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METHODS

An open-source regionalization approach for subnational EEMRIO insights and proof-of-concept application to EU steel circularity

Anniek J. Kortleve[1] · Nicolas Navarre[1] · Paul Behrens[1,2] · Hale Cetinay[1,5] · Franco Donati[1] · Benjamin Sprecher[3] · Arnold Tukker[1,4] · José M. Mogollón[1]

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Abstract

Environmentally extended multi-regional input–output (EEMRIO) analysis provides a robust methodology for assessing economic, social, and environmental footprints across nations and regions. Increasing its geographical resolution is essential for addressing local environmental issues and informing targeted policy decisions. While subnational EEMRIOs ideally rely on survey data, such data are often unavailable or resource-intensive to process. As a result, partitioners resort to proxies and algorithms. Yet, the transparency of these algorithms and the underlying data are often suboptimal. Here, we present a novel, open-source, top-down regionalization approach applicable to any EEMRIO database. Our method builds on location quotients (LQ), extending their application to a multi-regional framework. This extension ensures calculations remain traceable, eliminates the need for supplemental balancing procedures, and requires minimal, readily available additional proxy data, making it highly accessible for practitioners. Using European steel trade as a proof-of-concept, we demonstrate how this approach assesses local impacts, highlights local–global trade interactions, and identifies opportunities that national IO data often obscure.

Keywords Regionalization · Subnational EEMRIO · Location quotient · Circular economy · Ecological footprint · Environmental input–output analysis

1 Introduction

Environmentally extended multi-regional input–output (EEMRIO) models are useful for assessing the environmental impacts across supply chains (Tukker et al., 2009). They are often developed at a broader, national level, which provides key sectoral interconnections between trading nations. This lack of subnational information hinders detailed analyses of the many economically and environmentally diverse subregions of larger nations (Szabó, 2015). Although environmental targets are set at the international or national scale, it is often local governments which are responsible for meeting specific targets and sub-targets (Froemelt et al., 2021; Moran et al., 2022; Sun et al., 2019). Greater regional insight into environmental footprints is critical for these policy makers. Several of these targets relate to increasing the circularity of economies, especially in Europe. For example, the EU Green Deal requires broad economic and social transformations at all regional levels (European Commission, 2019). Circular economy targets place more urgency on developing local insights into local impacts and avenues for improving circularity.

Given that a circular transition requires efforts across many industrial systems and spatial scales while retaining a macroscopic economic view (McCarthy et al., 2018), regionalized EEMRIOs could provide an essential approach to better inform policy makers. They can identify sectors with opportunities to close material cycles by linking upstream

A. J. Kortleve and N. H. Navarre have contributed equally to this work.

✉ Anniek J. Kortleve
a.j.kortleve@cml.leidenuniv.nl

1 Institute of Environmental Sciences, CML Leiden University, P.O. Box 9518, 2300 RA Leiden, The Netherlands

2 Oxford Martin School, University of Oxford, Oxford, UK

3 Faculty of Industrial Design Engineering, Delft University of Technology, Delft, The Netherlands

4 Netherlands Organisation for Applied Scientific Research TNO, Hague, The Netherlands

5 Asset Management, Stedin Netbeheer B.V., 3011 TA Rotterdam, The Netherlands

and downstream production, minimizing waste and increasing material reuse (Aguilar-Hernandez et al., 2018; MacArthur, 2013). Ideally, subnational IO data would be created on the basis of local survey data or other basic statistics, but local data are often limited, and their collection requires expensive and time-consuming surveys by national statistical agencies (Hermannsson, 2016; Lampiris et al., 2020). In response, non-survey and partial non-survey approaches have been developed to derive subnational tables from national tables algorithmically (Lampiris et al., 2020; Zhao & Choi, 2015).

Survey-based efforts can be categorized as 1) bottom-up construction of subnational EEMRIO models and 2) integrating subnational supply and use tables (SUTs), subnational input–output tables (IOTs) or subnational consumer expenditure surveys within existing EEMRIOs. For example, Wilting et al. (2021) integrated the survey-based, subnational EUREGIO database (Thissen et al., 2018) with environmental extensions to calculate subnational European greenhouse gas (GHG) footprints for 16 EU countries. They found substantial variation in subnational per-capita GHG footprints (Wilting et al., 2021). However, bottom-up construction is time-consuming and often sacrifices sectoral resolution. Garcia et al. (2020) constructed an EEMRIO of blue virtual water flows for the United States regions, but it is not nested in a global EEMRIO. Ivanova et al. (2017) calculated subnational European (EU27) household consumption-based carbon footprints by integrating subnational consumer expenditure surveys with an EEMRIO model and Lee et al. (2021) performed a similar integration with household-level consumer surveys for the districts of India. However, both studies did not fully disaggregate other final demand categories, local production, or interregional trade structures. Osei-Owusu et al. (2020), Jiang et al. (2019) and Rum et al. (2022) nested regional EEMRIOs (for Denmark's, China's, and Indonesia's subregions, respectively) into EXIOBASE but relied on a reconciliation approach to harmonize the databases which is limited to specific regions. These studies provide unique insights into the value of higher spatial resolution, but are often case-specific or data-dependent, not always connected to the global system, and/or disaggregate only parts of the EEMRIO.

Examples of non-survey approaches include single region analyses (e.g., Piñero et al. (2020) for Galicia, Spain and Christis et al. (2017) for Flanders, Belgium) but trade between subnational regions is often omitted (i.e., domestic trade). Boero et al. (2018) disaggregated national data based on subnational labor markets and transport costs for the United States, but the approach does not differentiate trade flows between intermediate and final consumption (so cannot be used in a full EEMRIO analysis). Towa et al. (2020) regionalized the SUT of Belgium and nested it within the global EEMRIO EXIOBASE, but the approach is very data-intensive, precluding its use for many countries with lower data availability. Wenz et al. (2015) proposed a flexible and comprehensive disaggregation algorithm, but it requires substantial user experience in IO disaggregation. Többen and Kronenberg (2015) extended the Cross-Hauling Adjusted Regionalization Method (CHARM) for multi-regional frameworks, but their approach assumes that subnational cross-hauling shares match national ones, which leads to a systemic overestimation of intraregional trade and subnational multipliers. Even when CHARM is applied under optimal conditions, it captures only half of the actual cross-hauling effects, limiting its ability to fully address trade imbalances (Többen & Kronenberg, 2015). Zheng et al. (2021) developed an entropy-based framework to construct city-level MRIO tables for China, integrating available data with entropy-maximizing techniques to estimate missing trade flows. However, the accuracy of this approach depends on the quality and availability of data constraints, and in data-scarce subregions, entropy maximization may yield unrealistic trade flows. Lenzen et al. (2017) produced balanced subnational multi-regional SUTs for Australia using the Industrial Ecology Virtual Laboratory (IELab). IELab has also been applied to several other countries including Indonesia (Faturay et al., 2017), Taiwan (Faturay et al., 2020a), Japan (Wakiyama et al., 2020), the United States (Faturay et al., 2020b), China (Wang, 2017) and Switzerland (Froemelt et al., 2021). However, not all regionalized countries are connected to a global EEMRIO model (Fry et al., 2022; Li et al., 2020). The IELab relies on initial estimates based on non-survey methods which are fed into a constrained-optimization algorithm that produces balanced subnational SUTs (using a RAS-variant called 'Konfliktfreies' RAS). The constraint-optimization algorithm relies on data which are generally not available and in practice are based on expert judgement, opening work to ideological critiques (Lenzen et al., 2017).

Despite significant progress in regionalizing EEMRIO models, the existing literature reflects key trade-offs. Some approaches rely on balancing procedures such as RAS or entropy maximization which may introduce uncertainty or require intensive computation. Others depend on survey-based or proprietary subnational datasets, limiting their transferability across countries. In many cases, the required data or procedural details are not fully accessible, which hinders replication or reuse. The examples discussed above illustrate these challenges across a range of methodological families, from SUT-based models to constrained optimization frameworks.

To address these issues, we present a novel, top-down, regionalization approach, specifically developed for EEMRIO analysis. This method is applicable to any EEMRIO database and builds on location quotients (LQs), extending their use to multi-regional frameworks. It produces a balanced system without requiring supplemental balancing procedures such as RAS, while keeping data modifications traceable and computationally efficient (Çetinay et al., 2020).

Compared to existing approaches, our method offers three key advantages: (1) It ensures that subnational accounts remain fully consistent with national IO data. By nesting the regionalized nation within its multi-regional framework, it preserves connections to environmental extensions and enables disaggregated analysis at the subnational, national, and international scales, while maintaining high industry and product resolution; (2) It minimizes data requirements by using simple, widely available proxies such as subnational employment and household income; and (3) It is fully transparent, reproducible, and open access, allowing practitioners to apply it to any EEMRIO database using any type of proxy on subnational industry output and subnational size (https://doi.org/10.5281/zenodo.15789999). While applying this approach requires an understanding of fundamental IO principles, it eliminates the need for complex disaggregation techniques and balancing procedures, making it more accessible than many existing regionalization methods.

While regionalization is a form of disaggregation, it specifically refers to the process of spatially disaggregating national accounts into subregions. Here, 'nations' and 'subregions' denote two separate spatial scales, where a nation is composed of several subnational subregions.

We demonstrate proof-of-concept by applying this approach to EXIOBASE 3.3 (Stadler et al., 2018), integrating subnational employment and income data from Eurostat to estimate subnational coefficients and flows. By regionalizing Spain and France into their Nomenclature of Territorial Units for Statistics (NUTS 2, Eurostat, 2020) regions, we show how this method assesses regional trade patterns and local environmental impacts that are often obscured in the national-level analysis. Finally, we reflect on this approach for informing circular economy policies and assessing local environmental impacts.

2 Methods, framework, and small-scale example

2.1 Fundamentals of input–output analysis

EEMRIO databases are composed of a transaction matrix (**Z**), a final demand matrix (**Y**), and the direct emissions coefficient matrix (**B**). The technical coefficient matrix (**A**) is derived as:

$$\mathbf{A} = \mathbf{Z}\widehat{\mathbf{X}}^{-1} \tag{1}$$

here $\widehat{\mathbf{X}}$ denotes the diagonal matrix of vector $\boldsymbol{x}$, the total output. **A** can be transformed into the total requirement matrix (**L**) also called the Leontief Inverse, which is derived from:

$$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} \tag{2}$$

Each extension in **B** can be introduced to the model as:

$$\boldsymbol{r} = \boldsymbol{b}'\mathbf{L}\mathbf{Y} \tag{3}$$

where $\boldsymbol{r}$ represents the consumption-based environmental, socio-economic or material footprint. Finally, $\boldsymbol{v}$ denotes the value-added, derived as:

$$\boldsymbol{v} = \boldsymbol{x} - \mathbf{Z}\mathbf{1} \tag{4}$$

(details in Supplementary Materials SM1).

The input–output model can also be expanded to a multi-regional framework (Eq. 5) when the diagonal of **A** and **Y** represent the domestic consumption for each region and the vertical and horizontal off-diagonals represent imports and exports, respectively:

$$\boldsymbol{r1r2r3} = \begin{pmatrix} \boldsymbol{b}_{11} & 0 & 0 \\ 0 & \boldsymbol{b}_{22} & 0 \\ 0 & 0 & \boldsymbol{b}_{23} \end{pmatrix} \left(\mathbf{I} - \begin{pmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} & \mathbf{A}_{13} \\ \mathbf{A}_{21} & \mathbf{A}_{22} & \mathbf{A}_{23} \\ \mathbf{A}_{31} & \mathbf{A}_{32} & \mathbf{A}_{33} \end{pmatrix} \right)^{-1} \begin{pmatrix} \mathbf{Y}_{11} & \mathbf{Y}_{12} & \mathbf{Y}_{13} \\ \mathbf{Y}_{21} & \mathbf{Y}_{22} & \mathbf{Y}_{23} \\ \mathbf{Y}_{31} & \mathbf{Y}_{32} & \mathbf{Y}_{33} \end{pmatrix} \boldsymbol{i} \tag{5}$$

2.2 Expansion of the EEMRIO model

When a nation is regionalized into subregions, the global EEMRIO is expanded by increasing the matrices' dimensions. Let us regionalize nation 1 in the three-region model of Eq. 5 into subregions 4 and 5 (Eq. 6). Region 1 is set to 0 to avoid double counting and subregions 4 and 5 are added to the outer edges of the matrices. The unregionalized nations (nations 2 and 3) remain unchanged. The diagonal of subregion 4 and 5 now represents the subnational consumption and the vertical and horizonal off-diagonals represent imports and exports, where imports and exports among regions 4 and 5 represent the domestic trade among the subregions.

$$\boldsymbol{r1r2r3\bar{r}4\bar{r}5} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & \boldsymbol{b}_{22} & 0 & 0 & 0 \\ 0 & 0 & \boldsymbol{b}_{33} & 0 & 0 \\ 0 & 0 & 0 & \boldsymbol{b}_{44} & 0 \\ 0 & 0 & 0 & 0 & \boldsymbol{b}_{55} \end{pmatrix} \left(I - \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & \mathbf{A}_{22} & \mathbf{A}_{23} & \mathbf{A}_{24} & \mathbf{A}_{24} \\ 0 & \mathbf{A}_{32} & \mathbf{A}_{33} & \mathbf{A}_{34} & \mathbf{A}_{35} \\ 0 & \mathbf{A}_{42} & \mathbf{A}_{43} & \mathbf{A}_{44} & \mathbf{A}_{45} \\ 0 & \mathbf{A}_{52} & \mathbf{A}_{53} & \mathbf{A}_{54} & \mathbf{A}_{55} \end{pmatrix} \right)^{-1} \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & \mathbf{Y}_{22} & \mathbf{Y}_{23} & \mathbf{Y}_{24} & \mathbf{Y}_{25} \\ 0 & \mathbf{Y}_{32} & \mathbf{Y}_{33} & \mathbf{Y}_{34} & \mathbf{Y}_{35} \\ 0 & \mathbf{Y}_{42} & \mathbf{Y}_{43} & \mathbf{Y}_{44} & \mathbf{Y}_{45} \\ 0 & \mathbf{Y}_{52} & \mathbf{Y}_{53} & \mathbf{Y}_{54} & \mathbf{Y}_{55} \end{pmatrix} \boldsymbol{i} \tag{6}$$

In the following, bold capital letters refer to matrices, bold italic lowercase letters refer to vectors, and italic letters to scalars. A bar on top of an uppercase or lowercase letter indicates the disaggregated matrix, vector, or scalar. 'Nation' and 'subnational region' (or subregion for short) are used to denote two separate spatial scales (i.e., a nation is composed of subnational regions). Lastly, international trade refers to trade between nations (across international borders), whilst interregional trade refers to the intranational trade, i.e., domestic trade between the subregions within a nation.

2.3 Disaggregation of national data to subnational estimates

The developed approach builds upon the "more than two-region" logic of Miller and Blair (2009) in combination with the Simple Location Quotient (SLQ). However, in our approach, the regionalization is set up in such a way that the subregions are balanced to the national account and to the IO without requiring a supplemental balancing procedure. We adopted the SLQ approach due to its reduced data requirements without further need for adjustment or reliance on historical subnational data. Kronenberg (2009) demonstrated that LQs can be applied to not only intermediate demand but also final demand, ensuring consistency between regional industrial structures and consumption patterns. This approach aligns with our extension of SLQ to final demand, which maintains balance within the regionalized MRIO framework while avoiding additional reconciliation procedures.

As with other non-survey approaches, this approach requires the economic assumption of similarity between the subnational and national economies: that is, the homogeneity of technology and consumer preferences across the nation (Sun et al., 2019). Additionally, to estimate interregional trade, export, and import-oriented subregions are isolated, assuming that no intranational cross-hauling occurs. This method allows for consistency between national and subnational tables. In other words, if all the subregions are summed, the national table is recovered.

The SLQ for sector i in subregion r is defined according to Eq. 7, where x_i^r and x^r indicate the gross output of sector i in subregion r and the total output of all sectors in subregion r, respectively, and x_i^n and x^n indicate these gross outputs at the national level. In cases where subnational output data are not consistently available, proxies of subnational and national economic activity are used, such as subnational employment by sector data.

$$SLQ_i^r = \frac{x_i^r / x^r}{x_i^n / x^n} \tag{7}$$

The SLQ_i^r measures the ability of subnational sector i to supply the demands placed upon it by other industries and by final demand in subregion r. If sector i has less activity in subregion r than across the nation on average ($SLQ_i^r < 1$), it is less able to meet local final demand, and its subnational coefficients are calculated by taking the national coefficients and then multiplying them by SLQ_i^r to reduce the value. However, if sector i has more activity in a subregion ($SLQ_i^r \geq 1$), then it is assumed that the national input coefficients from sector i apply to the subregion, and the subnational surplus produced by i will be exported to the rest of the nation (Miller & Blair, 2009). The SLQ_i^r quantifies the specialisation of each sector within a subregion compared to the parent nation (Lamonica & Chelli, 2017; Lampiris et al., 2020).

To disaggregate a nation into any number of subregions while maintaining consistency with the national IO account, we introduce an adjustment factor to calculate internal domestic trade between subregions. We propose the factor f_i^r, which adjusts the domestic import demand for each sector-subregion combination based on the gross output of the domestically trading subregions. We define $c^{(r)}$ as the gross output share of the importing subregions and $c^{(r\prime)}$ as the gross output share of the exporting subregions (Eq. 8).

$$f_i^r = \frac{c^{(r\prime)}}{1 - c^{(r)}} \tag{8}$$

To estimate intraregional trade (i.e., domestic trade among subregions), we isolate import- and export-oriented subregions. Import-oriented subregions are defined as subregions with excess demand (i.e., local supply is not sufficient to meet local demand) and export-oriented subregions are defined as regions with excess supply (i.e., local supply is more than sufficient to meet local demand). The excess supply of the export-oriented subregions is allocated using the adjustment factor of Eq. 8 (Fig. 1).

We assume that the international imports to the subregions follow the total subnational sizes. In our proof-of-concept, this proxy is the subnational household income. International imports then reflect the relative sizes of the subregions. International exports follow the sector-specific subnational output shares. In our proof-of-concept, this proxy is the subnational employment. International exports thereby reflect the size of the regional industries. If the EEMRIO export data are inconsistent with the subnational proxy data, i.e., if there are international exports present at the national level of the EEMRIO model but no employment in any of the subregions, the international exports are regionalized based on income share.

To perserve consistency with the national accounts, we ensure that the sum of the total output of each sector in

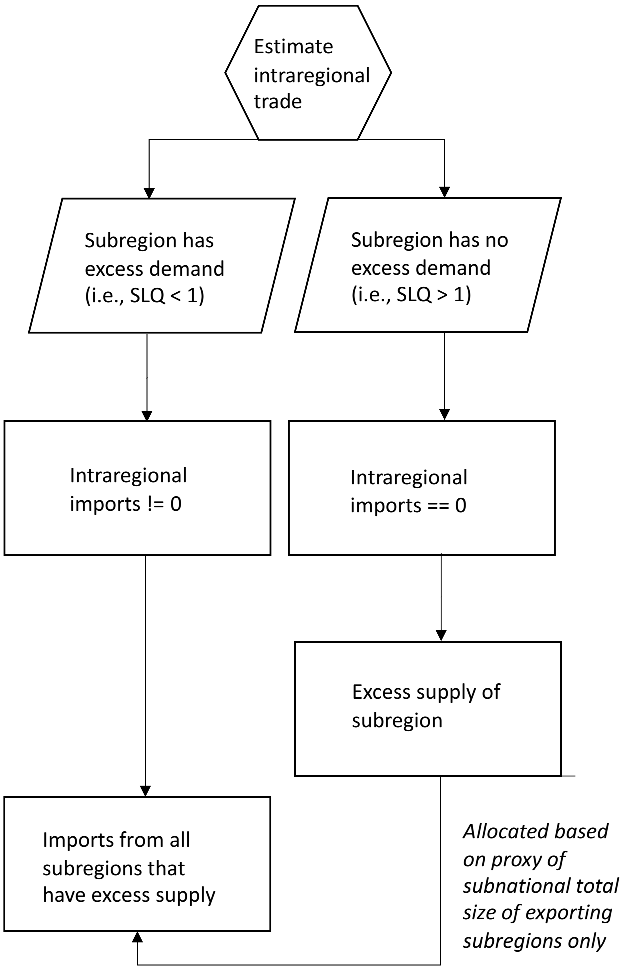

Fig. 1 Flow chart of estimating intraregional trade (i.e., domestic trade among subregions). Flow chart logic corresponds to the formulae in the intraregional trade cells of Table 1 (blue)

the disaggregated system matches the total output of that sector at the national level. This consistency is achieved by defining the value-added vector $\bar{\boldsymbol{v}}$ as the residual difference between total output vector $\bar{\boldsymbol{x}}$ and the column sum of matrix $\bar{\mathbf{Z}}$ (following Cabernard & Pfister, 2021). This ensures that aggregating subregions exactly reproduces the national IO table.

To ensure that the total output of each sector-country combination equals total input in the disaggregated system, we derive the subnational value-added vector $\bar{\boldsymbol{v}}$ as a residual:

$$\bar{\boldsymbol{v}}^{r} = \bar{\boldsymbol{x}}^{r} - \bar{\mathbf{Z}}^{r}\mathbf{1} \tag{9}$$

where gross output is $\bar{\boldsymbol{x}} = \bar{\mathbf{Z}}\mathbf{1} + \bar{\mathbf{Y}}\mathbf{1}$ (also used in Cabernard & Pfister, 2021). Because our regionalization procedure guarantees additivity to the transition blocks $\sum_r \bar{\mathbf{Z}}^{r} = \mathbf{Z}$ and $\sum_r \bar{\mathbf{Y}}^{r} = \mathbf{Y}$, summing Eq. 9 over all subregions yields: $\sum_r \bar{\boldsymbol{v}}^{r} = \boldsymbol{x} - \mathbf{Z}\mathbf{1} = \boldsymbol{v}$, i.e., the national value-added vector is exactly recovered without any further reconciliation. This self-balancing property, visualized in Fig. 2, means that no additional reconciliation is needed.

For the environmental and socio-economic extensions, we assume that the subnational direct emission coefficients are identical to the national ones. $\bar{\mathrm{Z}}$, $\bar{\mathrm{Y}}$, and $\bar{v}$ are validated by aggregating the subnational accounts and comparing them to the parent nation's account, and by verifying that total inputs equal total outputs.

Table 1 provides an overview of the multi-regional disaggregation procedure of each EEMRIO element and shows that all elements are disaggregated, although not all are based on sector-specific data. Figure 2 visualizes the workflow and, through its hatching, shows which steps are SLQ-driven and therefore rely on the location-quotient assumptions, and which steps apply additional allocation rules to distribute national IO imports, exports, value-added and extensions across the subregions.

The regionalization algorithm first estimates the subnational economies, then international trade, which is followed by intranational trade (Fig. 3). The latter is set up in such a way that the system is automatically balanced. Each element is disaggregated independently into their subnational equivalents and added to the outer edges of the matrices. The subregions maintain their connections to the global system making it possible to analyze the environmental and socio-economic supply-chain implications at the subnational, national, and international scale.

2.4 Application to EXIOBASE with subnational Eurostat data

As a proof-of-concept, we apply this method using subnational employment and household income data available for Spain and France. Spain and France were selected for the proof-of-concept because they share a border, resulting in substantial economic interactions. They are also large enough to be divided into many NUTS 2 regions, allowing for detailed regionalization. Further, Spain provides official subnational data that enables partial validation of the results. We create NUTS 2 IOTs for both countries and embed them into their national table within the existing global EEMRIO by expanding the matrices. For the gross subnational outputs, we use the proxies of sector-specific employment data and subnational household income data collected from (2022b; Eurostat, 2022a) as these are consistently available for all EU subregions. The EEMRIO of EXIOBASE 3.3 and subnational employment by sector data are harmonized using a concordance matrix that maps the sector classification of the employment data to the sector classification of EXIOBASE (See Zenodo for Concordance Table).

The EEMRIO database used in this study, EXIOBASE 3.3, includes 200 product, seven final demand and 60 direct

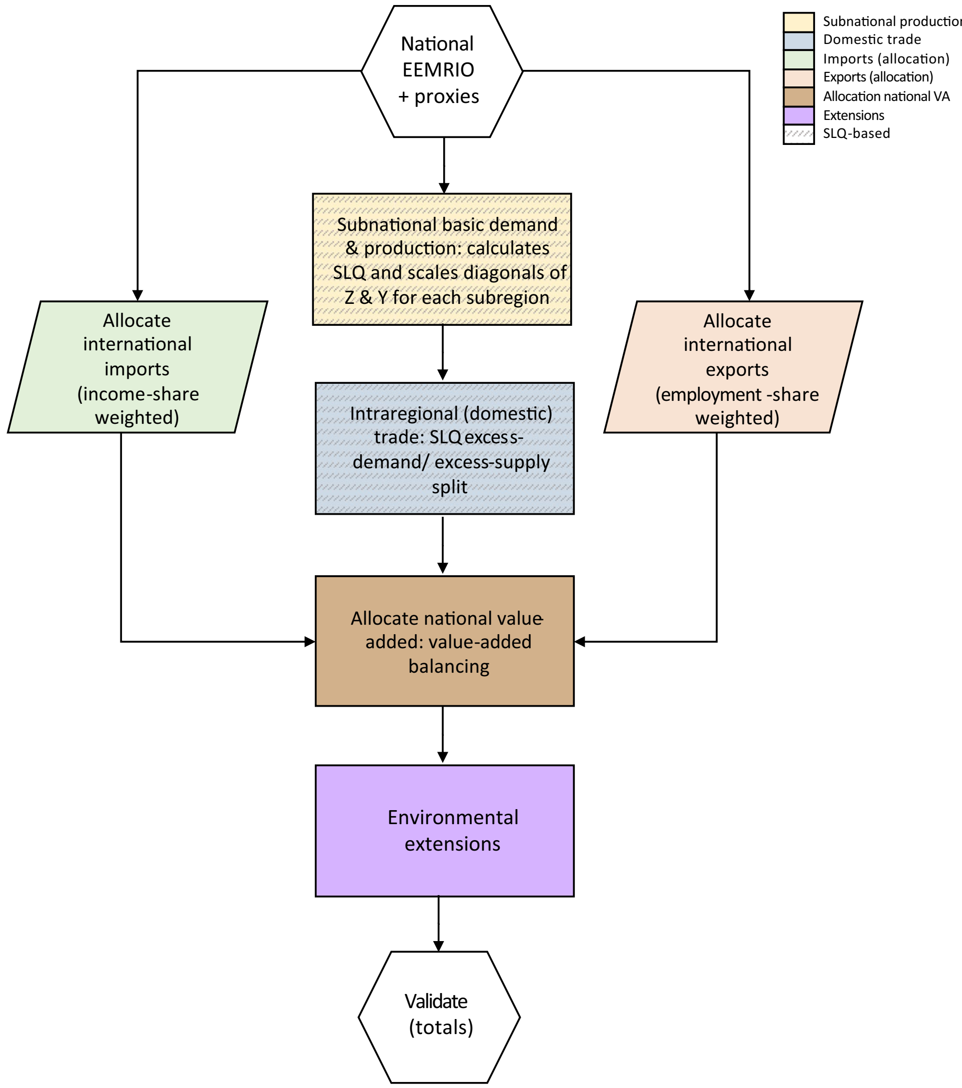

Fig. 2 Flow chart of the regionalization algorithm. Yellow blocks create subnational production and final demand; blue blocks estimate interregional trade; orange and green blocks allocate exports and imports between subregions and the rest of the world; the brown block computes value-added as a residual, and the purple block duplicates environmental extensions. Together, they yield a balanced EEMRIO table whose aggregation exactly reproduces the original national accounts

emissions coefficient categories, and comprises 44 countries, including all EU members, other larger economies, and five rest of the world regions (Stadler et al., 2018). The high sectoral detail alleviates some of the assumptions made in the regionalization approach regarding intranational trade (Sect. 3.3.1).

Spain and France were disaggregated sequentially, resulting in an EEMRIO model with 93 geographical entities (the original 49 minus the national level of France and Spain plus the 19 Spanish and 27 French subregions). The subnational economies, i.e., the diagonal in an EEMRIO (Table 1), are estimated using the subnational basic demand whitc is derived from the SLQs and are scaled using the subnational income share. The interregional trade is estimated based on the subnational excess demand derived from the SLQs and is also scaled using the subnational income shares. Due to mismatches between the Eurostat's employment data and EXIOBASE, total subnational income share was used instead of sector-specific employment share for disaggregation in 28 product categories for Spain and 52 for France (out of a total of 200). After disaggregation, the national accounts of Spain and France are set to zero to avoid double counting.

We assess the accuracy of the approach for sectors in which further subnational data are available. To assess the value flows of steel on a subnational level, subnational employment by sector data for the "Manufacture of basic metals" was used (Eurostat, 2022b). We use location and capacity of steel plants (Global Energy Monitor, 2022) and the territorial GHG emissions reported by MITECO (2020). We also compare the consumption-based footprints with those computed by the subnational MRIO of EUREGIO harmonized with EXIOBASE's environmental extentions (Wilting et al., 2021).

Table 1 Overview of multi-region regionalization approach

$\bar{A}$	RoW	Region 1	Region 2	R…n
Cn	fixed	$\bar{a}_{ij}^{mr} = a_{ij}^{mn}$		
Region 1	$\bar{a}_{ij}^{rm} = a_{ij}^{mn} \frac{x_j^r}{x_j^n}$	$\bar{a}_{ij}^{rr} = a_{ij}^{nn} c^{(r')}$ where $c^{(r')}$ denotes the income share of the exporting subregion (row)		
Region 2				
R…n				
$\bar{\boldsymbol{V}}$	fixed	$\bar{\mathbf{v}}^r = \bar{\boldsymbol{x}}^r - \bar{\mathbf{Z}}^r 1$		
$\bar{x}$	fixed	$\boldsymbol{x} = (\mathbf{I} - \mathbf{A})^{-1} \boldsymbol{y}$		
$\bar{\boldsymbol{B}}$	fixed	$\bar{b}_{ij}^{mr} = b_{ij}^{mn}$		

$\bar{Y}$			
RoW	Region 1	Region 2	R…n
fixed	$\bar{y}_{ij}^{mr} = y_{ij}^{mr} c^{(r)}$ where $c^{(r)}$ denotes the income share of the importing subregion (column)		
$\bar{y}_{ij}^{rm} = y_{ij}^{rm} c^{(r')}$ where $c^{(r')}$ is based on the employment share: $\frac{x_{ij}^r}{x_{ij}^n}$. In cases where subnational employment data are inconsistent with the export data of the EEMRIO, $c^{(r')}$ is based on the income share of the entire subregion: $\frac{x_j^r}{x_j^n}$	$\bar{y}_{ij}^{rr} = \begin{cases} SLQ_i^r \, y_{ij}^{nn} \frac{x_j^r}{x_j^n}, & if\ SLQ_i^r < 1 \\ y_{ij}^{nn} \frac{x_j^r}{x_j^n}, & if\ SLQ_i^r \geq 1 \end{cases}$	$\bar{y}_{ij}^{sr} = f_i^r y'_{rj}$ where $y'_{rj} = \begin{cases} (1 - SLQ_i^r) \, y_{ij}^{nn} \, c^{(r')}, & if\ SLQ_i^r < 1 \\ 0, & if\ SLQ_i^r \geq 1 \end{cases}$ and $f_i^r = \frac{c^{(r')}}{1 - c^{(r)}}$ where $c^{(r')}$ is the income share of the exporting subregion (row) and $c^{(r)}$ is the income share of the importing subregion (column)	

Yellow blocks refer to disaggregated subregions (Region 1, Region 2, R…n) added to EEMRIO, blue blocks the intranational trade, grey blocks the rest of the world (RoW) in the EEMRIO, green blocks the international exports from the RoW nations to the disaggregated subregions, and orange blocks the international imports of the disaggregated subregions to the RoW nations. $c^{(r)}$ refers to a general proxy-based subnational weight and serves as a flexible proxy input that may vary with the application context

2.5 Small-scale example

To illustrate how the regionalization algorithm works, we build a three-country, four-sector example (Tables 2–4). We spatially disaggregate Ireland's plastic-related sectors into its three NUTS 2 regions, while keeping its connection to the trading nations of Belgium and the Netherlands. All EXIOBASE sectors directly related to plastics are selected, namely: 'Plastics, basic' (p24.a, here S1), 'Secondary plastic for treatment, Re-processing of secondary plastic into new plastic' (p24.a.w, here S2), 'Plastic waste for treatment: incineration' (p90.1.c, here S3), and 'Plastic waste for treatment: landfill' (p90.5.c, here S4). The sector '*Manufacturing of rubber and plastic'* was not included as the small-scale example focuses exclusively on plastic-related flows, while this sector also includes rubber manufacturing. Ireland is one of the few countries that splits into three NUTS regions and plastic is one of the few products in EXIOBASE with primary and secondary products, as well as two waste processing sectors, making this a perfect combination for a small-scale example of 12 by 12 that expands to 20 by 20 (n_r*n_s). Table 2 shows the input data, where the IO elements are extracted from EXIOBASE and the proxy data includes the required subnational data (here, S3 and S4 are both regionalized based on the same proxy data, namely waste collection). The regionalized results are presented in Table 3 where the colored cells correspond to the colored cells in Table 1. After the system is regionalized, the subnational footprints can be computed (Table 4). The final demand matrix $\overline{\mathbf{Y}}$ also shows how the estimation of domestic trade is approached (Table 3) as domestic imports of export-oriented subregions are set to 0 and their excess supply is used to meet the excess demand of the import-oriented

Fig. 3 Flow chart of the regionalization algorithm. Hexagons mark the start/end point, the oval indicates the algorithm's start, snipped rectangles show data and other inputs, rectangles indicate calculation blocks, and parallelograms show other computational procedures. For an overview of the calculation blocks $\overline{\mathbf{A}}$, $\overline{\mathbf{Y}}$ and $\overline{\mathbf{B}}$ see Table 1

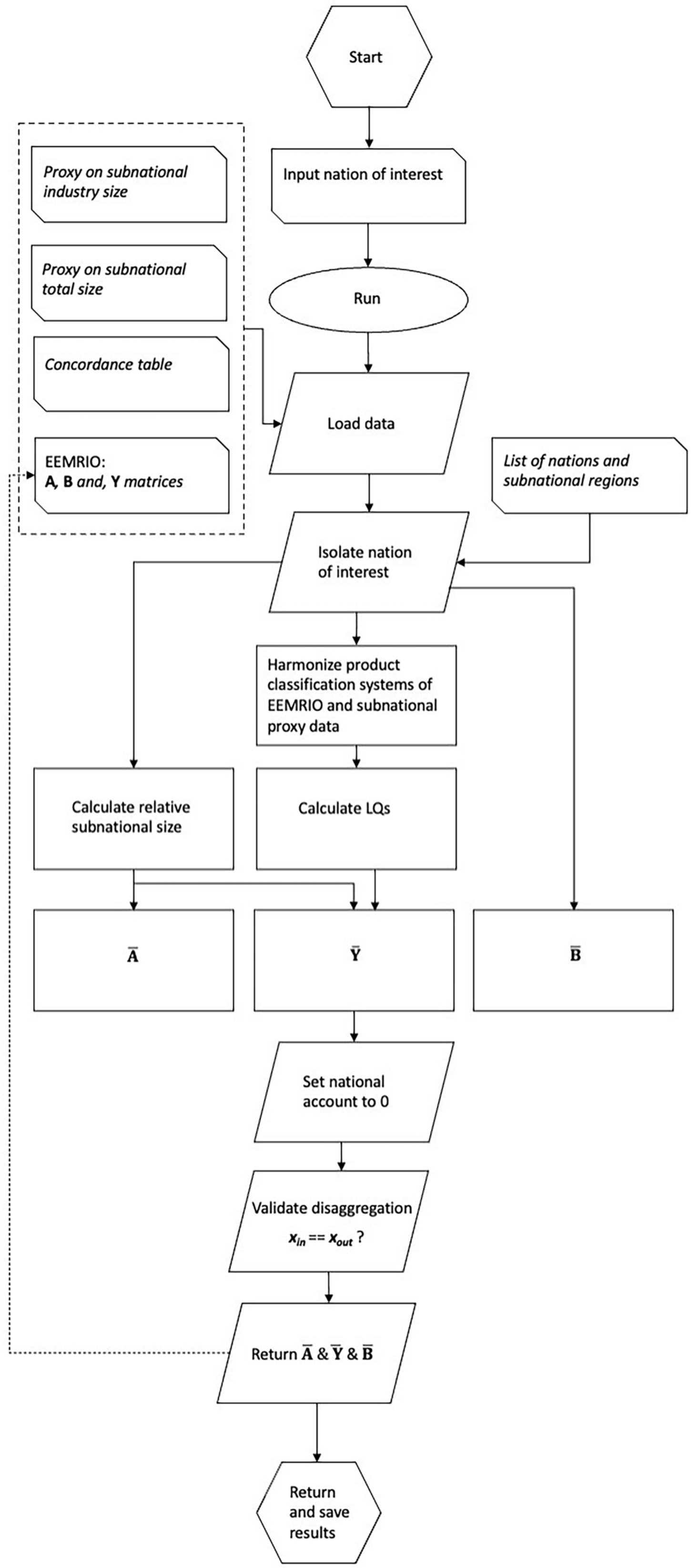

Table 2 Three-country, four-sector example from EXIOBASE: aggregated version

A		BE				IE				NL			
		S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
BE	S1	1.1E-2	8.6E-3	3.5E-3	9.2E-3	1.1E-4	1.2E-5	0.0	0.0	6.2E-5	7.2E-5	1.3E-5	7.0E-5
	S2	1.6E-4	1.2E-4	4.8E-5	1.3E-4	1.5E-6	1.7E-7	0.0	0.0	8.5E-7	9.9E-7	1.8E-7	9.6E-7
	S3	1.7E-9	1.2E-8	2.4E-2	1.0E-2	1.2E-11	3.0E-14	4.9E-10	1.8E-11	0.0	2.3E-6	1.1E-5	7.7E-5
	S4	4.6E-10	4.3E-9	7.1E-3	3.5E-3	1.2E-11	1.9E-13	9.3E-10	4.0E-10	0.0	3.4E-17	1.4E-16	0.0
IE	S1	1.3E-7	4.9E-6	1.6E-7	3.6E-7	8.8E-4	9.7E-4	0.0	0.0	1.2E-7	1.4E-7	2.6E-08	1.4E-7
	S2	1.6E-6	6.1E-5	2.0E-6	4.5E-6	1.1E-2	1.2E-2	0.0	0.0	1.5E-6	1.8E-6	3.2E-7	1.8E-6
	S3	0.0	0.0	0.0	0.0	7.5E-13	0.0	5.9E-15	2.5E-13	0.0	0.0	0.0	0.0
	S4	8.3E-13	5.6E-14	3.8E-9	2.3E-9	1.1E-10	1.1E-21	1.6E-11	5.2E-10	0.0	2.2E-17	8.8E-17	0.0
NL	S1	4.4E-5	1.6E-3	5.4E-5	1.2E-4	1.2E-4	1.4E-5	0.0	0.0	3.3E-3	4.0E-3	1.2E-5	2.6E-5
	S2	4.8E-5	1.8E-3	6.0E-5	1.3E-4	1.3E-4	1.5E-5	0.0	0.0	3.6E-3	4.4E-3	1.3E-5	2.9E-5
	S3	8.1E-12	4.4E-11	7.4E-5	1.6E-6	1.2E-11	2.9E-14	4.7E-10	1.8E-11	3.1E-4	3.6E-4	6.2E-3	5.4E-5
	S4	9.4E-13	6.3E-14	4.3E-9	2.6E-9	6.3E-12	1.0E-13	5.0E-10	2.2E-10	2.8E-5	2.8E-5	4.7E-4	3.0E-6
	B	6.9E+5	2.5E+4	1.6E+5	5.5E+5	3.3E+4	7.7E+3	7.2E+4	4.6E+4	2.6E+5	1.8E+5	1.1E+6	3.0E+5

Y			*X*	Proxy data	S1 subnational employment	S2 subnational employment	S3 subnational employment	S4 subnational employment	Income (M€)
BE	IE	NL							
2.0E+3	7.2E-2	9.0	2.0E+3	IE04	0	1.6	104.158	104.158	123072
2.7E+1	9.9E-4	1.2E-1	2.8E+1	IE05	1.5625	8.1625	112.368	112.368	106590
6.0E+1	0.0	0.0	8.4E+1	IE06	1.5625	8.1625	112.368	112.368	57374
2.5E+1	0.0	0.0	3.1E+1						
4.5E-3	2.2E+2	1.8E-2	2.2E+2						
5.6E-2	2.7E+3	2.3E-1	2.7E+3						
0.0	4.2E-1	0.0	4.2E-1						
1.2E-1	1.3E+01	0.0	1.3E+1						
1.5	8.2E-2	1.0E+3	1.1E+3						
1.7	9.1E-2	1.1E+3	1.2E+3						
7.0E-1	0.0	1.3E+2	1.4E+2						
1.4E-1	0.0	7.9	8.6						

Grey blocks indicate blocks that remain unchanged, and white cells will be regionalized in Table 3. For more information, see Table 1. Proxy data is included as subnational employment by sector and income data for the Irish NUTS 2 regions

regions. The **Z** matrices are provided in the Tables S1 and S2 of Supplementary Information SI1.

3 Results and discussion

3.1 Case study of steel flows between Spain and France

Spain and France are important trade partners of steel and steel scraps. In 2011, Spain exported €559 million in iron and steel products to France (~9% of Spain's total steel output), while France exported €347 million in steel scraps to Spain (~5% of France's total steel scrap output). The exported steel flows from Spain and the exported steel-scrap flows from France are overlaid on the location of steel production plants (Fig. 4). France has 13 operating steel plants and Spain has d 9 (Fig. 4, Global Energy Monitor, 2022).

Subnational trade patterns indicate that most of the steel and steel products flows from four subregions of Spain (Comunidad de Madrid (ES30), Cataluña (ES51), Comunidad Valencia (ES52), and Andalucía (ES61)) to Île-de-France (FR10), while the major steel scraps flow to Spain from three subregions of France (Pays de la Loire (FRG0), Rhône-Alpes (FRK2), and Provence-Alpes-Côte d'Azur (FRL0)). The Northern Spanish subregions (Galicia (ES11), Principado de Asturias (ES12), Cantabria (ES13), and País Vasco (ES21)) are also known for their steel plants and accessibility to large ports. These subregions export llimited steel to France, instead, the model allocates most of their steel exports to non-EU countries (Fig. 4). Aggregating subnational steel flows recovers the national-level steel flows.

3.2 Comparison of subnational footprints

The total territorial GHG emissions of each Spanish NUTS 2 region show a moderate to strong alignment with those reported by the Spanish autonomous communities (MITECO 2020); $R^2 = 0.60$, $R^2 = 0.77$ if the outlier ES30 is removed). This alignment suggests that the regionalized results capture broad subnational patterns, although differences in source data, sectoral aggregation, and reporting methods contribute to deviations. Most subnational territorial GHG emissions are lower than the values reported by the Spanish government (Fig S1 of Supplementary Information SI1; 281 kt CO_2 eq. vs. 358 kt CO_2 eq.), because only industrial emissions are included here. Direct household emissions are excluded and account for ~20% of Spain's total in EXIOBASE 3.3 (69 kt CO_2 eq.). A key advantage of the EEMRIO is that it provides a footprint of international-subnational embodied GHG flows. In contrast, MITECO reports subnational territorial emissions only, whereas the regionalized EEMRIO supports assessment of production- and consumption-based impacts of the Spanish subregions.

We compare the subnational consumption-based footprints in this study with those reported by Wilting et al., (2021, Supplementary Information S3) and find a reasonable alignment for France (Fig. S2 of Supplementary Information SI1). To match the spatial scale of EUREGIO, we aggregate

Table 3 Two-country, three-subregion, four-sector example from EXIOBASE: disaggregated version

$\bar{A}$		BE				NL				IE04				IE05				IE06			
		S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
BE	S1	1.1E-2	8.6E-03	3.5E-03	9.2E-03	6.2E-05	7.2E-05	1.3E-05	7.0E-05	1.1E-04	1.2E-05	0.0E+00	0.0E+00	1.1E-04	1.2E-05	0.0E+00	0.0E+00	1.1E-04	1.2E-05	0.0E+00	0.0E+00
	S2	1.6E-4	1.2E-04	4.8E-05	1.3E-04	8.5E-07	9.9E-07	1.8E-07	9.6E-07	1.5E-06	1.7E-07	0.0E+00	0.0E+00	1.5E-06	1.7E-07	0.0E+00	0.0E+00	1.5E-06	1.7E-07	0.0E+00	0.0E+00
	S3	1.7E-9	1.2E-08	2.4E-02	1.0E-02	0.0E+00	2.3E-06	1.1E-05	7.7E-05	1.2E-11	3.0E-14	4.9E-10	1.8E-11	1.2E-11	3.0E-14	4.9E-10	1.8E-11	1.2E-11	3.0E-14	4.9E-10	1.8E-11
	S4	4.6E-10	4.3E-09	7.1E-03	3.5E-03	0.0E+00	3.4E-17	1.4E-16	0.0E+00	1.2E-11	1.9E-13	9.3E-10	4.0E-10	1.2E-11	1.9E-13	9.3E-10	4.0E-10	1.2E-11	1.9E-13	9.3E-10	4.0E-10
NL	S1	4.4E-5	1.6E-03	5.4E-05	1.2E-04	3.3E-03	4.0E-03	1.2E-05	2.6E-05	1.2E-04	1.4E-05	0.0E+00	0.0E+00	1.2E-04	1.4E-05	0.0E+00	0.0E+00	1.2E-04	1.4E-05	0.0E+00	0.0E+00
	S2	4.8E-5	1.8E-03	6.0E-05	1.3E-04	3.6E-03	4.4E-03	1.3E-05	2.9E-05	1.3E-04	1.5E-05	0.0E+00	0.0E+00	1.3E-04	1.5E-05	0.0E+00	0.0E+00	1.3E-04	1.5E-05	0.0E+00	0.0E+00
	S3	8.1E-12	4.4E-11	7.4E-05	1.6E-06	3.1E-04	3.6E-04	6.2E-03	5.4E-05	1.2E-11	2.9E-14	4.7E-10	1.8E-11	1.2E-11	2.9E-14	4.7E-10	1.8E-11	1.2E-11	2.9E-14	4.7E-10	1.8E-11
	S4	9.4E-13	6.3E-14	4.3E-09	2.6E-09	2.8E-05	2.8E-05	4.7E-04	3.0E-06	6.3E-12	1.0E-13	5.0E-10	2.2E-10	6.3E-12	1.0E-13	5.0E-10	2.2E-10	6.3E-12	1.0E-13	5.0E-10	2.2E-10
IE04	S1	1.3E-7	4.9E-06	1.6E-07	3.6E-07	1.2E-07	1.4E-07	2.6E-08	1.4E-07	1.3E-04	1.4E-04	0.0E+00	0.0E+00	1.3E-04	1.4E-04	0.0E+00	0.0E+00	1.3E-04	1.4E-04	0.0E+00	0.0E+00
	S2	1.6E-6	6.1E-05	2.0E-06	4.5E-06	1.5E-06	1.8E-06	3.2E-07	1.8E-06	1.6E-03	1.8E-03	0.0E+00	0.0E+00	1.6E-03	1.8E-03	0.0E+00	0.0E+00	1.6E-03	1.8E-03	0.0E+00	0.0E+00
	S3	0.0	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	1.1E-13	0.0E+00	8.6E-16	3.6E-14	1.1E-13	0.0E+00	8.6E-16	3.6E-14	1.1E-13	0.0E+00	8.6E-16	3.6E-14
	S4	0.0	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	1.5E-11	1.5E-22	2.3E-12	7.5E-11	1.5E-11	1.5E-22	2.3E-12	7.5E-11	1.5E-11	1.5E-22	2.3E-12	7.5E-11
IE05	S1	0.0	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	2.7E-04	3.0E-04	0.0E+00	0.0E+00	2.7E-04	3.0E-04	0.0E+00	0.0E+00	2.7E-04	3.0E-04	0.0E+00	0.0E+00
	S2	0.0	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	3.4E-03	3.8E-03	0.0E+00	0.0E+00	3.4E-03	3.8E-03	0.0E+00	0.0E+00	3.4E-03	3.8E-03	0.0E+00	0.0E+00
	S3	0.0	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	2.3E-13	0.0E+00	1.8E-15	7.7E-14	2.3E-13	0.0E+00	1.8E-15	7.7E-14	2.3E-13	0.0E+00	1.8E-15	7.7E-14
	S4	3.0E-13	2.0E-14	1.4E-09	8.4E-10	0.0E+00	7.9E-18	3.2E-17	0.0E+00	3.3E-11	3.3E-22	4.9E-12	1.6E-10	3.3E-11	3.3E-22	4.9E-12	1.6E-10	3.3E-11	3.3E-22	4.9E-12	1.6E-10
IE06	S1	0.0	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	4.8E-04	5.3E-04	0.0E+00	0.0E+00	4.8E-04	5.3E-04	0.0E+00	0.0E+00	4.8E-04	5.3E-04	0.0E+00	0.0E+00
	S2	0.0	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	5.9E-03	6.6E-03	0.0E+00	0.0E+00	5.9E-03	6.6E-03	0.0E+00	0.0E+00	5.9E-03	6.6E-03	0.0E+00	0.0E+00
	S3	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	4.1E-13	0.0E+00	3.2E-15	1.3E-13	4.1E-13	0.0E+00	3.2E-15	1.3E-13	4.1E-13	0.0E+00	3.2E-15	1.3E-13
	S4	5.3E-13	3.6E-14	2.4E-09	1.5E-09	0.0E+00	1.4E-17	5.6E-17	0.0E+00	5.8E-11	5.8E-22	8.7E-12	2.8E-10	5.8E-11	5.8E-22	8.7E-12	2.8E-10	5.8E-11	5.8E-22	8.7E-12	2.8E-10
	$\bar{B}$	6.9E+5	2.5E+4	1.6E+5	5.5E+5	2.6E+5	1.8E+5	1.1E+6	3.0E+5	3.3E+4	7.7E+3	7.2E+4	4.6E+4	3.3E+4	7.7E+3	7.2E+4	4.6E+4	3.3E+4	7.7E+3	7.2E+4	4.6E+4

$\bar{Y}$					$\bar{X}$
BE	NL	IE04	IE05	IE06	
2.0E+3	9.0	1.0E-2	2.2E-2	3.9E-2	2.0E+3
2.7E+1	1.2E-1	1.4E-4	3.1E-4	5.4E-4	2.8E+1
6.0E+1	0.0	0.0	0.0	0.0	8.4E+1
2.5E+1	0.0	0.0	0.0	0.0	3.1E+1
1.5	1.0E+3	1.2E-2	2.5E-2	4.5E-2	1.1E+3
1.7	1.1E+3	1.3E-2	2.8E-2	4.9E-2	1.2E+3
7.0E-1	1.3E+2	0.0	0.0	0.0	1.4E+2
1.4E-1	7.9	0.0	0.0	0.0	8.6
0.0	0.0	0.0	0.0	0.0	5.7E-1
5.0E-3	2.0E-2	1.6E+2	0.0	0.0	1.6E+2
0.0	0.0	6.1E-2	3.3E-3	8.8E-3	7.3E-2
3.9E-2	0.0	1.9	1.0E-1	2.7E-1	2.3
2.2E-3	9.1E-3	1.1E+1	6.7E+1	0.0	7.9E+1
2.5E-2	1.0E-1	8.5E+1	8.3E+2	0.0	9.3E+2
0.0	0.0	0.0	1.1E-1	1.9E-2	1.3E-1
4.2E-2	0.0	0.0	3.5	5.8E-1	4.1
2.2E-3	9.1E-3	2.0E+1	0.0	1.2E+2	1.4E+2
2.5E-2	1.0E-1	1.5E+2	0.0	1.5E+3	1.6E+3
0.0	0.0	0.0	1.2E-2	2.0E-1	2.1E-1
4.2E-2	0.0	0.0	3.8E-1	6.2	6.6

Colored blocks correspond to the colors in Table 1

the French NUTS 2 regions to the NUTS classification prior to 2016 (excluding the overseas departments and regions, 'FRA', as done by Wilting et al., 2021). The observed difference of roughly 20% is mainly due to the inclusion of direct household emissions in Wilting et al. (2021). For Spain, this difference is also evident. The consumption-based GHG footprints for Extremadura (ES43) and Región de Murcia (ES62) are particularly noteworthy, with values exceeding 16 t CO_2/capita, largely driven by international imports, which accounted for more than 80% of the footprints according to Wilting et al. (2021). In our study, the Spanish consumption-based footprints are less influenced by international imports as these were assumed to be uniformly distributed across subregions and scaled down according to subnational sizes (Fig. S3 of Supplementary Information SI1). Wilting et al. constructed a bottom-up survey-based MRIO, which sacrificed sectoral resolution. In addition, EUREGIO regional coverage is highly aggregated (25 European countries and 12 "extra-Europe trading partners"). Most pertinent research questions employing footprint analyses demand greater spatial and sectoral detail similar to that offered by existing global MRIOs such as EXIOBASE (Sun et al., 2019).

Although the disaggregation of improves subnational footprint resolution, validation of non-survey approaches remains limited by the lack of subnational IO data, especially interregional trade data (Froemelt et al., 2021; Lenzen et al., 2017). However, when comparing the subnational production- and consumption-based footprints of Spain and France, this simpler approach shows broad alignment with previous regionalization attempts, despite certain sectoral and methodological differences. This comparison demonstrates the method's effectiveness in estimating subnational patterns with minimal data inputs. Further refinements, such as addressing data limitations, sectoral assumptions, and methodological constraints, are discussed in the next section.

3.3 Advantages and limitations of the regionalization approach

SLQs are widely applied to single regions or multiple unconnected single regions, but domestic trade or embedding in multi-regional frameworks are often omitted. Traditional SLQ approaches allow for an exploration of activities within one specific subregion, whereas the proposed approach traces trade at the subnational scale. This approach is useful because it does not require large amounts of additional data, which are often not available. The code open access, facilitating its application to any EEMRIO by potential users. Our approach minimizes the prerequisite formal knowledge on IO disaggregation, requiring only the input of subnational proxies – should users opt to deviate from the provided EU proxies – thus fostering accessibility and ease of use for a wide range of practitioners. This approach is relatively time-efficient compared to other approaches as it does not rely on supplemental balancing. However, the iterative process means that regionalizing all or many nations would significantly increase computational efforts. The regionalization approach has several limitations rooted in assumptions behind the SLQ and the properties of the regionalized EEIOA model.

3.3.1 Location quotients

The main limitations of SLQs are well-established (Miller & Blair, 2009). Firstly, SLQs assume that national technology is uniform across subregions, which implies that subnational coefficients can only vary because of varying subnational capacities to satisfy local demand (Miller & Blair, 2009). This assumption of similarity may overestimate intraregional self-sufficiency and underestimate interregional trade flows, particularly in specialized industrial clusters or urban consumption centers. Secondly, SLQs do not allow for cross-hauling to occur because a specific sector can either be a net exporter or net importer of a particular product based on its level of self-sufficiency, i.e., SLQs cannot capture gross interregional imports or exports (cross-hauling at the international scale may occur as international trade is not disaggregated using LQs). These first two limitations are alleviated when subnational estimation occurs at the lowest level of industrial aggregation as the likelihood of non-uniformity in production recipes and cross-hauling decreases when product detail increases (Fujimoto, 2019; Kronenberg, 2009; Miller & Blair, 2009). Thirdly, when a sector is export-oriented ($SLQ_i^r \geq 1$), no adjustments are made to the national coefficient, revealing an asymmetry in the approach (Miller & Blair, 2009, Zhao & Choi, 2015). If the national coefficient truly represents the nation's average, an increase in the subnational coefficients compared to the national ones would also be expected (Miller & Blair, 2009).

Additionally, SLQs are typically reliant on employment data to allocate production and consumption activities regionally. This reliance can introduce inaccuracies if employment is assigned to regions based on enterprise headquarters rather than establishments. For example, workers or facilities located in smaller regions might be attributed to larger regions where company headquarters are situated. This misallocation could result in overestimating production and associated emissions in some regions, which is particularly problematic when analyzing local pollutants rather than GHG emissions. One way to overcome this limitation is by using local production data directly, where available. For example, detailed subnational production data for EU agricultural products (e.g., Eurostat, 2024) can provide more accurate regionalization of the agricultural sector.

We adopt the SLQ because it relies only on employment shares that are available for every subregion in the EU. Extensions such as Flegg's Location Quotient (FLQ) incorporate a regional-size term and a calibration parameter δ that can further account for cross-hauling, but they require consistent regional output data and credible δ estimates; data that do not yet exist for the EU. Performance comparisons remain inconclusive (Flegg & Webber, 2000; Fujimoto, 2019; Jahn et al., 2020; Lampiris et al., 2020). Nevertheless, Table 1 and Fig. 2 indicate exactly where an FLQ (or another LQ extension, see e.g., Miller & Blair, 2009) could replace the SLQ coefficients if future users have access to the requisite inputs.

3.3.2 Regionalized EEMRIO model

SLQs offer a straightforward regionalization approach with limited data inputs, yet it is still difficult to get a good concordance between product/sector coverage in the proxy dataset and the EEMRIO model. Here, we used subnational employment by sector data. However, as no employment by sector data are available in this Eurostat dataset for the agricultural sectors, those are still disaggregated, but not using sector-specific proxy data (See Zenodo for Concordance Table). This lack of employment data means that, although accurate when summed up to the national accounts, the subnational agricultural estimates are probably less accurate than the subnational estimates of sectors where sector-specific data are available.

Besides data availability, the regionalization of Spain and France emphasizes the importance of the accuracy and resolution of the proxy data. Primary and secondary steel were disaggregated based on the employment by sector data for the manufacturing of basic metals. This category includes the manufacturing of other valuable metals such as aluminum, which is produced in Spain and France in relatively large quantities. The aggregated metal sectors in the proxy data may explain the imperfect correlation between the presence and capacity of steel plants and their modelled export flows of steel and steel products (Fig. 4).

The regionalization assumes that all subregions resemble the nation's production technology, although spatial heterogeneity in domestic production likely exists. As a result, this approach is less suited for detailed analysis

Table 4 GHG footprints calculated based on the regionalized system of Table 3 (i.e., small scale example impacts only)

		$\overline{M}$
BE	S1	1.4E+9
	S2	1.1E+6
	S3	1.1E+7
	S4	1.4E+7
NL	S1	2.7E+8
	S2	2.0E+8
	S3	1.4E+8
	S4	2.3E+6
IE04	S1	1.1E+6
	S2	3.0E+6
	S3	4.4E+3
	S4	8.6E+4
IE05	S1	2.3E+6
	S2	6.5E+6
	S3	9.3E+3
	S4	1.8E+5
IE06	S1	4.0E+6
	S2	1.1E+7
	S3	1.6E+4
	S4	3.2E+5

of product flows dominated by interindustry transactions but remains robust for environmental footprint assessments. Similarly, we assume that international imports to subregions follow total subnational sizes, meaning that larger regional economies receive a proportionally larger share of imports. However, international imports are also influenced by factors such as regional industrial specialization, infrastructure and trade logistics. As a result, this assumption may overestimate imports in economically large but service-oriented urban areas while underestimating imports in smaller, highly trade-dependent subregions such as major port cities or industrial hubs. Additionally, subnational sector information may not accurately represent subnational consumer preferences at the household level, although the subnational household footprints in this study are consistent with those computed by Ivanova (2017), who integrated subnational consumer expenditure surveys.

The consistency with national accounts, i.e., when subregions are aggregated the national account is recovered, allows for simpler nesting into the multi-regional framework. However, this scalability also means the propagation of potential errors across different spatial scales (Boero et al., 2018).

Value-added is calculated as a residual to preserve system balance without altering the underlying data. This approach reduces computational demands compared to iterative methods such as RAS and is in line with prior studies showing no consistent performance advantages for either method (Cabernard & Pfister, 2021; Geschke et al., 2014; Wiebe & Lenzen, 2016). Its simplicity supports tractability at scale, and the aggregate results are robust: subnational GDP aligns closely with the subnational value-added ($R^2 = 0.99$ for Spain and France at NUTS 2). However, since value-added is not explicitly regionalized, this approach is less suitable for sector- or product-level analysis of value-added. Environmental and socio-economic footprint calculations remain unaffected.

Finally, we acknowledge that, for the environmental extensions in this study, we assume subnational direct emission coefficients are identical to the national ones. While this assumption is empirically unavoidable due to data limitations, the relatively detailed industry resolution of EXIOBASE mitigates its potential impact. In less detailed IO systems, where sectors like agriculture may be aggregated, this assumption would be more problematic, especially in regions with varying degrees of specialization in crops versus livestock, which could lead to significant differences in GHG emission factors. Similarly, as the main limitations of the SLQ (see Sect. 3.3.1), the potential errors are alleviated when subnational estimation occurs at a fine industrial resolution.

3.4 Outlook and potential application

The proposed regionalization method provides a transparent basis after which subnational survey data can be introduced when available, which would alleviate some of the common, but strong assumptions in non-survey regionalization methods. Introducting subnational direct emission data is straightforward as this addition will not intervene with the system balances. The regionalized results can identify candidate sectors for targeted data collection. Additionally, EXIOBASE also exists in a hybrid format, i.e., a mixed-unit framework, and considers waste products in physical units, which is crucial for circular economy policy assessment (Aguilar-Hernandez et al., 2018). The extension of the regionalization approach to also be applicable for the mixed-unit framework is important as monetary frameworks may not always accurately represent physical economies (Vunnava & Singh, 2021).

The regionalized EEMRIO has several potential policy applications. For example, for the circular economy, regionalization offers opportunities for possible sector linkages which may be masked in national EEMRIO analyses. A selection of waste products that are currently not processed circularly can be identified within a subnational context. In the example of steel, which already has a very high recycling rate, the subnational context indicates which Spanish regions supply the majority of the steel products to France and which French regions supply the majority of steel scraps back to Spain. The export flows are now presented as value flows but may also be translated into embodied GHG emission flows, which is essential information for carbon trading

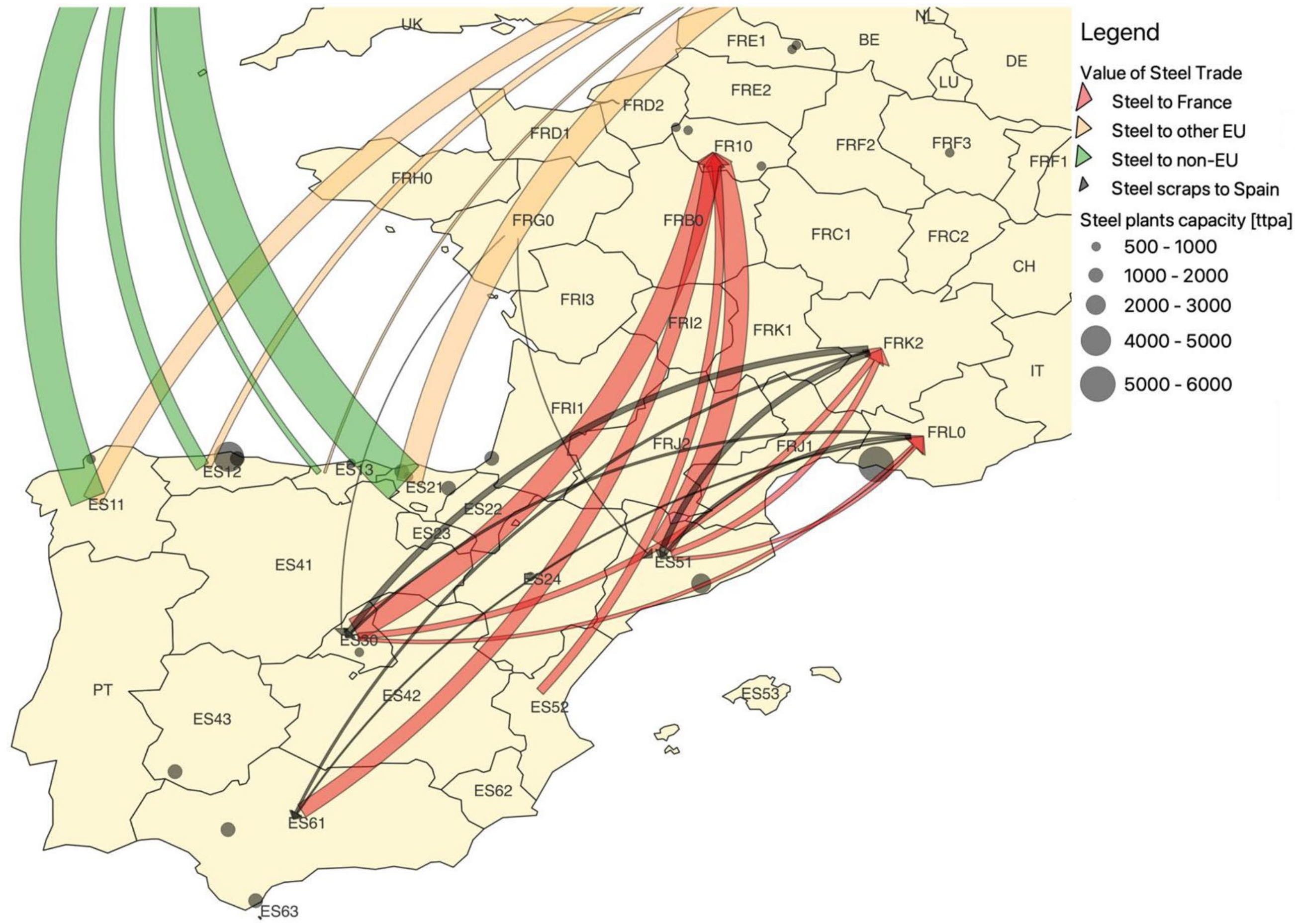

Fig. 4 International export flow of steel and steel scraps between Spanish and French NUTS 2 regions (each region is labelled with its NUTS code). Major subnational trade flows of steel (> 5 M.EUR) from Spain to France and major subnational trade flows of steel scraps (> 5 M.EUR) from France to Spain as well as the aggregated EU and non-EU export flows of steel of the four Northern Spanish regions with steel plants are highlighted

policy mechanisms. Additionally, analysis of other environmental extensions is also possible. Such analysis allows for the identification of local emission hotspots but also of local opportunities by the analysis of local trade and consumption patterns. Locality is especially important for the environmental impacts which have strong local impacts such as water use and biodiversity loss (Sun et al., 2019). Finally, as the input–output model is linear in nature, it lends itself to rapid computations as well as flexibility in computing the effects of changes in final demand, facilitating scenario building and the exploration of a variety of circular policy implementations at the subnational scale.

4 Conclusion

In EEMRIO analysis, regionalization is crucial for capturing subnational heterogeneity, as subnational differences can be as large as national differences. This paper proposes a top-down approach to increase the geographical resolution of EEMRIO data for environmental footprint analysis. The method provides a reasonable estimate of subnational accounts while maintaining a balanced system without the need for supplemental balancing procedures such as RAS. The generalized framework can be applied to a variety of EEMRIO databases at any spatial scale using various types of subnational proxies and is designed to be practitioner friendly. By applying this method to EXIOBASE using subnational Eurostat data we demonstrate that it is possible to obtain EEMRIO tables for all subregions in the EU including their environmental extensions. The regionalization method and proxy data for all EU member states are available at Zenodo. The approach has several limitations rooted in assumptions of the location quotients and other properties of the regionalized EEMRIO model including available data. The regionalization approach offers potential for improvements regarding the data accuracy through hybridization of the method, e.g., the introduction of subnational survey data or the application to the mixed-unit framework of EXIOBASE.

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Data availability All data used in the study are publicly available and cited. The algorithm employed for regionalizing EEMRIOs is available on Zenodo: https://doi.org/10.5281/zenodo.15789999. The proxy data and the concordance table used to link with EXIOBASE for Fig. 4 are also provided here.

Declarations

Conflict of interest The authors have no competing interests to declare. This research has been performed as part of the project '70by30 Denmark: Getting the data right', funded by the KR Foundation. This research is partially funded by the CircuMAT project (funded by the European Institute of Innovation and Technology on RawMaterials (EIT RM)). P.B. was supported by a British Academy Global Professorship award.

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