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Green Efficiency and Productivity Change in Wood Waste Utilization Across EU Countries: A Directional Distance Function Approach

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Abstract

Efficient wood waste utilization supports the circular bioeconomy, but comparative evidence on national treatment systems remains limited. This study benchmarks 21 EU member states using radial and non-radial directional distance functions (DDFs), distinguishing pathway-specific adjustment potential. Eurostat data cover seven biennial reporting years from 2010 to 2022 (147 observations). Domestic wood waste generation is the input; material and energy recovery are desirable outputs; landfilling and incineration without energy recovery constitute the undesirable output. Productivity is assessed using a radial Global Malmquist–Luenberger index and an additive non-radial Luenberger indicator. Poland, Germany and France are closest to the non-radial frontier. Spain and Portugal show the largest baseline non-radial scores, dominated by proportional energy-recovery adjustments. Input adjustments are zero in the estimated solutions, but this does not establish independence from waste volume; across the 21 country averages, the association is negative and borderline non-significant at the 5% level (Spearman $\rho = -0.43$, $p = 0.051$); the observation-level association ($\rho = -0.27$, $p = 0.001$; n = 147) is not independent because it involves repeated observations within countries. Rankings remain similar under an aggregate treatment-volume cap ($\rho = 0.96$). A generation-normalized direction removes the extreme values and shifts the dominant adjustment towards material recovery. Results identify specification-dependent benchmark gaps rather than physically attainable targets or causal policy prescriptions, supporting pathway-specific monitoring alongside assessments of waste quality and environmental impacts.

Keywords: circular bioeconomy; wood waste management; DEA; directional distance function; efficiency; Malmquist–Luenberger Index

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1. Introduction

The bioeconomy is an inherently multidimensional concept. Early interpretations emphasized the contribution of genetics and molecular biology to industrial development [1], whereas later approaches distinguish visions based on biotechnology, bio-resources, and

bio-ecology [2] and stress that no single definition captures its interconnected dimensions of sustainability, circularity, renewability, and resource efficiency [3]. Resource efficiency is particularly important in the forest-based sectors, where renewable biological resources must satisfy competing material and energy demands. The management and valorization of forestry and wood-processing residues have therefore become central to the transition towards a circular bioeconomy, and bio-residual streams from the forestry sector are increasingly regarded as valuable secondary resources [4].

The utilization of wood waste generated by the woodworking and furniture industries has received increasing scientific attention. Pinho et al. [5], combining Life Cycle Assessment, SWOT analysis, and circularity indicators [6–8], identified complementary pathways for improving wood waste utilization: cascading use that preserves material value for as long as possible [9–11], industrial symbiosis networks for exchanging secondary resources [12–14], and efficient markets for recovered wood [15]. In a systematic review, Korba et al. [16] identified persistent barriers to these pathways, including limited technological development, inconsistent waste wood classification, and insufficient use of Life Cycle Assessment (LCA) and Life Cycle Costing (LCC). Subsequent studies address several of these barriers. Elginoz et al. [17] showed for Sweden that the sustainability of wood waste utilization depends not only on the quantity recovered but also on the recovery technology and its system-level impacts; Mancini et al. [18] demonstrated that multivariate classification can assign waste wood categories to suitable reuse or recovery pathways; and Zucaro et al. [19] found for the Bulgarian wood supply chain that the benefits of substituting fossil-based products with bio-based alternatives generally exceed the burdens of producing them.

Despite this potential, the wood waste chain remains comparatively underdeveloped in terms of circularity, mainly because of limited industrial symbiosis, insufficient collaboration among enterprises, and weak resource-sharing networks [4]. Increasing circularity does not necessarily require substantial additional costs: cascading use and recycling can improve resource efficiency and generate economic value at the same time [20]. Energy recovery is an important pathway for residues that are technically or economically unsuitable for material recovery [21–24], but, in accordance with cascading-use principles, material applications should generally precede final energy recovery [9,25,26]. As both a major consumer of wood and an important generator of secondary materials and residues, the wood-processing industry occupies a central position in this transition [27–30]. Together, these findings highlight the strategic importance of integrating cascading use, material recovery, industrial symbiosis, and appropriate final energy recovery within circular economy strategies for wood waste management.

What this literature does not provide is a comparative assessment of how efficiently national systems convert the wood waste available to them into material recovery, energy recovery, and disposal. Existing studies concentrate on individual countries, specific waste streams, or particular technologies, and benchmarking methods such as Data Envelopment Analysis (DEA) have received little attention in this field. This gap matters at the national level, where differences in waste generation, recovery infrastructure, and utilization patterns lead to markedly different performance and where waste policy is implemented. DEA-based benchmarking can identify the countries operating closest to the observed efficiency frontier, quantify the improvement potential of less efficient systems, and reveal whether inefficiency arises from the scale of available resources or from their allocation among competing utilization pathways.

Much of the existing research relies on Life Cycle Assessment (LCA) and related process-level approaches, which evaluate specific products, technologies, or treatment pathways against predefined reference systems. These methods are not designed to benchmark

multiple national systems or to identify the best observed performance within a heterogeneous sample. DEA provides a complementary perspective: it constructs an empirical efficiency frontier directly from observed data, so that countries differing substantially in waste volumes, treatment structures, and technological conditions can be evaluated relative to the best-performing systems in the sample. Directional Distance Functions (DDFs) are particularly suited to this purpose because they accommodate desirable and undesirable outputs simultaneously. Against this background, the present study contributes to the existing literature in three principal ways. First, it applies a non-radial DDF specification alongside the conventional radial approach, enabling aggregate efficiency estimates to be decomposed into pathway-specific adjustment requirements for material recovery, energy recovery, and undesirable disposal outputs. This comparison reveals whether proportional efficiency measures conceal structural differences among individual waste utilization pathways. Second, the study extends the static assessment of efficiency into the temporal dimension through the Global Malmquist–Luenberger productivity framework, allowing productivity change to be decomposed into efficiency change and best-practice-gap change. Third, it provides a systematic cross-country comparison of national wood waste utilization systems across 21 EU member states, addressing a gap in the literature that has largely focused on individual countries, specific waste streams, or particular recovery technologies. In practical terms, the pathway-specific results indicate, for each country, which recovery route offers the largest model-implied improvement and thus provide an evidence base for targeting national measures under the EU waste hierarchy.

Accordingly, the aim of the present research was to investigate, evaluate, and compare the green efficiency of wood waste utilization across 21 EU member states over the period 2010–2022 using a DEA framework based on radial and non-radial DDF, and to examine changes in productivity over time through the Global Malmquist–Luenberger framework. Specifically, the study addresses three research questions: (1) Which countries operate closest to the best-practice efficiency frontier, and which wood waste utilization pathways account for the observed differences in efficiency? (2) Where inefficiency occurs, is it primarily associated with the volume of available wood waste or with its distribution among material recovery, energy recovery, and undesirable disposal pathways? (3) How do productivity dynamics differ between radial and non-radial specifications, and what do these differences reveal about the evolution of wood waste utilization efficiency and its implications for the European circular bioeconomy?

2. Materials and Methods

2.1. Directional Distance Functions

DEA framework is widely applied in evaluating performance within the circular economy and waste management sectors. Milanović et al. [31] proposed a methodology for constructing a Waste Management Composite Index using DEA. Their approach reflected a typical eco-efficiency framework by distinguishing between desirable outputs, such as recycling and cascading use of materials, and undesirable outputs, including landfilling and unsorted waste [32]. This classification enables a more nuanced assessment of environmental and operational efficiency in line with circular economy principles. Halkos and Petrou [33] estimated the environmental efficiency of the EU 28 member states using classical (radial) DEA CCR and BCC models as well as bootstrapping procedure for efficiency scores bias during the estimation. Their analysis employed output-oriented models aimed at maximizing desirable outputs. In a different context, Yang and Li [34] applied the SBM DEA model to assess the efficiency of waste gas control across various industrial sectors in China, demonstrating the flexibility of the DEA framework in addressing sector-specific environmental performance. Giannakitsidou et al. [35] ranked the European

countries on the basis of their environmental and circular economy performance. The authors implemented weighted DEA with common weights. They used Municipal Solid Waste (MSW) generated, basic human needs and foundations of wellbeing opportunity as inputs, and recycling rate of MSW and circular material use rate as outputs. Studies such as those by Robaina et al. [36], Marques and Teixeira [37], and Horvat et al. [38] employed a wide range of input variables in their DEA models, including capital investment, labor employed, energy consumption, and value added. While input selection varies across studies, a notable commonality lies in their choice of output variables. Most of these studies utilized indicators such as the recycling rate, circular material use rate, and gross domestic product (GDP) to capture performance in relation to circular economy objectives. Zhang and Xu [39] used DEA for evaluating forest enterprises' efficiency with environmental variables included for eco-efficiency estimation. This approach was also adopted by several other authors, including Alizadeh et al. [40] and Tan et al. [41], particularly in studies focused on recycling and the use of renewable materials.

This study employs a nonparametric Data Envelopment Analysis (DEA) framework extended with Directional Distance Functions (DDFs) [42–44] to evaluate the efficiency of wood waste utilization systems. DDF-based models are particularly suitable for environmental and green-efficiency assessments because they can simultaneously account for desirable and undesirable outputs and define an explicit direction of performance improvement [45,46]. Specifically, the approach allows desirable outputs to be expanded while inputs and undesirable outputs are contracted, thereby representing improvements in resource utilization and environmental performance within a unified analytical framework. Introduced by Chambers et al. [47,48], the DDF generalizes conventional distance-function approaches by measuring the maximum feasible movement of a decision-making unit towards the efficient frontier along a specified direction vector. In the present study, this property enables wood waste utilization efficiency to be assessed by considering available wood waste as an input, material and energy recovery as desirable outputs, and disposal and incineration without energy recovery as undesirable outputs. In accordance with [42–44,47,48], the DDF is expressed as follows:

$$\vec{D}(x, y, b, g) = \sup \{\beta : ((x, y, b) + \beta \times g) \in T\} \quad (1)$$

where x is the vector of inputs, y is the vector of desirable outputs, and b is the vector of undesirable outputs. g = (−gx, gy, −gb), with gx, gy, gb ≥ 0, denotes the direction vector, which specifies the direction in which inputs and undesirable outputs are contracted and desirable outputs are expanded. The direction vector therefore defines the improvement path along which a DMU (Decision-Making Unit) moves toward the technological frontier. β is the scalar that represents the common proportional movement of inputs and outputs toward the frontier under the radial specification. T denotes the technology set, which is also referred to in the literature as the production possibility set P [49].

The specification of model (1) assumes proportional changes in inputs and outputs. This approach is useful for business analysis and policy-making purposes because of its simplicity, but it does not allow for individual adjustments to each input and output. For this reason, the DEA literature also provides non-radial DDF models, which include separate scalars for the adjustment of each input and output independently [50–53]. The non-radial directional distance function model is presented in Equation (2) [52,53].

$$\vec{DDF}(x, y, b, g) = \sup \left\{ w^t \beta : ((x, y, b) + g \times diag(\beta)) \in T \right\} \quad (2)$$

where w = (wx, wy, wb) is the vector of weights assigned to the inputs, desirable outputs, and undesirable outputs, and β = (βx, βy, βb) ≥ 0 is the vector of individual adjustment

factors for the inputs, desirable outputs, and undesirable outputs, respectively; the signs of the adjustments are carried by the direction vector g = (−gx, gy, −gb), as in Equation (1).

The selection of variables defining the inputs and outputs of the DDF is crucial for model consistency and the validity of the results. This study adopts the widely accepted hierarchy of waste-management options established by the Waste Framework Directive 2008/98/EC (WFD) [54]. The hierarchy ranks waste-management options from most to least preferable. Prevention is the preferred option, whereas landfilling and incineration without energy recovery are the least preferable [46]. Reuse, recycling, and energy recovery lie between these extremes. Accordingly, the following variables were selected for the DDF model:

- Input: Wood waste generated within each country (DMU), denoted as STOCK. Unlike conventional waste-management DEA studies where waste generation is treated as an undesirable output, the present study focuses on the efficiency of waste utilization systems conditional on the generated quantity of waste. Wood waste generation is used as the quantity-based input proxy for national treatment activity; STOCK is retained solely as the variable name and does not denote a measured physical inventory. The generation input is measured by the total quantity of wood waste generated in the country by all economic activities and households, as reported by Eurostat. Cross-border shipments of wood waste are not included in this measure, because they are not reported at the same level of detail; the generation input therefore approximates, and does not exactly equal, the quantity available for treatment within the national system. Although waste generation is commonly modeled as an undesirable output in DEA-based studies, it is specified here as an input for two reasons. First, treating generation as an undesirable output would implicitly penalize countries with larger wood-processing and furniture industries simply for generating more residual material, even where that material is subsequently recovered at a high rate; specifying it as an input instead conditions the efficiency score on domestic generation, so that a country is evaluated on its treatment outputs relative to domestic generation rather than on generation volume alone. Second, the desirable and undesirable outputs already describe the destination of the treated volume, so classifying the generation input as an additional undesirable output would change the interpretation from treatment performance conditional on generation to joint generation-and-treatment performance. It should be noted that the generated quantity and the treated quantities are different concepts and come from different Eurostat datasets: the generation input is the quantity of wood waste generated in the country, whereas DO1, DO2, and UO are the quantities treated in the country, which include imported waste and exclude exported waste and may also differ from generation because of storage and differences in reporting scope. The two do not coincide; across the 147 observations, the ratio of generation to total treated quantity has a median of 1.23 and ranges from 0.39 to 7.37. In the estimated models, the adjustment factor for the generation input is zero for all observations (Section 3.1). This is an outcome of the optimization and not, in itself, evidence that inefficiency is unrelated to waste volume; the relationship with volume is therefore examined separately in Section 3.1.
- Desirable Output 1 (DO1): Material recovery (Recycling and backfilling). Recycling corresponds to a higher level in the waste management hierarchy, while backfilling is positioned lower as a form of recovery [15]. These pathways are aggregated into a single desirable output representing material recovery, following the joint Eurostat category “recovery—recycling and backfilling”. The aggregation has little effect on the results because backfilling of wood waste is marginal: at EU level it amounted to at most about 30 thousand tonnes per reporting year and declined to zero by

2022 [55], compared with 17–22 million tonnes of material recovery per year in the 21 countries analysed. A separate backfilling output would therefore be zero or close to zero for almost all countries, which the baseline observed-output direction cannot accommodate. Differences in wood waste quality and contamination are not recorded in these statistics and are not taken into account; the model-implied adjustments therefore indicate potential relative to observed best practice and not the technically feasible reallocation of specific waste fractions (see Section 5). They contribute to reducing environmental impacts and enhancing the domestic supply capacity of wood resources.

- Desirable Output 2 (DO2): Energy recovery represents the second desirable output. It constitutes a lower-tier circular economy pathway that reduces reliance on landfill disposal [56].
- Landfill disposal. This variable represents the first component of the undesirable output, capturing the amount of wood waste directed to landfill. Landfilling is widely recognized as a significant source of greenhouse gas (GHG) emissions, making it an environmentally burdensome disposal pathway relative to material and energy recovery [25].
- Incineration without energy recovery. This variable represents the second component of the undesirable output and captures the quantity of wood waste subjected to incineration without energy recovery. This disposal pathway is associated with substantial environmental concerns related to combustion emissions [17].
- Common undesirable output (UO). The common undesirable output is constructed by aggregating landfill disposal and incineration without energy recovery, representing total environmentally harmful waste treatment. This aggregation was necessary to avoid zero values in the DDF models: because of differences in technology or in reporting practices, many countries report a zero value for one of the two individual undesirable outputs.

The wood waste utilization system for each country included in the analysis is presented in Figure 1.

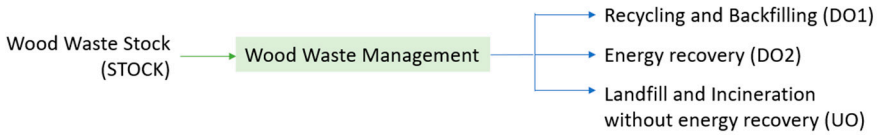


Figure 1. Conceptual framework of wood waste management as a system generating utilization efficiency.

Figure 1 presents each country included in the study as a wood waste management system. Domestic generation is used as the input proxy, and quantities treated nationally are represented by material recovery, energy recovery and disposal. Generation is a flow, not a physical inventory, and need not equal total national treatment because of trade, storage and reporting differences. The framework compares treatment outputs conditional on generation; it does not establish independence from generation volume. Inefficiencies arise when a country allocates excessive quantities of wood waste to less desirable treatment pathways or underutilizes recovery options compared to the best-performing countries that define the efficiency frontier. These benchmark countries represent the observed best practices within the sample and establish the reference levels for efficient waste utilization. Although countries differ substantially in terms of technologies, institutional frameworks, management practices, and historical development of their waste sectors, all of them face the common challenge of utilizing wood waste as an economic resource. Consequently, directing larger shares of wood waste toward the lower levels of the waste hierarchy,

particularly disposal and incineration without energy recovery, results in lower resource efficiency and increased environmental impacts. In contrast, greater utilization through material recovery and energy recovery contributes to improved system performance and supports the transition toward a more circular economy.

To account for technological changes over time and associated shifts in the production frontier, this study applies a global (non-contemporaneous) model [57]. The global specification provides a common benchmark for intertemporal comparison and helps avoid large fluctuations in efficiency scores that may arise from period-specific frontier adjustments [45]. A sequential technology assumption may also lead to infeasibility problems. Using a production frontier constructed from observations over the entire study period therefore provides a persistent benchmark and ensures consistency with the productivity analysis. Accordingly, models (1) and (2) are reformulated as the global models in Equations (3) and (4), which evaluate each observation against the best technology observed over the full period rather than only against the frontier for the corresponding year. Variable returns to scale (VRS) are assumed because EU countries differ substantially in economic size, waste-generation capacity, and waste-treatment infrastructure. The models follow a non-oriented framework, allowing simultaneous reductions in undesirable outputs and increases in desirable outputs. Each country is treated as a decision-making unit (DMU), giving 21 DMUs in the analysis.

For the radial model:

$$\begin{aligned}
&\overrightarrow{DDF}^{G}(STOCK, DO1, DO2, UO, g) = \max \beta \\
&\quad \text{s.t.} \ \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t STOCK_j^t \le STOCK_o^t - \beta g_{STOCK,O}^t \\
&\quad \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t DO1_j^t \ge DO1_o^t + \beta g_{DO1,O}^t \\
&\quad \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t DO2_j^t \ge DO2_o^t + \beta g_{DO2,O}^t \\
&\quad \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t UO_j^t = UO_o^t - \beta g_{UO,O}^t \\
&\quad \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t = 1
\end{aligned} \tag{3}$$

For the non-radial model:

$$\begin{aligned}
&\overrightarrow{NDDF}^{G}(STOCK, DO1, DO2, UO, g) = \max(\beta_{STOCK} + \gamma_{DO1} + \gamma_{DO2} + \alpha_{UO}) \\
&\quad \text{s.t.} \ \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t STOCK_j^t \le STOCK_o^t - \beta_{STOCK} g_{STOCK,O}^t \\
&\quad \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t DO1_j^t \ge DO1_o^t + \gamma_{DO1} g_{DO1,O}^t \\
&\quad \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t DO2_j^t \ge DO2_o^t + \gamma_{DO2} g_{DO2,O}^t \\
&\quad \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t UO_j^t = UO_o^t - \alpha_{UO} g_{UO,O}^t \\
&\quad \sum_{t=1}^{T}\sum_{j=1}^{N} \lambda_j^t = 1 \\
&\quad \beta_{STOCK}, \gamma_{DO1}, \gamma_{DO2}, \alpha_{UO}, \lambda_j^t \ge 0
\end{aligned} \tag{4}$$

where λjt denotes the intensity variable associated with DMU j in period t and defines the convex combination of benchmark observations. The left-hand side of the constraints represents the global technology set constructed from observations over the full study period. The right-hand side contains the input and output adjustments for the DMU under evaluation (subscript o): βSTOCK, γDO1, γDO2, and αUO in the non-radial model, and the common scalar β in the radial model. Equal weights are used because no prior theoretical basis exists for assigning different weights to the individual components. For the same reason, the direction vector g is defined using the observed values of each DMU [45,46,52].

A DMU is green efficient when NDDF = 0; positive NDDF values indicate model-implied adjustment requirements in one or more inputs or outputs.

For reproducibility, the specification is summarized as follows. The global technology set is $T = \{(x, y, b): \Sigma\lambda x \leq x, \Sigma\lambda y \geq y, \Sigma\lambda b = b, \Sigma\lambda = 1, \lambda \geq 0\}$, where the sums run over all 147 observations. Inputs and desirable outputs are thus strongly (freely) disposable, the undesirable output is weakly disposable (equality constraint), and returns to scale are variable. In Models (3) and (4), gSTOCK, gDO1, gDO2 and gUO denote the non-negative magnitudes of the direction components, and the signs are written explicitly in the constraints: the evaluated point is moved to (STOCK—βgSTOCK, DO1 + βgDO1, DO2 + βgDO2, UO—βgUO). The magnitudes are set equal to the observed values of the DMU under assessment (gSTOCK = STOCK, gDO1 = DO1, gDO2 = DO2, gUO = UO), which corresponds to the signed direction vector g = (−STOCK, DO1, DO2, −UO), so that β in the radial model and βSTOCK, γDO1, γDO2 and αUO in the non-radial model are proportional adjustment factors and the scores are independent of the units of measurement. The objective of the radial model is the common factor β; the objective of the non-radial model is the unweighted sum of the four factors. STOCK is a discretionary input: its adjustment factor is free and carries the same weight as the other factors. All variables enter in tonnes, without normalization or transformation. In the radial model, the common adjustment factor and all reference intensities are constrained to be non-negative.

2.2. Global Malmquist–Luenberger Productivity Index and Non-Radial Luenberger Indicator

After obtaining the efficiency scores reported in Section 3.1, the productivity measures are specified as follows; the details are needed to reproduce the results in Section 3.3. Two technologies are used: the global technology, constructed from all 147 observations, and the contemporaneous technology of each reporting year, constructed from the 21 observations of that year. Both are estimated under constant returns to scale, i.e., as in Models (3) and (4) but without the convexity constraint Σλ = 1, with weak disposability of the undesirable output. This differs from the efficiency scores in Section 3.1, which are estimated under variable returns to scale; constant returns are used here because productivity measures are conventionally defined relative to a benchmark technology with constant returns. For the radial index, the signed direction vector is g = (0, DO1, DO2, −UO), following Chung et al. [58]: desirable outputs are expanded and the undesirable output is contracted at a given generation input. For the non-radial indicator, the same direction is used, g = (0, DO1, DO2, −UO), with a separate adjustment factor for each of the three outputs and equal weights; the generation input is thus held fixed in both productivity measures. Both measures were estimated with the gtfpch command [59].

The Malmquist productivity index is widely applied within DEA to evaluate changes in productivity over time [60]. Its conceptual foundations originate from the work of Malmquist [61], who introduced a distance-based approach for comparing relative performance between different periods. Building on this concept, Caves, Christensen, and Diewert [62] developed a productivity-index framework based on distance functions, thereby establishing the theoretical foundation for what became known as the Malmquist productivity index. This approach enables changes in productivity between consecutive periods to be assessed without requiring explicit assumptions about the functional form of the underlying production technology.

Färe et al. [63] subsequently operationalized the Malmquist productivity index within the DEA framework, enabling productivity changes in individual DMUs to be evaluated over time relative to an empirically constructed production frontier. Chung, Färe, and Grosskopf [58] further extended this framework by incorporating undesirable outputs through DDF, leading to the development of the Malmquist–Luenberger (ML) productivity

index. This extension made the approach particularly suitable for environmental and green-efficiency assessments, in which improvements in desirable outputs must be considered simultaneously with reductions in environmentally undesirable outputs. The ML framework has since been widely applied to productivity and environmental-efficiency analyses across various sectors, including aquaculture [64], agriculture [65], and forestry [66], as well as broader productivity-theory and environmental-economics applications [67,68]. Oh [69] subsequently proposed the Global Malmquist–Luenberger (GML) productivity index, which evaluates observations against a global technology set constructed from the entire study period. This formulation improves intertemporal comparability and addresses the potential infeasibility and circularity problems associated with conventional period-specific ML indices. The GML index is given in Equation (5).

$$GML_o^{t,t+1} = \frac{1 + \overrightarrow{DDF}^{G}(t)}{1 + \overrightarrow{DDF}^{G}(t+1)} \tag{5}$$

where $\overrightarrow{DDF}^{G}$ denotes the global directional distance function evaluated against the global technology specified above, and (t) and (t+1) abbreviate its evaluation at the observed vector (STOCK, DO1, DO2, UO; g) of DMU o in periods t and t+1. The index can be decomposed into efficiency change (EC) and best-practice gap (BPG) change (BPC).

$$GML_o^{t,t+1} = EC_o^{t,t+1} \cdot BPC_o^{t,t+1} \tag{6}$$

The efficiency change (EC) component captures the variation in the relative distance of a decision-making unit (DMU) to the contemporaneous production frontier. It reflects movements toward or away from the frontier over time, thereby indicating improvements or deteriorations in relative efficiency. The EC is estimated through Equation (7).

$$EC_o^{t,t+1} = \frac{1 + \overrightarrow{DDF}^{t}(t)}{1 + \overrightarrow{DDF}^{t+1}(t+1)} \tag{7}$$

where $\overrightarrow{DDF}^{t}$ and $\overrightarrow{DDF}^{t+1}$ denote the contemporaneous directional distance functions in years t and t+1.

The best-practice-gap change (BPC) captures changes in the gap between the contemporaneous (period-specific) frontier and the global best-practice frontier between periods t and t+1. In conventional non-global Malmquist–Luenberger formulations, related frontier-shift effects are commonly described as technological change (TC); however, in the global framework used here, the term best-practice-gap change is retained throughout to avoid conflating the two concepts. BPC therefore indicates whether the contemporaneous frontier moves closer to or farther from the global benchmark. The best-practice-gap change is estimated using Equation (8).

$$BPC_o^{t,t+1} = \frac{BPG_o^{t+1}}{BPG_o^{t}} = \frac{\left(1 + \overrightarrow{DDF}^{t+1}(t+1)\right) / \left(1 + \overrightarrow{DDF}^{G}(t+1)\right)}{\left(1 + \overrightarrow{DDF}^{t}(t)\right) / \left(1 + \overrightarrow{DDF}^{G}(t)\right)} \tag{8}$$

Equations (5)–(8) apply to the radial model. Its results are therefore reported as a multiplicative index: values above (below) unity indicate productivity improvement (decline), and GML = EC × BPC. For the non-radial model, the distance function is a sum of pathway-specific adjustment factors, so a ratio-based index is not appropriate, and

productivity change is measured instead by the additive global Luenberger productivity indicator based on the non-radial DDF (NL) [70,71], given in Equations (9)–(11).

$$NL_o^{t,t+1} = \vec{NDDF}^{G}(t) - \vec{NDDF}^{G}(t+1) \quad (9)$$

$$EC_o^{t,t+1} = \vec{NDDF}^{t}(t) - \vec{NDDF}^{t+1}(t+1) \quad (10)$$

$$BPC_o^{t,t+1} = \left[\vec{NDDF}^{G}(t) - \vec{NDDF}^{t}(t)\right] - \left[\vec{NDDF}^{G}(t+1) - \vec{NDDF}^{t+1}(t+1)\right] \quad (11)$$

so that NL = EC + BPC. For this indicator, a value of zero indicates no change, positive values indicate improvement and negative values indicate decline; the same reading applies to its EC and BPC components. Because the indicator is a difference between NDDF scores, which are unbounded for the desirable outputs under the direction vector used, its magnitude is not comparable with that of the radial index, and large absolute values arise when the non-radial inefficiency score of a country changes sharply between two periods. No transformation was applied to either measure. The relationships between the distance functions and the productivity measures at zero are as follows. A DMU with DDF = 0 (NDDF = 0) lies on the corresponding frontier. If it lies on the global frontier in both periods, GML = 1 and NL = 0. If it lies on the contemporaneous frontier in both periods, EC = 1 in the radial and EC = 0 in the non-radial model, and any productivity change is attributed entirely to BPC, as is the case for Poland. Equations (5)–(8) are mutually consistent in that EC × BPC reproduces Equation (5) exactly, and Equations (9)–(11) in that EC + BPC reproduces Equation (9). Because of the differences in returns to scale and in the direction vector, the productivity changes in Section 3.3 are not simple differences between the underlying efficiency scores, andcountries that are efficient under variable returns to scale may still record non-zero productivity change.

2.3. Data and Variables

The empirical analysis is based on harmonized panel data obtained from Eurostat for EU member states over the period 2010–2022. The dataset comprises seven biennial reporting years (2010, 2012, 2014, 2016, 2018, 2020, and 2022), providing a consistent basis for cross-country efficiency benchmarking and intertemporal productivity analysis. The data cover wood waste generation (dataset env_wasgen, all NACE activities plus households) [72] and waste-treatment operations (dataset env_wastrt) [55]. All series refer to the waste category "wood wastes" (W075), hazardous and non-hazardous combined, and are expressed in tonnes. Waste statistics are collected every second year under Regulation (EC) No 2150/2002, so the seven reporting years are the original observations and no temporal aggregation was performed. Wood wastes in this classification comprise wood packaging, sawdust, shavings, cuttings and bark from wood processing and from pulp, paper and furniture production, wood from construction and demolition, and separately collected wood from municipal waste; the hazardous fraction consists of wood containing dangerous substances.

The statistics do not distinguish these fractions further. The treatment operations are energy recovery (R1), recycling and backfilling (R2–R11), landfill (D1, D5, D12), and incineration without energy recovery (D10); the undesirable output is the sum of the last two. Specifically, the variables include total wood waste generation, material recovery (recycling and backfilling), energy recovery, disposal through landfilling and incineration without energy recovery. Country selection followed a two-stage procedure. First, the analysis was restricted to EU member states to improve institutional and regulatory comparability within the common European framework for waste management and circular-economy

policy. Second, only countries with sufficiently complete and consistent observations for all model variables across the study period were retained, thereby allowing construction of a balanced and comparable panel for DEA estimation and productivity analysis. Countries for which the Eurostat series did not provide a complete set of strictly positive observations for all model variables across the seven reporting years were excluded. This resulted in the exclusion of Austria, Cyprus, Latvia, Luxembourg, Malta, and Sweden For Austria and Sweden, values are confidential: energy recovery and incineration in Austria from 2014 onwards, and generation, energy recovery, and landfilling in Sweden in 2022. Cyprus, Luxembourg, and Malta report zero values for at least one model variable in several years: energy recovery (2012, 2014) and disposal (2020, 2022) in Cyprus, disposal in all years in Luxembourg, and energy recovery in all years in Malta. Latvia reports zero energy recovery in 2022.

Under the baseline non-radial specification, a zero desirable output gives a zero direction component. Its adjustment factor then enters the objective but not the effective constraints, making the optimization unbounded. Such observations were therefore excluded under this specification; this is not a general limitation of DDF methods, since a non-zero alternative direction can accommodate zero outputs. A balanced panel was selected to keep country coverage consistent across reporting years and to evaluate all six transitions for every retained country. A balanced panel is a design choice rather than a general requirement of DEA.

Interpolating missing observations could introduce artificial reference points that themselves define the frontier. The exclusion has two implications. First, the results describe the 21 retained countries and not the EU as a whole, which is relevant because Austria, Sweden, and Latvia have sizeable forest-based sectors. Second, DEA scores are relative to the observed sample: adding countries can only leave the frontier unchanged or shift it outwards, so the exclusion cannot lead to an overstatement of the inefficiency of the retained countries, but their inefficiency may be understated if an excluded country were to define best practice. No temporal interpolation was applied.

Reported Eurostat values were used except for two explicit substitutions described below. The landfilled quantity for Germany in 2016 is confidential; as the reported values for 2014 and 2018 are zero, it was set to zero, so that the undesirable output for that observation equals incineration without energy recovery (1443 t). This is an imputed value, not an observed zero; the neighbouring observations do not establish the confidential quantity, and uncertainty in this substitution is a limitation of the analysis. The second exception is a single zero observation in the retained countries (disposal in Ireland in 2014). Because this zero concerns the undesirable output and a single year, the country was retained and the value was replaced by a small positive quantity (120 t, about 0.04% of the Irish generation input in that year). The sensitivity check indicates an unchanged country rank, although the score varies: with replacement values between 1 t and 1000 t, the average NDDF of Ireland varies between 3.87 and 4.43, its rank (11th) does not change, and the scores of all other countries are virtually unaffected. The data are summarized in Table 1, which reports country-level averages and coefficients of variation for the variables used in the analysis.

Data in Table 1 reveal significant differences across the countries examined. Germany, France, Finland, and Italy account for the largest volumes, while smaller economies such as Greece, Croatia, and the Baltic states operate at substantially lower levels. This disparity is also reflected in the coefficient of variation across countries (VARIATION(STOCK) = 1.42), indicating a high degree of cross-country dispersion. Meanwhile, within-country variability of the generation input variable across reporting years remains relatively moderate on average (31.49%), suggesting that the generated quantity is structurally stable over time. A similar pattern is observed for material recovery (DO1), where France, Italy, Germany, and

Poland report the largest material-recovery volumes. Cross-country variability remains high (VARIATION(DO1) = 1.34), and within-country variation across reporting years is also considerable (48.87%, against 31.49% for the generation input), indicating larger period-to-period adjustments in recycling and backfilling activity. This suggests that, although the leading countries maintain their relative positions, the intensity of material recovery evolves more actively over time than the generated quantity does. Energy recovery (DO2) exhibits even greater heterogeneity (VARIATION(DO2) = 1.90), driven primarily by very high levels in Germany, Finland, France, and the Netherlands; the correspondingly high within-country variation (52.52%) indicates that this pathway is subject to substantial temporal fluctuation. The greatest heterogeneity is observed for the undesirable output (UO)—landfill disposal and incineration without energy recovery—where the coefficient of variation reaches its highest value (VARIATION(UO) = 2.09). Despite generally lower absolute levels than the recovery pathways, countries such as France, Belgium, Greece, Finland, and Spain report relatively higher volumes of landfilling and incineration without energy recovery. At the same time, extremely high within-country variation (110.83%) points to substantial variability in disposal practices between reporting years, suggesting ongoing structural adjustment. Overall, these results confirm that cross-country differences are substantial and persistent, and that they exceed the temporal variation observed within individual countries.

Table 1. Descriptive statistics of wood waste generation and treatment pathways across EU countries (average values in thousand tonnes and coefficient of variation in %, 2010–2022).

Country	Generation		DO1		DO2		UO	
	Average	Variation	Average	Variation	Average	Variation	Average	Variation
Belgium	3369.21	16.50%	670.57	30.01%	651.73	42.19%	206.71	112.85%
Bulgaria	321.74	45.34%	105.03	55.26%	156.37	55.52%	5.88	146.08%
Czechia	261.41	13.26%	317.25	66.43%	20.22	38.51%	10.81	52.38%
Denmark	575.28	33.28%	253.20	23.61%	50.70	51.88%	2.98	84.34%
Germany	12,254.96	6.32%	2925.09	9.25%	7894.90	5.33%	24.13	227.89%
Estonia	450.96	63.49%	192.83	85.54%	169.91	50.46%	0.39	122.49%
Ireland	305.62	30.37%	126.32	24.00%	48.99	32.98%	5.10	134.75%
Greece	123.03	76.85%	23.21	108.69%	13.02	83.44%	47.27	149.78%
Spain	1171.30	16.96%	968.64	34.93%	70.76	79.77%	39.84	88.89%
France	7224.25	15.02%	4184.13	6.23%	2495.47	40.68%	281.63	62.62%
Croatia	120.68	27.99%	43.40	90.42%	34.40	56.13%	2.61	117.33%
Italy	4719.27	17.24%	3433.99	11.02%	799.75	8.21%	9.98	157.21%
Lithuania	169.88	32.92%	95.71	46.89%	45.43	67.33%	1.06	53.42%
Hungary	171.42	36.72%	156.50	33.07%	16.08	74.35%	1.36	46.31%
Netherlands	2692.48	6.10%	882.86	9.73%	1199.69	13.74%	36.39	76.08%
Poland	2652.61	40.08%	2134.67	40.08%	1461.93	61.28%	1.02	114.24%
Portugal	396.14	28.01%	201.03	38.54%	21.56	115.35%	3.10	90.11%
Romania	2593.88	14.46%	1484.70	17.89%	1314.12	18.00%	1.84	105.66%
Slovenia	201.47	50.90%	50.14	89.57%	96.57	75.44%	0.97	214.48%
Slovakia	398.29	26.38%	174.71	66.20%	136.82	74.39%	4.33	66.01%
Finland	6132.85	62.97%	872.18	138.92%	4225.58	58.03%	40.26	104.59%
Average	2205.08	31.49%	918.86	48.87%	996.38	52.52%	34.65	110.83%
Variation coefficient	1.42		1.34		1.90		2.09	

The efficiency scores and the productivity measures were estimated in Stata 17 with the community-contributed commands teddf and gtfpch [59]. The efficiency scores and the productivity measures were estimated in Stata 17 (StataCorp LLC, College Station, TX, USA) with the community-contributed commands teddf and gtfpch [59]. Three sets of results were not computed in Stata but with a separate Python implementation (version 3.13; Python Software Foundation, Wilmington, DE, USA) of the same linear programmes, produced with the generative AI tool described below:: (i) the estimates for Portugal in Sections 3.1 and 3.3, which were recomputed after the 2022 energy-recovery value had been corrected from 3100 t to the 310 t reported by Eurostat; (ii) the rank correlations, the outlier check and the values plotted in Figure 2 (Sections 3.1 and 3.2); and (iii) the robustness analyses in Section 3.4. For the other 20 countries, the results in Sections 3.1 and 3.3 are the Stata results dominated by energy recovery (Section 3.1), which the Python implementation reproduces. The radial results are reported as the multiplicative GML index (Equations (5)–(8)), whereas the non-radial results are reported as the additive Luenberger indicator (Equations (9)–(11)) [70,71] and are therefore signed.

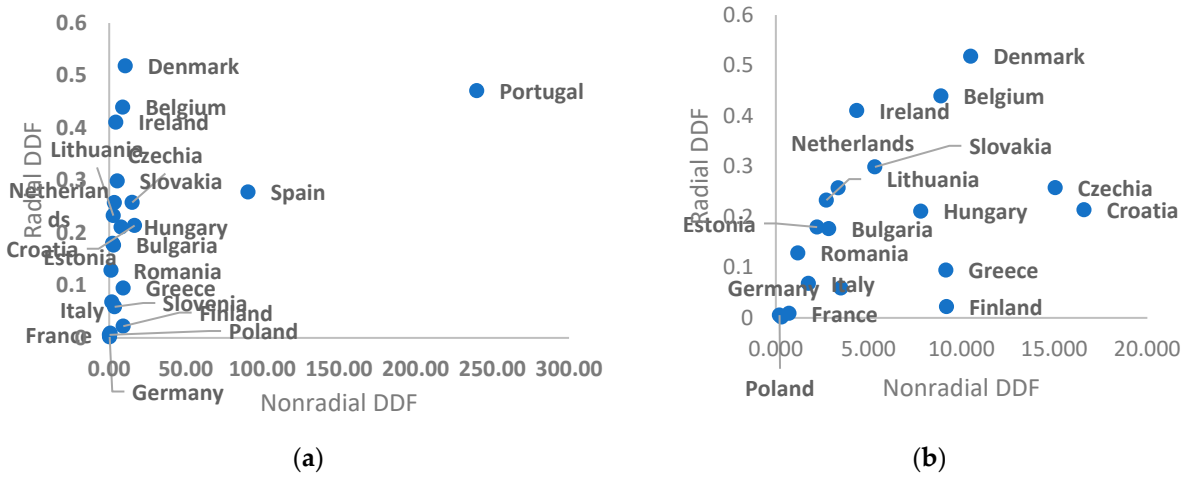


Figure 2. Average radial (DDF) and non-radial (NDDF) inefficiency by country, 2010–2022: (**a**) all 21 countries; (**b**) enlargement of the area marked in (**a**), without Spain and Portugal. The vertical axis is identical in both panels; the horizontal axis differs. Symbols in (**b**) are as in the legend of (**a**). The visual categories are descriptive; Denmark, although plotted in the blue group, has an adjustment dominated by energy recovery (Section 3.1).

In the Stata commands, wgen denotes wood waste generation (STOCK), recbfill recycling and backfilling (DO1), enrec energy recovery (DO2), disp the undesirable output (UO), id the country identifier and year the reporting year. The non-radial efficiency scores (Section 3.1) were estimated with

teddf wgen = enrec recbfill:disp, nonr vrs dmu(id) time(year) glo

where nonr, vrs and glo select the non-radial model, variable returns to scale and the global technology; the default direction vector is (−x, y, −b) with unit weights. The radial efficiency scores correspond to the same command without the option nonr. The radial GML index (Section 3.3) was estimated with

gtfpch wgen = recbfill enrec : disp, dmu(id) global

and the non-radial indicator with the same command and the non-radial option (nonr), for which the productivity change is obtained in the additive Luenberger form. In gtfpch, returns to scale are constant and the default orientation is output-oriented, i.e., the direction

(0, y, −b). The country values in Section 3.3 are the means and sample standard deviations of the six period results.

A generative artificial intelligence (GenAI) tool, Claude (Anthropic, San Francisco, CA, USA), was used during the preparation of this manuscript. It was used (i) to assist in writing and debugging the Stata code with which the DDF and GML models were estimated; (ii) to translate author-written text from the authors' native languages into English and to edit language and style; (iii) to assist in refining and extending the written presentation of the analyses, including the wording of figure and table captions and of the descriptions of the results; and (iv) to independently replicate the reported efficiency and productivity estimates with a separate linear-programming implementation in Python, as a verification step during revision, to compute the additional statistics and robustness analyses requested during review (Sections 3.1, 3.2 and 3.4), and to recompute the estimates for Portugal after a data-entry error in the 2022 energy-recovery value was corrected. The tool was not used for the study design, data collection or the generation of data. The model specifications were defined by the authors, and the Stata code was executed by the authors in Stata 17 on the original Eurostat data. The Python computations listed under (iv) were carried out with the assistance of the generative AI tool named above (Claude, Anthropic), and the authors checked their results against the Stata output wherever both exist.

3. Results

3.1. Directional Distance Functions Results

The first results present the average inefficiency scores estimated for the investigated EU member states, together with their decomposition across the input, desirable outputs, and undesirable output included in the model. The reported values represent averages calculated from the seven biennial observations covering the period 2010–2022 (Table 2).

Table 2. Average NDDF inefficiency and its decomposition by country (dimensionless proportional adjustment factors; a value of 1 corresponds to an adjustment equal to 100% of the observed quantity).

Country	NDDF	STOCK	DO1	DO2	UO
Belgium	8.893	0.000	3.920	4.004	0.969
Bulgaria	2.853	0.000	1.997	0.253	0.604
Croatia	16.592	0.000	15.810	0.462	0.321
Czechia	15.042	0.000	11.965	2.547	0.531
Denmark	10.499	0.000	0.357	9.663	0.479
Estonia	2.223	0.000	1.530	0.127	0.566
Finland	9.192	0.000	8.899	0.001	0.292
France	0.716	0.000	0.000	0.189	0.527
Germany	0.313	0.000	0.038	0.001	0.274
Greece	9.163	0.000	6.456	2.226	0.482
Hungary	7.810	0.000	0.479	7.297	0.033
Ireland	4.364	0.000	1.291	2.698	0.375
Italy	1.759	0.000	0.000	1.410	0.349
Lithuania	2.724	0.000	1.111	1.137	0.476
Netherlands	3.364	0.000	2.342	0.108	0.914
Poland	0.196	0.000	0.000	0.161	0.035
Portugal	239.857	0.000	0.012	239.653	0.193
Romania	1.185	0.000	0.449	0.121	0.615
Slovakia	5.334	0.000	2.362	2.573	0.398
Slovenia	3.506	0.000	3.286	0.000	0.220
Spain	90.615	0.000	0.142	89.602	0.871

Notes: NDDF = non-radial directional distance function inefficiency score; STOCK = wood waste input adjustment; DO1 and DO2 = desirable outputs; UO = undesirable output.

Table 2 presents the average non-radial directional distance function (NDDF) inefficiency scores and their decomposition into input and output adjustments. The adjustment for STOCK is zero for all countries. STOCK is a discretionary input in the model, so this is a result of the optimization and not an imposed restriction: in the estimated sample, the reported optimal solutions use the full input quantity and locate the adjustment potential in the outputs. This is an empirical property of these solutions, not a general theorem about the non-radial specification. The zero adjustment therefore shows where the model locates the improvement potential; it does not by itself show that inefficiency is unrelated to volume. That question was examined directly: the Spearman rank correlation between NDDF and STOCK is -0.27 ($p = 0.001$) across the 147 observations and -0.43 ($p = 0.051$) across the 21 country averages. The 147 observations are repeated measurements on 21 countries and are not independent, so the country-level coefficient is the appropriate basis for inference; with only 21 country averages, it is borderline non-significant at the 5% level. The association between inefficiency and volume is therefore negative but weak, and it should be interpreted cautiously. In the model, the improvement potential is thus located entirely in the desirable (DO1, DO2) and undesirable (UO) outputs, so that the measured inefficiency concerns the composition of treatment. Poland (NDDF = 0.196), Germany (0.313), and France (0.716) operate closest to the efficiency frontier, requiring only negligible output adjustments despite processing the largest waste volumes. A second group, including Italy, Romania, Estonia, Lithuania and Bulgaria, exhibits relatively low inefficiency, where improvements are limited to moderate reallocations between recycling and energy recovery. The largest inefficiencies are observed in Portugal (239.857) and Spain (90.615), followed by Croatia (16.592), Czechia (15.042), Denmark (10.499) and Greece (9.163). In Portugal, Spain, and Denmark, the adjustment is concentrated in energy recovery (DO2), whereas in Croatia, Czechia, and Greece it is concentrated in material recovery (DO1). Spain and Portugal combine relatively developed recycling systems with very limited energy recovery, indicating an unbalanced waste treatment structure. The results indicate that, within the modelled benchmark structure, the largest adjustment potential in these countries is associated with energy recovery rather than with material recovery alone. Croatia and Czechia illustrate different structural deficiencies. Croatia requires substantial improvements in material recovery (DO1 = 15.810), whereas Czechia exhibits its largest adjustment in material recovery (DO1 = 11.965), with a smaller adjustment in energy recovery (DO2 = 2.547). Overall, in the baseline model the differences in efficiency are associated with the balance between recovery pathways. Countries combining strong material recovery, energy recovery and low disposal operate close to the efficiency frontier, while systems relying predominantly on a single recovery option exhibit significantly higher inefficiency. These findings indicate that improved system performance is associated with a better balance between material recovery and energy recovery, together with lower levels of disposal.

3.2. Radial Model Implementation Results

The non-radial DDF (NDDF) in model (4) estimates variable-specific adjustment requirements. Its results therefore identify the particular outputs that account for each country's distance from the efficiency frontier. Because the adjustment pattern depends on the observed utilization structure and the benchmark technologies, the non-radial specification may emphasize one recovery pathway while indicating little or no adjustment for another. To complement this pathway-specific information, the analysis compares the NDDF results with the radial DDF in model (3), which imposes proportional adjustment across the variables. This comparison provides an additional perspective on potential efficiency improvements, including adjustments that may not emerge from the non-radial solution. The average inefficiency estimates from the two models are compared in Figure 2.

Figure 2 compares the results obtained from the non-radial and radial DDF models and provides additional insight into the sources of inefficiency in national wood waste utilization systems. Countries located close to the origin of both axes, such as Germany, France and Poland, exhibit very low inefficiency scores in both models, indicating that their waste utilization systems are well balanced and operate close to the best-practice frontier. These countries combine high levels of material recovery and energy recovery with very limited undesirable outputs, resulting in an efficient allocation of the domestic wood waste generation. In Figure 2a, Spain and Portugal appear as outliers. They are the only countries whose average NDDF exceeds the upper outer fence of the distribution (third quartile plus three interquartile ranges, 30.1), and neither country is on the frontier in any year. A leave-out test confirms that they do not influence the other results: when all Spanish and Portuguese observations are removed from the reference set, the radial and non-radial scores of the remaining 19 countries are unchanged to three decimal places. Their extremely high non-radial inefficiency scores indicate that inefficiency is concentrated in a specific utilization pathway rather than being evenly distributed across all variables. As demonstrated by the decomposition results in Table 2, the main source of inefficiency in both countries under the baseline direction vector is energy recovery (DO2). Despite relatively developed recycling activities, energy recovery remains substantially below the levels observed in the benchmark countries. Consequently, the non-radial model identifies very large adjustment requirements for this specific pathway. In contrast, the radial model produces considerably lower inefficiency scores because it assumes proportional improvements across all variables. That a radial measure does not register non-proportional slack is a known property of the method; the contribution here is to quantify how much the two specifications diverge for wood waste. Across the 21 country averages, the Spearman rank correlation between DDF and NDDF is 0.66 (p = 0.001) and Kendall's τ is 0.50; without Spain and Portugal, the values are 0.59 and 0.45. Country ranks differ by 4.1 positions on average and by up to 12 positions: Finland ranks 4th under the radial model and 16th under the non-radial model. At the level of individual observations (n = 147), the rank correlation is 0.71. The two specifications therefore agree on the broad ordering of countries but not on the position of those whose inefficiency is concentrated in one pathway.

After excluding Spain and Portugal (Figure 2b), two distinct patterns of inefficiency become visible. The first group includes Italy, Romania, Estonia, Bulgaria, Lithuania, the Netherlands, Slovakia, Ireland, Belgium and Denmark. These countries are positioned along a relatively steep trajectory in the scatterplot. Their geometric position should not be equated with a decomposition across pathways. Several countries require adjustments in more than one output, whereas Denmark is a clear exception: energy recovery accounts for approximately 92% of its total NDDF score (9.663 out of 10.499). The pathway contributions should therefore be assessed directly from Table 2. This pattern suggests a more general structural inefficiency in wood waste utilization.

The second group consists of Hungary, Slovenia, Greece, Finland, Croatia, and Czechia, together with the excluded outliers Spain and Portugal. In these countries, non-radial inefficiency is substantially higher relative to radial inefficiency, indicating that inefficiency is concentrated in particular utilization pathways. The decomposition analysis reveals that in these countries the adjustment is concentrated in a single pathway: material recovery in Czechia, Croatia, Finland, Greece, and Slovenia, and energy recovery in Hungary, Spain, and Portugal. As a result, the non-radial model assigns large adjustment values to that pathway, whereas the radial model, by construction, reports only the common proportional adjustment. Finland represents a particularly interesting case. Although its overall wood waste utilization system performs relatively well and operates with very high levels of energy recovery in absolute terms, the country still exhibits a noticeable

non-radial inefficiency score. This result suggests that, relative to the benchmark structure defined by the efficiency frontier, further improvements could be achieved through a more balanced combination of recovery pathways rather than through a simple increase in treatment volumes.

Overall, Figure 2 demonstrates that the combination of radial and non-radial DDF models provides complementary information. The divergence between the radial and non-radial results confirms that the observed inefficiency is largely non-proportional. While the radial model assumes uniform improvements across all variables, the NDDF shows that inefficiency is concentrated in individual pathways: under the baseline direction vector, in energy recovery for Spain, Portugal, and Hungary, and in material recovery for Czechia, Croatia, Finland, Greece, and Slovenia. As shown in Section 3.4, this attribution depends on the direction vector. In both models, the measured inefficiency thus concerns the allocation of the available waste among competing utilization options.

3.3. Productivity Change: Radial GML Index and Non-Radial Luenberger Indicator

The radial GML index and the non-radial Luenberger indicator (NL) are presented in Table 3. All values are averages over the six biennial transitions between 2010 and 2022.

The summary statistics in Table 3 further highlight the contrasting behavior of the radial GML index and the non-radial Luenberger indicator. In the radial specification, average productivity growth remained close to unity for almost all countries, indicating relatively balanced long-term productivity dynamics. The highest average total factor productivity growth was observed in Italy (1.09), Hungary (1.08), Czechia (1.07), Germany (1.06), France and Estonia (both 1.05), whereas Bulgaria (0.97), Lithuania (0.99) and Belgium (1.00) remained at or below unity. These results suggest that productivity changes under the radial assumption were generally moderate and convergent across countries. The decomposition indicates that countries with above-average productivity growth were typically characterised either by stronger efficiency improvements (e.g., Czechia, Hungary and France) or by positive best-practice-gap change (e.g., Italy and Spain). Bulgaria represents a distinct case where average best-practice-gap change exceeded unity (BPC = 1.05), while efficiency change remained below one (EC = 0.94), implying that improvements in the best-practice gap only partly compensated for the decline in efficiency relative to the contemporaneous frontier. An equally important finding concerns the stability of productivity development. The radial model exhibits relatively low standard deviations for all three indices, indicating stable productivity trajectories throughout the observation period. Belgium and Greece show almost perfectly stable productivity evolution (σ GML ≈ 0), while Portugal (0.02), Denmark (0.03), Croatia (0.04), Poland (0.06) and France (0.07) also demonstrate highly consistent performance. Higher temporal variability is observed in Bulgaria (0.32), Ireland (0.31), Hungary (0.24), Slovenia (0.23) and Romania (0.22), although these fluctuations remain modest compared with the non-radial results. Spain illustrates just how large that contrast can be: the non-radial Luenberger indicator for Spain averages 57.73 with a standard deviation of 134.85. Because this indicator is additive and unbounded, its magnitude is not directly comparable with that of the radial index, but it is among the most extreme values in the sample.

Table 3. Average radial Global Malmquist–Luenberger (GML) productivity index (multiplicative; GML = EC × BPC; unity = no change) and average non-radial Luenberger productivity indicator (NL) (additive; NL = EC + BPC; zero = no change), with their decomposition into efficiency change (EC) and best-practice-gap change (BPC), by country (averages over the six biennial transitions, 2010–2022; σ denotes the sample standard deviation across the six transitions).

Radial GML						
Country	**Average GML**	**σ GML**	**Average EC**	**σ EC**	**Average BPC**	**σ BPC**
Belgium	1.00	0.00	1.04	0.09	0.97	0.07
Bulgaria	0.97	0.32	0.94	0.33	1.05	0.23
Croatia	1.01	0.04	1.11	0.18	0.93	0.13
Czechia	1.07	0.21	1.17	0.41	0.96	0.21
Denmark	1.00	0.03	0.99	0.09	1.02	0.10
Estonia	1.05	0.15	1.06	0.32	1.04	0.23
Finland	1.03	0.19	1.03	0.07	1.01	0.19
France	1.05	0.07	1.12	0.28	1.02	0.39
Germany	1.06	0.16	1.03	0.07	1.03	0.09
Greece	1.00	0.00	1.00	0.00	1.00	0.00
Hungary	1.08	0.24	1.15	0.39	0.99	0.29
Ireland	1.03	0.31	1.10	0.47	0.97	0.12
Italy	1.09	0.13	1.01	0.15	1.09	0.10
Lithuania	0.99	0.15	1.05	0.31	0.98	0.20
Netherlands	1.01	0.15	1.07	0.24	1.00	0.30
Poland	1.00	0.06	1.00	0.00	1.00	0.06
Portugal	1.01	0.02	1.04	0.19	1.00	0.18
Romania	1.01	0.22	1.02	0.09	0.98	0.15
Slovakia	1.04	0.18	1.12	0.32	0.97	0.20
Slovenia	1.04	0.23	1.03	0.19	1.01	0.11
Spain	1.01	0.09	0.99	0.28	1.07	0.21
Non-radial Luenberger indicator (NL)						
Country	**Average NL**	**σ NL**	**Average EC**	**σ EC**	**Average BPC**	**σ BPC**
Belgium	0.81	9.30	0.52	7.33	0.29	2.78
Bulgaria	1.55	6.33	−0.72	2.62	2.27	6.95
Croatia	1.05	71.35	0.78	36.95	0.27	34.56
Czechia	7.70	17.08	3.57	9.84	4.12	9.23
Denmark	0.79	7.83	0.95	8.46	−0.16	1.69
Estonia	−0.26	2.53	0.11	3.12	−0.38	1.02
Finland	−4.24	22.17	0.45	16.65	−4.69	18.02
France	0.47	0.74	0.74	0.76	−0.27	0.59
Germany	0.38	1.03	0.46	1.82	−0.08	1.59
Greece	−0.05	7.05	0.62	6.70	−0.67	1.29
Hungary	−5.36	16.80	1.19	2.60	−6.55	16.66
Ireland	0.38	1.85	0.61	3.54	−0.24	3.90
Italy	0.44	1.94	0.00	1.98	0.44	1.55
Lithuania	−0.17	2.11	0.28	1.97	−0.45	0.97
Netherlands	−0.24	0.54	0.13	0.83	−0.37	0.74
Poland	0.00	1.03	0.00	0.00	0.00	1.03
Portugal	−242.10	535.10	−130.86	281.40	−111.24	254.00
Romania	0.01	1.31	0.08	1.21	−0.07	0.58
Slovakia	−1.71	3.64	0.50	1.51	−2.21	4.38
Slovenia	−1.90	10.94	−1.38	7.76	−0.52	4.62
Spain	57.73	134.85	−0.29	11.04	58.03	136.59

A fundamentally different picture emerges from the non-radial Luenberger indicator (NL). Because the indicator is additive, zero denotes no change, positive values denote

improvement and negative values denote decline; its values are not interpreted relative to unity. The average NL ranges from −242.10 in Portugal to +57.73 in Spain and, apart from these two countries, from −5.36 in Hungary to +7.70 in Czechia. The extreme averages are driven by individual biennial transitions rather than by a sustained trend. For Spain, the transition 2012–2014 alone (NL = 330.99, of which BPC = 336.46 and EC = −5.47) accounts for almost the entire average. For Portugal, the negative average is dominated by the transition 2020–2022 (NL = −1333.13), when reported energy recovery fell to 310 t; the transitions 2014–2016 (−56.15) and 2018–2020 (−53.61) are also clearly negative. For Croatia, a sharp decline in 2012–2014 (−120.52) is almost fully reversed in 2014–2016 (+103.62), which explains a small average combined with a very large standard deviation. These magnitudes follow from the direction vector: the adjustment factor for an output is the ratio between the benchmark and the observed quantity minus one, so it becomes very large when the observed quantity is small. Reported energy recovery was only 2612 t in Spain in 2012 and 310 t in Portugal in 2022, against benchmark levels that are larger by a factor of several hundred or more. The values are therefore not numerical artefacts: they were reproduced to four decimal places with an independent solver. They are, however, sensitive to single observations, and medians are more robust than means. The median NL is 7.76 for Spain and −29.49 for Portugal, compared with means of 57.73 and −242.10, and among the other countries the sign of the median differs from that of the mean only for Hungary and Italy. Apart from Portugal, negative average values are observed for Hungary (−5.36), Finland (−4.24), Slovenia (−1.90), Slovakia (−1.71), Estonia (−0.26), the Netherlands (−0.24), Lithuania (−0.17), and Greece (−0.05), whereas, apart from Spain, the largest positive averages are recorded for Czechia (7.70), Bulgaria (1.55), and Croatia (1.05). The dispersion of productivity change is also considerably larger under the non-radial specification. Portugal (σ NL = 535.10) and Spain (σ NL = 134.85) show by far the highest temporal variability, followed by Croatia (σ NL = 71.35), Finland (22.17), Czechia (17.08), and Hungary (16.80). Conversely, the Netherlands (0.54), France (0.74), Germany (1.03), Poland (1.03), and Romania (1.31) show comparatively lower variability. Similar heterogeneity is observed in both efficiency change and best-practice-gap change. The BPC component is substantial in several countries, but it should be interpreted specifically as movement in the gap between the contemporaneous frontier and the global benchmark rather than as a direct measure of technological change. Overall, the comparison shows that the radial and non-radial specifications provide different but complementary perspectives: the former imposes proportional adjustment, whereas the latter captures pathway-specific, non-proportional changes.

3.4. Robustness and Interpretation of Projected Quantities

Four additional analyses address the physical interpretation of the scores and their sensitivity to the specification. First, the input constraint was examined. Although the adjustment factor for STOCK is zero, the constraint is binding for every observation: the input slack is zero, and the projected input quantity equals the observed input quantity. In real terms, a zero-input adjustment means that each country is compared with a benchmark combination at the same input level, with output adjustments toward greater recovery and lower disposal. This does not establish that the benchmark is a physically attainable treatment plan for that country.

Second, Models (3) and (4) contain no explicit material-balance constraint, so the desirable outputs may be expanded without a corresponding reduction elsewhere. The projected quantities were therefore compared with the generated quantity. The projected total treated quantity exceeds the generation input in 124 of the 147 observations (median ratio 1.40, maximum 2.56); in 26 observations the observed treated quantity already exceeds

the generation input. The baseline scores should consequently be read as distances to best practice and not as physically attainable targets. To assess the consequences, the non-radial model was re-estimated with an additional aggregate treatment-volume cap: the sum of projected DO1, DO2 and UO may not exceed max (STOCK, observed DO1 + observed DO2 + observed UO). This cap preserves feasibility of the observed treatment vector where reported treatment exceeds domestic generation. It is a sensitivity restriction, not a complete national material balance: imports, exports and changes in inventories are not observed in the model, and the restriction does not establish physical attainability of the projections. The scores decrease, most strongly for the outliers (Spain from 90.62 to 11.02; Portugal from 239.86 to 137.88), but the ranking of countries is almost unchanged (Spearman $\rho = 0.96$).

Third, the extreme values arise because the baseline direction vector is proportional to the observed outputs, which are very small for energy recovery in some observations. An alternative direction vector that expresses all adjustments as shares of the generated quantity, $g = (-\text{STOCK}, \text{STOCK}, \text{STOCK}, -\text{STOCK})$, was therefore applied. Under this normalization, the scores are bounded (country averages between 0.02 and 1.53) and Spain (0.91) and Portugal (1.29) are no longer outliers; the highest average is recorded for Greece. The rank correlation with the baseline is 0.72 across countries and 0.84 across observations. The attribution to pathways also changes; because a tonne of energy recovery and a tonne of material recovery now count equally, the larger part of the adjustment falls on material recovery in 18 of the 21 countries, including Spain (0.59 against 0.29 for energy recovery) and Portugal (1.07 against 0.21). The finding that inefficiency in Spain and Portugal is concentrated in energy recovery therefore holds under the baseline direction vector, which measures each pathway relative to its own observed level, and not under a direction that measures adjustments in common units.

Fourth, the aggregation of recycling and backfilling was tested by re-estimating the model with recycling as the only material-recovery output. Backfilling is reported by seven of the 21 countries and represents 0.09% of material recovery in the sample, with a maximum of 19.9% in a single observation (Ireland). The country ranking is unchanged (Spearman $\rho = 1.00$); the average NDDF changes noticeably only for Czechia (from 15.04 to 16.30) and Ireland (from 4.36 to 5.13). Contamination, conversion efficiency in energy recovery, displaced fuels, emissions and retained material value could not be measured with the available statistics and remain outside the analysis (Section 5).

4. Discussion

To facilitate interpretation of the DEA results and describe the relative position of each country with respect to the efficiency frontier, an interval-based classification was applied to the non-radial estimates. The interval width was calculated as $(\text{maxNDDF} - \text{minNDDF})/3$, allowing the countries to be divided into three descriptive groups: (i) countries closest to the efficiency frontier, (ii) countries with intermediate inefficiency, and (iii) countries furthest from the frontier. With a minimum of 0.196 (Poland) and a maximum of 16.592 (Croatia), the interval width is 5.465 and the two thresholds are 5.661 and 11.127. Slovakia (NDDF = 5.334) and Denmark (NDDF = 10.499) are the last countries below the first and the second threshold, respectively. Spain and Portugal were excluded from this grouping because their exceptionally high NDDF values reflect distinct structural patterns and would substantially distort the intervals for the remaining countries. The thresholds of an interval-based classification are to some extent arbitrary. This grouping is used only as a descriptive aid and does not imply statistically estimated thresholds.

The first group includes Poland, Germany, France, Romania, Italy, Estonia, Lithuania, Bulgaria, the Netherlands, Slovenia, Ireland and Slovakia. Their average non-radial ineffi-

ciency amounts to NDDF = 2.38, against an average radial inefficiency of just DDF = 0.15, meaning these countries sit close to the production frontier overall. Wood waste treatment in this group is fairly evenly split: on average across the countries of the group, recycling and backfilling account for around 53.4%, energy recovery for around 45.4%, and disposal for just 1.2% of the volume treated. Yet the NDDF decomposition provides a more nuanced interpretation than these shares alone. The average adjustment needed comes to 1.20 for recycling and backfilling, 0.73 for energy recovery, and only 0.45 for disposal—indicating that even the strongest performers still have room to improve, mostly in how recovered material is allocated rather than in cutting disposal further. In other words, the remaining inefficiency here is less about landfill and more about routing recovered wood toward higher-value recycling. This interpretation is consistent with earlier work: Zbieć et al. [73] attribute Poland's leading position to its advanced use of wood residues in engineered wood and composite products, Greinert et al. [74] point to the economic payoff of energy-recovery technologies, and Ratajczak et al. [75] find that most residues from the Polish wood-processing industry re-enter circular production chains rather than ending up as waste. Comparable patterns emerge elsewhere in this group: Garcia and Hora [76] describe a similarly mature and diversified wood waste supply chain in Germany, while Zlateva et al. [77] report growing market development for waste biomass in combined energy production in Bulgaria, consistent with the balanced recycling-energy split observed here for both countries. Taken together, these studies suggest that efficient systems combine high recovery rates with the ability to steer wood residues toward their most economically valuable use.

In the baseline model the generation input itself carries no adjustment, and the differences between countries arise from how the recovery pathways are organized. Agyemang et al. [78] make a similar point, arguing that sustainable wood waste management rests on balancing recycling, cascading use and energy recovery rather than maximizing any single option. Besserer et al. [9] further show that these pathways are technologically interconnected and should be treated as complementary rather than competing. Greinert et al. [74] reach a comparable conclusion, describing recycling, cascading use and energy recovery as mutually reinforcing elements of an integrated circular system. This body of evidence helps explain why the countries in the first group sit closest to the efficiency frontier.

Productivity trends add another dimension to the comparison. Under the radial Global Malmquist–Luenberger index, average productivity change was positive (GML = 1.03), reflecting increases in both efficiency change (EC = 1.05) and best-practice-gap change (BPC = 1.01). By contrast, the non-radial productivity measure was essentially stable on average (NL = −0.09), with only a small efficiency-change component (EC = 0.07) and a slightly negative best-practice-gap change (BPC = −0.16). The difference between the two measures indicates that proportional improvements captured by the radial specification may coexist with pathway-specific constraints identified by the non-radial model. This pattern is consistent with relatively mature treatment systems in which further improvements may depend more on the management and allocation of individual waste streams than on uniform expansion across all pathways. Nevertheless, the first group is heterogeneous, and its members differ in the structure of wood waste utilization.

The productivity decomposition also reveals important differences within the group. Germany, France, Ireland and Romania record a non-negative non-radial indicator that is driven by positive efficiency change (EC), which offsets a negative best-practice-gap change (BPC). Estonia, the Netherlands and Lithuania show the same combination of positive EC and negative BPC, but there the BPC component dominates and the indicator is slightly negative (−0.26, −0.24 and −0.17, respectively). Poland remains on the contemporaneous frontier throughout, with an average indicator of zero. Bulgaria and Italy differ from

this pattern with positive best-practice-gap contributions, indicating improvements in specific recovery pathways rather than uniform improvements across the waste-utilization system—an interpretation that is also consistent with the NDDF decomposition. In Bulgaria the largest adjustment sits in recycling, pointing to improvement in the material-recovery pathway as the main opportunity ahead; in Italy the opposite holds, with the adjustment concentrated almost entirely in energy recovery, so future progress there should focus on expanding and refining that pathway. These differing trajectories are nonetheless consistent with the integrated strategy Besserer et al. [9] propose, in which recycling, cascading use and energy recovery evolve together as a balanced system.

Slovenia is the only country in this group where both efficiency change and best-practice-gap change are negative under the non-radial indicator (EC = −1.38; BPC = −0.52). Slovakia records the most negative best-practice-gap change in the group (BPC = −2.21), which outweighs its positive efficiency change (EC = 0.50)—a finding that matches Čulková et al. [79], who conclude Slovakia still needs substantial investment in both recycling technology and energy recovery capacity to lift the overall efficiency of its wood waste system.

The second group—Hungary, Belgium, Greece, Finland and Denmark—presents a different pattern. Their non-radial inefficiency values are fairly similar (average NDDF = 9.11), but the underlying utilization structures and productivity dynamics differ substantially from one another. On average, 52.2% of wood waste goes to recycling and backfilling, 33.2% to energy recovery and 14.5% to disposal—a notably higher disposal share than in the first group. But again the NDDF decomposition tells more than the shares do: the average adjustment needed comes to 4.64 for energy recovery, 4.02 for recycling and backfilling, and only 0.45 for disposal. So intermediate efficiency here is not mainly a capacity problem—it is an imbalance between the two desirable recovery pathways. Unlike the first group, where adjustments stay small and evenly spread, each country in this group tends to have one dominant source of inefficiency, which is what makes their development trajectories so varied.

The productivity results confirm just how varied this group is. Under the radial Global Malmquist–Luenberger index, it still shows moderate growth (average GML = 1.02), helped by gains in both efficiency (EC = 1.04) and positive best-practice-gap change (BPC = 1.00). The non-radial Luenberger indicator tells a different story—an overall decline (average NL = –1.61), and this happens despite positive efficiency change (EC = 0.75), because that gain is outweighed by negative best-practice-gap development (BPC = –2.35). Proportional improvements are clearly still achievable here, but changes in the best-practice gap across individual recovery pathways have become uneven, and that unevenness is what drives the growing structural inefficiency.

Looking at individual countries makes this diversity concrete. Finland runs a highly specialized, energy-oriented system: more than 82% of wood waste goes to energy recovery, and only 17% is recycled. That specialization shows up directly in the decomposition, where energy recovery needs almost no adjustment (DO2 = 0.001), while nearly all the inefficiency sits in recycling (DO1 = 8.899). Finland is widely regarded as one of Europe's most advanced users of wood biomass for combined heat and power and district heating, backed by an extensive supply chain and mature combustion technology [80,81], though Finnish researchers themselves stress the importance of cascading use and preserving recyclable wood before it is finally burned for energy [82,83]. Taken together, this suggests Finland has already optimized energy recovery, and further gains will have to come mainly from expanding higher-value material recovery.

Denmark exhibits an almost opposite pattern. Roughly 82.5% of wood waste is recycled, and only 16.5% goes to energy recovery. Yet the decomposition finds the dominant adjustment need sits with energy recovery (DO2 = 9.663), while recycling is already close to

the efficiency frontier (DO1 = 0.357). Denmark has built one of Europe's most comprehensive regulatory frameworks for waste wood, with a strong emphasis on recycling quality and environmental protection [84,85]. Even so, several authors argue that energy recovery still needs further optimization, particularly for contaminated waste wood streams and better integration of cascading-use principles [84,85]—a conclusion that lines up closely with what the decomposition shows here.

Belgium exhibits a different pattern. Where Finland and Denmark each have one pathway that clearly dominates their adjustment needs, Belgium's values for energy recovery (DO2 = 4.004) and recycling (DO1 = 3.920) are nearly identical. So the remaining inefficiency is spread fairly evenly across both desirable outputs rather than concentrated in one, and it is this balanced-but-incomplete picture that keeps Belgium in the intermediate group despite otherwise stable productivity indicators.

Greece exhibits the least balanced system in this group. More than 56% of wood waste still ends up disposed of, while only 27.8% is recycled and 15.6% goes to energy recovery. That structure largely accounts for Greece's relatively high NDDF value, even though the radial specification shows almost no change in productivity (GML≈ 1.00). The decomposition confirms that the largest adjustment needed is in recycling (DO1 = 6.456), while the improvement needed in energy recovery (DO2 = 2.226) is much smaller. The real challenge, then, is not simply expanding energy use but diverting recoverable wood waste away from disposal and toward higher-value recovery. Recent studies back this reading: Greece has considerable biomass resources but still struggles with fragmented collection, thin circular-bioeconomy infrastructure and weak links between biomass producers and recovery industries [86,87]. The high disposal share found here therefore reflects structural gaps in waste management rather than a lack of available biomass.

Hungary differs markedly from the other countries within this group. Almost 90% of wood waste is recycled, and only 9.2% goes to energy recovery. Yet the decomposition identifies energy recovery as the dominant source of inefficiency (DO2 = 7.297), while recycling needs only a marginal adjustment (DO1 = 0.479). Hungary, in other words, already has an effective material recovery system but shows substantial model-implied adjustment potential in energy recovery. The strongly negative best-practice-gap component under the non-radial indicator reinforces this: future gains will likely hinge on modernizing the energy recovery sector rather than expanding recycling further.

Overall, the second group shows that intermediate efficiency has no single explanation. Countries reach similar NDDF values through substantially different structural configurations: Finland and Hungary are both highly specialized, just in opposite directions; Belgium spreads moderate adjustment needs across both pathways; Denmark shows what an advanced recycling-oriented strategy still lacks in energy recovery; and Greece remains held back by how little wood waste is diverted from disposal toward higher-value recovery. The common thread is that recovering more wood, on its own, does not guarantee better efficiency—what matters is the balance between recycling and energy recovery alongside a low disposal share, a relationship only the non-radial framework captures directly.

The third group, comprising Czechia and Croatia, is furthest from the non-radial efficiency frontier after Spain and Portugal are treated separately as outliers. Their average non-radial inefficiency is NDDF = 15.82, compared with a substantially lower average radial inefficiency (DDF = 0.24). This difference indicates that proportional radial adjustments can mask structural inefficiencies associated with individual treatment pathways. On average, approximately 73% of wood waste is directed to recycling and backfilling, 24% to energy recovery, and 3% to disposal, although the two structures differ: material recovery accounts for 91% in Czechia and 54% in Croatia. The NDDF decomposition, however, shows that the largest model-implied adjustment concerns material recovery: the average adjustment

for recycling and backfilling is 13.89, compared with 1.50 for energy recovery and 0.43 for disposal. Thus, the high NDDF values are associated primarily with the configuration of material recovery rather than with excessive disposal. Within the model, a high recycling share alone is therefore not sufficient to place a country close to the best-practice frontier.

Productivity dynamics also distinguish this group from the previous two. Under the radial index, the two countries record an average GML of 1.04, accompanied by EC = 1.14 and BPC = 0.94. Under the additive non-radial specification, the average NL is positive (4.38), with positive average contributions from both efficiency change (EC = 2.18) and best-practice-gap change (BPC = 2.20). Thus, although both countries remain relatively distant from the non-radial efficiency frontier, the productivity indicator points to positive structural change over the study period. The high NDDF values should therefore be interpreted as remaining model-implied adjustment potential rather than as evidence of stagnation.

Czechia is strongly oriented toward material recovery. More than 91% of wood waste goes to recycling and backfilling, and only 5.8% goes to energy recovery. That specialization shows directly in the decomposition, where almost all the inefficiency traces back to material recovery (DO1 = 11.965), with much smaller adjustments needed in energy recovery (DO2 = 2.547) and disposal (UO = 0.531). So simply recycling more is unlikely to substantially improve efficiency here unless it comes with better allocation of recovered materials and tighter integration with the other recovery pathways. This interpretation is supported by the literature: Procházka et al. [88] find the Czech wood-processing sector increasingly reliant on recovered wood for composite production, intensifying competition for secondary raw materials; Dudík et al. [89] describe material recovery as a strategic priority of the Czech forest-based bioeconomy; Kalt and Kranzl [90] note that energy recovery still has considerable room to grow despite the advanced recycling sector; and Sujová et al. [91] argue that better monitoring of wood flows and secondary-material allocation is becoming increasingly important for the sector's long-term sustainability. These findings are consistent with the decomposition here, which points future efficiency gains toward organizing and allocating recovered materials rather than simply recycling more.

Croatia presents a different utilization profile. Approximately 54% of treated wood waste is directed towards material recovery, while about 43% is used for energy recovery. Nevertheless, the NDDF decomposition indicates that the dominant model-implied adjustment is associated with material recovery (DO1 = 15.810), whereas the corresponding adjustment for energy recovery is comparatively small (DO2 = 0.462). Croatia therefore exhibits the largest average proportional material-recovery adjustment among the countries in the sample, suggesting that increasing recovery volumes alone may not be sufficient to improve overall efficiency; greater attention should also be given to the effectiveness and value retention of material-recovery pathways. This interpretation is broadly consistent with previous research. Šegotić et al. [92] reported that substantial quantities of wood-processing residues remain directed towards relatively low-value applications despite the availability of technologies for higher-value utilization. Milovanović et al. [93] demonstrated the potential of wood biomass residues for value-added applications, including their incorporation into construction materials, while Meštrović et al. [94] similarly highlighted opportunities for improving the valorization of Croatian wood-processing residues. Taken together, these findings support the interpretation that Croatia's remaining efficiency potential is associated primarily with strengthening material recovery and promoting higher-value applications of secondary wood resources.

The comparison between Croatia and Czechia further illustrates the analytical value of the non-radial approach. Both countries exhibit relatively high material-recovery rates and low disposal shares yet remain comparatively distant from the non-radial efficiency fron-

tier because substantial adjustment requirements persist in individual recovery pathways. Thus, a high recycling rate alone should not be interpreted as evidence of an efficient wood waste management system. Rather, the results emphasize the importance of examining the performance of individual utilization pathways and their integration within the broader recovery system. From a circular bioeconomy perspective, these findings support a coordinated cascading strategy in which higher-value material recovery is prioritized wherever technically and economically feasible, while energy recovery provides a complementary final utilization pathway for wood residues that are unsuitable for further material use.

Spain and Portugal warrant separate treatment because their results depart fundamentally from the rest of the sample. Both post the highest NDDF values in the study (Portugal = 239.86; Spain = 90.62), but their decomposition differs markedly from that of the preceding groups. Where the second and third groups spread their inefficiency across recycling, energy recovery and disposal, in Spain and Portugal almost the entire adjustment is concentrated in energy recovery: 89.60 for Spain and 239.65 for Portugal, against negligible recycling inefficiencies (0.14 and 0.01) and only marginal disposal contributions (0.87 and 0.19). This attribution is specific to the baseline direction vector, which measures each pathway relative to its own observed level; when adjustments are expressed in common units (Section 3.4), material recovery accounts for the larger part in both countries. The discussion that follows therefore concerns the relative under-representation of energy recovery in the two treatment structures, and not an absolute shortfall in tonnes. The extreme NDDF values, then, do not signal an overall failure of the waste management system—they signal a sharp imbalance between recovery pathways.

Recent research on the circularity of the European wood-products industry supports this reading. Diaz-Balteiro et al. [95] place Spain among Europe's leading countries for overall wood-sector circularity, driven mainly by well-developed recycling and high resource productivity. They also show that circularity depends on more than recycling rates alone—trade intensity, industrial structure and research and innovation capacity all play a role, which is consistent with a highly circular system still having a bottleneck in one specific pathway rather than across the whole chain. Spanish research also points to a range of high-value uses for recovered wood. Pedreño-Rojas et al. [96] show that waste wood from construction and demolition can be worked into recycled gypsum products, cutting the environmental footprint while improving thermal performance and keeping mechanical properties within acceptable limits. Routes like this strengthen circularity without necessarily expanding the role of energy recovery, which matches the decomposition obtained here.

Martínez-García et al. [97] add another example, highlighting waste wood ash as a valuable secondary raw material for geopolymer and eco-concrete production—a further high-value pathway that sits outside conventional energy use. Their review argues that wood waste supports sustainable development best when it is routed through material recovery before any final energy use, which reinforces the picture of Spain having built sophisticated recycling routes while its largest proportional gap under the baseline specification sits in energy recovery rather than recycling. Pazzaglia and Castellani [98] offer a complementary explanation with a decision-support framework showing that the best utilization route depends mainly on wood quality and contamination: clean and moderately contaminated streams should go to material recycling, while only the lower-quality fractions are suited to energy recovery. On that logic, a country with mature recycling infrastructure can legitimately post low recycling inefficiency while still carrying real adjustment potential in energy recovery, depending simply on the composition of what it recovers.

Portugal follows a similar profile, and on average the imbalance is even more pronounced than in Spain, mainly because reported energy recovery fell to only 310 t in 2022.

Both countries recycle the large majority of recoverable wood while sending comparatively little to energy recovery, which is why almost the entire NDDF adjustment lands on the energy recovery side. The Portuguese literature, though, suggests this reflects the structure of the biomass supply chain rather than weak circular-economy performance. Portugal has abundant forest resources and a well-developed bioenergy sector, but the supply of recoverable woody biomass is constrained by competing industrial uses, logistics and feedstock availability. Nunes et al. [99] estimate that even fully mobilising residual woody biomass would not be enough to continuously supply a large converted biomass power plant, and argue that biomass should mainly complement existing energy systems while supporting rural development and circular value chains. Recent life-cycle assessments also show Portuguese policy leaning increasingly toward higher-value biomass valorization rather than conventional combustion alone. Simões et al. [100] compared open burning, energy recovery and pyrolysis of woody residues and found that advanced routes—pyrolysis especially—achieve substantially lower, and sometimes negative, global warming potential through carbon sequestration and better resource efficiency. Their results suggest woody residues are increasingly treated as valuable secondary resources within circular-economy strategies rather than fuel destined solely for energy production, which is consistent with the baseline result that Portugal's recycling inefficiency is relatively low while its largest proportional adjustment sits in energy recovery.

The productivity results further differentiate the two countries. Under the radial framework, Spain records GML = 1.01 with BPC = 1.07, while Portugal also records GML = 1.01. Under the additive non-radial specification, Spain records the highest positive average productivity change in the sample (NL = 57.73), associated almost entirely with a large positive best-practice-gap component (BPC = 58.03) and a slightly negative efficiency-change component (EC = −0.29). Portugal exhibits the opposite pattern, with a strongly negative average non-radial productivity change (NL = −242.10) and negative average contributions from both efficiency change (EC = −130.86) and best-practice-gap change (BPC = −111.24). These results indicate markedly different productivity dynamics despite broadly similar waste-utilization structures. Given the extreme magnitudes and variability of the non-radial estimates, however, these country-level results should be interpreted cautiously.

The findings explained above are broadly consistent with the wider literature on the environmental and economic trade-offs between recycling and energy recovery. For countries such as Spain and Portugal, where the baseline model identifies energy recovery as the pathway with the largest proportional gap despite already mature recycling systems, this is consistent with life-cycle evidence indicating that energy recovery from wood waste delivers greater CO_2 savings and energy-security benefits than recycling, particularly when it substitutes fossil sources such as coal or gas [56,101,102]. Some studies report greater energy-saving potential from recycling instead [103,104], though they note this depends heavily on the quality and purity of the incoming waste stream—a limiting factor that may help explain why countries such as Czechia and Croatia, despite high recycling shares, remain far from the efficiency frontier if sorting or allocation constraints are present; these factors were not measured in this study. This pattern is consistent with system-level waste-management assessments showing that efficiency depends jointly on high recycling rates and low landfill rates, rather than on either pathway alone [105–107], a pattern echoed in country-level efficiency analyses across the EU [108,109]. Emerging chemical-conversion technologies such as organosolv treatment [110–112] and pressurized-hydrolysis depollution [113] are also expanding the range of wood waste that can feasibly be recycled, including more contaminated material, while industrial symbiosis between producers and waste processors has been shown to meaningfully raise recycling rates within specific sectors [114,115]. The economic viability of recycling, more broadly, depends on

market conditions and supporting legislation [116,117], and can be shaped further through targeted subsidy design and price-competition effects [17,118]—factors that likely explain part of the cross-country variation observed in the present study, alongside the structural allocation issues identified through the NDDF decomposition.

5. Conclusions

This study evaluated wood waste utilization efficiency across 21 EU member states over 2010–2022 using radial and non-radial Directional Distance Functions together with the Global Malmquist–Luenberger productivity framework. The models locate the adjustment potential in the composition of wood waste treatment rather than in the generated quantity, and the association between inefficiency and generation volume is weak and negative. Poland, Germany, and France operated closest to the best-practice frontier, while countries with similar overall efficiency often exhibited markedly different combinations of material recovery, energy recovery, and disposal. Czechia and Croatia demonstrate that high material-recovery shares alone do not ensure overall efficiency, as the non-radial model reveals substantial pathway-specific adjustment requirements that are less apparent under the radial specification. Spain and Portugal exhibit the highest non-radial inefficiency, with the largest model-implied adjustments under the baseline direction vector concentrated in energy recovery. The productivity analysis further confirms substantial differences between radial and non-radial specifications, highlighting the importance of accounting for non-proportional changes in individual utilization pathways.

The results should be read as model-implied adjustment potential relative to the best practice observed in the sample, and not as causal prescriptions. In this sense, and under the baseline direction vector, the largest potential for Portugal and Spain lies in energy recovery, and for Czechia and Croatia in material recovery; for the latter two countries, the result suggests that recovery volumes alone are a weak indicator of performance. Whether this potential can or should be realized is a separate question, which depends on factors outside the model, such as the quality and contamination of the waste, existing treatment capacity, and the environmental performance of each pathway. With this caveat, two cautious policy implications follow. First, aggregate recycling rates may conceal pathway-specific inefficiencies, so monitoring individual pathways is informative. Second, the results are consistent with cascading-use principles, under which higher-value material recovery is prioritized, disposal is minimized, and energy recovery is retained for residues unsuitable for further material use.

Several limitations should be considered. DEA efficiency scores are relative to the observed sample and depend on model specification, variable selection, and the direction vector; the frontier reflects the 21 countries analysed, and six member states, including Austria, Sweden, and Latvia, could not be included because of confidential or zero values in the source data. Differences in national reporting practices may also influence the results, while the extreme values for Spain and Portugal require cautious interpretation. In particular, the baseline projections are not constrained by a complete material balance, and both the extreme values and the attribution of inefficiency to energy recovery in these two countries depend on the direction vector (Section 3.4). Data comparability is a further limitation: national reporting practices, the classification of wood waste, and the delimitation between recycling, backfilling, and energy recovery differ among member states and over time, and the generated quantity and the treated quantities come from separate datasets that do not coincide. Wood waste is also heterogeneous in quality. The statistics do not distinguish clean from treated or contaminated wood, so two countries with the same quantities may face very different technical options for material recovery. Furthermore, the model does not explicitly account for wood quality, contamination, greenhouse gas emissions,

carbon-storage effects, or other life-cycle impacts. Consequently, model-implied adjustment potential should not automatically be interpreted as an environmental or policy preference for a particular recovery pathway. The confidential landfill value for Germany in 2016 was imputed as zero and introduces additional data uncertainty. The factors underlying the observed productivity changes, particularly after 2018, also remain outside the scope of the present analysis.

Future research should incorporate life-cycle environmental indicators and waste-quality characteristics, apply network DEA to distinguish individual stages of the wood waste value chain, and test alternative model specifications and direction vectors. Extending the dataset beyond 2022 and broadening the analysis to non-EU European countries would further clarify long-term productivity trends and the influence of different institutional and market conditions. Overall, the complementary use of radial and non-radial approaches provides a valuable diagnostic framework for identifying pathway-specific improvement potential and supporting more resource-efficient wood waste management within the European circular bioeconomy.

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Abbreviations

The following abbreviations are used in this manuscript:

BCC	Banker–Charnes–Cooper (DEA model)
BPC	Best Practice Gap Change
BPG	Best Practice Gap
CCR	Charnes–Cooper–Rhodes (DEA model)
DDF	Directional Distance Function
DEA	Data Envelopment Analysis
DMU	Decision-Making Unit
DO1	Desirable Output 1 (material recovery: recycling and backfilling)
DO2	Desirable Output 2 (energy recovery)
EC	Efficiency Change
EU	European Union
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GML	Global Malmquist–Luenberger (index)
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
LDA	Linear Discriminant Analysis
ML	Malmquist–Luenberger (index)
MSW	Municipal Solid Waste
NDDF	Non-radial Directional Distance Function
PCA	Principal Component Analysis
SBM	Slacks-Based Measure
STOCK	Domestic wood waste generation (input variable; not a physical inventory)
SWOT	Strengths, Weaknesses, Opportunities, Threats
TC	Technological Change
UO	Undesirable Output (landfill disposal and incineration without energy recovery)
VRS	Variable Returns to Scale
WFD	Waste Framework Directive

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