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LCI METHODOLOGY AND DATABASES

Identifying marginal suppliers of construction materials: consistent modeling and sensitivity analysis on a Belgian case

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Abstract
Purpose The identification of marginal suppliers is a key element of consequential LCA. This study investigates how systematically the identification of marginal suppliers can be performed across different products, while maintaining consistent modeling choices. Some products relevant for the Belgian construction sector are taken as a case study.
Methods To gain insight in the current practice of identifying marginal suppliers, 30 recent studies have been reviewed. Based on the findings of the review, a method was proposed to identify geographical market boundaries from trade data and sensitive suppliers from production data. Both retrospective and prospective approaches to anticipate the future effect of a change in demand were taken into account. The method was applied to compute both a retrospective and a prospective marginal supplier's mix per product. Finally, the effect of the modeling choices on the size of geographical market boundaries and marginal mixes was estimated via regression analysis.
Results and discussion The forecasts and marginal mixes obtained matched with those from the existing literature, although clear differences in results are observed between the retrospective and prospective approach. Deviations from default assumptions in LCA were observed as well, such as large regional geographical markets for cement and aggregates instead of local ones. The statistical sensitivity analysis showed that identifying geographical market boundaries has the largest effect on the final marginal mix and that these markets are relative stable over time.
Conclusions The proposed method and corresponding sensitivity analysis is an attempt to gain insight into the effect of modeling choices in the context of the identification of marginal suppliers for consequential LCA. It can in principle be applied to any product for which trade and production data are available. The proposed method helps to identify marginal mixes on a consistent and transparent way, to improve the robustness of the results in future consequential LCAs.

Keywords Consequential · Construction sector · Geographical market delimitation · Life cycle assessment · Marginal suppliers · Sensitivity analysis

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1 Introduction

The number of life cycle assessment (LCA) studies based on a consequential modeling approach has increased in recent years, in particular studies focusing on energy systems (Escobar et al. 2014; Styles et al. 2015) and agricultural products (Dalgaard et al. 2014; Schmidt 2015). Consequential LCA describes how environmentally relevant flows will change in response to possible decisions (Curran et al. 2005). A key assumption in consequential LCA is that only specific activities will be affected by a change in demand for a product, the so-called marginal suppliers (Ekvall and Weidema 2004). These suppliers must be identified by taking into account a number of constraints and the suppliers' potential to adjust production capacity (Weidema et al. 1999). The identification of marginal suppliers is therefore a critical aspect of consequential LCA, affecting the results of a LCA study to a great extent. The four-step[1] procedure of Weidema et al. (2009) is to date the most well-described theoretical framework for marginal supplier identification. The four steps are: (1) identifying the scale and time horizon of the potential change studied, (2) identifying the limits of a market, (3) identifying trends in the volume of a market, and (4) identifying suppliers most sensitive to a change in demand. However, the diversity of studies which define themselves as consequential shows that this procedure has been implemented in many different ways. Zamagni et al. (2012) note that the application of the consequential modeling is often done in a non-systematic and inconsistent way. If results of consequential studies are not consistently repeatable due to excessive subjectivity in the modeling choices, the credibility of consequential LCA for decision support might be affected.

In this context, the goal of this paper is to investigate how systematically the identification of marginal suppliers can be performed across different products while maintaining consistent modeling choices. The objectives of this research are (1) to review current practice of marginal supplier identification, (2) to propose a procedure for marginal supplier identification that is specific and detailed while maintaining general applicability and practical feasibility, and (3) to perform a sensitivity analysis on the effect of the modeling choices and identify the most influential parameters. The importance of other aspects of consequential LCI modeling is acknowledged but beyond the scope of this research (e.g., the handling of processes with multiple outputs).

The Belgian construction sector is taken as a case study and the analysis focuses on six products that are interesting in LCAs of construction projects: aggregates (sand and gravel), cement, sawnwood, particle board, steel, and electricity. The construction sector is an example of a material-intensive sector, requiring many different products. The identification of marginal suppliers of electricity is included in the study because substantial amounts of electricity are used both in the building construction and the use phase. This diverse set of products was selected to verify the robustness and general applicability of the proposed method. Additionally, there is a lack of studies on construction products following a consequential modeling approach.

The article is structured as follows: first, a systematic literature review is presented which is used as problem formulation and to justify the focus of the study. Then, methods for geographical market delimitation, the identification of the most sensitive suppliers and a sensitivity analysis of modeling choices are presented, including different perspectives on development as well. Subsequently, results are discussed, focusing on the validity of the procedure and the estimated effect of the modeling choices. The article concludes with recommendations for further improvements in marginal suppliers' identification.

2 Literature review of marginal suppliers identification in consequential studies

Zamagni et al. (2012) and Earles and Halog (2011) have previously reviewed consequential LCA studies. However, a more systematic review was necessary within the context of this study, in order to gain specific insight into what is the current practice of identifying marginal suppliers. Thirty recent case studies were reviewed covering a broad variety of products. A selection of the most detailed studies regarding marginal suppliers identification is presented in Table 1. Full details of the review can be found in Annex 1 including additional criteria, for example how multi-functionality is handled and which criteria are applied for identifying avoided products (see Electronic Supplementary Material).

The four-step procedure of Weidema et al. (2009) was taken as a starting point for the systematic review. LCA studies were classified according to the topic of the study and how strict they follow the four-step procedure. The scale and time horizon of the studied change in each study was identified. The level of detail of the geographical market delimitation,[2] identification of trends in the volume of the market, identification of production constraints, and identification of the suppliers most sensitive to a change in demand was rated on a three-point ordinal scale. The criteria used and the models applied to identify the most sensitive suppliers, and the perspective on development adopted in the LCA studies were determined. The perspective on development is the approach used to anticipate the future effect of a change in demand. The two possible perspectives considered in this study are the retrospective and the prospective ones. A retrospective approach assumes the future represents a logical extension of the past, so that historical trends can be used to predict future ones. A prospective approach on the other hand implies that future trends can be different from the historical ones (Weidema 2003).

The review showed a lack of consistency in the application of consequential LCA modeling principles from theory into practice. Weidema (2003) defines consequential LCA as a

[1] Previous versions of this procedure included five-steps, see Weidema (2003). Here the latest published version available is used, which is also a synthesis of previous versions.

[2] In this study and in the systematic review exercise, temporal market delimitation is not taken into account.

Table 1 Summary of literature review

Author(s)	Topic	Scale	Time horizon	Market delimitation	Market trend	Production constraints	Sensitive suppliers	Criteria and applied models for identifying sensitive suppliers	Perspective development
Deng and Tian (2015)	Plastics	Small	Long	+	+/++	−	++	Regression model based on production volume	Retro
Alvarez-Gaitan et al. (2014)	Water treatment – electricity	Small	Long	+	++	+++	+/+++	Partial equilibrium model based on costs and elasticities	Mix retro—pro
Sevigné-Itoiz et al. (2015)	Plastics	n.s.	n.s.	+	+	+	+	Mass flow analysis based on production volume	Retro
Schmidt (2015)	Vegetable oils	Small	Long	+	+	++	++	Regression model based on production volume	Retro
Pizzol and Scotti (2017)	Forestry	Small	n.s.	+++	−	−	+++	Regression model based on production volume	Retro
Dalgaard et al. (2014)	Food and agriculture	Large and small	n.s.	++	−	++	+/++	Regression model based on production volume	Mix retro—pro
Vieira and Horvath (2008)	Construction waste	Small	Short	+	−	−	+++	Regional partial equilibrium model based on costs and elasticities	Retro
Chalmers et al. (2015)	Food and agriculture	Large	Short	++	+	++	+/+++	Conditional demand system model based on costs and elasticities	Pro
Menten et al. (2015)	Biofuels	Small – meso	long	+	+	+++	+/+++	Regional partial equilibrium model based on costs and elasticities	pro
Schmidt and Thrane (2009)	Aluminum	Small	Long	+	++	++	+++	Regression model based on production volume	retro, pro
Lund et al. (2010)	Electricity	Small	Long	+	−	+++	+++	Energy system analysis based on costs and elasticities	pro
Eriksson et al. (2012)	Construction – wood	Small, large	Long	+	++	++	−/++	Global partial equilibrium model based on costs and elasticities	pro

retro retrospective, *pro* prospective, *n.s.* not specified, − not included, + low level of detail, ++ medium level of detail, +++ high level of detail. If two results are given (e.g., +/+++) not all parts of the study have the same level of detail steady-state, linear, homogeneous modeling approach and proposes a well-defined procedure, whereas according to other studies performing a consequential LCA study simply means avoiding allocation through substitution (Zink et al. 2014; Crossin 2015; Turk et al. 2015). Many studies lack a transparent presentation of the applied methods and a justification of the modeling choices. Other general conclusions from the review exercise are:

- A proper delimitation of the geographical market boundaries is missing in most studies. Dalgaard et al. (2014) and Buyle et al. (2016) include an elementary analysis based on trade data, Pizzol and Scotti (2017) perform an advanced analysis of the geographical market boundaries for wood products.
- Different criteria and models to identify the most sensitive suppliers are applied. Two approaches can be observed: regression models for determining trends in production volume (Schmidt and Thrane 2009; Deng and Tian 2015) and equilibrium models based on costs and elasticities (Lund et al. 2010; Eriksson et al. 2012; Chalmers et al. 2015; Menten et al. 2015; Rajagopal 2017). However, most studies lack a detailed analysis of the most sensitive suppliers: results are taken from literature or sensitive suppliers are presented without any justification (Supekar and Skerlos 2014; Prateep Na Talang et al. 2016) or the identification of sensitive suppliers is replaced by the use of average values of current practice (Sandin et al. 2013).
- Only five out of 30 studies adopt a prospective approach (Schmidt and Thrane 2009; Lund et al. 2010; Eriksson et al. 2012; Chalmers et al. 2015; Menten et al. 2015). Four other studies mix the two perspectives on development: these studies primarily follow a retrospective approach and only for the electricity mixes a prospective approach is adopted (Alvarez-Gaitan et al. 2014; Dalgaard et al. 2014; Deng and Tian 2015; Tonini et al. 2016).

Summing up, the review indicates that despite a growing interest for consequential modeling and the existence of a general theoretical framework, there is a large variability in the type and level of detail of the operational procedures used and modeling choices being made.

3 Methods

This study investigated the effect of making specific modeling choices when following the four-step procedure of Weidema et al. (2009). Building on the findings of the systematic review, a method is proposed focusing on three aspects of marginal supplier identification with a potential for improving current practice: the delimitation of geographical market boundaries, a systematic identification of market volume trends and the suppliers the most sensitive to a change in demand and finally the inclusion of two perspectives on development. The first two aspects focus is on modeling choices to be made (see Table 2), while the last aspect mainly relates to the type of input data used. As for the remaining steps of the procedure of Weidema et al. (2009), only small and medium-scale changes in demand are considered in this study and only long-term effects are considered, thus assuming fully elastic

Table 2 Summary of modeling steps, criteria, parameters, and values used in the analysis

Modeling step, identification of:	Parameters used in the modeling		Parameter name	Number and range of included values
Geographical market boundary	$\frac{n_i}{N}$ (1)	- n_i = number of times supplier i is included in the geographical market - N = total number of years analyzed	T_{year}	3 [50–90%]
	$\frac{t_i}{\sum p}$ (2)	- t_i = amount of import from supplier i to suppliers already included in the geographical market for one year - $\sum p$ = total production volume of all suppliers already included in the geographical market	T_{market}	28 [0.1–35%]
Market volume trends and most sensitive suppliers	$f_i = \frac{s_i}{\sum s}$; *and* $s > 0$ (3)	- f_i = share of the marginal mix, supplier i - s_i = slope of linear regression of production time series of supplier i for 1 year - $\sum s$ = sum of all positive slopes of unconstrained suppliers	T_{share}	17 [0.1–10%]
	$\frac{p_i}{\sum p}$ (4)	- p$_i$ = production volume of supplier i for 1 year - $\sum p$ = total production volume of all suppliers	T_{prod}	17 [0.1–10%]

markets. The latter is the default assumption in the ecoinvent consequential system model as well (Weidema et al. 2013).

In the methods described in the following sections, trade data are used to define geographical market boundaries and production data to identify market volume trends and sensitive suppliers. Hence, the analysis is applicable consistently and systematically to different products. In accordance with the four-step procedure of Weidema et al. (2009), geographical market boundaries were identified without taken into account any type of constraints. However, constrained products were excluded prior to the identification of market volume trends and sensitive suppliers. The constrained products were identified qualitatively, based on literature information. For example, Belgian electricity produced with nuclear technology was excluded from the analysis of market volume trends due to a policy-related constraint (i.e., the political decision for a nuclear phase out in Belgium). Dependent (non-determining) by-products are another typical constraint because in multi-functional processes a change in demand for the dependent by-product would not result in production increase. The burdens and benefits of these by-products when substituting other (marginal) products need to be taken into account when modeling an increase in demand of the determining product. For example, ground granulated blast-furnace slag cement was excluded from the analysis of market volume trends of cement as it is a by-product of the steel making process. It could be noted that the method proposed in this study can be used in the process of analyzing product substitutions, because the substituted activity is always the marginal one (Weidema et al. 2009). However, the analysis of how the substitution process should be done and when is beyond the scope of this study. A complete overview of all constraints is presented in Annex 2 – Table 1 (see Electronic Supplementary Material).

Since most of the available data are aggregated at country level the analysis treats individual countries as suppliers. Where data on multiple technologies were available per country, specific technologies were identified per country as the most sensitive suppliers. For example, suppliers of electricity to the Belgian grid can be Belgian wind turbines, Dutch gas plants, etc.

3.1 Identification of geographical market boundaries

A precondition for a supplier being able to respond to a change in demand is that both the supply and demand sides operate within the same market (Weidema 2004). A consistently and systematically applicable way of defining what the geographical boundary of a market is using trade data, i.e., data on product import and export quantities between countries.

In this study, geographical market boundaries were defined by comparing the volume of traded products to the total production volume of a market, with an iterative procedure (Fig. 1). The procedure starts with delimiting an initial market, for example, the area where the analyzed change of demand takes place. Then, the import per supplying country is evaluated by dividing the amount of import by the total production volume of the initial market (see Eq. (2), Table 2). The outcome is compared to a chosen value, the parameter T_{market}. If the result is higher than T_{market}, the exporting country is considered to become part of the geographical market, otherwise it is not. After adding the countries that satisfy the equation to the market, the procedure is

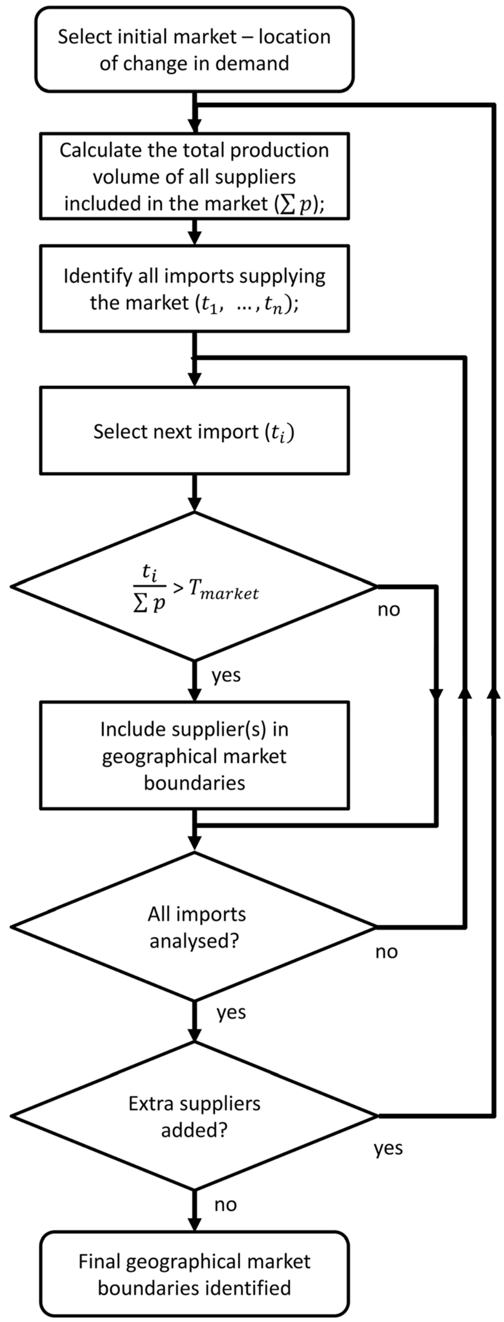

Fig. 1 Iterative procedure for identifying geographical market boundaries

iterated until no further countries can be added. To understand the effect of setting the parameter T_{market}, 28 different values of this parameter were tested in the analysis, ranging from 0.1 to 35%.

In order to clarify this procedure, a simplified example is given for identifying the market boundaries in the case of an increased demand for cement in Belgium. The market is assumed to be geographically limited to Belgium, which is the initial market. In 2013, Belgium produced 6119 ktonnes cement, imported 72 ktonnes from Luxembourg (whose production is 1200 ktonnes), and imported 640 ktonnes from Germany (whose production is 31,308 ktonnes) (USGS 2014; United Nations 2016). If T_{market} is set at 2%, Luxembourg would not be included in the geographical market (72/6119 < 2%), but Germany should (640/6119 > 2%). Hence, the next iterative round would start from a market including Belgium and Germany with a total production volume of 37,427 ktonnes, taking into account import from other countries such as Denmark, Poland, etc.

Trade and production data are typically collected on yearly bases, so geographical market boundaries can be identified for multiple years for a specific value of T_{market}. However, trade and production may change over time. The previous procedure is therefore repeated using data from different years, thus defining yearly geographical markets (the analysis covers 11–13 years depending on the data availability of a specific product). Then, with a constant value of T_{market}, a second parameter T_{year} is used to define the required minimum frequency a supplier should be included in a market over the analyzed period (see Eq. 1, Table 2). The higher the value of T_{year}, the stronger the corresponding country needs to be represented in the geographical markets. Three values for T_{year} were considered in the analysis (50, 75, and 90%).

3.2 Identification of market volume trends and sensitive suppliers

Within a growing market, the suppliers most sensitive to a change in demand are identified based on their potential for expanding production capacity, a proxy measure of their competitiveness (Weidema et al. 2009). Depending on the time horizon of the study and the market trend observed, different types of data have been used in literature to quantify competitiveness: production cost, production volume, additional installed capacity, or capacity utilization (Weidema 2004). In this study, the increment in production volume over a certain period was chosen, under the assumption that the suppliers yielding the largest increment in production volume also are the most competitive ones (Schmidt and Thrane 2009). Production data at country level can be retrieved for many products consistently and systematically, thus ensuring the general applicability of the proposed procedure.

The increment in production volume was calculated by applying a linear regression analysis to the time series of the production data. The slope of the regression line served as an indicator of the market volume trend. By selecting only the suppliers showing a positive production trend and excluding all others, a so-called “marginal mix” of suppliers can finally be identified. The sum of all positive slopes of unconstrained suppliers represents the total increment in production volume of a market. The share of a supplier in the marginal mix is then determined by dividing the slope of the supplier’s regression line by the total increment (see Eq. (3), Table 2). Similar to the procedure followed when defining geographical market boundaries, two parameters were introduced to exclude non-sensitive suppliers. T_{share} is the minimum contribution a supplier needs to make to the total increment of the market. T_{prod} is the minimum value for the production volume of a supplier to be considered having a relevant contribution to the total production volume of a market (see Eq. (4), Table 2). For both T_{share} and T_{prod}, 17 values were considered in the analysis ranging from 0.1 to 10%.

3.3 Perspective on development

The parameters described in Section 3.1 and 3.2 can be estimated using historical time series or forecasted time series, adopting a retrospective or prospective approach, respectively. Historical production and trade data are available from statistical agencies, whereas forecasted production and trade data are to be obtained from models.

Forecasting the future volumes of production and trade with the same level of detail and disaggregation as by using historical statistics is challenging, and these estimates are inherently uncertain. Since both past statistics and future projections of production data were available in this study, it was possible to apply both the retrospective and prospective approaches to identify the most sensitive suppliers. On the other hand, market boundaries were only identified based on historical trade data due to the lack of detailed future trade forecasts, thus applying a retrospective approach.

3.4 Identification of marginal mixes

Using the parameters described in Sections 3.1, 3.2, and 3.3, retrospective and prospective mixes of marginal suppliers were identified for the six products under analysis: aggregates, cement, sawnwood, particle board, steel, and electricity, and for different choices of parameter values. Since the aim of this study is to examine how consequential modeling is applied to different products rather than to compare product alternatives, products are analyzed based on a reference flow instead of a functional unit. The reference flow is the supply of one additional product unit (kg, m^3, or kWh) to the Belgian market.

The marginal mixes under the most relaxed assumptions were used in the analysis of the results. This mixes represent the largest number of potential marginal suppliers and can be obtained by choosing the lowest possible value for all parameters (50% for T_{year}; 0.1% for T_{market}, T_{share}, and T_{prod}). It was not possible to perform the complete analysis when prospective data were unavailable. In these cases, the geographical market boundaries were defined quantitatively according to the proposed method based on retrospective data, constrained suppliers were excluded and finally a marginal mix was identified qualitatively based on literature on expected future developments. These additional marginal mixes were only included in the qualitative discussion handling the results of the market mixes and not in the quantitative sensitivity analysis. All results were compared with qualitative information available from literature on the expected size and development of each product's marginal mix.

3.5 Statistical modeling for sensitivity analysis

The effect size of the parameters (T_{year}, T_{market}, T_{share}, and T_{prod}, the independent variables) on the final predicted outcome (number of suppliers in the geographical market boundaries and in the marginal mix, the dependent variables) was analyzed with a log-linear Poisson regression model. Poisson models are generalized linear models for count data with Poisson error and link log (Rodríguez 2007). The Poisson distribution is thus appropriate to model the count data of this specific study, i.e., the count of suppliers within the geographical market boundaries and marginal suppliers in the marginal mix.

The effect of varying the values of T_{year} and T_{market} on the geographical market boundaries was analyzed first and separately, since the same markets are used in both the retro- and prospective approach. 84 different market boundaries were obtained from all possible combinations of T_{year} and T_{market} values (see Table 2). Then, the effect of changing the values of all four parameters on the final marginal mix was quantified. 24,276 marginal mixes were obtained from all possible combinations of T_{year}, T_{market}, T_{share}, and T_{prod} values. Each mix differs in terms of number of marginal suppliers included and their contribution to the mix. The number of suppliers was chosen as the dependent variable in the regression model, as preliminary tests have shown it was the most sensitive indicator and the most useful one for the interpretation of the results.

The fitting of the model was evaluated by the Akaike Information Criterion (AIC), which is a measure of the relative quality of statistical models for a given set of data (Mazerolle 2006). The parameters were transformed in order to improve the model fit. A log transformation for T_{market}, T_{share}, and T_{prod} resulted in a better model fit, whereas transforming T_{year} did not affect the model fit. Therefore, all variables were log transformed to facilitate the interpretation of the results. No interaction between the variables was considered. The general model formulations are reported in Eq. (5a) and (5b).

$$y_{MB} = \beta_{MB,0} + \beta_{MB,1}.log(T_{year}) + \beta_{MB,2}.log(T_{market}) \quad (5a)$$

$$y_{MS} = \beta_{MS,0} + \beta_{MS,1}.log(T_{year}) + \beta_{MS,2}.log(T_{market}) + \beta_{MS,3}.log(T_{share}) + \beta_{MS,4}.log(T_{prod}) \quad (5b)$$

With:

- y_{MB} = number of suppliers included in the geographical market boundaries
- y_{MS} = number of suppliers included in the marginal mix
- β_x = parameter estimates

The effect size exp.(β) was calculated for the reference model of all products, i.e., including all transformed variables. The effect size expresses the factor of change of the predicted output in percentage: it is the change in the value of the dependent variable for a unitary change of a single independent variable, maintaining all other independent variables constant. The change of one unit relates to the variables included in the model. For example, one log-transformed unit corresponds to a change by a factor 10 of the original untransformed variable. A limitation of Poisson models is that is no coefficient of determination can be calculated in analogy with linear regression models. For instance, the fact that the effect of a variable is significant does not necessarily mean that this variable has a relevant effect on the final outcome. To gain more insight into the explanatory value of the variables, the reference model based on all variables was compared to models leaving out variables one-by-one. If the AIC remained approximately the same, the excluded variable did not add much information to the reference model and is of minor importance. Additionally, for all models the observed and predicted values were compared. In contrast to the Poisson model this relationship should be linear, so a simple linear regression model was applied. The coefficient of determination r^2 was calculated, providing a well-known indicator for comparing results. Similar to the first additional step, if r^2 is not affected by leaving out a certain variable, this variable has little effect in the reference model.

A precondition for applying a Poisson regression model is that the variance of the independent variables equals the mean. Descriptive statistics of the results pointed out that in many cases, the variance was much higher compared to the mean thus indicating overdispersion. Other models without this precondition were tried as well, such as a negative binominal with log link, but they resulted in a worse model fit. Therefore, it was decided to use a quasi-Poisson model with Pearson chi-square as a scaling method, thus accommodating the overdispersion yet maintaining the high level of the model fit. Parameter estimates and predicted values remained unchanged, but the corresponding confidence interval has been widened (see Annex 4 in Electronic Supplementary Material).

4 Results

4.1 Market volume trends for each product

The market volume trends calculated for each product are presented in Table 3. Three time frames were considered: the pre-crisis trend (2000–2005), the trend during the financial crisis (2006–2013), and a forecasted trend. The percentages express the evolution in production volume relative to the reference year (2000, 2006, and 2014). The production of aggregates and cement decreased during the financial crisis. In the future however, all the analyzed markets are assumed to grow at least to a certain extent. Since none of the markets has a strong declining trend, the marginal suppliers are the most competitive ones.

4.2 Identified marginal mixes for each product

Since only historical trade data were available, geographical market boundaries were identified with a retrospective approach for all products. However, detailed forecasted trade data of electricity were available so it was possible to identify a geographical market for electricity with a prospective approach as well. Prospective and retrospective market trends and sensitive suppliers were identified for all products except aggregates and cement. Due to a lack of data for these two products, only one prospective marginal mix was included. Data sources and geographical coverage of the data are reported in Table 4 and the marginal mixes were obtained using the lowest threshold for all parameters (i.e., the most relaxed assumption) are reported in Table 5. An example of the Excel files used in the calculation[3] as well as the full results can be found in Annex 5 - Annex 7 (see Electronic Supplementary Material).

Aggregates are typically assumed to be a local commodity (Brown et al. 2015); however, in the retrospective approach, more than 70% of the marginal supply in Belgium is covered by import. Germany is an important supplier of sand, Norway of gravel. The large share of import of German sand does not necessarily mean that aggregates are not a local product. Trade of aggregates in Europe is not limited by national borders but by distance, for example 50 km for transport by truck (LNA-ALBON 2014). The large share of import from Norway on the other hand contradicts the default assumption of a local market. The latter is confirmed in the prospective scenario. Even though aggregates are abundantly available locally, regulations regarding nature conservation are putting pressure on the domestic Belgian supply resulting in a policy-related constraint (Kamp et al. 2006; LNA-ALBON 2014). A similar trend occurs in neighboring countries as well. In particular, aggregates from Germany and France and gravel from the Netherlands are likely to be policy-constrained in the near future (De Smet et al. 2009). As a result, only two suppliers are showing an increasing trend and are identified as prospective marginal suppliers: sand from the Netherlands and gravel from Norway.

In the case of cement, geographical market boundaries were identified based on data of Portland cement only due to the lack of other data, thus excluding cement produced with other technologies. However, Portland cement represents more than 90% of European cement production, so the effect on the results will be negligible (Cembureau 2012). Cement is a product with a high weight-to-price ratio with transport distances as a limiting factor, which suggests a narrow and local geographical market boundary (Weidema 2003). However, only China and Turkey are identified as potential marginal suppliers in the retrospective approach, since all other suppliers in the market are European countries with a decreasing production trend. The retrospective results are supported by the additional prospective marginal mix, albeit only Turkey was identified as a marginal supplier (Boston Consulting Group 2008; Cook 2011; Baeza et al. 2013; Global Cement 2015). The importance of geographical proximity is expected to decrease because of reducing transport costs and the decline of the competitiveness of the European cement sector on a global scale, especially regions with good access to a port, such as Belgium, are more likely to be affected (Ecorys 2013; Brown et al. 2015; United Nations 2016). The European cement sector is reforming, with firms merging to increase their competitiveness. Such multinational corporations operate at a global scale to optimize plant efficiencies (Boyer and Ponssard 2013). However, this does not mean that cement becomes a global commodity as most of the exported volumes stay within a region. Consequently, China is not considered as a stable long-term supplier of cement to the Belgian market and Turkey is identified as only prospective marginal supplier (HeidelbergCement 2016).

In contrast to aggregates and cement, the market for sawnwood is larger and more globalized, yet not completely global, i.e., large suppliers such as China are not represented in the market. Geographical market boundaries span over multiple continents. Comparing the retro- and prospective results show some clear differences in the composition of the marginal mixes: suppliers from Latin America and Western Europe are replaced by suppliers from Eastern European countries. What does not change is the importance of Russia as a sawnwood supplier. In literature similar results can be

[3] All calculation sheets can be obtained under request to the corresponding author

Table 3 Trends in production volume relative to reference years 2000, 2006, and 2014

Product	Region	2000–2005	2006–2013	Predictions	Time horizon predictions	References
Aggregates	EU	16%	−23%	1–2%[a]	2020	(Taylor et al. 2006; Brown et al. 2010; IHS Economics 2013; Brown et al. 2015)
Cement	EU	4%	−9%	−2–+12.5%	2050	(Taylor et al. 2006; Brown et al. 2010; Brown et al. 2015; Van Ruijven et al. 2016)
Sawnwood	Global	17%	−8%	10%	2020	(FOA 2009; FAO 2016)
Particle board	Global	40%	41%	25%	2020	(FOA 2009; FAO 2016)
Steel	Global	35%	44%	30%	2030	(World Steel Association 2015a)
electricity	Global	19%	27%	42%	2030	(IEA 2015a; IEA 2015b)

[a] Data for growth of the total construction sector, which is the main driver for the use of aggregates

found: even though the forestry sector is at a turning point which reduces the reliability of forecasts, a shift from West to East due to faster economic growth and smaller labor costs is acknowledged (Hänninen et al. 2014; Hurmekoski 2016). The competition between eastern European, Russian, and Chinese producers, both in the European markets and in the export markets outside Europe, is likely to increase (Hetemäki 2014).

The market for particle board is less globalized compared to sawnwood, with only European countries being included. There are some big differences between the prospective and retrospective approach, in particular the increasing contribution of Germany and Spain in the former at the expense of Romania in the latter. When comparing the result of sawnwood and particle board, it can be observed that the contribution of Western European countries is shifting from sawnwood to particle board. This evolution was found by Manninen (2014) as well, with traditional sawnwood being replaced by engineered wood products such as panels, I-joists and cross-laminated timber (CLT).

Since steel is mostly traded as an intermediate (semi-steel) or a finished product, geographical markets were identified based on trade data of semi-steel while production data of crude steel were used to determine the marginal mixes. Steel is considered a global commodity in literature (Zweig et al. 2016). The geographical market boundary identified with the method described in Section 3.1 resulted in a list of 33 countries (see Annex 7). Nevertheless, the identified geographical market seems to be a good proxy of a global market. The top 20 of the largest producing countries are included, representing 98% of the total world production. For the marginal mixes, the extreme growth of Chinese steel simply overrules all other countries in the retrospective approach. In future, the Chinese steel industry is expected to become more mature with a moderate growth, which results in a more diverse set of suppliers in the prospective mix. The prospective approach matches well with the aggregated outlook of the World Steel Association, predicting the slowdown of Chinese production and the increasing importance of India, Brazil, Russia, and to a lesser extent South Korea (Zweig et al. 2016).

In contrast to the other products relevant for the construction sector, electricity has limited storage possibilities. Geographical markets were identified based on net import to Belgium. The most important difference in applying the retrospective and prospective approach to geographical market delimitation is the inclusion of France in the prospective

Table 4 Data collection and geographical coverage

Commodity	Trade data	Production data – retrospective	Production data – prospective	Geographical coverage
Aggregates	CEPII (2016)	Taylor et al. (2006); Brown et al. (2010); Brown et al. (2015)	–	EU
Cement	CEPII (2016)	U.S. Geological Survey (2016)	–	Global
Sawnwood	FAO (2016)	FAO (2016)	UNECE/FAO (2011); FAO (2012); UNECE/FAO (2012); FIM Services Limited (2015)	Global
Particle board	FAO (2016)	FAO (2016)	UNECE/FAO (2011)	EU
Steel	CEPII (2016)	World Steel Association (2006); World Steel Association (2015b)	Ito et al. (2006); Firoz (2014); OECD (2015); Zweig et al. (2016)	Global
Electricity	FPB (2014); FPB (2015); ENTSO-E (2016)	ENTSO-E (2016)	Capros et al. (2013); FPB (2014); FPB (2015)	EU

Table 5 Composition of marginal mixes identified with the lowest values for all parameters. This is the mix of marginal suppliers for a unitary increase in demand of each product to the Belgian market

country	Aggregates		Cement		Sawnwood		Particle board		Steel		Technology	Electricity	
	Retro	Pro	Retro	Pro	Retro	Pro	Retro	Pro	Retro	Pro		Retro	Pro
Australia										0.7%	BE – biofuels	29.6%	5.9%
Austria							5.3%	4.5%			BE – gas	2.7%	23.5%
Belarus					3.1%	1.1%					BE – oil		2.1%
Belgium	28.8%										BE – solar	22.6%	12.5%
Brazil					7.1%				0.3%	6.3%	BE – wind	32.3%	41.1%
Canada										1.3%	DE – biofuels	0.8%	0.3%
Chile					6.5%	4.9%					DE – gas		1.1%
China			97.8%						89.9%	56.2%	DE – hydro		0.1%
Czech Republic					2.3%	2.0%	5.8%	6.0%			DE – solar	0.7%	0.6%
Estonia					0.3%	0.1%					DE – wind	0.7%	3.1%
France						7.3%	8.3%	9.3%			FR – biofuels		0.3%
Germany	27.3%				22.1%			26.6%			FR – solar		0.4%
India									1.6%	12.3%	FR – wind		2.7%
Iran										1.6%	NL – biofuels	1.2%	0.6%
Ireland								0.6%			NL – hydro	0.3%	
Japan									0.3%		NL – nuclear	6.3%	0.2%
Latvia						6.3%					NL – oil		0.1%
Lithuania						1.7%					NL – solar	0.7%	
Luxembourg							0.9%				NL – wind	2.1%	5.5%
Mexico									0.2%	1.4%			
Netherlands		50.0%				0.1%			0.2%				
New Zealand					0.6%	2.6%							
Norway	43.8%	50.0%				1.3%	0.0%	2.8%					
Poland					2.9%	16.0%	36.9%	27.0%					
Romania							42.7%	5.8%					
Russian Federation					50.0%	53.2%			1.3%	8.6%			
South Africa										0.7%			
South Korea									2.9%	7.9%			
Spain								8.3%	0.1%				
Sweden					4.4%								
Switzerland								3.9%					
Taiwan									1.7%	3.1%			
Turkey			2.2%	100%					0.7%				
Ukraine					0.7%	3.3%			0.8%				
United Kingdom								5.3%					
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	Total	100%	100%

geographical market. In the last decade, the trade of electricity between France and Belgium has seen large variations: a net Belgian import in some years and a net Belgian export in some others. However, in the future a structural need for imported electricity from France is expected (FPB 2014). The identified marginal mixes show similarities for both perspectives (see Table 5). The main difference is the larger share of Belgian gas plants in the prospective approach. This can be explained by the planned phase out of nuclear energy and the need for flexible base load capacity. Basically, all other technologies are renewables, with a shift from solar to wind power between the two approaches.

Summarizing the results presented, some general observations can be made. Clear differences exist between the retrospective and prospective approach. When the results are compared to literature, similar trends are identified for most products, suggesting that the proposed procedure leads to valid results. However deviations from default assumptions in LCA were observed as well, such as the existence of large regional geographical markets instead of local ones for cement and aggregates.

4.3 Results of the sensitivity analysis

With a few exceptions, all models returns significant results for the entire Poisson model and the individual independent variables. In other words, the distribution fits the data and the independent variables have an effect on the dependent variable. Results for the market boundaries and marginal mixes are presented in Table 6 and Table 7, respectively. The observed versus the predicted number of countries for geographical market boundaries, retrospective and prospective marginal mixes of sawnwood, particle board, and steel are shown in Fig. 2 (similar figures for the other products are provided in Annex 3 of the Electronic Supplementary Material)

Both T_{year} and T_{market} influence the identification of geographical market boundaries. All effect sizes lie below one, indicating that setting a higher threshold will result in delimiting a smaller market. T_{year} has the biggest effect size, though this number should be nuanced: the values for T_{year} vary from 0.5 to 0.9 (Δlog = 0.25) compared to the range 0.001 to 0.35 (Δlog = 2.5) for T_{market}. The retrospective electricity market for example has the most divergent results for both parameters (effect sizes of 0.09 and 0.49 for T_{year} and T_{market}). If T_{year} is increased from the minimum to the maximum value (0.5 to 0.9) the number of countries in the market decreases with 46%. If the same is done of T_{market} (0.001 to 0.35), the decrease is 86%. This means that T_{market} is the most sensitive parameter.

Leaving out variables one-by-one shows results in only a slight increase of the AIC if T_{year} is left out, while this is not the case for T_{market} where the AIC increases substantially. A similar observation can be made for the r^2. The retrospective

Table 6 Geographical market delimitation: effect size; goodness of fit; and r^2

		Effect size exp.(B)			Goodness of fit – AIC			r^2 – observed vs. predicted		
Commodity		Intercept	Log (T_{year})	Log (T_{market})	model 1: ref.	Model 2: excl. T_{year}	Model 3: excl. T_{market}	Model 1: ref.	Model 2: excl. T_{year}	Model 3: excl. T_{market}
Retro	Aggregates	1.35	0.76	0.58	77,406	77,482	91,954	0.85	0.85	0.01
	Cement	0.53	0.23	0.45	69,684	71,461	94,614	0.93	0.81	0.06
	Sawnwood	1.83	0.42	0.43	104,094	106,160	194,726	0.91	0.89	0.02
	Particle board	0.36	0.22	0.32	75,563	78,342	141,172	0.94	0.86	0.03
	Steel	1.03	0.32	0.32	101,221	105,302	273,166	0.94	0.91	0.02
	Electricity	0.30	0.09	0.46	62,223	65,390	77,142	0.83	0.64	0.11
Pro	Electricity	1.17	[a]	0.56	–	–	25,578	–	–	0.73

[a] No time series available

Table 7 Marginal mixes: effect size; goodness of fit; and r^2

Commodity		Effect size exp.(B)					Goodness of fit – AIC					r^2 – observed vs. predicted				
		Intercept	Log (T_{year})	Log (T_{market})	Log (T_{share})	Log (T_{prod})	Model 1: ref.	Model 2: excl. T_{year}	Model 3: excl. T_{market}	Model 4: excl. T_{share}	Model 5: excl. T_{prod}	Model 1: ref.	Model 2: excl. T_{year}	Model 3: excl. T_{market}	Model 4: excl. T_{share}	Model 5: excl. T_{prod}
Retro	Aggregates	0.82	0.75	0.73	[a]	0.91	61,632	61,669	63,891	61,630	61,772	0.52	0.50	0.04	0.52	0.47
	Cement	0.00	[b]	0.24	0.94	0.95	10,405	19,873	14,414	10,409	10,407	0.77	0.13	0.38	0.76	0.76
	Sawnwood	0.39	0.57	0.60	0.75	0.78	79,455	79,737	90,662	81,865	81,234	0.68	0.67	0.17	0.54	0.55
	Particle board	0.06	0.38	0.27	0.97	0.88	49,768	50,118	75,997	49,781	49,970	0.74	0.72	0.02	0.74	0.72
	Steel	0.02	0.58	0.35	0.45	0.62	63,419	63,567	88,312	73,562	67,263	0.74	0.73	0.24	0.39	0.57
	Electricity	0.56	0.54	0.89	0.78	0.61	82,784	83,159	83,472	84,670	90,209	0.54	0.50	0.47	0.42	0.16
Pro	Sawnwood	0.05	0.32	0.40	0.67	0.56	74,773	75,697	100,794	78,258	82,261	0.68	0.67	0.19	0.56	0.45
	Particle board	0.08	0.33	0.25	0.90	0.87	63,881	64,683	114,228	64,127	64,322	0.75	0.73	0.03	0.74	0.73
	Steel	0.02	0.35	0.26	0.76	0.55	64,889	65,488	104,390	66,161	70,943	0.64	0.64	0.11	0.58	0.46
	Electricity	0.55	[c]	0.82	0.67	0.58	31,660	31,660	32,658	34,395	36,372	0.71	0.71	0.58	0.41	0.27

[a] No significant effect

[b] No relevant results could be obtained

[c] No time series available

electricity market is the only exception where T_{year} has substantial effect on the AIC. The latter can be explained by the large variations in the quantities of imported electricity, among others due to a temporal shut down of multiple Belgian nuclear reactors for safety reasons.

The results of the marginal mixes based on all four variables show a larger variability across products. Hence, it is not possible to draw general conclusions. Again almost all variables have a highly significant effect, but the effect sizes vary substantially. For example, the effect size of T_{share} and T_{prod} is negligible in the case of aggregates, cement, and particle board but not for the other products.

The small differences of AIC and r^2 values between the reference model and the models obtained by leaving out T_{year} show the limited importance of this variable compared to the other ones. The only exception is the case of cement, since the only two potential marginal suppliers Turkey and China are only included if T_{year} is 50% at most. For higher values of T_{year} no marginal suppliers could be identified.

Additionally, the AIC and r^2 of the different models indicate that across all products, T_{market} is the most important variable, while T_{share} and T_{prod} have a smaller effect on the composition of the final mix of marginal suppliers. Electricity is an exception where T_{prod} has a larger effect than T_{market}. This is explained by the fact that the renewable energy technologies merely contribute for a small share of the total electricity production volume in a market, but they are the only technologies showing an increasing trend in production volume.

Concluding on the sensitivity analysis, T_{year} shows a significant but very limited contribution to the final result, both for the market boundaries and the marginal mixes. Since T_{year} quantifies the frequency of a supplier being included in a market over a certain period, this may be interpreted as a sign that markets are relative stable over the analyzed period. This supports the approach proposed in this study, i.e., to define geographical markets with the retrospective approach, and assume they are valid for prospective analysis of market trends as well. The identification of geographical market boundaries, based on T_{market}, has the biggest effect on the results both for the size of the market boundaries and the marginal mixes, while the identification of the sensitive suppliers, based on T_{share} and T_{prod}, is less important.

5 Discussion and conclusions

In this study a method is proposed to systematically identify marginal suppliers for different products. There was a particular focus on modeling choices regarding the identification of geographical market boundaries, trends in production volumes and sensitive suppliers, and under different perspectives on development. To quantify the effect of the modeling

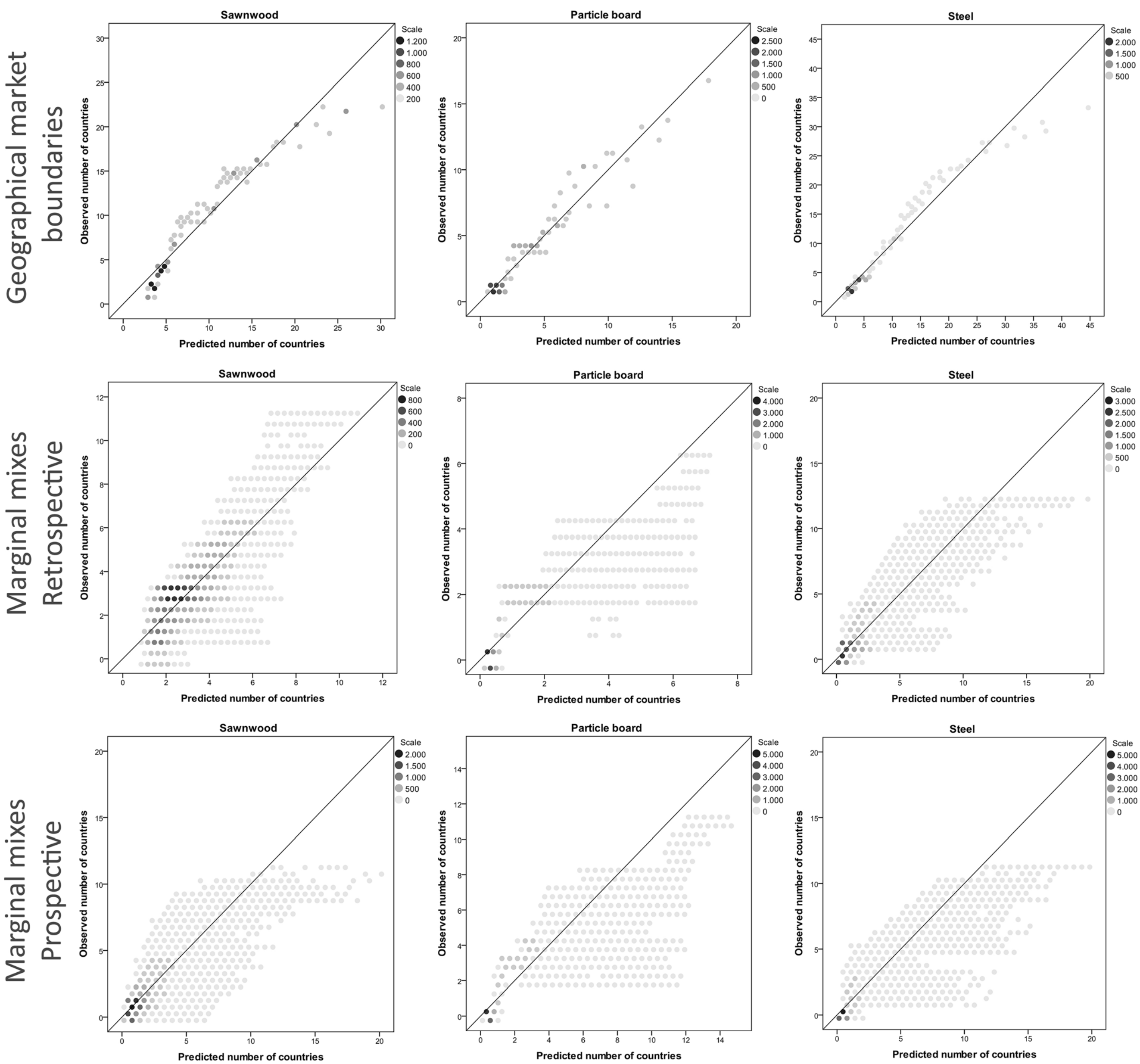

Fig. 2 Number of observed vs. predicted countries for geographical market boundaries. Retrospective and prospective marginal mixes for sawnwood, particle board, and steel

choices four parameters were introduced and applied to a case study of six products relevant for the Belgian construction sector. To validate the procedure, results were compared with other (non-LCA related) studies, and in most cases similar conclusions could be drawn. Some deviations from typical default assumptions in LCA were observed as well.

The marginal mixes presented in Table 5 were obtained by setting the lowest values for all parameters. As a consequence, the marginal mixes reflect the maximum number of potential suppliers included in a marginal mix, reaching up to a maximum of 13 suppliers. By increasing the values of the parameters, marginal mixes of smaller size are obtained. To ensure the practical implementation of the method, a smaller set of values for all parameters might be desirable as well. T_{market} is the most influential parameter in the model, affecting the size of a geographical market. This parameter is not related to the competitiveness of suppliers, so increasing its value does not necessarily mean that the least important suppliers are excluded from the final marginal mix. T_{year} has only a minor effect, so it can be sufficient to analyze it for only 1 year instead of in a time series—or one default value can be chosen if a time series is desired. T_{share} is closely related to the competitiveness of the suppliers. When a threshold is set for this parameter, the suppliers with the smallest contribution are excluded from the marginal mix. T_{prod} can result in the exclusion of suppliers with a positive increment, as demonstrated in the case of electricity.

The importance of defining geographical market boundaries is one of the main findings of this study. Besides the work of Pizzol and Scotti (2017) on wood products, there is a lack of studies focusing on this topic. Pizzol and Scotti (2017) applied a clustering technique from network analysis on global trade data from FAOSTAT (FAO 2016) to identify geographical markets. This is a top-down approach identifying clusters from a global network, as opposed to the bottom-up approach used in this study where boundaries are delimited taking one country as a starting point. A second difference is that in a network analysis trade flows in both directions (import and export) are taken into account. A comparison between the geographical markets of sawnwood identified in this study (assuming $T_{\text{year}} = 50\%$ and $T_{\text{market}} = 0.1\%$), and those identified by Pizzol and Scotti (2017) is presented in Table 8. The results of both studies show a good match, suggesting that the simpler approach presented in this study returns results similar to the more complex network analysis.

Clear differences in result were observed when applying the retrospective or the prospective approach. Both approaches have their strengths and weaknesses. The retrospective approach is characterized by a high availability of data with a low level of uncertainty. A key assumption in this case is that historical trends are representative for future situations. Such data are in particular relevant for a relative short time horizon. In reality, however, development is typically not a linear process, but it follows rather a S-shaped curve (Hetemäki 2014). The prospective approach relies on forecasting models. They can provide a more nuanced image of expected future developments and they are relevant when a structural reformation of a segment of the economy can be expected. The latter can be market driven, e.g., a decreasing demand for pulpwood in the paper industry, combined with a sharp increasing demand for wood fuel (Hetemäki 2014), or due to legislation, e.g., the prevalence of renewable electricity production in expected newly installed generation capacity (Capros et al. 2013). Yet, future predictions are per definition uncertain. For example, future predictions for the forestry sector differ notably between studies (Buongiorno et al. 2012; Hetemäki 2014; UNECE/FAO 2014). Special care should be taken when comparing results which have been obtained with both the retrospective and prospective approach. Even if a similar trend is found for both perspectives, the underlying causal relationship can differ. For example after the collapse of the USSR, the Russian forestry sector suffered severely and the historical trend basically reflects its recovery. The forecasted increment on the other hand represents its expected modernization and increased competitiveness (FAO 2012).

The analysis of other possible modeling choices was beyond the scope of this study, which is a limitation. Only one criterion was included for defining market boundaries, based on incoming trade flows and the size of a market. Only one way of assessing the competitiveness was considered, based on a linear regression analysis on time series of production data. Even though this procedure is the state of the art in LCA studies focusing on marginal supplier identification (Deng and Tian 2015; Schmidt 2015), more advanced regression techniques could have been used as well as other types of data such as information on costs and capacity adjustments.

Table 8 Comparison market delimitation of Sawnwood and Particle board with Pizzol and Scotti (2016)

Country	Sawnwood		Particle board	
	Pizzol & Scotti (2016)	This study	Pizzol & Scotti (2016)	This study
Australia			o	
Austria		o	X	X
Belarus	X	X		
Belgium	o	o	o	o
Brazil		X		
Canada		o		
Chile		X		
Czech Republic	X	X	X	X
Estonia	X	X		
Finland	o	o		o
France	X	X	X	X
Germany	X	X	X	X
Ireland	o			o
Italy			o	o
Latvia	X	X		
Lithuania	X	X		
Luxembourg	o	o	o	o
Netherlands	o	o	o	o
New Zealand		X		
Norway	o	o		o
Poland	X	X	X	X
Portugal	o		o	o
Romania				X
Russian Federation	X	X		
Slovakia			o	
Spain	o		X	X
Sweden	X	X	o	
Switzerland	o		X	X
Turkey	o			
United Kingdom	o		X	X
Ukraine		o		
United States of America		o		

X countries with a contribution to the marginal mixes, *o* countries without a contribution to the marginal mixes

Detailed data on production volumes and trade quantities are required to be used as input data for the method presented in this study. Often these data are only available at country level or even more aggregated. However the analysis of the Belgian electricity grid mix illustrates that the method can be used for identifying marginal technologies as well. Further research should investigate how to systematically build specific life cycle inventories, once the marginal supplying countries have been identified. Electricity mixes, technology mixes, transport scenarios, climate zones, and geography could all be analyzed per country. A further subdivision in supplying regions might be appropriate as well, for example if a country covers a large geographical area with multiple climate zones (e.g., wood production in Russia).

Summarizing, the method and the corresponding sensitivity analysis are an attempt to gain insight into the effect of modeling choices in the context the identification of marginal suppliers for consequential LCA. Further research will have to focus on refining the method, with special attention to validating the procedure for defining geographical market boundaries. In the process of calculating environmental impacts, the current method can serve as a starting point for practical use and further discussion.

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