-0.663***	0.301**	0.339*
	(0.105)	(0.129)	*(0.101)*	*(0.123)*
Pop			0.942***	0.931***
			(0.033)	*(0.037)*
N	30	31	30	31
R^2	0.721	0.664	0.969	0.960
F-statistic	34.9	27.62	274.7	217.8
JB X-squared	0.585	0.539	0.305	0.406
SW	0.953	0.987	0.973	0.986
B-P Koenker	6.763*	2.904	4.152	7.957*
RESET	0.900	1.126	0.792	0.470
Chow-test	2.991**		2.442 *	

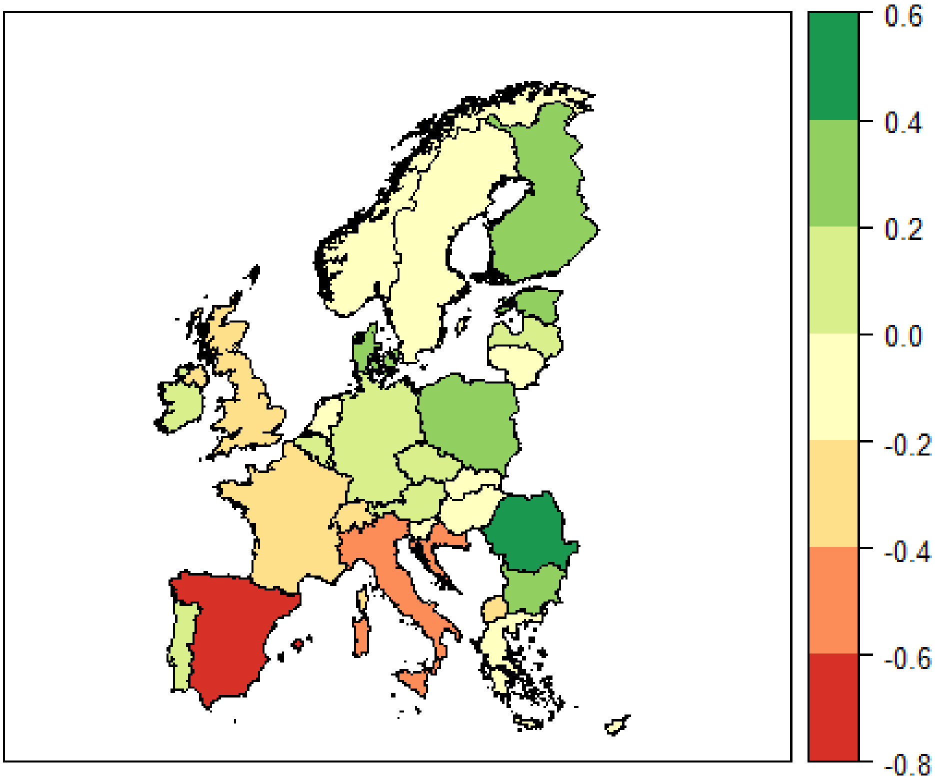
*Note: '***' significant at 1%; '**' significant at 5%; '*' significant at 10%; Standard errors in parenthesis; JB: Jarque Bera; SW: Shapiro-Wilk; BP: Breusch-Pagan test using Koenker's studentized version; RESET test applied for quadratic and cubic powers; In 2006 figures for North Macedonia were not available.*
Source: own elaboration.

For the following analyses we selected the model (a), which, according to the regression results, presents the best statistical properties for the most recent year. In addition, the use of variables in their intensive forms allowed use to test the model for spatial correlation, which, from a first overview of spatial distribution of residual, seemed to affect the model. In fact, as it can be seen from Map 1, a sub-estimation seems occurring

[4] The same regression showed a GDP/Pop coefficient equal to 0.538*** for 2000, 0.301** for 2006 and finally 0.339* for 2014.

mostly in the bigger western and southern economies of Europe (i.e. United Kingdom, France, Italy and Spain), and an over-estimation in eastern European countries (Romania, Estonia, Bulgaria and Poland). One possible explanation for this spatial pattern could be the presence of spatial correlation between the economies based on their geographical proximity, however the Moran's I[5] statistic performed on the residual presented a Z-score not significant (-0.045). This is clear indication that there is no formal evidence of spatial autocorrelation in our sample.

Map 1: Residual distribution of model (a)



Source: own elaboration

Based on all the tests performed[6], we conclude that model (a) is correctly specified and can be applied in the optimization phase to estimate country-specific parameters.

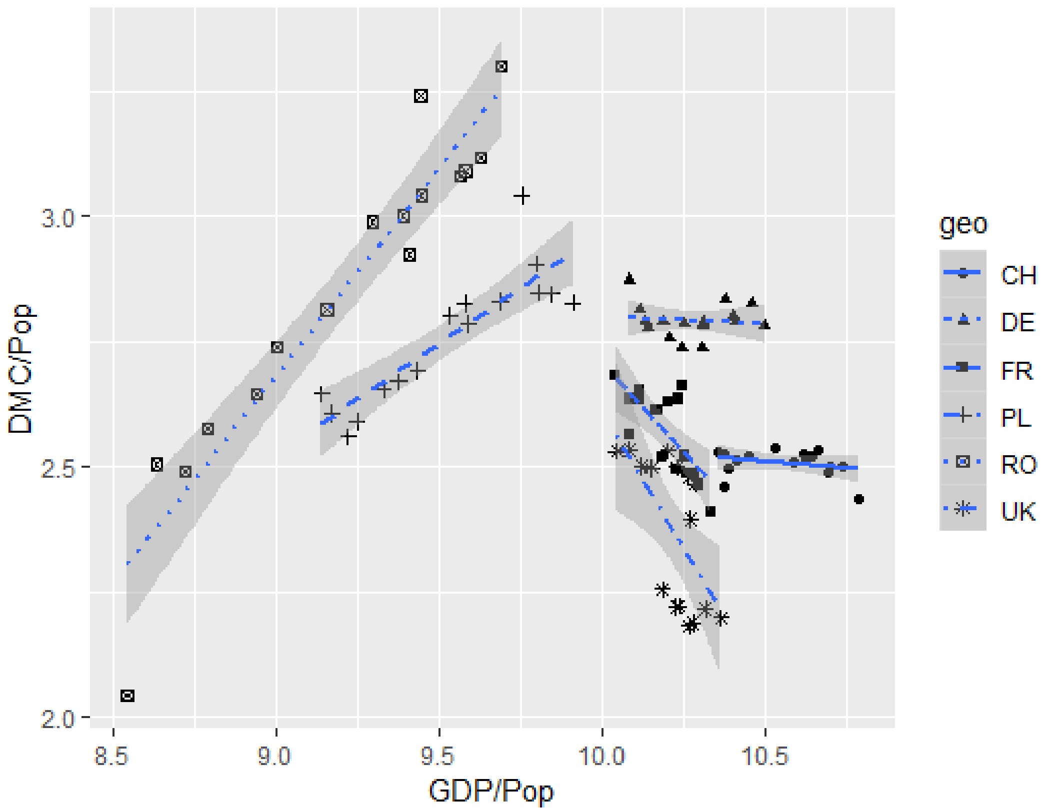
Step 2: Parameters optimization

[5] Moran's I is a measure of spatial autocorrelation defined as: $I = \frac{N}{W}\frac{\sum_i\sum_j w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_i(x_i-\bar{x})^2}$, where N is the number of countries indexed by i and j; x is the variable of interest DMC/GDP; $\bar{x}$ is the mean of x; w_{ij} is a matrix of spatial weights with zeroes on the diagonal and W is the sum of all w_{ij}. Values of I usually range between -1 to +1. For statistical hypothesis testing, Moran's I values can be transformed in Z-scores and compared with the expected value of Moran's I under null hypothesis of no spatial correlation that is E(I)=(-1)/(N-1). Values significantly below -1/(N-1) indicate negative spatial autocorrelation and values significantly above -1/(N-1) indicate positive spatial autocorrelation. The value of I might also be conditioned by the assumptions built into the spatial-weights matrix w_{ij} so that it is common practice to test different weighting matrixes to check (i) that all matrixes converge, to some extent, to the same hypothesis, and (ii) to identify and select the weighting matrix that better responds to specification tests.

[6] Besides the global spatial autocorrelation tests conducted on residuals, we also conducted a LISA analysis to see whether the spatial pattern of over and under predictions provides clues on potential countries clustering. The LISA map suggested the presence of two clusters: one for material-intensive countries and the other for capital-intensive ones. We made an attempt to include such clusters within the regression as factor variables, however the final results did not show significant improvements. Therefore, we favoured the simpler version.

The parameters β_g for $\frac{Pop}{Area}$ and $\frac{GDP}{Pop}$ estimated in step 1 are global, that is to say, they apply indifferently to all countries, without taking into account any kind of country-specific regimes being these sociological, economic and/or geophysical. However, it is well-known that the DMC of an economy is strongly related with the contextual factors characterising the territory. For instance Dong et al. (2017) distinguished between developing, primary developed and mature industrialized countries, while Steinberger et al. (2013) highlighted the difference between the metabolic regime of China and Germany. Figure 3 shows a scatterplot of DMC per capita and GDP per capita for a sample of European countries over the 2000-2015 period. The observations for each country depict distinctive metabolism regimes. For example, economies such as Germany and Switzerland, are characterised by a rather stable DMC/Pop despite a growing GDP/Pop. The economies of France and United Kingdom show a rather declining pattern in DMC/Pop vs GDP/Pop (i.e. declining material consumption per capita and increasing GDP per capita). In contrast, expanding economies such as Poland and Romania show a DMC/Pop that grows at similar pace as GDP/Pop. Therefore, the use of global parameters computed at European scale would likely produce unrealistic regional estimates since these do not account for the observed heterogeneity in national metabolic regimes.

Figure 3: Examples of socio-metabolic regimes at country level.



Note: figures are in logarithmic forms. Fitted lines are generate by OLS regressions for each country.
Source: own elaboration;

We propose an optimization procedure that automatically adjusts global parameters to country-specific structures. This systematisation is a pragmatic way to reflect countries regimes and overcome the poor data context that would otherwise strongly limit the application of more elaborated methods, like the switching regressions approach (Chasco, 2003; Quandt, 1958). The optimization algorithm, which is based on the general nonlinear programming problem (Ye, 1988), has been implemented in R through the "Rsolnp" Package (Ghalanos and Maintainer, 2015) and can be defined as:

$$\text{Min } f(x) \text{ such that:}$$

$$l_{\beta_g} \leq \beta_g \leq u_{\beta_g}$$
$$f(x) = Y_n$$

Where $f(x)$ is the result of the regression from model (a); β_g are the estimated global parameters for $\frac{Pop}{Area}$ and $\frac{GDP}{Pop}$; $\left[l_{\beta_g}, u_{\beta_g}\right]$ are the respective confidence intervals based on the standard errors; and Y_n the DMC/GDP observed at country level. Essentially, through this approach, we are allowing the parameters for β_g to vary within their confidence interval such that for each country the estimated DMC/GDP will match the real DMC/GDP. In this way, the β_g coefficients are calibrated to better capture the country-specific regime. Table 4 shows the estimated parameters for all countries on years 2006 and 2014.

Table 4: Country-specific parameters generated by the optimization algorithm

	Global parameters (β_G)							
	2006				2014			
	Income		Pop. density		Income		Pop. density	
Coefficients	-0.689		-0.225		-0.663		-0.251	
Confidence interval (5%)	-0.903	-0.474	-0.329	-0.122	-0.923	-0.400	-0.367	-0.134
	Country-specific parameters (β_{cs})							
GEO code	Income		Pop. density		Income		Pop. density	
AT	-0.670		-0.223		-0.646		-0.249	
BE	-0.678		-0.224		-0.655		-0.250	
BG	-0.670		-0.223		-0.630		-0.248	
CH	-0.723		-0.229		-0.685		-0.253	
CY	-0.668		-0.223		-0.670		-0.251	
CZ	-0.675		-0.224		-0.654		-0.250	
DE	-0.689		-0.225		-0.645		-0.249	
DK	-0.649		-0.221		-0.634		-0.248	
EE	-0.678		-0.224		-0.626		-0.248	
EL	-0.706		-0.227		-0.678		-0.252	
ES	-0.684		-0.225		-0.721		-0.256	
FI	-0.663		-0.224		-0.643		-0.250	
FR	-0.720		-0.229		-0.691		-0.253	
HR	-0.711		-0.228		-0.707		-0.255	
HU	-0.694		-0.226		-0.669		-0.251	
IE	-0.637		-0.221		-0.656		-0.250	
IT	-0.697		-0.226		-0.711		-0.256	
LT	-0.726		-0.229		-0.678		-0.252	
LU	-0.669		-0.223		-0.649		-0.249	
LV	-0.683		-0.225		-0.649		-0.250	
MK	n.a.		n.a.		-0.687		-0.253	
MT	-0.681		-0.224		-0.624		-0.245	
NL	-0.712		-0.229		-0.672		-0.252	
NO	-0.716		-0.227		-0.666		-0.251	
PL	-0.687		-0.225		-0.637		-0.248	
PT	-0.672		-0.223		-0.657		-0.250	
RO	-0.672		-0.223		-0.611		-0.246	
SE	-0.720		-0.227		-0.668		-0.251	
SI	-0.672		-0.223		-0.674		-0.252	
SK	-0.703		-0.227		-0.674		-0.252	
UK	-0.716		-0.229		-0.693		-0.254	

Source: own elaboration

Step 3: Data extrapolation and reconciliation

The next step in our procedure consists on the direct application of the country-specific parameters for $\frac{Pop}{Area}$ and $\frac{GDP}{Pop}$ for model (a) to the exogenous variables measured now at the regional (NUTS 2) level, generating regional DMC estimates (i.e. from eq. 1 to eq. 2):

$$Log\left(\frac{DMC}{GDP}\right)_i = const + \beta_g Log\ \left(\frac{Pop}{Area}\right)_i + \beta_g Log\ \left(\frac{GDP}{Pop}\right)_i + e\ ; \qquad country\ i = 1,2, \dots 31; \qquad (1)$$

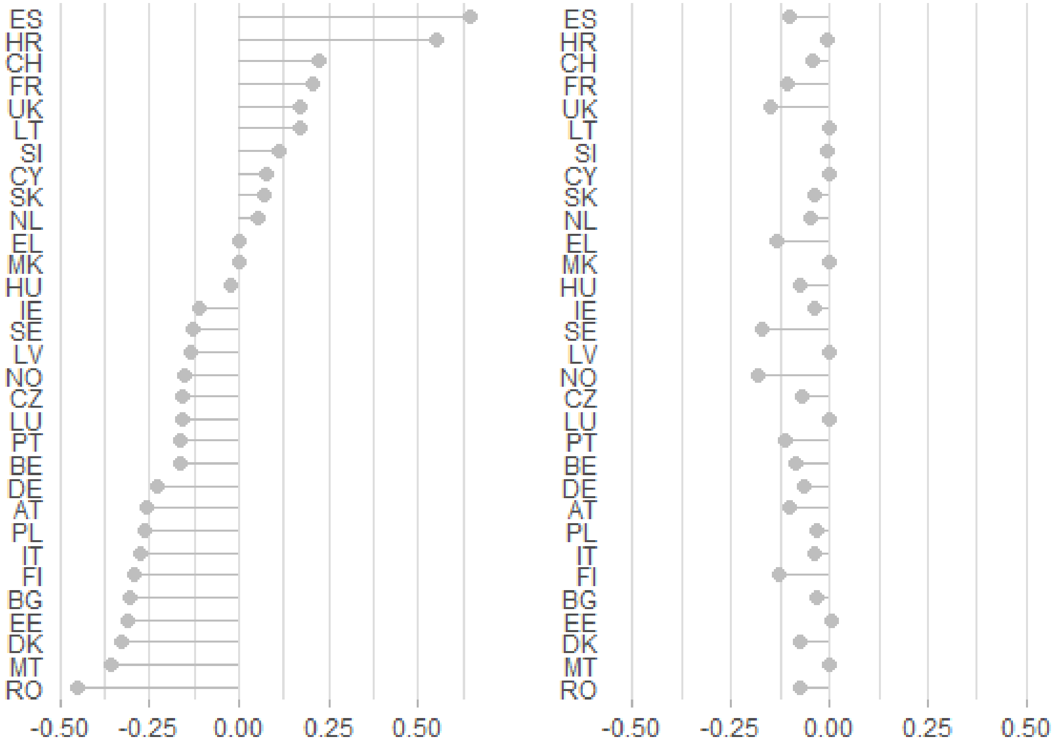
$$Log\left(\frac{\widehat{DMC}}{GDP}\right)_j = const + (\beta_{cs})_i\ Log\ \left(\frac{Pop}{Area}\right)_j + (\beta_{cs})_i\ Log\ \left(\frac{GDP}{Pop}\right)_j + e\ ; \quad region\ j = 1,2, \dots 280; \qquad (2)$$

$$country\ i = 1,2, \dots 31;$$

Where (1) represents the regression model (a) estimated at EU level, and (2) represents the country-specific regression models applied to each country in order to extrapolate regional $\left(\frac{\widehat{DMC}}{GDP}\right)$. As it can be seen in (2) we substitute β_g with β_{cs}, and the variables $\left(\frac{Pop}{Area}\right)$ and $\left(\frac{GDP}{Pop}\right)$ with their equivalents measured at regional level.

In general, the only reliable way to assess the validity of the estimates is to compare these with direct statistics for those same administrative areas (e.g. NUTS 2). However, since we estimated at once all regions within Europe, we can first check whether the sum of regional values for each country reflects the real national value. Even if this approach does not ensure that regional figures are correctly distributed within a country, it can provide some insights on the goodness of the model applied. In Table 5 we provide an overview of the deviation of results generated by (1) our approach and (2) the results that would have been generated by global parameters (β_g) (i.e. without optimization procedure). According to the figures, the use of optimized parameters improves significantly the goodness of regional estimates, as these deviates significantly less from the real values. The perfect matching for countries having just one region (i.e. Republic of Macedonia, Lithuania, Latvia, Luxemburg, Estonia and Malta) simply indicates that the optimization algorithm adjusted the parameters to fit exactly the national value.

Table 5: Deviations of estimates from real values in the case of global- and country-specific approach



(β_g) (β_{cs})

Deviation for each country has been computed as $\left(\frac{\widehat{DMC}-DMC}{DMC}\right)$*. Source: own elaboration*

Once the consistency of our regional estimates was confirmed, we performed a reconciliation of these values with the national figures. Reconciliation is a procedure that seeks to ensure coherence of results between different scales of analysis (Courtonne et al., 2015). In this specific study, reconciliation consisted on a rescaling the regional estimates to fit exactly the respective national values. Mathematically, $\tilde{y} = \frac{\hat{y}_i * Y}{\sum_{i=0}^{n} \hat{y}_i}$ where $\tilde{y}$ is the final rescaled regional estimate (i.e. DMC/GDP), $\sum_{i=0}^{n} \hat{y}_i$ is the sum of regional estimated values $\hat{y}_i$ of a country Y. The final results are presented in the following section, along with a discussion and a comparison of a set of estimated and *real* DMC values produced by previous studies for a sample of selected regions.

3. Results and discussion

Table 6 compares our results with DMC figures estimated by other metabolism studies for a sample of selected regions. Although the analyses differ in term of scopes, methods, approaches, timeframes and assumptions, a comparison of these studies with our results allows to assess the consistency of our estimates, as well as to understand and recognise the limitations of our method.

Table 6: Estimates for selected regions and comparison with other studies

Geo code	Region name	Our results DMC (t/cap)		Other studies		Sources
		2006	2014	DMC (t/cap)	Year	
FR10	Ile de France	10.69	8.97	7.10	2003	Barles (2009)
				11.85	2011	Duarte (2016)
				14.72	2000	Duarte (2016)
				15.50	2000	Pina et al. (2015)

DE30	Berlin	8.91	8.73	17.86	2011	Duarte (2016)
DE60	Hamburg	12.44	12.06	20.90	2011	Duarte (2016)
				12.10	2001	Hammer and Giljum (2006)
PT17	Lisbon	16.23	10.91	10.40	2005	Rosado et al. (2013)
				18.97	2011	Duarte (2016)
				17.10	2000	Pina et al. (2015)
ES30	Comunidad de Madrid	15.55	5.90	5.90	2010	Sastre et al. (2015)
				12.91	2011	Duarte (2016)
UKD7	Merseyside (Liverpool)	7.93	5.87	8.32	2011	Duarte (2016)
UKD3	Greater Manchester	8.26	6.06	9.05	2011	Duarte (2016)
UKE2	North Yorkshire (York)	16.91	13.32	11.94	2000	Barret et al. (2002)
NL32	Noord-Holland (Amsterdam)	10.69	9.80	16.00	2012	Voskamp et al. (2016)
SE11	Stockholm	14.77	16.08	19.19	2011	Duarte (2016)
				10.34	2011	Rosado et al. (2016)
				10.10	2011	Kalmykova et al. (2015)
AT13	Wien	13.19	9.64	9.20	2003	Hammer and Giljum (2006)
Mean		12.32	9.76	12.09		

Source: own elaboration

Starting with the results for Ile de France (8.97 t/cap), we can see that our estimates are in line with the most recent studies, based on Input-Output analysis (Duarte, 2016; Pina et al., 2016). Moreover, similarly to these studies our estimates also suggest a decreasing trend on DMC in Ile de France between years 2006 and 2014. The major discrepancy is with Barles' results. This can be justified by the different assumptions made by this author when characterising waste flows. Indeed, Barles considers waste as an exported material, which is consequently subtracted from the calculation of the domestic material consumption indicator. In turn, the EW-MFA framework considers waste material flowing to landfill as a material flow within the economy and thus includes it in the calculation of the DMC indicator.

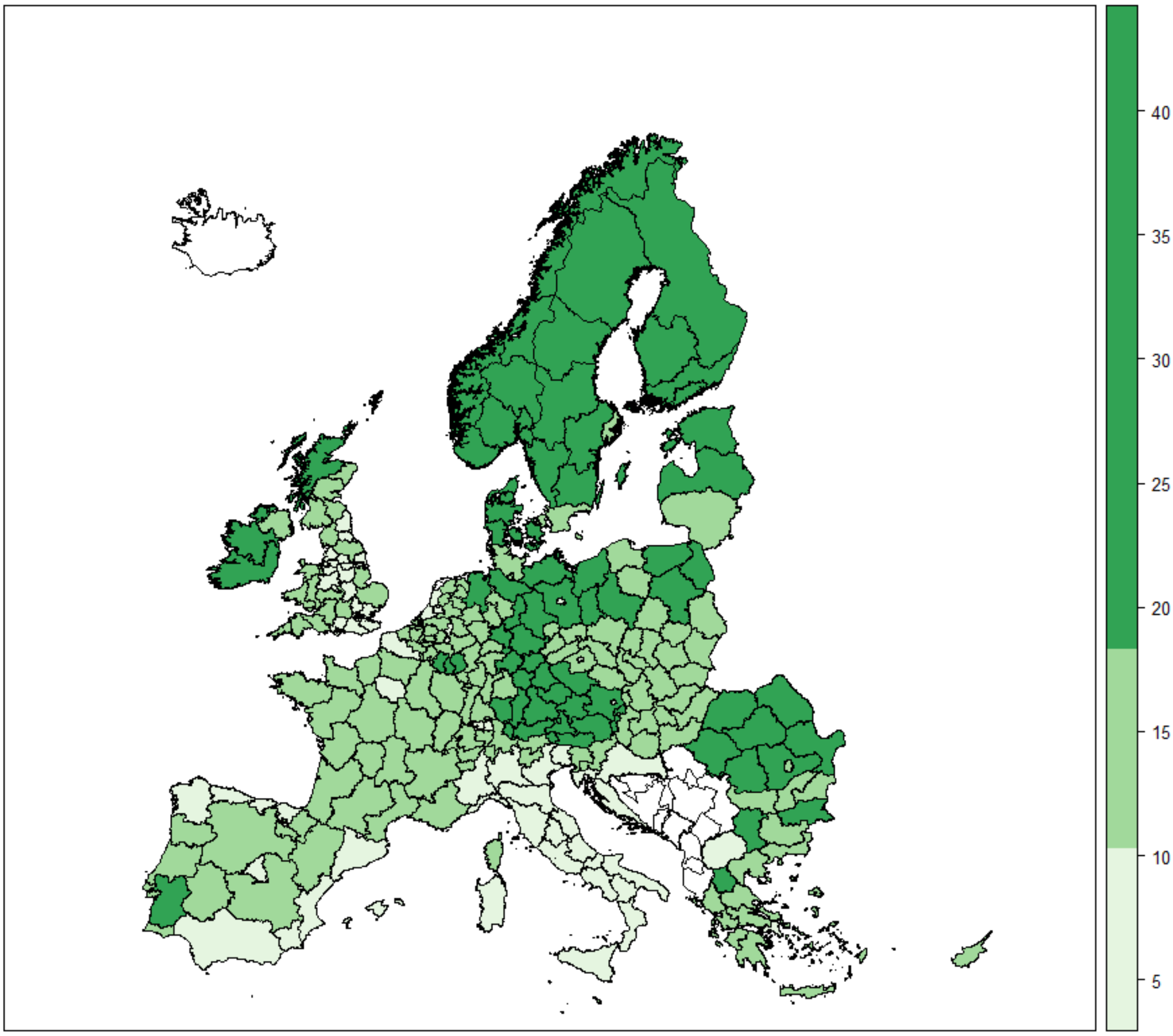
With respect to Hamburg, Berlin, Stockholm and Amsterdam, we also noted some divergences with previous studies. The difference for Hamburg might be explained by the so-called "Rotterdam Effect". In commercial harbour areas, material flows tend to be overestimated due to trade exchanges and the difficult statistical allocation of transit goods. Still, our estimate for Hamburg are in line with those provided by Hammer and Giljum (Hammer et al., 2003). In the case of Amsterdam, the difference between our estimates and those from previous studies could be justified by the inclusion of water flows in the analysis conducted by Voskamp and colleagues, which are normally excluded in standard EW-MFA statistics. The order of magnitude of water flows are much larger than other material flows, to a point that not only dominate the accounts, but also 'dilute' the flows of other materials (EUROSTAT, 2018: 18). Finally, for the regions of Lisbon, Madrid, Liverpool and Manchester, all the estimated values are close to previous studies.

Our conclusion from this evaluation fully confirms the hypothesis that the divergence between the various assessments strongly depends on the specific methods and underlying assumptions that are made. This said, in general, our results seem to be pretty much aligned with those from previous studies.

Map 1 provides an overview of the regional DMC per capita in 2014 across Europe. Regions with large urban agglomerations and strong tertiary economies are those characterised by lower material consumption per capita (i.e. Ile de France, Madrid, London area etc.). As said before, this could be a natural consequence of the economic specialization in these areas, in contrast to the less densely populated areas. In fact, rural, peripherical regions feature greater availability of land for the cultivation of biotic resources and extraction activities. Frequently, natural resources are pre-processed or pre-transformed locally as a strategy to minimise transport costs, which could increase the DMC intensity of these economies in comparison to other regions that only import or consume finished products.

Again, regional economic specialization seems to have an impact on DMC per capita. As clearly shown on Map 2, peripherical regions, which coincide largely with the Eastern regions, Southern Portugal, Ireland, Scotland and Scandinavia peninsula, tend to drive on material intensive sectors. Romanian regions feature among the ones with higher economic dependency on building and construction sector, many Polish regions keep large industrial facilities that process large amounts of materials, while the Scandinavian peninsula and Ireland are specialised in timber and livestock production, respectively. Similarly, interior regions are those characterised by more de-materialised economies thanks to a strong service and finance sector.

Map 2: Quantile map of DMC per capita (T/CAP) in 2014[7]



Note: the three tonalities of green refer to sample quantiles corresponding to the three probability intervals [0% – 25%], [25% – 75%] and [75% – 100%]. The numbered scale reflects the DMC per capita measured in t/cap.
Source: own elaboration

4. Conclusion

[7] We estimated also regional figures for 2006 but due to space limitation we present only the map for 2014.

This article presents a novel econometric modelling approach to derive regional estimates for the Domestic Material Consumption (DMC) indicator. The model was applied to more than 280 EU and EFTA regions (NUTS-2 level) in two periods (2006 and 2014). Our results provide policy-makers with granular information on material consumption that would be otherwise unavailable for policy formulation. In particular, this input is critical to the design of place-based policies and strategies in support of circular economies at sub-national levels.

The approach addresses several methodological caveats of previous studies. In particular, our method:

- Provides harmonised and comparable figures: The limited number of regional metabolism studies and the lack of harmonisation among them undermines comparability between regions (Decker et al., 2000). By applying a consistent and systematic approach, we provided a harmonised material consumption dataset at European regional level that is not only exhaustive (all EU and most EFTA regions are covered), but also comparable over time and across regions. This paves the way for comparative research that advances the general understanding of metabolic systems and the factors that influence them (Kennedy et al., 2015; Rosado et al., 2014) allowing decision-makers to acquire significant knowledge about the effects of measures and policies adopted in a region with those applied in other regions (Voskamp et al., 2017).
- Accounts for correlation: Unlike similar studies where the extrapolation of larger regional datasets is based on simpler ratio-based normalization approaches, our method considers multiple correlations between material consumption and its potential drivers. Using correlations to extrapolate regional data not only provides regional estimates that better capture the magnitude of the relationship between drivers and material consumption, but also gives useful insights into how the relationship evolve over time, i.e. whether these are reinforcing or weakening.
- Overcomes data constraints at sub-national levels: The lack of regional and local data is arguably the most important barrier to conduct local metabolism studies (Hammer et al., 2003; Sastre et al., 2015). This assertion can be extrapolated to many other policy domains as well. By taking advantage of available general statistical information and reflecting territorial heterogeneity by the optimization algorithm, we propose a method that can be sufficiently automated to permit the estimation of larger datasets at once. Furthermore, its systematisation makes it suitable for application to other territorial contexts, geographical scales, thematic domains and indicators. It provides a pragmatic but reliable solution to deal with data scarcity at sub-national levels.

Moreover, our approach provides reliable estimates for DMC data. The comparison of our figures with previous studies on regional metabolism shows that, overall, the DMC values obtained through our method are consistent with those obtained by earlier studies adopting a bottom-up approach.

Still, our method could be further improved in various ways. In this study we considered static indicators and annual explanatory 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 a given indicator at some point in time, such variables say little about the dynamics of change of the regionalised indicators. Further analyses might focus on the selection of progress variables such as population and/or income growth for a selected period instead of static time-cuts. 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 material consumption. Similarly, it would be useful to compare our regional estimates with freight transport data to determine whether regions are genuinely decreasing their material footprint. This would allow to understand if territories are really decreasing their material consumption or simply "shifting the burden" to other areas (Marra Campanale and Femia, 2013; Satterthwaite, 2008).

List of abbreviations

CE	Circular Economy

DMC	Domestic Material Consumption
DMC/Pop	Domestic Material Consumption per capita
DMC/GDP	Domestic Material Consumption intensity
EFTA	European Free Trade Association
EU	European Union
GDP	Gross Domestic Product
GDP/Pop	Gross Domestic Product per capita
Pop	Population
Pop/Area	Population density
PPS	Purchasing power standard

References

Barles S (2009) Urban metabolism of Paris and its region. *Journal of Industrial Ecology* 13(6): 898–913. DOI: 10.1111/j.1530-9290.2009.00169.x.

Baynes TM and Musango JK (2018) Estimating current and future global urban domestic material consumption. *Environmetal Research Letters*.

Binder CR, Van Der Voet E and Rosselot KS (2009) Implementing the results of material flow analysis progress and challenges. *Journal of Industrial Ecology* 13(5): 643–649. DOI: 10.1111/j.1530-9290.2009.00182.x.

Bourguignon D (2016) Closing the loop New circular economy package. *European Parliamentary Research Service* (January): 9. DOI: 10.1111/j.1742-1241.2010.02575.x.

Chasco CY (2003) *Econometría espacial aplicada a La Predicción-Extrapolación De Datos Microterritoriales*.

Corvellec H, Campos MJZ and Zapata P (2013) Infrastructures, lock-in, and sustainable urban development: The case of waste incineration in the Göteborg Metropolitan Area. *Journal of Cleaner Production* 50. Elsevier Ltd: 32–39. DOI: 10.1016/j.jclepro.2012.12.009.

Courtonne JY, Alapetite J, Longaretti PY, et al. (2015) Downscaling material flow analysis: The case of the cereal supply chain in France. *Ecological Economics* 118: 67–80. DOI: 10.1016/j.ecolecon.2015.07.007.

Decker EH, Elliott S, Smith FA, et al. (2000) Energy and material flow through the urban ecosystem. *Annual Review of Energy and the Environment* 25: 685–740.

Dietz T, Rosa EA and York R (2007) Driving the human ecological footprint. *Frontiers in Ecology and the Environment* 5(1): 13–18. DOI: 10.1890/1540-9295(2007)5[13:DTHEF]2.0.CO;2.

Dong L, Dai M, Liang H, et al. (2017) Material flows and resource productivity in China, South Korea and Japan from 1970 to 2008: A transitional perspective. *Journal of Cleaner Production* 141. Elsevier Ltd: 1164–1177. DOI: 10.1016/j.jclepro.2016.09.189.

Duarte ARQ (2016) *Analysis of the urban metabolism of European metropolitan areas*.

European Commision (2015) An EU action plan for the circular economy. *Com* 614: 21. DOI: 10.1017/CBO9781107415324.004.

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 (2018) *Economy-wide material flow accounts HANDBOOK*. DOI: 10.2785/158567.

Fischer-Kowalski M, Krausmann F, Giljum S, et al. (2011) Methodology and indicators of economy-wide material flow accounting: State of the art and reliability across sources. *Journal of Industrial Ecology* 15(6): 855–876. DOI: 10.1111/j.1530-9290.2011.00366.x.

Fischer-Kowalski M, Haberl H, Fischer-Kowalski M, et al. (2013) Conceptualizing, Observing and Comparing Socioecological Transitions. In: *Socioecological Transitions and Global Change*. DOI: 10.4337/9781847209436.00008.

Fratini CF, Georg S and Jørgensen MS (2019) Exploring circular economy imaginaries in European cities: A research agenda for the governance of urban sustainability transitions. *Journal of Cleaner Production* 228: 974–989. DOI: 10.1016/j.jclepro.2019.04.193.

Ghalanos A and Maintainer ST (2015) Package 'Rsolnp' Type Package Title General Non-Linear Optimization.

Ghisellini P, Cialani C and Ulgiati S (2016) A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production* 114. Elsevier Ltd: 11–32. DOI: 10.1016/j.jclepro.2015.09.007.

Gierlinger S and Krausmann F (2012) The Physical Economy of the United States of America. *Journal of Industrial Ecology* 16(3): 365–377. DOI: 10.1111/j.1530-9290.2011.00404.x.

Giljum S, Dittrich M, Lieber M, et al. (2014) Global Patterns of Material Flows and their Socio-Economic and Environmental Implications: A MFA Study on All Countries World-Wide from 1980 to 2009. *Resources* 3(1): 319–339. DOI: 10.3390/resources3010319.

Haas W, Krausmann F, Wiedenhofer D, et al. (2015) How circular is the global economy?: An assessment of material flows, waste production, and recycling in the European union and the world in 2005. *Journal of Industrial Ecology* 19(5): 765–777. DOI: 10.1111/jiec.12244.

Hammer M, Giljum S, Hinterberger F, et al. (2003) Material flow analysis on the regional level: Questions, problems, solutions. *NEDS Working Paper* 2. Available at: Hamburg. www.seri.at/ index.php?option=com_docman&task=search_ result&search_mode=phrase&search_phrase=C. OWP&Itemid=39.

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.

Kalmykova Y, Sadagopan M and Rosado L (2018) Circular economy – From review of theories and practices to development of implementation tools. *Resources, Conservation and Recycling* 135(February 2017). Elsevier: 190–201. DOI: 10.1016/j.resconrec.2017.10.034.

Kennedy CA, Stewart I, Facchini A, et al. (2015) Energy and material flows of megacities. *Proceedings of the National Academy of Sciences* 112(19): 5985–5990. DOI: 10.1073/pnas.1504315112.

Kovanda J, Weinzettel J and Hak T (2009) Analysis of regional material flows : The case of the Czech Republic. *Resources , Conservation and Recycling* 53: 243–254. DOI: 10.1016/j.resconrec.2008.12.004.

Krausmann F, Fischer-Kowalski M, Schandl H, et al. (2008) The global sociometabolic transition: Past and present metabolic profiles and their future trajectories. *Journal of Industrial Ecology* 12(5–6): 637–656. DOI: 10.1111/j.1530-9290.2008.00065.x.

Krausmann F, Gingrich S, Eisenmenger N, et al. (2009) Growth in global materials use, GDP and population during the 20th century. *Ecological Economics* 68(10): 2696–2705. DOI: 10.1016/j.ecolecon.2009.05.007.

Krausmann F, Gingrich S and Nourbakhch-Sabet R (2011) The metabolic transition in Japan: A material flow account for the period from 1878 to 2005. *Journal of Industrial Ecology* 15(6): 877–892. DOI: 10.1111/j.1530-9290.2011.00376.x.

Lahti L, Huovari J, Kainu M, et al. (2019) Retrieval and Analysis of Eurostat Open Data with the eurostat Package. *The R Journal* 9(1): 385. DOI: 10.32614/rj-2017-019.

Macarthur E (2015) Circular Economy. *Ellen Macarthur Foundation*: 6–9. DOI: 10.1038/531435a.

Marra Campanale R and Femia A (2013) An Environmentally Ineffective Way to Increase Resource Productivity: Evidence from the Italian Case on Transferring the Burden Abroad. *Resources* 2(4): 608–627. DOI: 10.3390/resources2040608.

Niza S, Rosado L and Ferr P (2009) Urban Metabolism Methodological Advances in Urban Material Flow Accounting Based on the Lisbon Case Study. 13(3). DOI: 10.1111/j.1530-9290.2009.00130.x.

Pina A, Ferrão P, Ferreira D, et al. (2016) The physical structure of urban economies — Comparative assessment. *Technological Forecasting and Social Change* 113. Elsevier Inc.: 220–229. DOI: 10.1016/j.techfore.2015.05.012.

Quandt RE (1958) The Estimation of the Parameters of a Linear Regression System Obeying Two Separate Regimes. *Journal of the American Statistical Association* 53(284): 873–880. DOI: 10.1080/01621459.1958.10501484.

Rosado L, Niza S and Ferr P (2014) A Material Flow Accounting Case Study of the Lisbon Metropolitan Area using the Urban Metabolism Analyst Model. *M E T H O D S , T O O L S , A N D S O F T WA R E* 18(1). DOI: 10.1111/jiec.12083.

Sastre S, Carpintero Ó and Lomas PL (2015) Regional material flow accounting and environmental pressures: The Spanish case. *Environmental Science and Technology* 49(4): 2262–2269. DOI: 10.1021/es504438p.

Satterthwaite D (2008) Cities' contribution to global warming: Notes on the allocation of greenhouse gas emissions. *Environment and Urbanization* 20(2): 539–549. DOI: 10.1177/0956247808096127.

Schandl H and West J (2010) Resource use and resource efficiency in the Asia-Pacific region. *Global Environmental Change* 20(4). Elsevier Ltd: 636–647. DOI: 10.1016/j.gloenvcha.2010.06.003.

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.

Steinberger JK, Krausmann F, Getzner M, et al. (2013) Development and Dematerialization: An International Study. *PLoS ONE* 8(10). DOI: 10.1371/journal.pone.0070385.

Talmon-Gros L (2014) Material Productivity Measurement., pp. 81–97. DOI: 10.1007/978-3-319-02538-4_5.

Ten Brink P, Kettunen M and Watkins E (2017) Expert Group on Green and Circular Economy in the Outermost Regions Final Report. (June). Available at: https://ieep.eu/uploads/articles/attachments/48cc702e-9e86-4383-9ff6-64bfee597bd9/IEEP (2017) Green and Circular Economy in Outermost Regions - FINAL.pdf?v=63668287356.

UNEP (2016) *Global Material Flows and Resource Productivity. An Assessment Study of the UNEP International Resource Panel*.

van Buren N, Demmers M, van der Heijden R, et al. (2016) Towards a circular economy: The role of Dutch logistics industries and governments. *Sustainability (Switzerland)* 8(7): 1–17. DOI: 10.3390/su8070647.

Voskamp IM, Stremke S, Spiller M, et al. (2017) Enhanced Performance of the Eurostat Method for Comprehensive Assessment of Urban Metabolism: A Material Flow Analysis of Amsterdam. *Journal of Industrial Ecology* 21(4): 887–902. DOI: 10.1111/jiec.12461.

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.

Wiedmann TO, Schandl H, Lenzen M, et al. (2015) The material footprint of nations. *Pnas* 112(20): 6271–

6276. DOI: 10.1073/pnas.1220362110.

Wolman A (1965) The metabolism of cities. *Scientific American* 213: 179–90. Available at: http://www.ncbi.nlm.nih.gov/pubmed/14338520.

Ye Y (1988) *Interior algorithms for linear, quadratic, and linearly constrained convex programming*. *ProQuest Dissertations and Theses*. Available at: https://search.proquest.com/docview/303706000?accountid=188395.

York R, Rosa EA and Dietz T (2003) STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics* 46(3): 351–365. DOI: 10.1016/S0921-8009(03)00188-5.