An analysis of the degree of circularity of the wood products industry in Europe

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Abstract
By developing products derived from materials included in what is nowadays called bioeconomy, the wood products industry is today receiving considerable attention for its potential to provide more environment-friendly materials. At the same time, this and other industries are transforming to obtain more circular production systems. This study aims to analyze circularity in this type of industry at a European Union level, by establishing a ranking of countries based on their performance in an aggregate circularity index. This task has been set up by taking an initial joint set of indicators for all countries and covering a time horizon of up to 19 years. After proceeding to normalize those indicators and applying an analysis of correlation, a biannual ranking (from 2008 to 2018) was made, using for this purpose a multicriteria decision-making model that includes three different types of solutions. Next, a statistical model that helped to explain the rankings previously obtained was proposed, in which a set of 15 explanatory variables were defined. The results showed that Sweden, and to a lesser extent Portugal, are the countries presenting a more circular wood products industry, whereas the Benelux countries give the worst result. Moreover, the statistical models showed that the variables related to trade had a negative relationship with circularity, but some of them exerted a strong effect, such as the ratio “production/exports.” Global competitiveness also tended to diminish wood circularity. Other variables, like those related to research and development, had a strong effect positively linked to circularity.

KEYWORDS
bioeconomy, circular economy, forest products, industrial ecology, multicriteria decision-making

1 INTRODUCTION
1.1Circularity and wood products industry
There is very little room for argument when it comes to considering that nowadays the environment, in a broad sense, presents clear limitations in its double function of providing inputs to production systems, as well as of assimilating the waste generated from both production and consumption processes (Diaz-Balteiro, González-Pachón, et al., 2020). That is why it is becoming increasingly peremptory to make the transition from the classical
linear model to a circular one, which permits a sustainable interaction between the environment and the economic production and consumption systems. In this sense, and taking as a starting point the circular economy (CE) model proposed by Pearce and Turner (1990), diverse proposals have been made to carry out this transition since the last quarter of the twentieth century (Stahel, 2020). Those proposals have been promoted by different governments and organizations, both individually and at the European Union (EU) level (Korhonen et al., 2018).

When focusing on the case of wood, a clear example of a renewable resource, the first question is whether it makes sense to go ahead with circularity lines in the production of goods derived from this output. The answer to this question should be in the affirmative for several reasons. First, wood at a world level represents 2% of the global waste composition (Liu & Ramakrishna, 2021), but this percentage is doubled in the wealthiest countries (Kaza et al., 2018). On these lines, Lacy et al. (2020, p. 163) provide data on the high percentage (35%) of wood employed in the manufacture of furniture, parquet flooring, and so on that ends up as waste. Parallely to this reality, there is a contrasting one, in which a certain rise has been observed in the use of wood as a construction element instead of materials like concrete and steel (WBGU, 2021). In this sense, mention should be made of the appearance of new wood products, such as fiber-based materials, wood–plastic composites, or wood-based fibers (Hurmekoski et al., 2018). The latter are called “generically modified” wood products, with a future potential closely connected to CE (Heräjärvi et al., 2020). At the same time, the firms making up the wood products industry are increasing their efforts to optimize the reuse, recycling, and recovery of their products, in what is known as wood cascading (Jarre et al., 2020; Mair & Stern, 2017). Furthermore, the replacement of fossil fuels by wood-derived residues is also being encouraged (Hildebrandt et al., 2019). All this reflects the appropriateness of making a profound analysis on the degree of circularity in this sector, on which some bibliographic reviews of some products can be found (de Carvalho Araújo et al., 2019). In the latter, the idea of circularity is already beginning to hybridize with the bioeconomy concept (D’Amato et al., 2020), with a great potential in the forest industry (Hansen & Justs, 2018; Hansen et al., 2021).

1.2 Indicators, circularity, and aggregate indices

Although no particular consensus exists on how the CE can be conceptualized (Kirchherr et al., 2017), there are many publications and official documents in this respect, such as those at the European Commission level (Völker et al., 2020). Most of those works address the multiple dimensions of the CE through a set of indicators (Moraga et al., 2019). This view is upheld by European organizations due to the need to dispose of tools to characterize it and quantify its progress (Saidani et al., 2019; Völker et al., 2020). For these reasons, it is not unusual to find works analyzing CE indicators applied either regionally (Avdiushchenko & Zaja, 2019), entrepreneurially (Howard et al., 2019), or even at a product level (Kristensen & Mosgaard, 2020). However, to facilitate the understanding of the results, in different areas it is being proposed to work with aggregate or composite indices due to the greater ease in interpreting the results obtained or their comparison with other measurements (Diaz-Balteiro et al., 2018). This type of orientation is especially valuable for comparing performances between countries (OECD, 2008). In the CE case, it also enables one to address complex realities that are very problematic to assess with a single indicator. Numerous examples in the literature of composite indices at the national level are linked to sustainability. Some have been expressly defined to address this topic as the ecological footprint, but several authors (Pillarissetti & van den Bergh, 2010; Siche et al., 2008) have analyzed them and concluded that none can be a reliable, sustainable aggregate index. This fact justifies building a specific aggregate index to cover aspects like sustainability, and the same idea could be translated to circularity. In short, there is no accepted aggregate index of CE suitable for measuring it at the product (Linder et al., 2017) or the macro levels (García Bernabeu et al., 2020).

1.3 Multicriteria decision-making and circular economy

Since the need to construct an aggregate index of circularity has become imperative, the following question is how the information from the chosen indicators be aggregated efficiently. One option would be to use techniques belonging to the field of multicriteria decision-making (MCDM) to obtain a ranking of different economic units, or an aggregate circularity index. Some studies at a macro level like that of Garcia-Bernabeu et al. (2020) stand out in the CE field. An aggregate circularity index for EU countries has been set up using a specific MCDM technique called TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), and the information provided by 17 indicators for the year 2016. Recently, in Skvarciany et al. (2021), two MCDM techniques were hybridized to analyze the CE of the OECD countries with 2019 data, while Üsas et al. (2021) used three different multicriteria techniques to make a circularity ranking for EU countries except the United Kingdom, and with 2016 data.

However, these methodologies are commonly used in other multidimensional areas where a multidimensional feature is present. A good example is the use of MCDM techniques to approach sustainability issues. The bibliography on this field is much more extensive (Diaz-Balteiro et al., 2017), and this concept appears in a quarter of the studies that, using MCDM techniques, have been performed on renewable resources management in the past few years (Diaz-Balteiro, Iglesias-Merchan, et al., 2020). However, despite this boom, these techniques are not always applied consistently (Diaz-Balteiro et al., 2018). Thus, necessary normalization systems are sometimes not well developed, and the number of indicators is excessive; some indicators may probably be correlated with others.
Bearing all this in mind, the aim of this work is threefold. First, to propose an MCDM methodology to analyze circularity at the country level, using a set of official indicators. Second, to apply this methodology to study the evolution of circularity in the wood products industry in Europe during the period 2008–2018, establishing a ranking of countries in terms of their degree of circularity. The third objective consists of taking one more step to attempt to explain the circularity ranking of each country. For that purpose, the results obtained through the multicriteria methods have been taken and a series of independent variables defined, with the aim of detecting, by statistical techniques, which of them explains, as far as possible, the circularity associated with each country.

2 METHODS AND DATA

Following the chart in Figure 1, this section is divided into three parts, corresponding to the phases covered in that figure.

2.1 Selection of circular economy indicators

Given that this analysis was aimed at investigating at a country level, aggregate data from various international sources have been employed. As the initial interest was in analyzing circularity, not in a specific year but throughout a certain period, measurements of the indicators considered were taken from 2000 up to the last year available. However, it should be noted that following Mantau et al. (2019), there are no specific indicators that cover evaluations of circularity between different groups of wood-based industries (i.e., measuring the wood processing residues that feed pulp industries).

In the EU, there are different CE indicator groups. On one hand, there are those of the European Commission, that is, 16 indicators at a country level, grouped into three groups (European Commission, 2021). However, for the present analysis, there were indicator data corresponding only to the first group (“sustainable resource management”). On another note, EUROSTAT has also published a set of indicators to define CE. In this case, 10 indicators divided into 4 pillars make up the set. Data are only available for very few of them, considering a minimum number of years. Since the number of indicators presenting complete annual results (28 EU countries) for the wood products industry was not very abundant, other indicators have been sought like, for instance, FAO (Food and Agriculture Organization, 2021) data. This idea of completing official CE statistics with other indicators has already been proposed (Kardung et al., 2021).

The initial premise in this study was to include different industries related to the wood-based one (at least, wood products and paper industries). However, it has been preferred to focus the analysis only on the wood products industry. This decision was made for two reasons: On one hand, the disaggregated indicators available related to the paper industry were not very numerous and, on the other, as the industries are somewhat different regarding size, the number of establishments per country, and so on, it was thought that the interpretation of the results might be less accurate if both sectors were united.

Next, as the indicators included in Table 1 have different units, it was decided to normalize them, using a procedure permitting the values of all the indicators to belong to the closed interval [0,1] (Diaz-Balteiro et al., 2016). The sign that appears in the table refers to whether the indicators...
TABLE 1  Indicators finally chosen after normalization and correlation analysis

| Indicator                                      | Units                | Source | Type |
|------------------------------------------------|----------------------|--------|------|
| Domestic material consumption (wood fuel)      | Tonnes per capita    | EC     | +    |
| Generation of waste per capita (wood)          | Kilograms per capita | EUROSTAT| –   |
| Recycling packaging waste (wood)               | Rate                 | EUROSTAT| +   |
| Wood residues per wood production              | Rate                 | FAO    | –    |
| Export wood residues per wood residues production | Rate                   | FAO    | –    |
| Wood products (export/import)                  | Rate                 | FAO    | +    |

Note: "+": more is better; "-": less is better.

are of the type "more is better" (+) or "less is better" (−). Each type requires using a different formula for normalization, as shown in the following section. It is interpreted as: In an indicator of type "+", higher values would increase the circularity one, ceteris paribus. In contrast, if it was of the type "−", higher values would reduce the circularity one. Since one indicator (generation of waste per capita) was biannual and another began in 2007, the values normalized correspond to 2008, 2010, 2012, 2014, 2016, and 2018.

After the normalization process, and before applying any aggregation method to measure the circularity of the economy in the wood products industry, whether or not there was any correlation between them was investigated using a Pearson coefficient. After this filtering, the indicators finally selected appear in Table 1.

2.2 A methodology for determining a circularity ranking

Let us consider the following general scenario. There are \(i = 1, 2, \ldots, n\) countries to be evaluated according to \(j = 1, 2, \ldots, m\) circularity indicators. In this context, \(R_{ij}\) measures the outcome achieved by the \(i\)th country when it is evaluated according to the \(j\)th circularity indicator. The relative importance attached by an expert or by a panel of experts to the \(j\)th circularity indicator with respect to the others can be represented by parameter \(W_j\). The proposed model aims to have a general character so that parameters \(W_j\) have been incorporated to open it up to the possibility of discriminating the relative importance of the indicators considered. In short, \(W_j\) represents the preferential weight attached to the generic \(j\)th indicator. The problem posed lies in determining the ranking of the \(n\) countries in terms of circularity in the wood products industry, considering the plural perspective provided by the \(m\) indicators.

The first step in solving this problem consists of normalizing the values corresponding to the \(m\) circularity indicators. In fact, the circularity indicators \(R_{ij}\) are usually measured according to different units, and their absolute values are, in many cases, very different. In this situation, it does not make any sense to aggregate these values without a previous normalization process. The following normalization is usually implemented (El Gibari et al., 2021):

(a) When the indicator is of the type "more is better":

\[
\|R_{ij}\| = \frac{R_{ij} - \min_j (R_{ij})}{\max_j (R_{ij}) - \min_j (R_{ij})}
\]  \hspace{1cm} (1a)

(b) When the indicator is of the type "less is better":

\[
\|R_{ij}\| = \frac{\max_j (R_{ij}) - R_{ij}}{\max_j (R_{ij}) - \min_j (R_{ij})}
\]  \hspace{1cm} (1b)

Now, the new \(\|R_{ij}\|\) values given by Equation (1) have no dimension, since they represent percentages. It is also important to note that this process implies that all indicator values are now bound at between 0 and 1 (i.e., \(\|R_{ij}\| \in [0, 1]\)). In other words, the indicator takes value 1 when it achieves the maximum value (i.e., the ideal one) and takes value 0 when it achieves the minimum value (i.e., the anti-ideal one). In what follows, it will be seen that this way of normalizing is appropriate for undertaking the task proposed.

In order to calculate the ranking of the \(n\) units (countries), binary variables \(X_i\) are introduced into the analysis. It will be shown later that if \(X_i = 1\), the \(i\)th economic unit is chosen, otherwise \(X_i = 0\). It would seem sensible to minimize, for each economic unit (country), the distance (defined in a general sense) between the normalized outcome for each unit and the ideal vector of indicators (1,...,1) established. Being near the ideal is better than being far away from it. In other words, the shorter the distance to the ideal, the better the circularity aggregate index is. To address this task,
we propose the following binary compromise programming model (Yu, 1973; Zeleny, 1974):

\[
\min L_p = \left[ \sum_{j=1}^{m} W_j^p (1 - \|R_j\|) \right]^{1/p}
\]

Subject to
\[
\sum_{i=1}^{n} X_i = 1
\]
\[
X_i \in [0, 1] \quad \forall i
\]

(2)

where \( p \) is the metric, being a real number belonging to the interval \([1, \infty)\) or \(\infty\). It should be noted that, for each value of metric \( p \), a value for \( L_p \) is obtained, which implies that the distance function (2) represents a family of potential values for the measurement of the circularity of the \( i \)th country, and, consequently, its position in the respective ranking.

We shall now particularize expression (2) for three different situations that represent three rational orientations from a circularity perspective. Let us start, by making \( p = 1 \), then model (2) turns into the following linear binary programming formulation:

\[
\min L_1 = \left[ \sum_{j=1}^{m} W_j (1 - \|R_j\|) \right]
\]

Subject to
\[
\sum_{i=1}^{n} X_i = 1
\]
\[
X_i \in [0, 1] \quad \forall i
\]

(3)

In order to obtain the ranking of the \( n \) units, we need to solve model (3) \( n \) times, augmenting it in each iteration with an additional constraint like \( X_k = 0 \), when the \( k \)th economic unit is optimal. In this way, the ranking in terms of circularity of the \( n \) economic units considered is obtained. Given the linear structure of model (3), the computational burden implied by this strategy seems very acceptable.

It should be noted that model (3) implies calculating the sum of all the discrepancies with respect to the ideal values for the \( m \) indicators considered. If this figure is divided between the number of indicators considered (i.e., \( L_j/m \)), the average performance is procured, which takes into account the information provided by the \( m \) indicators. It should be noted that, by construction, the lower the value of \( L_1 \), the higher the position occupied by the \( i \)th country in the ranking. This approach is appealing, although it could imply a poor achievement for one of the indicators considered, which may be unacceptable in terms of the overall circularity criterion.

On the other hand, Yu (1973) demonstrated that increases in the value of metric \( p \) imply increases in the importance attached to the indicator most displaced with respect to the ideal value. In the limit, when \( p = \infty \), the discrepancy in the achievement of the ideal of the most displaced indicator defines the position of the respective economic unit in the ranking. In this way, this orientation might lead to a better balance among the achievement of the \( m \) indicators. The ranking corresponding to this orientation can be obtained by computing this new binary linear programming model (André & Romero, 2008):

\[
\min L_\infty = D_1
\]

Subject to:
\[
\max_i [W_i(1 - \|R_i\|)] X_1 + \max_j [W_j(1 - \|R_j\|)] X_2 + \cdots + \max_i [W_i(1 - \|R_i\|)] X_n - D_1 = 0
\]
\[
\sum_{i=1}^{n} X_i = 1
\]
\[
X_i \in [0, 1] \quad \forall i
\]

(4)

By applying the earlier-mentioned iterative procedure, the new ranking of the \( n \) countries is obtained. Again, by construction, the lower the value of \( L_\infty \), the higher the position occupied by the \( i \)th country in the ranking is. Summarizing, model (3) provides the ranking of the \( n \) countries from the point of view of the average performance, while model (4) provides the ranking from the perspective of optimizing the balance among the achievement of the \( m \) indicators.

Now the circularity ranking will be calculated following a seemingly different orientation. Thus, instead of making the calculations by minimizing the distance with respect to the ideal value, the distance with respect to the anti-ideal vector of indicators \((0,\ldots,0)\) will be maximized. Thus, to be as far away as possible from the anti-ideal would also seem to be a rational decision-making orientation. To address this task, the first step requires taking into account the following implication:

\[
\min \sum_{j=1}^{m} W_j (1 - \|R_j\|) = \max \sum_{j=1}^{m} W_j (\|R_j\| - 0) \forall j
\]

(5)

Hence, for metric \( p = 1 \), the same ranking is obtained by minimizing distances with respect to the ideal, which maximizes distances with respect to the anti-ideal. However, for \( p = \infty \), the best ranking from a balanced perspective might be different and can be obtained by formulating this new
By solving iteratively model (6), we obtain the ranking taking into account the maximization of the distance corresponding to the circularity indicator less displaced from the antiideal value.

In sum, by applying models (3), (4), and (6), three different rankings in terms of circularity can be obtained for the $n$ economic units considered, according to three different decision rules: Average achievement, balanced achievement in terms of proximity to the ideal, and balanced achievement in terms of remoteness with respect to the anti-ideal. These three decision rules and their respective rankings will be calculated for the case study in the following sections.

Furthermore, it would be worthwhile to determine rankings that combine the aspects considered up to now: Proximity with respect to the ideal value, remoteness with respect to the antiideal value, “average achievement,” and “balanced achievement.” In the Supporting Information available on the Journal’s website, an Extended Composite Programming formulation for coping efficiently with this combination of orientations is proposed.

### 2.3 Statistical models

Phase III of Figure 1 includes the statistical models used for explaining the possible causality behind the rankings obtained by employing the methodology described in the previous section. Logically, the first step in this direction would be to compile a set of explanatory variables for this purpose. Given that this analysis is aimed at a country level, data with this level of aggregation have been used, but some EU countries have been eliminated in this phase for the following reasons. First, some countries have no data for a particular variable; besides this, the scant importance represented by the wood chain in their industrial process justifies the noninclusion of some countries. In fact, for some variables, considering these types of countries would lead to the inclusion of too many outliers. To prevent this, it was proceeded to remove those countries whose employment of raw material (m³) was lesser for each one of the six years than 1% of the total EU. This has meant discarding nine countries: Croatia, Cyprus, Denmark, Estonia, Greece, Luxembourg, Malta, the Netherlands, and Slovenia. The other 19 countries deploy, for each year considered, over 95% of their wood production in the EU, so that, in principle, no generality is lost with the exclusion of those countries.

For these models, the numerical result reached by each country for each of the six years analyzed has been defined as a dependent variable. As explanatory variables, the widest set was initially considered, and those that were not contemplated as indicators in phase 2.1 were selected. The complete list of explanatory variables is shown in Table 2.

The first three variables attempt to define the importance of the wood products industry in each of the countries, in order to verify that they fulfill some initial conditions: The larger the sector, the higher the entrepreneurial production; and the higher the apparent consumption of wood per capita implies a stronger degree of circularity by those countries. Another variable from the FAO database has been included; the quotient between the wood products exported from a nation divided by the total production. Here the hypothesis is that countries with a stronger circularity would be inversely related to this variable (Üsas et al., 2021). Furthermore, two indicators related to research and innovation were computed. In this sense, it was assumed that the countries with a higher percentage of innovative firms related to the wood products industry were also more circular (Avdiushchenko & Zaja, 2019). In addition, and on the same lines, an indicator also measures, at a country level, research expenditure as a percentage of the GDP. Here, too, a positive relationship between expenditure and circularity has been assumed (Barbaritano et al., 2019).

Other variables at a country level have also been included. Some of them are associated with indexes habitually accepted for measuring certain environmental aspects. The first is the global competitiveness index, whereas the next two possess an environmental component: The ecological footprint and the environmental performance index (Wendling et al., 2020). It was assumed that the lower ecological footprint values (García-Bernabeu et al., 2020) and the higher values of the others would be related to a stronger circularity. The same relationship is expected with the following variable, also at the country level, that aims to measure the importance attached to the carbon storage in harvested wood products...
(Jarre et al., 2020; Lazaridou et al., 2021). Another variable would be the percentage represented by trade in the GDP of each country, which is assumed to have a negative relationship with the degree of circularity (Liu & Ramakrishna, 2021).

Another variable introduced reflects the environmental taxes levied in this sector, which has been used in other studies to go deeper into the circularity of some countries (Tantau et al., 2018). Following other authors, it would seem that these taxes are positively linked to circularity (Ghisellini et al., 2016). Finally, two more variables included are related to forest land at a country level: One has to do with the actual forest land, and the other with the area of forest plantations. Usually, from a circularity perspective, it has been assumed that the greater the endogenous supply available to a country, the lower its dependency on imports, and the higher its degree of circularity (Modak, 2021).

To test multicollinearity between the explanatory variables, the variance inflation factor (VIF) was calculated. The table below shows the estimated VIF values for the explanatory variables of our model. All the VIF values turned out to be below 5, indicating no significant multicollinearity problems in the selected model (James et al., 2017; Vittinghoff et al., 2012). Apart from the VIF analysis, a correlation analysis was conducted using the Pearson correlation coefficient. Both tables (S1, S2) have been added in Supporting Information.

With these variables, a panel data model with random effects was used to assess the influence of various indexes on the wood products industry circularity of the European countries chosen. Equation (7) shows the equation of the panel data model with random effects:

\[
y_{it} = \alpha + \beta' X_{it} + u_{it}
\]

\[
u_{it} = \mu_i + \nu_{it}
\]

where $\alpha$ is the intercept, $\beta'$ are the estimated coefficients, $X_{it}$ are the observable independent variables, $i$ is the individual dimension (country), and $t$ is the time dimension (year). $\mu_i$ are country-specific, time-invariant effects fixed over time, and $\nu_{it}$ is a time-varying random component.

The panel data model with random effects was selected based on various statistical tests for that type of model. To do so, three different models were run previously: The independently pooled panels model, fixed effects model, and random effects model. The Breusch–Pagan Lagrange Multiplier test was performed to decide between the independently pooled panel model and the random effects model. The null hypothesis in the test was that the variances across countries were zero. The Breusch–Pagan Lagrange Multiplier test showed evidence of significant differences across countries. Hence, a random effects model was suggested over the independently pooled panel model. Subsequently, the F Test for individual and/or time effects was conducted to compare the fixed effects and the independently pooled panel models. Since the $p$-value was < 0.05, the use of the
independently pooled panel model was discarded. Finally, a Hausman test was run to decide between the fixed effects model or the random effects model. The null hypothesis was that the model preferred was the random effects model vs. the fixed effects model (Green, 2008) by testing whether the unique errors \((u_i)\) were correlated with the regressors. As the \(p\)-value turned out to be nonsignificant, the null hypothesis was not rejected, and the random effects model was selected. Thus, that model was able to consider country variations as well as time-dependent ones, and eliminate biases from variables that are unobserved and change over time (Wooldridge, 2009).

3 | RESULTS

3.1 | Circularity rankings

Table 3 shows the results of the multicriteria model (see Equations (3), (4), and (6)), in which a ranking for the three possible solutions is proposed: the most efficient one, the most balanced one, and the one farthest away from the anti-ideal. Note that the higher the value appearing every year, the stronger the degree of circularity, 1 being the maximum. The results showed that Sweden had the strongest circularity in the wood products industry throughout the six years considered. In contrast, the Benelux countries were usually the least circular ones during the years analyzed, the same as the United Kingdom. Except for some countries, such as Estonia, the results were consistent throughout the years considered. Finally, the values provided for each country and year can trace the evolution of their circularity, which could be applied to design specific policies in each country.

3.2 | Statistical model

The explanatory variables of the model are as shown in Table 4: the ratio between the number of firms in the wood sector and the number of industrial companies, the ratio between wood products and exports, the global competitiveness index, the environmental performance index, the forest land area, research and development expenditure figure, and the trade indicator. Most estimated coefficients were significantly different from zero at the 10% level. The results suggest that the wood product ratio production/exports had the strongest effect and decreased the wood circularity index. To a lesser extent, the global competitiveness index and trade also tended to diminish wood circularity. Research and development expenditure had the strongest positive effect, followed by the forest land area, the ratio of the number of firms related to wood products industries to the number of enterprises in the manufacturing sector, and the environmental performance index.

4 | DISCUSSION

The multicriteria methodology proposed here has been a valuable tool for establishing a ranking of European countries for the wood products industry in terms of circularity. On the other hand, as shown in Table 3, the model results defined according to Equation (7) show a preponderance of Sweden over other countries. Although the indicators selected are not the same ones at an overall economy level, this result coincides with that reached by Skvarciany et al. (2021), in which in an analysis of CE in 32 OECD countries, Sweden was second after Japan, followed by, among the European countries, Finland and Denmark, which differs from the results obtained here.

On another note, it should be highlighted that the analysis covers a time horizon, which, a priori, could suggest some tendency associated with the performance of the countries in their relationship. As remarked earlier, the results are reasonably consistent in the rankings obtained. Except for some notable change in their placing (i.e., Estonia), that would merit special attention, the annual modifications in that ranking were minor. It would seem that no noteworthy event occurring in this period, such as the economic crisis that began in 2007 in the United States (Hansen & Juslin, 2018), has had any significant effect on those rankings. It is true that some indicators have undergone notable reductions, but the final circularity result in these countries has remained stable. This permits us to affirm that, at a country level, no changes in the strategy of these industries toward a greater circularity after a period of crisis have been detected.

Since the methodology employed here includes three types of solutions (average achievement, balanced achievement, and remoteness with respect to the anti-ideal values), it might be wondered what would happen when isolating the results separately for each one. Table 5 aims to answer this question.

Table 5 shows how there is always a single country that is the best each year in terms of wood products industry circularity for the first two solutions. However, for the third solution (remoteness with respect to the anti-ideal values), a set of countries (over five) reaching the best value always appears. It is also striking that only four different countries have reached the best value throughout the six years considered for the first two solutions.
## Table 3

Rankings obtained after applying multicriteria models

| Year | Rank | Value | Year | Rank | Value | Year | Rank | Value | Year | Rank | Value | Year | Rank | Value | Year | Rank | Value |
|------|------|-------|------|------|-------|------|------|-------|------|------|-------|------|------|-------|------|------|-------|
| 2008 | 1    | SWE   | 0.832| 2010 | 2    | DNK   | 0.646| 2012 | 3    | IRL   | 0.746| 2014 | 4    | SVK   | 0.723| 2016 | 5    | LTU   | 0.722|
|      |      |       |      |      |       |      |      |      |      |      |       |      |      |       |      |      |       |
|      | 6    | ESP   | 0.677| 2012 | 7    | DNK   | 0.669| 2014 | 8    | ITA   | 0.660| 2016 | 9    | ITA   | 0.660| 2018 | 10   | CYP   | 0.627|
|      |      |       |      |      |       |      |      |      |      |      |       |      |      |       |      |      |       |
|      | 11   | BGR   | 0.616| 2012 | 12   | CZE   | 0.610| 2014 | 13   | AUT   | 0.585| 2016 | 14   | POL   | 0.578| 2018 | 15   | LVA   | 0.561|
|      |      |       |      |      |       |      |      |      |      |      |       |      |      |       |      |      |       |
|      | 16   | ROU   | 0.527| 2012 | 17   | GBR   | 0.513| 2014 | 18   | FRA   | 0.497| 2016 | 19   | FIN   | 0.488| 2018 | 20   | LUX   | 0.476|
|      |      |       |      |      |       |      |      |      |      |      |       |      |      |       |      |      |       |
|      | 21   | GRC   | 0.459| 2012 | 22   | BEL   | 0.398| 2014 | 23   | MLT   | 0.378| 2016 | 24   | DEU   | 0.347| 2018 | 25   | SVN   | 0.345|
|      |      |       |      |      |       |      |      |      |      |      |       |      |      |       |      |      |       |
|      | 26   | HRV   | 0.321| 2012 | 27   | EST   | 0.316| 2014 | 28   | NLD   | 0.258|      |      |      |       |      |      |       |
|      |      |       |      |      |       |      |      |      |      |      |       |      |      |       |      |      |       |

Note: For a guide to the ISO 3-letter country code abbreviations used in this table and throughout this article, see [https://www.worlddata.info/countrycodes.php](https://www.worlddata.info/countrycodes.php).
Furthermore, one of the hypotheses implicit in this work is that, unlike other studies related to the wood-based industry (Diaz-Balteiro et al., 2011), or CE (Skvarciany et al., 2021), the same weight has been given to each indicator. That is, none of the different methods appearing in the literature either to elicit the weights or to aggregate them have been addressed (Diaz-Balteiro, Iglesias-Merchan, et al., 2020). Although, initially, it was contemplated to include a sensitivity analysis related to the idea of giving hypothetical weights to the indicators, this was not done, basically due to length constraints. A similar analysis could also have been made allocating, for example, different weights to each of the three solutions included in Equations (3), (4), and (6).

This study has identified a statistical model that could explain some determinants of the circularity associated with each country for the wood-based industry in Europe. Nevertheless, it is worth noting that this statistical model does not establish a ranking of countries based on their performance. This was done by the MCDM. Furthermore, despite all independent variables of the statistical model having a significant effect on the degree circularity, the proportion of its variation that was predictable from the independent variables turned out not to be relatively high. According to the used statistical measures (R-Squared: 0.249; Adj. R-Squared: 0.195), around 20% of the observed variation in the degree circularity of the wood-based industry could be explained by the selected independent variables.

On observing the results of the statistical models, it can be verified how two variables, a priori, would seem to have a negative relationship with circularity in the wood products industry as in the case of foreign trade. On the other hand, some significant variables in the statistical model, such as the weight of the wood sector within the wood products industry, R&D expenditure, as well the environmental performance index, have a positive sign, indicating that increases in these variables could entail intensifications in the circularity of these industries. It should be noted that variables referring to some famous aggregate indexes like the ecological footprint have not turned out to be significant. Also worth noting is that, in that model, no significant variables appear to explain the circularity of the consumption per capita of wood, neither the carbon capture made by wood-related products.

As mentioned previously, the links between circularity and sustainability have been widely accepted, both separately as well as within a bioeconomy context (Diaz-Balteiro, González-Pachón, et al., 2020; Kardung et al., 2021). Suppose it is intended to examine the issue as to whether the countries presenting a stronger circularity for the case of the wood industry are the most sustainable ones. In that case, there is not much information in this respect, except the study of Voces et al. (2012). Although that analysis is before 2008, the 14 indicators used for the 17 EU countries differ from those herein. These results show that, for the most efficient solution, Sweden is the second-most sustainable country, after Estonia. In this work, an econometric analysis was made to determine which independent variables could best explain the results reached, and some of them have also been included in this work. Comparing them, except for the Global Environment Index, there is no other significant variable to explain the sustainability and circularity of the wood products industry.

Possible weaknesses in this work could be the availability of data and the choice of indicators and explanatory variables, although the same happens with the SDGs (Adenle et al., 2020). In short, there is no corpus of indicators accepted univocally to define circularity. Some of the indicators need conceptual progress to provide their required usefulness. Specifically, it would be beneficial to have indicators that quantify the existing wood flows between the wood products industries at the country level. In addition, improved knowledge of wood chains could provide new explanatory

### TABLE 4  Results of the statistical model applied to explanatory variables

|                      | Estimate | Std. error | z-value | Pr(>|z|) | a  |
|----------------------|----------|------------|---------|----------|----|
| (Intercept)          | 0.553    | 0.090      | 6.147   | 0.000    | ***|
| Number of enterprises wood products industries/Number of enterprises manufacturing sector | 0.176    | 0.088      | 2.009   | 0.045    | ** |
| Wood products ratio production/exports | −1.204   | 0.389      | −3.095  | 0.002    | ***|
| Global Competitiveness Index | −0.350   | 0.127      | −2.748  | 0.006    | ***|
| Environmental Performance Index | 0.117    | 0.053      | 2.194   | 0.028    | ** |
| Forest land area     | 0.246    | 0.132      | 1.862   | 0.063    | *  |
| Research and development expenditure | 0.289    | 0.119      | 2.437   | 0.015    | ** |
| Trade                | −0.154   | 0.091      | −1.689  | 0.091    | *  |

Chi sq: 34.241 on 7 DF, p-value: 0.000***

R-Squared: 0.249
Adj. R-Squared: 0.195
### TABLE 5  Best countries regarding the three different multicriteria solutions

|       | 2008 | 2010 | 2012 | 2014 | 2016 | 2018 |
|-------|------|------|------|------|------|------|
|       | A    | B    | C    | A    | B    | C    |
| AUT   | X    |      |      |      |      |      |
| BEL   |      |      |      |      | X    |      |
| BGR   |      |      |      |      |      | X    |
| CYP   | X    |      |      | X    |      | X    |
| CZE   |      |      |      |      |      |      |
| DEU   |      |      |      |      |      |      |
| DNK   |      |      | X    |      |      | X    |
| ESP   |      |      |      |      |      |      |
| EST   |      |      |      |      |      |      |
| FIN   |      |      |      | X    |      | X    |
| FRA   |      |      |      |      |      |      |
| GBR   |      |      |      |      |      | X    |
| GRC   |      |      |      |      |      | X    |
| HRV   |      |      |      |      |      |      |
| HUN   |      |      |      |      |      | X    |
| IRL   |      |      |      |      |      |      |
| ITA   |      |      |      |      |      |      |
| LTU   |      |      |      |      |      |      |
| LUX   |      |      |      |      |      |      |
| LVA   |      |      |      |      |      |      |
| MLT   |      |      |      |      |      |      |
| NLD   |      |      |      |      |      |      |
| POL   |      |      |      |      |      |      |
| PRT   |      |      |      |      |      |      |
| ROU   |      |      |      |      |      |      |
| SVK   |      |      |      |      |      |      |
| SVN   |      |      |      |      |      |      |
| SWE   |      |      |      |      |      |      |

Notes: A: Solution with the average achievement; B: Solution with the balanced achievement; C: Solution with the remoteness with respect to the anti-ideal value.

variables, enriching and refining this study. Future research should also incorporate the opinions and preferences of the different stakeholders who have shown themselves to be of great use (Viholainen et al., 2021). Finally, this paper’s authors believe that the methodology presented here is sufficiently versatile to be applied to measuring circularity in other industries or sectors.

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**CONFLICT OF INTEREST**

The authors declare no conflict of interest.

**DATA AVAILABILITY STATEMENT**

These data were derived from the following resources available in the public domain: Domestic material consumption: [https://ec.europa.eu/eurostat/databrowser/view/ENV_AC_MFA_custom_1133009/default/table?lang=en](https://ec.europa.eu/eurostat/databrowser/view/ENV_AC_MFA_custom_1133009/default/table?lang=en)
Generation of municipal waste per capita: [https://ec.europa.eu/eurostat/databrowser/view/ENV_WASGEN_custom_1133049/default/table?lang=en](https://ec.europa.eu/eurostat/databrowser/view/ENV_WASGEN_custom_1133049/default/table?lang=en)

Recycling packaging waste: [https://ec.europa.eu/eurostat/databrowser/view/cei_wm020/default/table?lang=en](https://ec.europa.eu/eurostat/databrowser/view/cei_wm020/default/table?lang=en)

Recovered paper per capita. Recovered post consumer wood. Wood residues per wood production. Export wood residues per wood residues production. Forest products export/import: [http://www.fao.org/faostat/en/#data/FO http://www.fao.org/faostat/en/#data/FO/visualize](http://www.fao.org/faostat/en/#data/FO http://www.fao.org/faostat/en/#data/FO/visualize)

Persons employed manufacture wood products industries/Total persons manufacturing sector. Number of enterprises wood products industries/Number of enterprises manufacturing sector [https://ec.europa.eu/eurostat/databrowser/view/sbs_na_ind_r2/default/table?lang=en](https://ec.europa.eu/eurostat/databrowser/view/sbs_na_ind_r2/default/table?lang=en)

Annual production value per wood products industry enterprises [https://ec.europa.eu/eurostat/databrowser/view/for_sup_cp/default/table?lang=en](https://ec.europa.eu/eurostat/databrowser/view/for_sup_cp/default/table?lang=en)

Per capita wood consumption. Wood products ratio exports/production [http://www.fao.org/faostat/en/#data/FO](http://www.fao.org/faostat/en/#data/FO)

% Innovative enterprises in wood products industry [https://ec.europa.eu/eurostat/databrowser/view/inn_cis9_prod/default/table?lang=en](https://ec.europa.eu/eurostat/databrowser/view/inn_cis9_prod/default/table?lang=en)

Research and development expenditure [https://databank.worldbank.org/reports.aspx?source=2&series=GB.XPD.RSDV.GD.ZS&country](https://databank.worldbank.org/reports.aspx?source=2&series=GB.XPD.RSDV.GD.ZS&country)

Global Competitiveness Index [https://tcdata360.worldbank.org/indicators/gci?country=BRA&indicator=632&viz=line_chart&years=2007,2017](https://tcdata360.worldbank.org/indicators/gci?country=BRA&indicator=632&viz=line_chart&years=2007,2017)

Trade [https://tcdata360.worldbank.org/subtopics/trade?country=BRA](https://tcdata360.worldbank.org/subtopics/trade?country=BRA)

Ecological Footprint [https://data.footprintnetwork.org/#/compareCountries?type=EFCpc&cn=11&yr=2008](https://data.footprintnetwork.org/#/compareCountries?type=EFCpc&cn=11&yr=2008)

Environmental Performance Index [https://sedac.ciesin.columbia.edu/data/set/epi-environmental-performance-index-2018/data-download](https://sedac.ciesin.columbia.edu/data/set/epi-environmental-performance-index-2018/data-download)

Carbon capture HWP/Total country industry emissions [https://www.eea.europa.eu/data-and-maps/data/national-emissions-reported-to-the-unfccc-and-to-the-eu-greenhouse-gas-monitoring-mechanism-17](https://www.eea.europa.eu/data-and-maps/data/national-emissions-reported-to-the-unfccc-and-to-the-eu-greenhouse-gas-monitoring-mechanism-17)

Environmental Taxes Wood products industry/Total manufacturing environmental taxes [https://ec.europa.eu/eurostat/databrowser/view/ven_ac_taxind2/default/table?lang=en](https://ec.europa.eu/eurostat/databrowser/view/ven_ac_taxind2/default/table?lang=en)

Forest land area. Planted forest area [http://www.fao.org/faostat/en/#data/LC](http://www.fao.org/faostat/en/#data/LC)

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