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Household Solid Waste Eco-Efficiency in Slovak NUTS-3 Regions: A Two-Stage DEA Analysis

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Abstract
The study assesses the waste-related eco-efficiency across Slovakia's eight regions at the NUTS-3 level. The study examines time trends and efficiency changes between 2018 and 2023. The Data Envelopment Analysis method is used to measure efficiency, specifically a model assuming variable returns to scale. Three specific models were created for different types of household solid waste. These efficiencies are then bias-corrected using a double-bootstrap approach and subjected to a closer analysis of the effects of selected environmental variables, including population density, median age, and the age dependency index. The results indicated a negative impact of a higher share of the economically inactive population on the efficiency of generating all types of household solid waste. In terms of population density, the effects differed, with statistical significance less pronounced. Median age, i.e., the population's maturity, positively impacted household solid waste generation efficiency. The paper's conclusions include recommendations for policies focused on regional disparities, age management, and support for the education of selected population groups. The results of this study can also help identify factors for training AI models for predictive waste management.

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1. Introduction

The issue of waste generation and subsequent treatment has been a subject of research for many decades (Simões & Marques, 2012). The best form of waste management is not to generate it, but this situation is still unrealistic at present. Therefore, we are looking at ways to improve waste management processes to streamline economic, social, and governmental processes at various levels - international, national, regional, corporate, and even individual households. Currently, state-of-the-art procedures and technologies are used to help improve these processes. These include digital twins (Barth et al., 2023), mathematical solutions to routing problems (Han & Cueto, 2015; Neto et al., 2024), often combined with GIS (M. A. Khan et al., 2024), and last but not least, AI and IoT (Lakhouit, 2025). However, AI is also based on specific learned patterns and behaviors, which it then generalizes into various models. This study is also part of a broader project that aims to address the predictability and optimization of routing within waste management, not only in the Slovak Republic, but especially for household waste collection. In this paper, we will thoroughly examine how age and other indicators can influence the predictability of household solid waste generation, as well as various time trends in the waste-related eco-efficiency at the regional level. The study is organized as follows: in the literature review, we examine studies that are relevant to the objectives of this study and determine the current state of research, followed by a methodological section describing the methods, procedures, research object, and data used to verify the objective or research question of this study. This is followed by a chapter presenting the results of this study and a discussion chapter on the results obtained using research methods, and conclusions for policy-making and waste management practice.

2. Literature review

As we mentioned in the introduction, the ideal situation is to produce no waste. Although this is currently relatively unattainable, scientific research has identified. It continues to identify factors that help us understand how waste is generated, its impact, and, based on this, take essential measures. These serve to improve waste management and, ultimately, the state of the environment (Albores et al., 2016; Pais-Magalhães et al., 2021). Waste management and resource efficiency are increasingly treated as important pillars of sustainable development (Depczyński 2024). There is no doubt that a well-made solid waste policy can have a positive effect on solid waste management (Y. Liu & Cai, 2026), but not only positive (Sala-Garrido et al., 2024). Improving the solid waste-related eco-efficiency is a key to improving the level of the circular economy (Delgado-Antequera et al., 2021).

The scientific community has been studying factors that may influence waste generation for many years (Adeleke et al., 2021; Kim et al., 2023; Smailbegovic et al., 2025). Some studies confirm, for example, the negative impact of population density on the amount of waste generated (Monzambe et al., 2019; Voukkali et al., 2023; Ye et al., 2022), but they may not be statistically significant or have a considerable impact (Rybová et al., 2018; Soukiazis & Proença, 2020). The age and gender structures of the population (Novriadhy et al., 2021) are also essential, while unemployment may have a negative impact (Talalaj & Walery, 2015). Some results indicate a significant increase in waste production among people who have reached retirement age (Soukopová et al., 2017). In Iceland, older populations are associated with negative impacts on efficiency (Óskarsson et al., 2025). In contrast, in China, population aging is associated with reduced waste (Zhao et al., 2024). Not only demographic, economic (Zambrano-Monserrate et al., 2021) or social characteristics, or socio-economic (D. Khan et al., 2016), but also, for example, the size of bins, as demonstrated by a study on Sweden and Norway, which have some of the highest waste recycling rates in the world (Söderberg et al., 2025). Political factors, and indeed the very design of municipal waste collection policies, can also be a very important factor in effectiveness (Rella et al., 2025). It is precisely the heterogeneity of individual countries, or even smaller geographical units, that makes it challenging to generalize research results; therefore, research must be conducted for individual countries, regions, or cities (Khadivi & Fatemi Ghomi, 2012).

Studies on this issue are at various levels, with different political groups apparently the most geographically extensive (Ye et al., 2022). Slovakia and its regions are part of the European area, and EU policies and regulations also influence their policies (Agovino et al., 2025). A very timely and thorough analysis of these policies was conducted in a study that measured the performance of EU regions at the NUTS-2 level in sustainable waste management. Their results suggest that, despite continuous improvement, the regions of Eastern and Southern Europe still lag significantly behind the rest of the EU in terms of convergence (Chioatto et al., 2023, 2024). Other studies also point to heterogeneity in efficiency, though the differences between northern and southern Europe are more pronounced, according to different authors (Giannakitsidou et al., 2020). Of course, the granularity of the objects of study is quite significant in some studies, with authors referring directly to municipalities (Rogge & De Jaeger, 2012; Sarra et al., 2017). Despite the relative autonomy of individual regions, it is still necessary to take measures at higher levels of government (Mazzocchitti et al., 2022). One such area is the aging population, which is not just a problem for one city or region but for the EU as a whole, with consequences not only for healthcare but also for other areas of human life (Pais-Magalhães et al., 2022). Slovakia is also significantly affected by this problem, and we therefore consider it essential to verify the impact of age structure on household solid waste production, not only for predictive value in municipal waste collection modeling but also for national policy-making. A study evaluated the effectiveness of Slovak regions in MSW management, but the authors did not focus on the age structure factor; they did, however, demonstrate a positive correlation between MSWM and the level of education of the population. The authors also point out differences across Slovakia's regions and the need to focus policies on reducing regional disparities (Fandel & Marišová, 2025). A comprehensive assessment of legislative conditions in MSWM in Slovakia, along with a comparison with a neighboring country, is presented in a study that describes selected waste production indicators (Nieścior & Marišová, 2024). Some studies have examined Slovakia within broader political groupings and found that it has room for improvement in its waste management processes (Valenćiková & Fandel, 2023; Ye et al., 2022). Although a growing body of literature applies DEA to assess municipal solid waste management eco-efficiency, regionally comparable analyses for Central and Eastern European countries remain scarce. Existing studies differ in how they treat undesirable outputs, limiting methodological comparability and policy relevance. This study addresses three specific gaps. First, it evaluates Slovak NUTS-3 regions — a spatial scale where waste collection, sorting, and transport decisions are made — rather than national aggregates. Second, it applies three separate DEA models distinguished by waste type (mixed, sorted, and total municipal solid waste). Third, it tests robustness by comparing panel estimates (48 DMUs) against multi-year regional averages (8 DMUs). In the second stage, efficiency scores are related to demographic and logistical determinants: population density, age dependency ratio, median age, and road freight loading and unloading intensity to produce actionable regional policy recommendations aligned with EU circular economy targets.

Based on identified research gaps at the Slovak level and additional information on training models for predicting waste collection, this study aims to evaluate the regional eco-efficiency related to solid household waste (HSW) in Slovakia at the NUTS-3 level and to verify the impact of selected variables on this efficiency. The research question is whether there is a statistically significant impact of age structure on waste-related eco-efficiency, and if so, what that impact is.

3. Experimental

In this section, we present the methodological and methodical procedures that will be used to verify the objective and research question set out in the previous section. In many of the studies mentioned in the last paragraph, the Data Envelopment Analysis (DEA) method is used to measure efficiency in the field of waste-related processes, followed by the parametric Stochastic Frontier Analysis (SFA) method (Cordeiro et al., 2012). The foundations for measuring technical efficiency were laid in the 1960s (Farrell, 1957). In this paper, we will use the input-oriented DEA model variable returns to scale (VRS), as previous research suggests that this approach is more likely and appropriate than the constant returns to scale (CRS) assumption (Agovino et al., 2023; Sarra et al., 2017; Ye et al., 2022). The envelopment form of input-oriented envelopment can be found in equation 1:

$$min_{\theta,\lambda}\theta \quad (1)$$
$$\text{Subject to: } \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0}, i = 1, \ldots, m$$
$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, r = 1, \ldots, s$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0, j = 1, \ldots, n$$

where is the input-oriented VRS efficiency score, λj is the intensity variable (weight), is input i for decision-making unit (DMU) j, is output r for DMU j, is the number of DMUs, is the number of inputs, and is the number of outputs (Cooper et al., 2007; Charnes et al., 1985, 2013). These models will compute regional eco-efficiency related to household solid waste.

The object of study will be eight regions of Slovakia at the NUTS3 level: Bratislava (BA), Trnava (TT), Nitra (NR), Trenčín (TT), Banská Bystrica (BB), Žilina (ZA), Prešov (PO), and Košice (KE). We collected data from 2018 to 2023. This resulted in a panel of 48 observations – DMUs. The data were collected from the Eurostat database (Eurostat, 2025) and the Statistical Office of the Slovak Republic's datacube database (Statistical Office of the Slovak Republic, 2025). For this study, we used the size of the monitored region – area – as an input variable, which we included directly in the DEA model inputs and not as an explanatory variable (Lo Storto, 2021; Sarra et al., 2017); and the size of the population in the region – population (Alfiero et al., 2017; Fandel & Marišová, 2025; Mazzocchitti et al., 2022; Talalaj & Walery, 2015). As output variables, we used gross domestic product (GDP). In environmental and eco-efficiency DEA, the production process is frequently modeled as transforming conventional inputs into a desirable economic output (often GDP) jointly with undesirable by-products such as CO_2 or waste; this structure is widely used in eco-efficiency and environmental performance studies. (Agovino et al., 2023; Halkos & Papageorgiou, 2016; F.-B. Liu & Hu, 2023; Pais-Magalhães et al., 2021) and three types of household solid waste – mixed, sorted, and total (Mazzocchitti et al., 2022), based on which we will create DEA models that will differ in terms of undesirable output. We selected these three indicators of household waste generation because mixed and sorted waste are the most significant types of household waste produced in Slovakia, and total household solid waste is a comprehensive indicator. To verify the research questions, we will create regression models that use the following environmental variables in the second-stage analysis:. Population density captures collection-route geometry and service intensity conditions commonly treated as environmental variables in municipal solid waste efficiency and eco-efficiency studies. Demographic structure is controlled using the age dependency index and median age, which proxy household composition, consumption patterns, and participation-related differences relevant to waste generation and sorting behavior. Finally, we include road freight activity (loading/unloading) to proxy regional economic throughput and logistics intensity, reflecting differences in commercial activity and packaging/material flows that can affect waste volumes and service complexity (Baquero et al., 2022; Ke et al., 2022; Romano & Molinos-Senante, 2020; Rybová et al., 2018; Soukiazis & Proença, 2020; Soukopová et al., 2017; Talalaj & Walery, 2015; Ye et al., 2022). More detailed characteristics of the data panel are presented in Tables 1 and 2 in Appendix A. Since waste generation indicators can be considered undesirable outputs, and several approaches to addressing this issue are presented in the current literature, we decided to use the approach proposed by Korhonen and Luptacik (2004), i.e. to measure eco-efficiency using undesirable outputs as inputs, which has proven its applicability and robustness over the past two decades (Halkos & Petrou, 2019). In the waste-management context, the quantities of municipal waste are undesirable outputs because larger values represent environmental burdens generated jointly with the provision of economic activity and public services. Following Korhonen and Luptáčik's eco-efficiency DEA framework, we incorporate undesirable outputs directly into the efficiency assessment by treating them as factors that should be reduced in the same spirit as inputs, so that a unit is evaluated as eco-efficient only if it cannot simultaneously (i) proportionally reduce conventional inputs and environmental burdens (undesirable outputs) while (ii) maintaining the level of desirable output. This modeling choice is consistent with the eco-efficiency interpretation of DEA as a composite of technical and environmental performance and avoids the conceptual inconsistency of "rewarding" a unit for producing more waste (Long, 2021; Rashidi & Farzipoor Saen, 2015; Roshdi et al., 2018; Sahoo et al., 2011).

The smallest region in Slovakia in terms of area is the BA region, with 2,053 km2, while the largest is the BB region, with 8,973 km2, followed by the PO region, with 8,973 km2. Population trends vary across Slovakia's regions. While some regions saw a decline in population between 2018 and 2023 – BB (-4.8%), TN (-2.38%), KE (-2.24%), and PO (-1.7%) – the situation was stable in other regions, with the most significant increase recorded in BA (13.1%). The highest population was recorded in 2020 in the PO region (827,000), and the lowest in TT (563,000).

The highest absolute GDP value was recorded in BA (€33,492), with a significant increase of almost 28.5% compared to 2018. However, the most significant increase was recorded in the NR region, where it rose by 48.6%. In other regions of Slovakia, absolute GDP is comparable and ranged from €10,784 (BB) to €14,910 (KE) in 2023. All monitored regions saw an increase in GDP, with slightly weaker growth recorded in 2019 and 2020. In the case of mixed household solid waste, the decline in its production in almost all monitored regions is a positive development. The highest decline was in the TN region (-23.26%). In absolute terms, this represents approximately 30,000 tons of waste. The only region to see an increase in mixed waste between 2018 and 2023 was KE, with a 5.19% rise. Most mixed waste during the monitored period was produced in the BA region. In the case of sorted household solid waste, the situation was slightly different. There was indeed an increase until 2021, which, on the one hand, is positive because the recycling rate apparently increased; on the other hand, the absolute volume of sorted waste should decrease in parallel with mixed waste, along with an increased recycling rate. On average, 92,731 tons of sorted waste were produced per region, with 107,481 tons in the BA region and 87,963 tons in the PO region. The highest increase was recorded in the BA region (56%) and the lowest in the BB region (11.49%). Total household solid waste increased by an average of 10.1% across Slovakia. The highest increase was in the BA region (27.69%) and the lowest in the BB region (2.75%). The highest amount of waste in 2023 was produced in the BA region (431,813 tons, or 398,318 tons on average), and the lowest in the BB region (255,632 tons).

The highest population density was recorded in the BA region, with an average of 339 inhabitants/km2 and approximately 361.5 inhabitants/km^2 in 2023. We observed an increase of 11.51% compared to 2018. Conversely, the lowest values were recorded in the BB region – only 65.2 inhabitants/km^2 in 2023, with the most significant decline of -5.09%. The age dependency ratio in Slovakia increased by an average of 13.5% from 45.2% to 51.3%. In absolute terms, the indicator increased the least in BA by 4.8% and the most in the TN region by 7.6%. However, in BA, the age dependency ratio is highest in 2023 (54.2%), whereas in ZA it is lowest (49.6%). The median age is increasing across all regions, with the highest in 2023 in the NR region (44.3 years) and the lowest in the regions of eastern Slovakia, PO (39 years), and KE (40.3 years). On average, the median age in Slovakia increased by 4.64% (the highest increase was in ZA at 5.06%). Road freight transport loading averaged 16,295 tons per region. There was a 4.3% nationwide decrease, with the most significant increase recorded in KE (28.7%) and the most considerable reduction in TN (22.3%). In the case of road freight transport unloading, we also recorded a decline of 4.3% across Slovakia, with an increase of 26.5% in KE between 2018 and 2023 and a reduction of 29.8% in NR.

As mentioned above, in this study, we will use regression analysis to assess the impact of the selected explanatory variables. In this study, we will use the second algorithm according to (Simar & Wilson, 2007), which resamples efficiency using a double bootstrap to obtain bias-corrected eco-efficiency scores. In the first loop, we set 100, and in the second loop, 2000 replications. We will use these efficiencies as dependent variables and then use truncated regression (Chowdhury & Zelenyuk, 2016) to determine the impact and significance of selected variables on efficiency. Since the basic DEA VRS will give us three sets of efficiencies, we will also create three separate DEA models, as shown in equations 2, 3, and 4:

$$\widehat{\widehat{\delta_{MHSWE}}} = \beta_0 + \beta_1 Pod\_density + \beta_2 Age\_depend + \beta_3 Median\_age + \beta_4 Transport\_load + \beta_5 Transport\_unload + \varepsilon_i \quad (2)$$

$$\widehat{\widehat{\delta_{SHSWE}}} = \beta_0 + \beta_1 Pod\_density + \beta_2 Age\_depend + \beta_3 Median\_age + \beta_4 Transport\_load + \beta_5 Transport\_unload + \varepsilon_i \quad (3)$$

$$\widehat{\widehat{\delta_{THSWE}}} = \beta_0 + \beta_1 Pod\_density + \beta_2 Age\_depend + \beta_3 Median\_age + \beta_4 Transport\_load + \beta_5 Transport\_unload + \varepsilon_i \quad (4)$$

where is double bootstrapped mixed household SW efficiency, is double bootstrapped sorted household SW efficiency and is double bootstrapped total household SW efficiency. We have applied right-truncated regression at unity and a fixed random seed. We then re-estimate eco-efficiency using multi-year regional averages to avoid window-induced pseudo-replication; the qualitative patterns of key covariates are compared to the baseline panel results. The analysis was conducted in statistical software RStudio, using the package rDEA.

A diagram providing a comprehensive overview of the research steps in this study is shown in Figure 1 in Appendix B.

4. Results and discussion

In the introduction to this section, we present the results of the DEA VRS models as part of the first step of the analysis. Figure 2 shows the efficiency results for Model 1, where the undesirable output is mixed household solid waste.

Based on the results of the DEA VRS model 1 (Figure 2 – Appendix B), several interesting findings emerge regarding regional differences in the waste-related eco-efficiency. The only region that is efficient throughout the entire period under review is the BA region. The least efficient regions are those in eastern Slovakia – KE and PO. However, a positive fact is that efficiency is increasing, most notably in KE (from 0.7139 in 2019 to 0.8015 in 2023) and PO (from 0.7162 in 2018 to 0.8272 in 2023). The TN region also achieved positive results, even being efficient in 2021 and 2023. These results point to improvements in the processes for regional eco-efficiency related to mixed HSW.

Based on the results in Figure 3 (Appendix B), Model 2 shows that the BA, TN, and TT regions were efficient, with only minor deviations from their efficiency frontier for most of the period under review. There was a significant decline in the PO region (from 0.9386 in 2018 to 0.7534 in 2023, with a slight improvement in 2022 and 2023) and in the KE region (from 1 in 2019 to 0.7914 in 2023). The BB, ZA, and NR regions maintained similar levels of efficiency during the period under review. These results point to regional disparities in approaches to the production and management of sorted household solid waste.

Based on the efficiency results for Model 3 shown in Figure 4 (Appendix B), it is possible to reliably assess the situation with waste-related eco-efficiency in Slovakia. The BA, TN, and TT regions are again close to or at the limit of their efficiency frontier. In 2023, the BB region will join them. A very interesting fact is that in 2020 and 2021, efficiency declined significantly across most regions, particularly in BB, KE, and PO. One possible explanation for this situation is the COVID-19 pandemic. However, we view positively the fact that this change was not permanent and that efficiency is gradually improving in most regions. The least efficient regions in 2023 were NR (0.8546), ZA (0.871), and PO (0.883). Overall, the results of the DEA VRS model indicate different approaches and regional disparities in regional eco-efficiency related to HSW.

We assessed robustness to the panel structure by aggregating the 2018–2023 observations into a single multi-year average for each region (8 DMUs) and re-estimating DEA under the same input-oriented VRS specification. The resulting efficiency scores were highly consistent with the panel-based regional mean efficiencies, with correlations of 0.956 (mixed waste), 0.904 (sorted waste), and 0.986 (total waste). Rankings were nearly identical for the mixed and total waste models, while the sorted-waste specification showed some sensitivity (notably for ZA), indicating that temporal variability in separated collection may affect annual efficiency estimates.

We present the regional differences using the regional map of Slovakia in Figure 5.

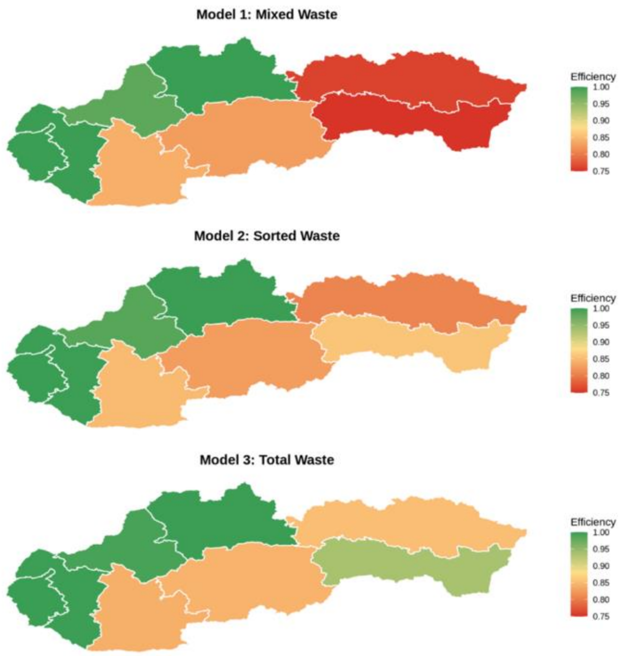

Fig. 5. Regional comparison of average efficiency results in three models

Source: own computation based on data obtained from Eurostat (2025) and Statistical Office of the Slovak Republic (2025).

Based on Figure 5, it is possible to clearly assess the static regional differences in average eco-efficiencies for all three types of household solid waste. In the case of mixed and sorted household solid waste, the differences are most pronounced between western and northwestern Slovakia and the second group, which consists of southern central Slovakia and eastern Slovakia. The differences in efficiency are relatively significant, averaging 0.20 to 0.25 points. In model 3, the KE region has improved significantly, but differences remain. The reason for these changes is, of course, the regional disparities in GDP between individual regions, which we described in the previous sections of this study. In the next part of this study, we continue with a comparison of original vs. bootstrapped efficiencies.

Based on the boxplots in Figure 6 (Appendix B), which show the efficiency of regional eco-efficiency related to mixed HSW in Slovak regions, the original DEA score shows an average efficiency of 0.88. The scores adjusted using the bootstrap method show an average efficiency of 0.83, which represents a statistically significant (expected) negative correction. Although the BA region achieves high DEA VRS efficiency, its average efficiency decreases significantly (by 0.29) after bootstrap resampling. This effect may be due to the sample size. There are even more significant differences in the KE region (a decrease of 0.05). However, based on these results, it is possible to point to significant regional disparities.

In Figure 7 (Appendix B), we compare the eco-efficiency of sorted solid waste. The original efficiency score averages 0.90, and the bootstrap efficiency score averages 0.86. The average correction is 4.8%, slightly lower than in model 1. The BA region retains its perfect original efficiency ($\theta = 1.00$), but after bootstrap, the average efficiency is again significantly lower (0.78). In contrast, the TN and TT regions retain their high efficiency even after accounting for statistical noise. The highest volatility is in the PO and KE regions.

According to model 3, shown in Figure 8, which includes the overall regional eco-efficiency related to HSW, it achieves the highest aggregate performance indicators, with original scores averaging 0.93 and bootstrap efficiency scores averaging 0.89, which are not significantly different. This decline is the smallest among the three model specifications, indicating greater reliability of the estimate when incorporating complex configurations of inputs and outputs. The BA region is again significantly worse in terms of bias-corrected efficiency than in terms of standard efficiency. We observed the highest variability in bias-corrected efficiency in the BB, KE, and PO regions. Before computing the regression, we computed Pearson's correlations among the explanatory variables, as shown in Table 3 (Appendix A).

We identified a higher degree of correlation only for the variables Road freight transport loading and Road freight transport unloading. Loading of goods should increase the regional eco-efficiency related to HSW (because final consumption is in most cases transferred to other regions or countries), and Unloading of goods should decrease the regional eco-efficiency related to HSW (because final consumption is in most cases in the given region). We decided to remove one of the variables: Road freight transport unloading. Table 4 in Appendix A shows the results of modeling the determinants of regional eco-efficiency related to HSW.

Population density has an identical positive effect on different types of waste. The effect is insignificant for mixed waste. This pattern suggests that higher density improves waste-related eco-efficiency due to economies of scale in collection systems and better infrastructure. This finding may also have practical implications for policy differentiation in areas with high population density, even at the lower local level. The ageing index (the proportion of children and seniors in the working population) has a significant negative effect on efficiency in models 1 and 2. This result can be interpreted in terms of changes in economic and social constraints: regions with a high proportion of people of non-productive age face limited resources, lower civic engagement, and higher social service costs, which reduce the capacity for efficient regional waste-related eco-efficiency. The median age of the population proved to be the strongest and most consistent predictor of regional eco-efficiency related to HSW. It achieves high statistical significance in all three models. The effect appears to be even stronger for mixed waste than for sorted waste, suggesting that a more mature population has better basic waste-related habits. Theoretically, this result reflects greater environmental awareness, discipline, and behavioral stability among the working-age adult population. This interpretation is consistent with Gabrielyan et al. (2024), who showed in the household sector that general environmental consciousness and social conditions directly influence the frequency of pro-environmental behaviour. In our case, this behavioural mechanism may partly explain why median age is positively associated with household waste-related eco-efficiency and why educational measures targeted at specific population groups remain policy-relevant. Transport loading shows a consistent, not significant positive effect across models 2 and 3; it is significant only in model 1. The coefficients vary, with the strongest effect being on total waste. This result reflects the importance of economic development for efficient waste management. Process improvement approaches in recycling-related operations have also shown that efficiency gains may be achieved together with reductions in resource use and improvements in process quality (Ramos, 2025). Regions with developed transport infrastructure are better equipped for efficient waste collection, transport, and processing, as well as for the region's trade balance. At the same time, infrastructure serves as a proxy for the region's overall economic maturity.

The second-stage truncated regression models show noticeably different explanatory strength across HSW streams. The Mixed HSW specification provides the strongest fit (R^2 = 0.712) with the lowest residual dispersion (σ = 0.051), indicating that the selected socio-demographic and structural covariates explain a substantial share of variation in bias-corrected eco-efficiency for the mixed stream. The Sorted HSW model achieves a moderate fit (R^2 = 0.511) with higher residual spread (σ = 0.065), suggesting meaningful but incomplete explanatory power, consistent with sorted-waste performance being influenced by additional unobserved operational and policy factors. The Total HSW model is comparatively weak (R^2 = 0.279, σ = 0.059), implying that aggregation into a total stream likely masks stream-specific mechanisms and that a large fraction of total eco-efficiency differences is driven by determinants not captured by the current covariate set.

The results indicate the significance of demographic structure in determining eco-efficiency related to HSW in Slovak regions. The difference between population maturity (median age) and age dependency ratio represents a theoretical contribution to understanding the demographic determinants of regional eco-efficiency sustainability. The effects of population density by waste type expand the literature on urbanization and regional eco-efficiency related to HSW. The results are consistent with life-cycle theory and behavioral economics, which predict greater environmental responsibility among mature populations (Gifford & Nilsson, 2014; M. Wiernik et al., 2013).

The above-mentioned opposite effects of median age (positive) and ageing index (negative in models 1 and 2) are explained by the fact that these variables measure different dimensions of population structure. We have used a ratio that includes a young population. Median age captures the maturity and behavior of the working population, while the age dependency ratio includes economically inactive inhabitants. A region can have both a high median age (40-44 years) and a high age dependency index. The most efficient regions are those with a concentrated working population: a high median age combined with a low age dependency index, indicating that people in retirement and those under age 15 are burdening the regional eco-efficiency related to HSW. This finding has important theoretical implications for understanding the relationship between demographic structure and regional eco-efficiency related to HSW. The results are also very similar to an analysis in the neighboring Czech Republic (Rybová et al., 2018), where the retirement-age population hurts waste production, and although statistically insignificant, higher population density also negatively affects total waste. Moreover, this study supports the results of other studies in terms of population density indicator, which, in fact, has a positive effect on eco-efficiency (Romano & Molinos-Senante, 2020)

A very interesting finding, which was not the aim of this study, is a significant decrease in efficiency during the COVID-19 pandemic. However, this fact can be attributed to many factors, such as morbidity, quarantines, curfews, and later apathy, as well as the uncertainty of government policies. We consider this result to be interesting for future research. Another important piece of information and finding is that management performance is improving after the pandemic. One possible reason for the increased regional eco-efficiency related to HSW is that in Slovakia, waste collection is mostly carried out by private companies, which aligns with the findings of other authors (Alfiero et al., 2017).

However, the main problem is that the effect of an aging population, which is also occurring in the Slovak Republic and for which the forecasts are significantly negative, means that this situation needs to be addressed urgently, as it could slow down or even reverse the positive trends in waste management performance in the coming years, not only in Slovakia but in most EU countries, which has also been confirmed in other studies dealing with environmental issues (Pais-Magalhães et al., 2022).

5. Summary and conclusion

Concerning policies at the national and EU levels, we offer several recommendations supported by the results of this study 1. Focus policies not only on increasing comprehensive waste separation, but also on economically unproductive populations – pensioners and young students under 15, according to other studies, it can also influence other regions through a spillover effect (Y. Liu & Cai, 2026). The ideal approach is environmental education in kindergartens and primary schools, as well as in the community of people of retirement age, similar to programs focused on digital skills development. 2. Differentiate approaches to raising awareness of waste management and responsibility based on geographical location and population density (different policies for urban areas to support the reduction of mixed solid waste, and different policies for rural areas to support the reduction of sorted solid waste, but not the reduction of recycling rates). 3. Promote environmental maturity (responsibility) for people in the early productive age. 4. Promote waste management even in crises.

One of the conclusions of this study is to highlight interregional differences in the management and generation of household solid waste not only at the transnational level but also at the regional level. These findings may also have a significant impact on predictive waste-collection models that use AI, helping to focus AI training on the socio-demographic characteristics of citizens.

Demographic maturity is the strongest and most reliable predictor of regional eco-efficiency related to HSW in Slovak regions. The paradox between the positive effect of median age and the negative effect of dependency burden is explained by the fact that they measure different aspects of population structure - maturity versus economic burden. Population density has opposite effects on different types of waste, which requires differentiated policies.

The main limitations of this paper include the unavailability of some variables at the NUTS-3 level, which could create more robust models, and the relatively small data panel, as some variables were not available for 2024 or the previous period. The next limitation of our design is the risk of pseudo-replication from treating each region-year observation (2018–2023) as an independent DMU. Observations from the same NUTS-3 region across years share persistent structural features and are therefore not statistically independent. We therefore interpret the second-stage results as associations reflecting both cross-regional differences and within-region changes over time rather than as strong causal estimates from a large independent sample, and we complement the main specification with robustness checks that collapse the time dimension to confirm that the main regional patterns are not driven by repeated measurements. Future research could include: spatial econometric models to capture spillover effects across regions, instrumental variables to address endogeneity, and possibly analysis at the municipal rather than the regional level.

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Appendix

Appendix A

Table 1. Input, output, and explanatory (environmental) variables of two-step DEA models

Type	Variable	Description	Units	Source
Input	Area	Total area of the NUTS3 region	km^2	Eurostat (2026)
	Population	Average annual population - persons	thousand	Eurostat (2026)
Output-desirable	GDP	Gross domestic product at current market prices	mil. EUR	Eurostat (2026)
Output-undesirable	Mixed household solid waste	Amount of mixed municipal solid waste produced by households	tonnes	SOSR (2026)
	Sorted household solid waste	Amount of sorted municipal solid waste produced by households	tonnes	SOSR (2026)
	Total household solid waste	Amount of total municipal solid waste produced by households	tonnes	SOSR (2026)
Environmental	Population density	Persons per square kilometer	p/km^2	Eurostat (2026)
	Age dependency	population 0 to 14 years and 65 years or over to population 15 to 64 years	%	Eurostat (2026)
	Median age	Median age of the population	year	Eurostat (2026)
	Road freight transport loading	Road freight transport by region of loading - total transported goods	thousand tonnes	Eurostat (2026)
	Road freight transport unloading	Road freight transport by region of unloading - total transported goods	thousand tonnes	Eurostat (2026)

Source: own processing.

Table 2. Descriptive statistics of the dataset

Variable	Mean	Median	SD	Min	Q1	Q3	Max	CV
Area	6129.38	6549.00	2349.37	2053.00	4413.00	7350.00	9454.00	0.38
Population	681.56	675.09	86.43	563.00	609.94	751.15	827.00	0.13
GDP	12793.99	10732.44	6422.12	7867.62	9275.97	12429.20	33491.67	0.50
Mixed HSW	137315.96	135228.00	18498.50	98445.00	125448.25	150287.00	175216.00	0.13
Sorted HSW	94784.15	92251.50	16536.21	68080.00	82241.00	103922.50	129614.00	0.17
Total HSW	315747.65	309508.00	51897.70	245845.00	273730.25	349014.75	447158.00	0.16
Pop_density	136.83	112.00	80.34	65.20	99.65	132.73	361.50	0.59
Age_depend	48.40	48.35	2.78	43.50	46.18	50.23	54.40	0.06
Median_age	41.31	41.60	1.82	37.30	39.98	42.68	44.30	0.04
Transport_load	15785.40	15568.50	2791.29	10559.00	13734.25	17979.00	21886.00	0.18
Transport_unload	15785.48	15535.00	2549.27	9915.00	14129.75	17820.00	21542.00	0.16

Source: own computation based on data obtained from Eurostat (2025) and Statistical Office of the Slovak Republic (2025).

Table 3. Correlation analysis of the explanatory variables

	Pop_density	Age_depend	Median_age	Transport_load	Transport_unload
Pop_density	1				
Age_depend	0.547387	1			
Median_age	0.023658	0.146881	1		
Transport_load	-0.31352	-0.46666	-0.0547	1	
Transport_unload	-0.43862	-0.48574	-0.12837	0.864351	1

Source: own computation.

Table 4. Truncated regression results of three models

Model	Mixed household solid waste			Sorted household solid waste			Total household solid waste		
Coefficient	Estimate	Pr(>|t|)	Sig	Estimate	Pr(>|t|)	Sig	Estimate	Pr(>|t|)	Sig
Intercept	-0.684710	0.0061	**	0.156190	0.6522		-0.137110	0.7715	
Pop_density	0.000185	0.1023		0.001280	<.001	***	0.001465	0.0080	**
Age_dependency	-0.009822	0.0445	*	-0.011319	0.0305	*	0.003651	0.5780	
Median_age	0.044169	<.001	***	0.024820	<.001	***	0.016341	0.0363	*
Transport_load	0.000008	0.0148	*	0.000006	0.1838		0.000003	0.5882	
Sigma	0.051071	<.001	***	0.064798	<.001	***	0.058640	<.001	***
Log-Likelihood		77.418 on 6 Df			79.032 on 6 Df			82.827 on 6 Df	
R-squared		0.7121			0.5114			0.2792	

Source: own computation.

Appendix B

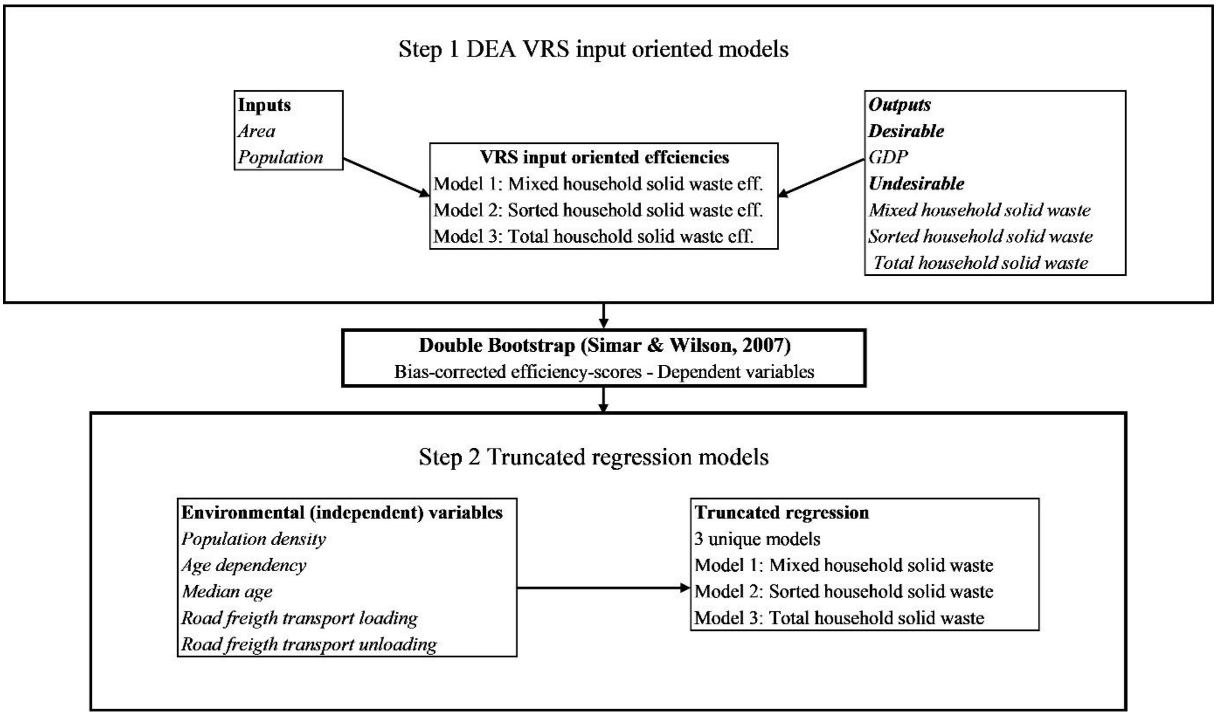

Fig. 1. Scheme of the research steps

Source: own processing.

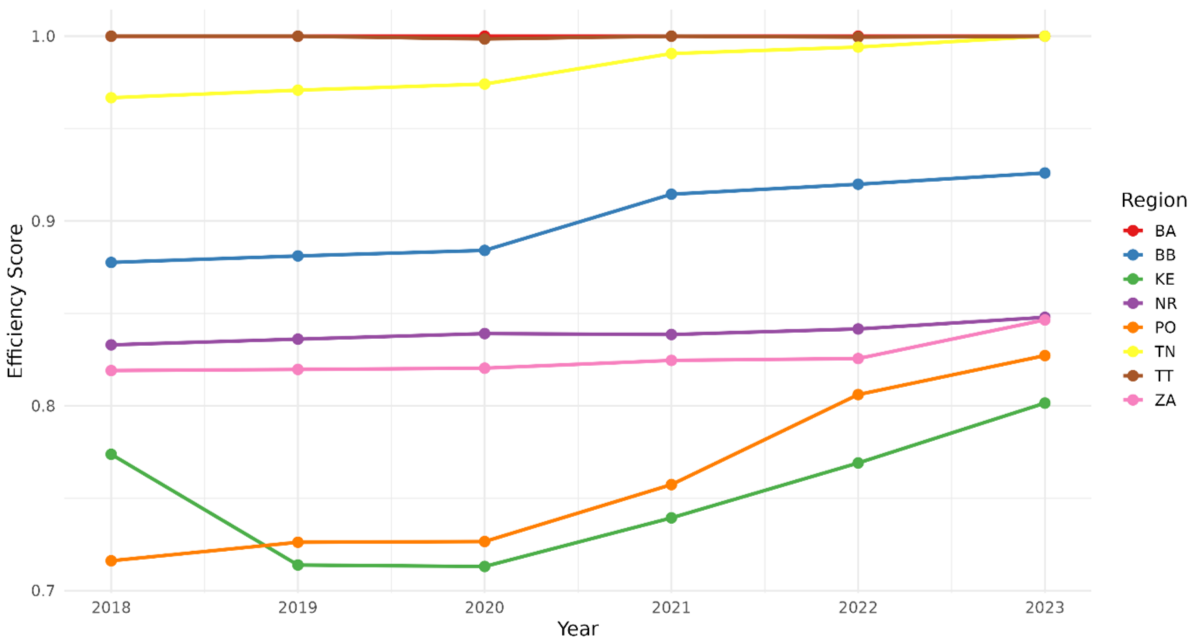

Fig. 2. Temporal analysis of Model 1 efficiency results

Source: own computation based on data obtained from Eurostat (2025) and Statistical Office of the Slovak Republic (2025).

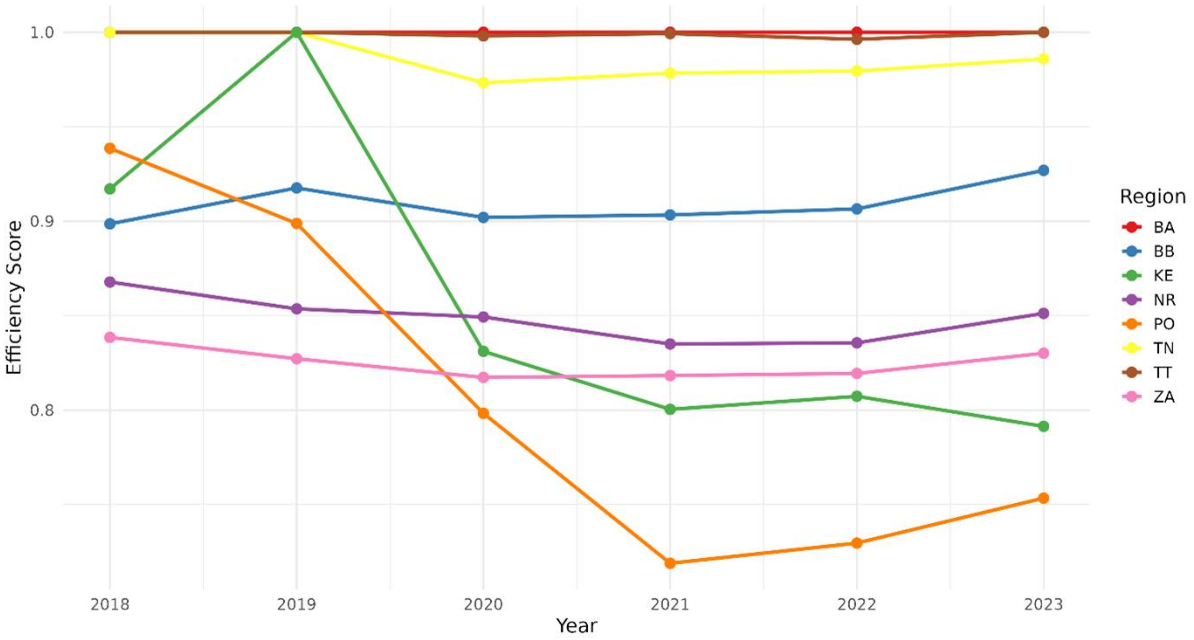

Fig. 3. Temporal analysis of Model 2 efficiency results

Source: own computation based on data obtained from Eurostat (2025) and Statistical Office of the Slovak Republic (2025).

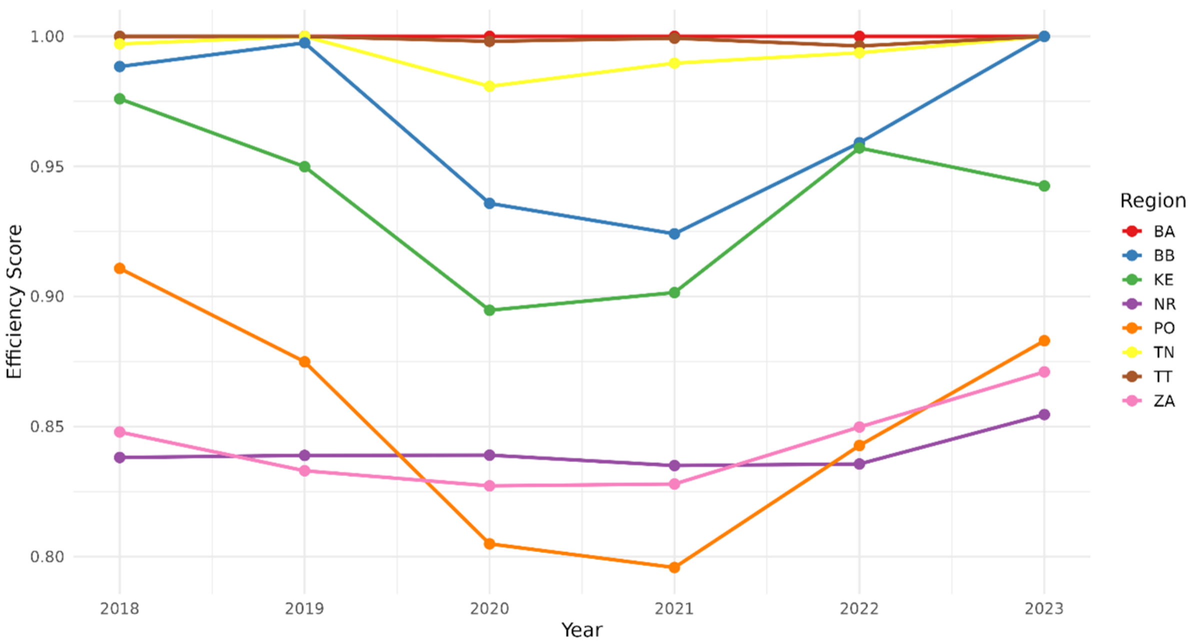

Fig. 4. Temporal analysis of Model 3 efficiency results

Source: own computation based on data obtained from Eurostat (2025) and Statistical Office of the Slovak Republic (2025).

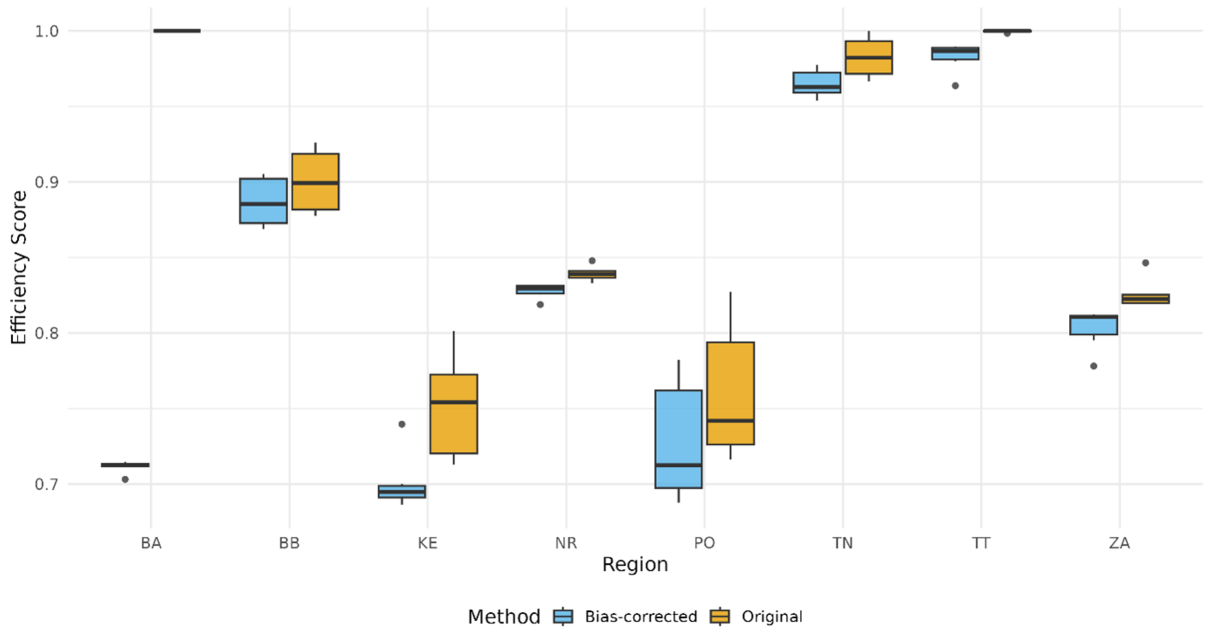

Fig. 6. Comparison of original efficiencies and bias-corrected efficiencies in Model 1

Source: own computation based on data obtained from Eurostat (2025) and Statistical Office of the Slovak Republic (2025).

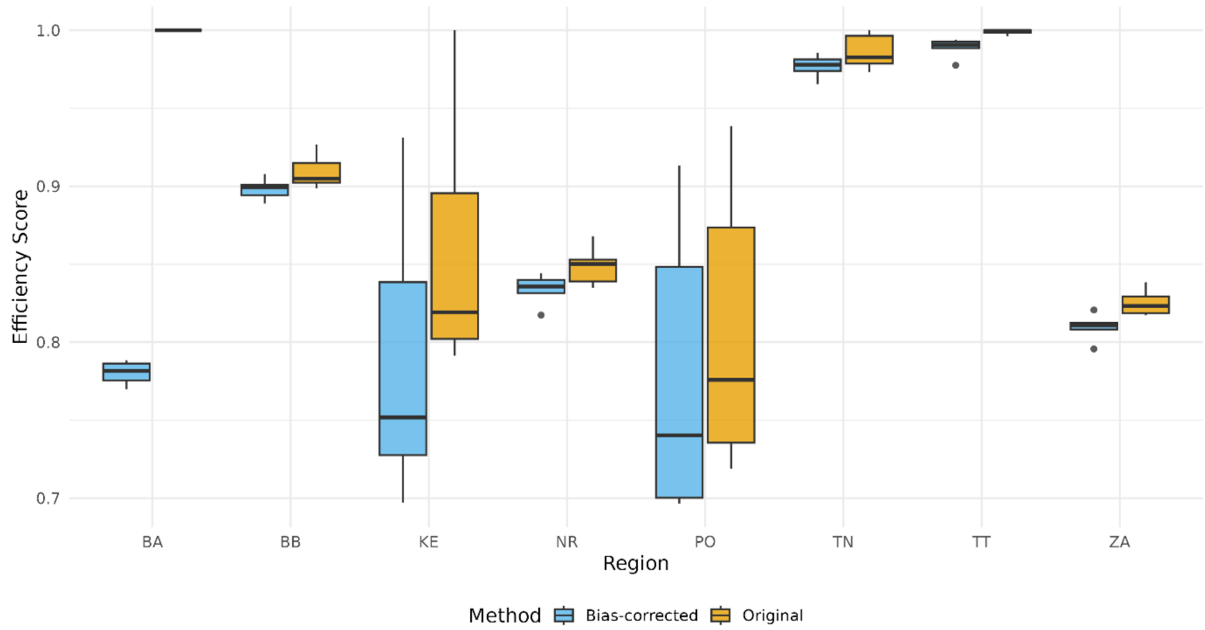

Fig. 7. Comparison of original efficiencies and bias-corrected efficiencies in Model 2

Source: own computation based on data obtained from Eurostat (2025) and Statistical Office of the Slovak Republic (2025).

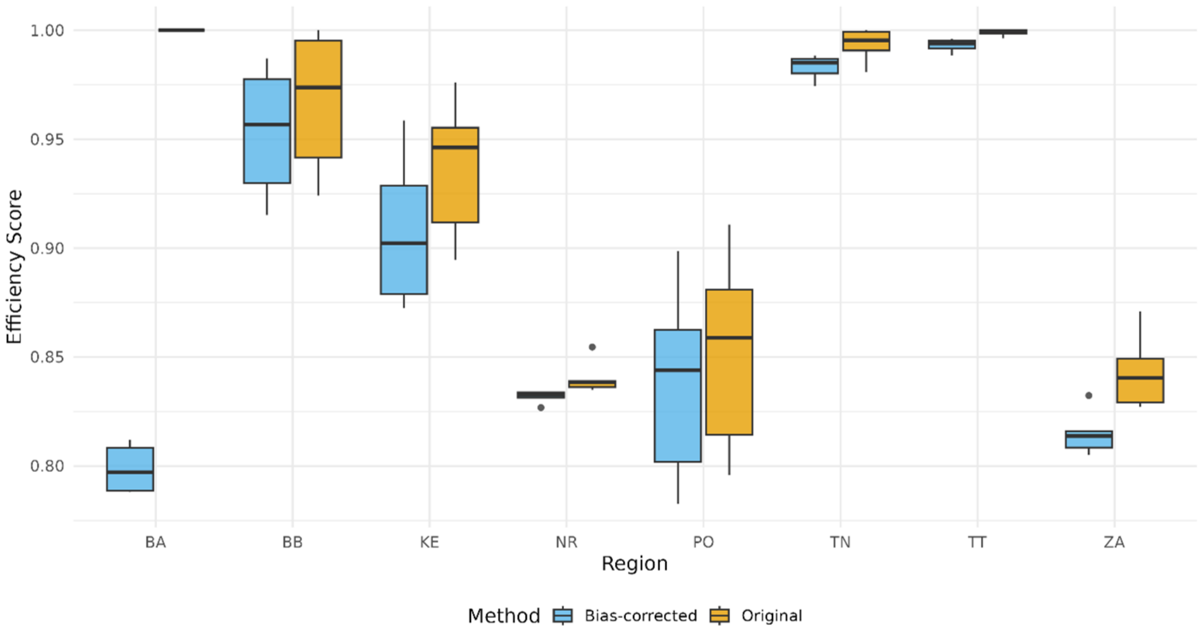

Fig. 8. Comparison of original efficiencies and bias-corrected efficiencies in Model 3

Source: own computation based on data obtained from Eurostat (2025) and Statistical Office of the Slovak Republic (2025).