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Measuring comparative eco-efficiency in the Eurasian Economic Union using MaxDEA X 12.2 software

Abstract

In recent years, Data Envelopment Analysis (DEA) has gained popularity as a robust approach for assessing the eco-efficiency of economic units of different scales. This paper demonstrates the capabilities of the latest standalone version of the open-access MaxDEA X 12.2 software to measure comparative eco-efficiency, using the countries of the Eurasian Economic Union (EAEU) as a case study for the period 2015-2023. The study uses a traditional "black box" DEA model with atmospheric emissions, waste generation, and water consumption as inputs, and GDP along with population as outputs, allowing for a structural eco-efficiency assessment focused on resource use and economic structure. Calculation results obtained using the window method show that Belarus and Kyrgyzstan have the highest eco-efficiency over the entire observation window, while Kazakhstan and Russia lag behind, correlating with their natural resource-dependent economies. The analysis also provides target reductions in emissions and resource use for inefficient countries to improve eco-efficiency. In addition, the paper highlights how the MaxDEA X 12.2 software simplifies data handling and model configuration for eco-efficiency assessments by supporting different model orientations and returns to scale assumptions. Finally, it discusses potential extensions to more complex two-stage DEA models for comprehensive eco-efficiency assessments, subject to data availability. This work highlights the usefulness of MaxDEA X 12.2 as an accessible tool for eco-efficiency benchmarking and managerial decision support in the context of regional economic integration.

1. INTRODUCTION

In recent years, the Data Envelopment Analysis (DEA) method has become particularly popular for assessing the eco-efficiency of economic objects of various sizes and functionality. It is used with equal efficiency and frequency to assess the comparative eco-efficiency of industrial enterprises, as well as the eco-efficiency of individual regions and countries. The reasons for the growing popularity of DEA are its developed mathematical apparatus, a wide variety of models that allow modeling objects (in DEA terminology - DMU) with different structure and properties, and, what is also important, the availability of several available software options that can be used to perform calculations and simulations.

One of the open access software products with good functionality and high computational power is MaxDEA. In previous versions, MaxDEA worked in conjunction with Microsoft Access and required a fully licensed version of Microsoft Office on the computer. In the latest version, however, MaxDEA X 12.2 is a standalone software product that can work equally well with different operating systems. As a result, the MaxDEA interface and its methods of working with the export of calculation results have undergone significant changes.

The purpose of this paper is to demonstrate the interface and capabilities of the latest version of the open access MaxDEA package using the example of solving the problem of assessing the comparative eco-efficiency of the countries of the Eurasian Economic Union in the period from 2015 to 2023. The chosen analytical task is highly relevant for the promotion of eco-innovation and circular economy in this region and represents a novelty in the existing literature. The article provides a comprehensive interpretation of the computational results and how this generated information can inform management decisions aimed at improving resource efficiency at the national level within each country.

Furthermore, this study demonstrates the flexibility of the MaxDEA package by outlining methods for adapting input and output data structures. This adaptation allows the solution of dynamic eco-efficiency problems using only the basic functionalities of the MaxDEA package, thus eliminating the need to access its paid version.

The rest of the paper is organized as follows: Section 2 presents a review of works that use the DEA method to assess the eco-efficiency of economic objects of different class, structure and characteristics. Attention is paid to the type of DEA problem and its peculiarities. Section 3 describes in detail the formulation and algorithm for solving the problem of comparative eco-efficiency of the countries of the Eurasian Economic Union in the MaxDEA X 12.2 package. Section 4 gives an interpretation of the obtained results and the possibility of using them to develop different management strategies. Section 5 describes the conclusions and possible alternative ways of formulating and solving the problem.

2. FEATURES OF DEA APPLICATION FOR SOLVING ECO-EFFICIENCY ASSESSMENT TASK

In general, the concept of eco-efficiency can be described as producing more with less, minimizing environmental impacts and resource consumption while maximizing economic output (Picazo-Tadeo et al., 2012). Therefore, in DEA models, resources are usually inputs, economic outcomes are desired outputs, and negative environmental impacts are undesired outputs. In eco-efficiency calculations, desired outputs are subject to maximization, while inputs and undesired outputs are subject to minimization.

Depending on how detailed the structure of the studied object (Decision Making Unit, DMU) and its production processes are modeled in the study, DEA models used to construct a comprehensive eco-efficiency indicator may differ in structure. One of the simplest models of eco-efficiency of regions is presented in (Ratner & Ratner, 2017). It uses as inputs the amount of pollution emitted to the atmosphere from stationary sources and motor traffic, the amount of unfiltered wastewater discharge, the amount of inadequately filtered wastewater discharge, the amount of industrial and household waste generation, and the amount of fresh water consumption from surface and underground bodies (millions of cubic meters). As outputs, the model uses regional GDP and population. This approach is somewhat unusual because it does not take into account the resources consumed by the regional economy - labor, energy, and capital - but only water consumption. In addition, negative environmental impacts, which are in fact undesirable outputs of the regional economy, are represented in the model as inputs. However, the authors prove the validity of this approach and its consistency with the general logic of the concept of eco-efficiency - to produce more and provide more to the population while consuming fewer resources and producing less negative impact on the environment. The paper constructs a constant returns to scale (CRS) model and applies the "window" method to track changes in eco-efficiency over a five-year period.

A similar approach is presented in Liu et al. (2017) to assess the eco-efficiency of Chinese coastal cities. The model considers different types of pollution from tourism and consumption of energy resources as inputs, and positive economic effects from tourism development - number of tourists and tourism sector revenues - as outputs. Another example of this approach to selecting inputs and outputs according to the logic of "minimizing the bad and maximizing the good" can be found in (Henriques et al., 2022).

The class of models with simple structure also includes models in which inputs and outputs are chosen in such a way that there are no undesired outputs. For example, in (Pais-Magalhães et al., 2021) the eco-efficiency of the waste management system in 15 European countries between 2001 and 2015 is studied. Each DMU is described with 4 inputs: 1) total GHG emissions from the waste sector per capita; 2) total amount of waste disposed per capita; 3) share of renewable energy fuel derived from waste; 4) electricity generated from waste per capita. Outputs are the ratio of GDP per capita and GHG emissions from waste disposal. The authors use an output-oriented DEA model under the VRS assumption.

Ratner et al. (2021) consider the problem of evaluating the eco-efficiency of regional environmental management systems, where inputs are inputs and outputs are reductions in negative environmental impacts (air emissions, wastewater collection, water consumption) that have occurred over time. The VRS model is used to estimate economies of scale for environmental investments.

A study Gastaldi et al. (2020) examines the efficiency of waste management services in the main cities of each Italian province in 2015 and 2016. In the authors' model, the inputs are the cost of waste management (per person and total), the total amount of waste collected, and the waste collection rate in the municipality. The outputs are the amount of sorted waste per person and total. Both CRS and VRS specifications of the output-oriented DEA model to capture the impact of scale size on the performance of the unit analyzed.

In Ezici et al. (2020), input-oriented DEA under CRS assumption is applied to measure the eco-efficiency of energy consumption in different industries of the USA. The same simple structure without undesirable outputs is found in the eco-efficiency estimation models of Lorenzo-Toja et al. (2015), Avadí et al. (2014), Moutinho et al. (2018) (VRS model with DEA-Malmquist productivity index), Wu et al. (2018), and others.

Models with undesirable outcomes have a slightly more complex design and methodology for calculating eco-efficiency (Figure 1). An example is a study to evaluate the eco-efficiency of the waste management system in 142 municipalities in Chile in 2018 (Llanquileo-Melgarejo & Molinos-Senante, 2021). Here, the total cost of waste management is used as an input, the amount of sorted waste - glass, organics, paper, plastic - as a desired output, and the amount of unsorted waste as an undesired output. The authors used both the CRS and VRS models to calculate the eco-efficiency index and compared the results.

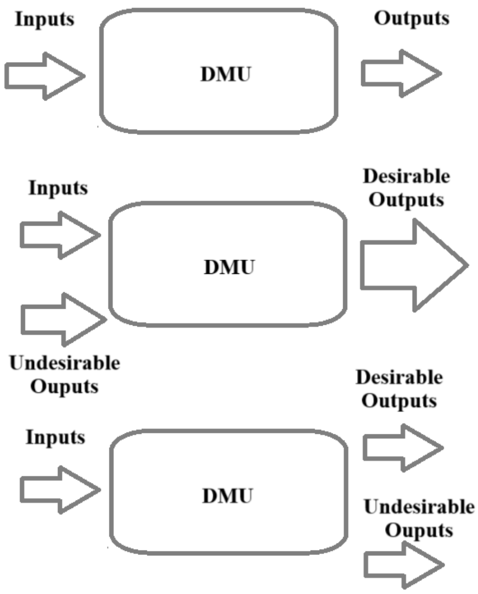

Fig. 1. Black Box" eco-efficiency DEA models

Another example is a study to evaluate the eco-efficiency of the waste management system in Italian municipalities (Romano et al., 2021). The inputs of the constructed model are the total cost of unsorted waste management; the total cost of waste treatment; the total assets of the waste separation system. Desired output: total sorted waste Unwanted output: total unsorted waste. There are no direct environmental variables in the model as in the previous one. A peculiarity of this research is the use of panel data. As a result, the Malmquist-Luenberger meta-frontier productivity index is used, a methodology suitable for dynamic problem solving. Unlike the standard Malmquist index, this approach allows the decomposition of efficiency changes into two components: those due to shifts in the efficiency frontier and those due to changes in the efficiency of the observed unit itself.

A similar approach is used to measure the eco-efficiency of the waste management system in Tuscan municipalities in (Romano & Molinos-Senante, 2020). But this task is static, all calculations are made for one year only (2016).

The environmental performance of Chinese provinces is also estimated in (Huang et al., 2020) using a model with undesirable outputs. Inputs are total water consumption, total energy consumption, urban consumption area, number of employees, and total fixed asset investment. The desired output is economic growth (regional GDP), and the undesired outputs are wastewater, solid waste discharge, and exhaust emissions. The study applies the super-efficiency SBM model, which helps to rank provinces strictly (no repetitions) according to eco-efficiency scores. A similar approach with separation of outputs in the model into desirable and undesirable is used to estimate the eco-efficiency of complex forestry enterprises in the study of Zhang & Xu (2022), to estimate the eco-efficiency of the Chinese transportation industry (Song et al., 2022), to evaluate the eco-efficiency of European and Asian countries (Tsai et al., 2016), to evaluate the eco-efficiency of electricity mixes of 28 EU countries (Zurano- Cervelló et al., 2018), to evaluate agricultural practices by eco-efficiency by Angulo-Meza et al. (2019), and many others.

The most complex structure of DEA models for eco-efficiency assessment found in the literature is the network structure. Network models themselves can be divided into several classes - models with a sequential structure, models with a parallel structure, models with a cyclical structure, and some variations of these (Ratner et al., 2023). Models with a sequential structure tend to be the simplest in this class, and in them eco-efficiency is often split into two parts - economic efficiency and environmental efficiency, or the efficiency of environmental protection systems (Fig. 2).

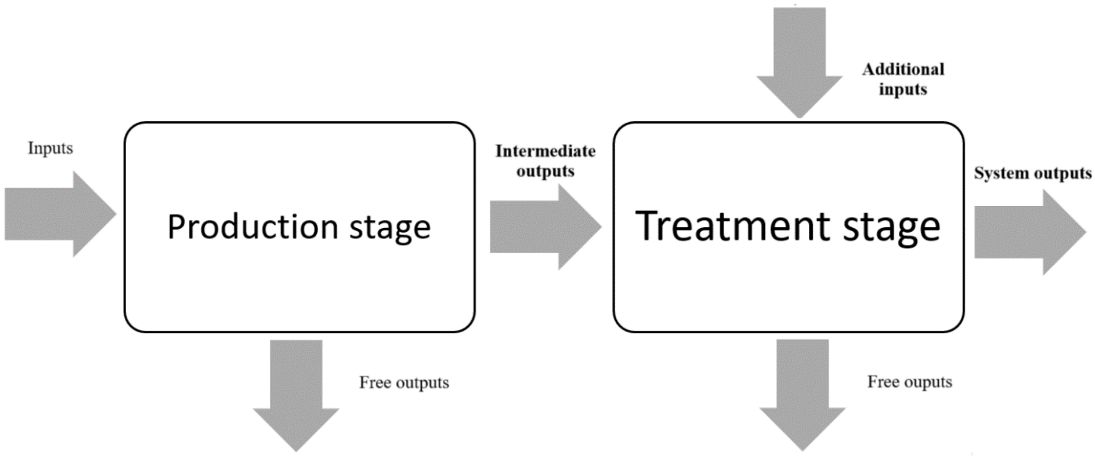

Fig. 2. General two-stage eco-efficiency DEA model

For example, Li et al. (2020) present a two-stage model of regional eco-efficiency with the production process in the first stage and the treatment process in the second stage. The inputs of the first stage are labor, capital stock, energy, water, and land, the output is regional GDP, and the intermediate outputs are wastewater, exhaust gas, and SO2 emissions. The additional input of the treatment stage is financing and the outputs of this stage are solid waste utilization, wastewater utilization and greening rate. The authors adopt the super-efficiency DEA model. The paper (Xiao et al., 2021) applies a two-stage network structure with government and industrial sectors to study the eco-efficiency of Chinese cities. In their model, the government sector uses urban construction land and public financial expenditure (inputs) to provide infrastructure, technology, education, and healthcare (intermediate outputs) to the industrial sector. The industrial sector uses infrastructure, technology, education, and health care as intermediate inputs and consumes energy, labor, and capital as additional (free) inputs. As a result, it generates GDP as a desired output and CO2 emissions as an undesired output.

Shao et al. (2019) measure the eco-efficiency of industrial sectors in China between 2007 and 2015, using the two-stage network structure of the DEA model. The industrial process is divided into three interrelated sub-processes: production (first stage), wastewater and exhaust gas treatment processes (second stage). The inputs of the production sub-process are energy, labor and capital. The desired output is industrial value added, and the undesired outputs are CO2, solid waste, COD generation, NH3-H generation, SO2 generation, and smoke dust generation. COD and NH3-H are intermediate outputs that enter the wastewater treatment process, while SO2 and PM are intermediate outputs that enter the exhaust treatment process. The inputs of the wastewater and flue gas treatment processes are treatment facilities and costs (specified for each sub-process). The outputs of the second stage are COD and NH3-H removal (for wastewater treatment) and SO2 and smoke dust removal (for flue gas treatment). Eco-efficiency is presented as the weighted sum of production efficiency, wastewater treatment efficiency, and exhaust gas treatment efficiency.

The study (Ren et al., 2020) investigates the regional eco-efficiency of China (30 provinces in China from 2003 to 2016). The model structure consists of three blocks: economic production stage, environmental governance stage, and social input stage. The economic production stage has 4 inputs: number of employees, capital stock, total energy consumption, and total water consumption. As output variables, the model uses GDP, wastewater discharge, industrial waste gas emissions, and solid waste emissions. They are all intermediate outputs that are passed on to the next stage. GDP is a desirable output, while all others are undesirable. The environmental governance stage has 2 inputs (investment in pollution treatment and municipal wastewater treatment rate) and 2 intermediate outputs (air quality in major cities and solid waste utilization rate). Social input stage has 2 inputs (proportion of R&D technology investment and social expenditure) and only one system output - human development index. The type of model is a network SBM model that takes into account undesirable outcomes. However, the article doesn't say how the distribution of data over time was taken into account.

A more complex matrix network structure of eco-efficiency is presented in the paper by Yu et al. (2020). It also considers eco-efficiency from three perspectives - economic, environmental and social. Each subsystem has its own inputs and outputs (called external), and is also connected by an input and output (links) to another subsystem. The economic subsystem transfers all kinds of industrial emissions to the environment and receives energy from it. The social subsystem transfers emissions from the residential sector to the environment and receives land and forest resources. The economic subsystem receives labor from the social subsystem and transfers income to it. The external input for the environment is investment in environmental protection, and the outputs are air quality, treated wastewater, and recycled waste. The external input for the economic subsystem is investment in fixed capital and technology, and the outputs are GDP per capita. The external input for the social subsystem is social insurance costs, and the outputs are years of education and share of health technicians. How the distribution of data over time was taken into account - the article does not say, most likely it is the window method.

A similar model is built in He and Jie (2025), only in the second stage three separate processes are included in the model - solid waste, sulfur dioxide and wastewater treatment. Industrial systems of Chinese provinces are considered as DMUs.

In Wang et al., 2021, an even more complex network model is constructed, which also takes into account that between each regional production and treatment system at the previous and subsequent points in time, additional intermediate outputs are connected, which meaningfully represent investments. A non-radial and non-oriented SBM model is used to correctly describe the linkages in such a complex system.

Yang et al. (2024) build a network model consisting of two parallel two-stage processes to evaluate the industrial eco-efficiency of 30 provinces in China from 2015 to 2021. The first stage considers the industrial production process in terms of water and energy efficiency. The second stage examines the process of achieving sustainable development goals in terms of return on investment in resource efficiency and development of environmentally friendly technologies.

Accordingly, a systematization of the Data Envelopment Analysis (DEA) eco-efficiency assessment models documented in the literature can be achieved. This classification divides the models into different categories based on the structure of the decision making units (DMUs), the methods used to account for temporal changes in eco-efficiency, and the type of optimization problem addressed. The latter includes constant returns to scale models, variable returns to scale models, slack-based models, and their variations (as shown in Figure 3).

Structure of the DMU	**Measuring changes in eco-efficiency in time**	**Type of the model**
• Basic • Basic with undesirable outputs • Two-stage • Network	• Statics (no change) • Malmquist productivity index • Meta-frontier Malmquist-Luenberger productivity index • Window	• CCR (CRS) • BCC (VRS) • Slack-based model (SBM)

Fig. 3. Classification of DEA models for eco-efficiency assessments by structure, the approach for measuring changes, and the type

In the following section, using the assessment of eco-efficiency among the member states of the Eurasian Economic Union as a case study, it will be examined which of these analytical tasks can be solved within the free version of the MaxDEA X 12.2 software. Furthermore, this section will detail the preliminary data preparation operations necessary to expand the scope of solvable problems.

3. FORMULATION OF THE DEA PROBLEM AND ALGORITHM OF ITS SOLUTION IN MAXDEA X 12.2

The analysis will use a "black box" structural model. The inputs to this model are defined as: air pollutant emissions from stationary sources (measured in thousands of tons), water withdrawals from natural water sources (measured in billions of cubic meters), and production and consumption waste generation (measured in millions of tons). Note that two of their selected inputs are actually undesirable outputs. The desired outputs are GDP at current prices in US dollars and population. The choice of inputs and outputs in this case is limited to the set of indicators that are collected in the EAEU countries according to a common methodology and can be considered comparable. Data source: official website of the Eurasian Commission (2025).

In this case, the DMUs are the economic systems of the EAEU countries. Data are available for the period from 2015 to 2023, so it is possible to assess changes in eco-efficiency of the countries during this period.

Download the Lite version of the package that is suitable for your computer operating system (Windows/MacOS/Linux) (MaxDEA, 2025). Then unzip the .zip archive and run the MaxDEA.exe program. As mentioned in the introduction, no additional software is needed to run later versions of the program. The interface of the program is very simple and at the initial stage of work the user has only two options - to create a model or to open an existing one (Fig. 4).

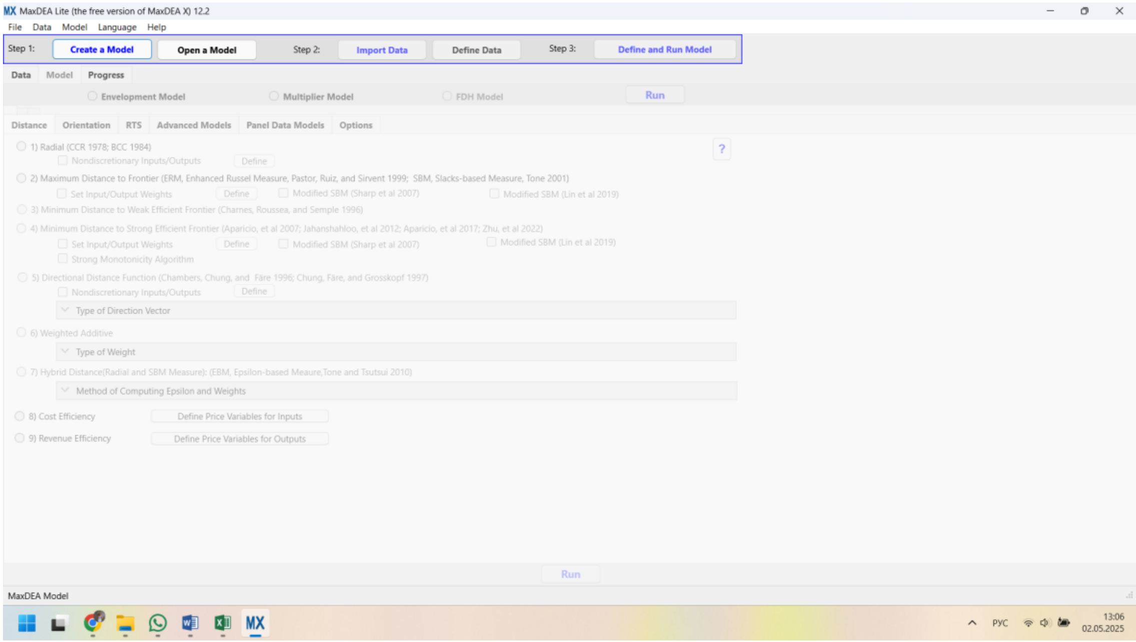

Fig. 4. Starting MAXDEA X 12.2

After creating a file in which the work on building the model will be saved, the options of importing data, defining data, defining the model type and starting the model (Run) will be available in the main window of the program (Fig. 5).

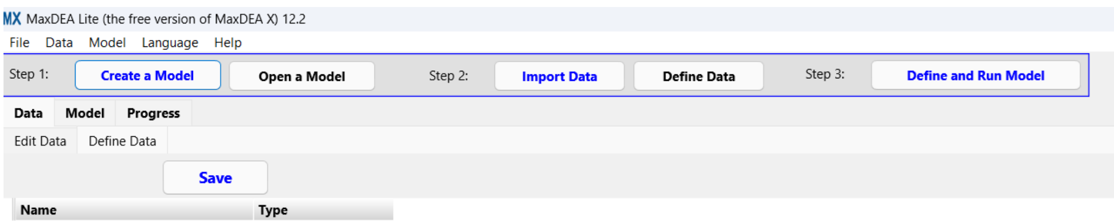

Fig. 5. Starting MAXDEA X 12.2: import and definition of data and model

In the free version of the software, there are two efficiency measures to choose from - Radial, which is used in most tasks, and Maximum Distance to Frontier (Figure 6). All possible model orientations are available:

input-oriented, output-oriented, and non-oriented. In addition, there is access to all possible types of returns to scale - constant (CRS), variable (VRS), non-increasing (NIRS), and non-decreasing (NDRS). The decomposition of efficiency (or total factor productivity, TFP) into scale efficiency and scale effect is also available.

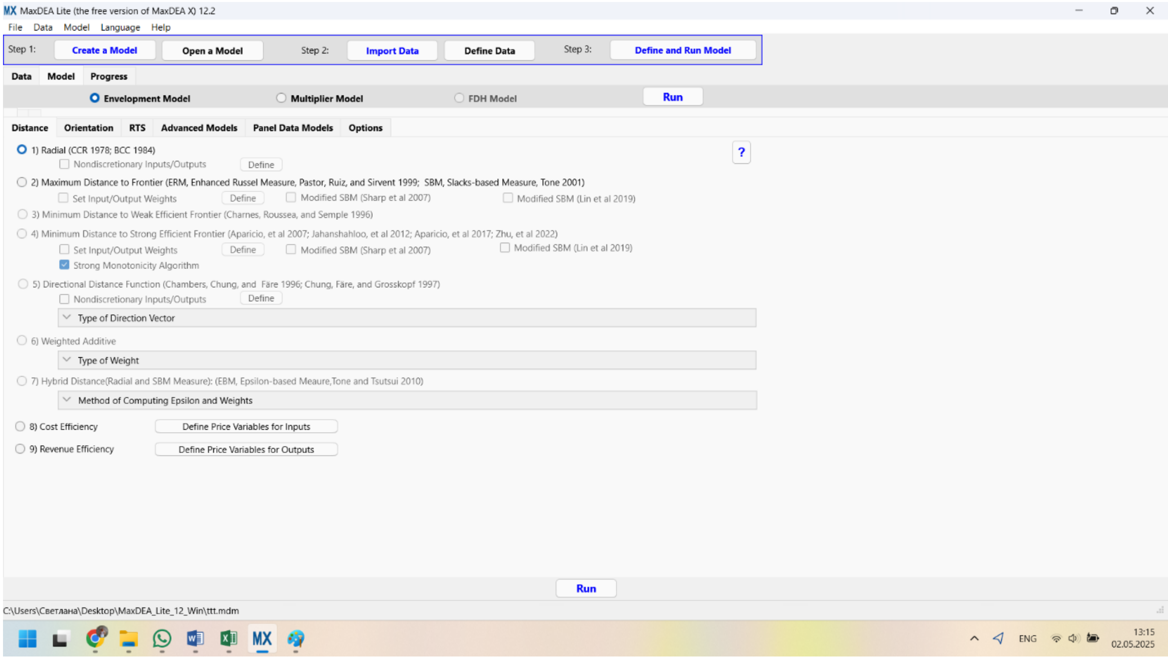

Fig. 6. Starting MAXDEA X 12.2: defining measure of efficiency, orientation and return on scale

As for advanced models, all of them (super-efficiency models, models with undesirable outcomes, and customized benchmarking models) are available only in the paid version of MaxDEA X 12.2. The same is true for panel data models, including Window DEA models (Figure 7).

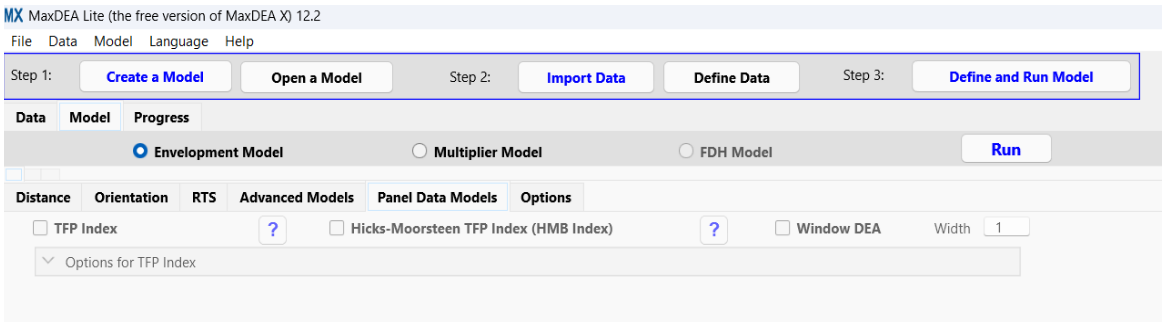

Fig. 7. Starting MAXDEA X 12.2: Advanced Options and Panel Data Models options

In order to export the data to the program, it must first be prepared in an Excel file so that the first column contains the name of the DMU, followed by the columns with inputs and outputs. The first row should contain the names of the columns. All cells in the Excel sheet that are not occupied by DMU names, inputs and outputs must be empty. If the data is a panel (object year), it should first be arranged in the Excel sheet by year, with the year explicitly highlighted in the DMU name, so that the software can interpret each DMU in each year as a separate object (Window DEA methodological approach, more details in (Ratner & Ratner, 2017). For the present task, the data will look as shown in Fig. 8.

	A	B	C	D	E	F
5	Armenia -18	114.0	67.6	2714.4	12 458	2 972 732
6	Armenia -19	89.7	67.9	2865.4	13 619	2 965 269
7	Armenia -20	86.2	74.0	2829.8	12 642	2 959 694
8	Armenia -21	93.8	88.7	2966.5	13 879	2 963 251
9	Armenia -22	105.7	79.1	3071.8	19 513	2 961 367
10	Armenia -23	116.7	58.4	2917.6	24 086	2 937 487
11	Belarus - 15	458.3	49.9	1447.5	55 317	9 453 058
12	Belarus - 16	453.1	49.4	1450.8	47 479	9 469 093
13	Belarus - 17	453.4	55.5	1397.5	54 698	9 469 665
14	Belarus - 18	453.3	60.7	1390.2	59 954	9 448 312
15	Belarus - 19	426.1	60.8	1357.9	64 465	9 429 257
16	Belarus - 20	450.8	61.2	1328.6	61 613	9 410 259
17	Belarus - 21	464.9	62.3	1425.1	69 637	9 349 645
18	Belarus - 22	456.2	39.2	1414.1	73 947	9 255 524
19	Belarus - 23	489.5	50.4	1434.6	72 656	9 200 617
20	Kazakhstan-15	2180.0	320.0	21661.0	184 387	17 415 715
21	Kazakhstan-16	2271.6	320.9	21634.0	137 278	17 669 896
22	Kazakhstan-17	2357.8	405.1	22454.0	166 806	17 918 214
23	Kazakhstan-18	2446.7	445.4	23542.0	179 338	18 157 337
24	Kazakhstan-19	2483.1	515.9	23516.0	181 666	18 395 567
25	Kazakhstan-20	2441.0	457.9	24585.0	171 084	18 631 779
26	Kazakhstan-21	2407.5	777.8	24518.0	197 056	18 879 552
27	Kazakhstan-22	2314.8	1052.1	24966.7	225 342	19 503 159
28	Kazakhstan-23	2257.4	1033.9	24365.8	261 757	19 766 807
29	Kyrgyzstan-15	61.0	45787.0	7569.0	6 678	5 971 460
30	Kyrgyzstan-16	52.8	45759.0	7333.7	6 813	6 108 611
31	Kyrgyzstan-17	49.6	45850.0	7657.8	7 703	6 242 064
32	Kyrgyzstan-18	56.7	182.7	7758.0	8 271	6 371 327

Fig. 8. Preparing data for Window DEA model

Data in Excel should be imported using the Import Data tab and further defined as shown in Figure 9. Each non-empty column can be defined as Period (relevant for advanced models), DMU Name, Cluster (relevant for advanced models), Input, Output or Not Defined.

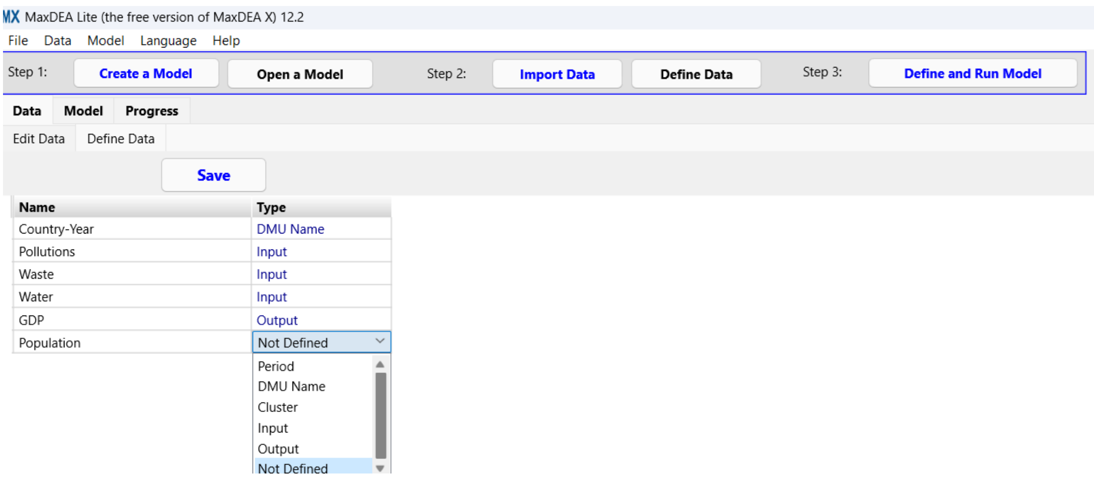

Fig. 9. Defining data for DEA model

Next, the model type is selected and the model is run using the "Run Model" command. For the illustrative task of assessing the eco-efficiency of the countries of the Eurasian Economic Union, a radial efficiency measure with input orientation and constant returns to scale is chosen. The orientation of the model determines the approach to the optimization problem: inputs are minimized while maintaining the current level of outputs, or conversely, outputs are maximized while maintaining the current level of inputs. In this particular application, a more logical approach is to minimize pollution and resource consumption while maintaining economic growth (as measured by GDP) and population levels.

Variable returns to scale models are more informative because they allow us to determine whether or not the "size" of the DMU is at its optimal value. Such information is useful when the inputs to the model are inputs and the return on those inputs can be determined. In the case under consideration, the inputs to the problem, except for the input that determines water consumption, are unwanted outputs. Therefore, it makes no practical sense to search for economies of scale in this case.

After the model is run, the results are saved to a separate folder on the user's computer with a name corresponding to the date. The name of the results file will be Result_Envelopment.csv or Result_Multiplier.csv, depending on how you defined the model.

4. RESULTS AND DISCUSSION

The structure of the file with the results of the calculation of eco-efficiency of the EAEU countries is presented in Fig. 10.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	DMU	Score	Rank	Benchmark(lambda)	Proportionate M	Proportionate M	Proportionate M	Proportionate M	Proportionate M	Slack Movement	Slack Movement	Slack Movement	Slack Movement	Slack Movement	Projection(Pollut
2	Armenia -15	0.619562	29	Belarus - 19(0.159638),Kyrgyzstan-	-49.038399	-18.196826	-1244.677502	0	0	0	0	0	1557.238778	0	79.861601
3	Armenia -16	0.616415	31	Belarus - 19(0.164859),Kyrgyzstan-	-50.55653	-21.350786	-1220.529763	0	0	0	0	0	1870.037559	0	81.24347
4	Armenia -17	0.617563	30	Belarus - 19(0.181825),Kyrgyzstan-	-54.038354	-22.990738	-1095.835105	0	0	0	0	0	1808.46635	0	87.261646
5	Armenia -18	0.709724	26	Belarus - 19(0.163293),Kyrgyzstan-	-33.091478	-19.627339	-787.925498	0	0	0	0	0	0	0	80.908522
6	Armenia -19	0.846986	21	Armenia -23(0.034881),Belarus - 22	-13.725372	-10.388255	-438.44684	0	0	0	0	0	0	0	75.974628
7	Armenia -20	0.840314	22	Belarus - 19(0.07495),Belarus - 22(	-13.764905	-11.810736	-451.878527	0	0	0	0	0	0	0	72.435095
8	Armenia -21	0.817987	24	Armenia -23(0.043685),Belarus - 22	-17.072825	-16.15111	-539.941729	0	0	0	-11.109263	0	0	0	76.727175
9	Armenia -22	0.920868	20	Armenia -23(0.61433),Belarus - 22(	-8.364227	-6.25838	-243.076932	0	0	0	-10.462637	0	0	0	97.335773
10	Armenia -23	1	1	Armenia -23(1)	0	0	0	0	0	0	0	0	0	0	116.7
11	Belarus - 15	0.980036	14	Belarus - 19(0.424683),Belarus - 22	-9.149386	-0.995498	-28.897676	0	0	0	0	0	15529.97022	0	449.150614
12	Belarus - 16	0.991113	12	Belarus - 19(0.429813),Belarus - 22	-4.02653	-0.439428	-12.892539	0	0	0	0	0	23327.13594	0	449.07347
13	Belarus - 17	0.987919	13	Belarus - 19(0.379531),Belarus - 20	-5.477314	-0.670542	-16.882195	0	0	0	0	0	12502.73608	0	447.922686
14	Belarus - 18	0.975518	16	Belarus - 19(0.454051),Belarus - 20	-11.097889	-1.486657	-34.036195	0	0	0	0	0	4405.110641	0	442.202111
15	Belarus - 19	1	1	Belarus - 19(1)	0	0	0	0	0	0	0	0	0	0	426.1
16	Belarus - 20	1	1	Belarus - 20(1)	0	0	0	0	0	0	0	0	0	0	450.8
17	Belarus - 21	0.974151	18	Belarus - 19(0.109724),Belarus - 20	-12.017147	-1.609093	-36.837479	0	0	0	-12.692176	0	0	0	452.882853
18	Belarus - 22	1	1	Belarus - 22(1)	0	0	0	0	0	0	0	0	0	0	456.2
19	Belarus - 23	0.975098	17	Belarus - 20(0.062782),Belarus - 22	-12.189347	-1.255142	-35.723004	0	0	-24.63484	-8.879129	0	0	0	452.675813
20	Kazakhstan-15	0.501636	37	Armenia -23(1.378729),Belarus - 22	-1086.433724	-159.47651	-10795.06463	0	0	0	0	-3952.359191	0	5556547.015	1093.566276
21	Kazakhstan-16	0.360012	45	Armenia -23(0.919591),Belarus - 22	-1453.797866	-205.40194	-13845.51111	0	0	0	0	-2109.103981	0	0	817.802134
22	Kazakhstan-17	0.413039	43	Armenia -23(1.731262),Belarus - 22	-1383.937123	-237.733022	-13179.62683	0	0	0	0	-1830.814758	0	2826357.416	973.862877
23	Kazakhstan-18	0.425208	41	Armenia -23(2.070441),Belarus - 22	-1406.343769	-256.022277	-13531.75502	0	0	0	0	-1493.681946	0	4129550.029	1040.356231
24	Kazakhstan-19	0.418114	42	Armenia -23(2.587849),Belarus - 22	-1444.882187	-300.229015	-13683.64122	0	0	0	-1.504992	0	0	4142775.854	1038.217813
25	Kazakhstan-20	0.405189	44	Armenia -23(2.081954),Belarus - 22	-1451.932641	-272.382266	-14623.41827	0	0	0	0	-1574.572621	0	2621104.591	989.067359
26	Kazakhstan-21	0.463949	39	Armenia -23(3.095962),Belarus - 22	-1290.543589	-416.921913	-13142.90663	0	0	0	-115.296517	0	0	5545807.587	1116.956411
27	Kazakhstan-22	0.548013	35	Armenia -23(3.814746),Belarus - 22	-1046.259712	-475.551345	-11284.62604	0	0	0	-283.27717	0	0	8407173.783	1268.540288
28	Kazakhstan-23	0.652684	27	Armenia -23(4.435309),Belarus - 22	-784.05007	-359.07515	-8462.637159	0	0	0	-333.89011	0	0	12653467.75	1473.403114
29	Kyrgyzstan-15	1	1	Kyrgyzstan-15(1)	0	0	0	0	0	0	0	0	0	0	61
30	Kyrgyzstan-16	1	1	Kyrgyzstan-16(1)	0	0	0	0	0	0	0	0	0	0	52.8315
31	Kyrgyzstan-17	1	1	Kyrgyzstan-17(1)	0	0	0	0	0	0	0	0	0	0	49.6

Fig. 10. Results

The first column of the file contains the names of the DMUs, then column B contains the efficiency coefficients, column C contains the rank of the facility, and column D contains the benchmarks for each DMU. A DMU is considered efficient if its score = 1, otherwise the DMU is inefficient. The lower the score value, the higher the degree of inefficiency. Typically, there are multiple efficient DMUs in a task, so multiple objects may have the same rank in the ranking.

Benchmarks are the efficient objects on the efficiency frontier that are closest to a given DMU. For efficient DMUs, the benchmark is the DMU itself. Inefficient DMUs may have multiple benchmarks.

The next columns are Proportional Movements and Slack Movements, which show the necessary changes in the input values of the object to make it efficient. When solving an input-oriented problem, such changes are calculated only for inputs. For output-oriented problems, the opposite is true. Proportional movements refer to the percentage change in an input or output required for an inefficient DMU to reach the efficiency frontier. These changes are proportional to the original value of the input or output. If a DMU is inefficient, DEA aims to find the "best practice" frontier and project the inefficient DMU onto it. The proportional movement indicates how much each input must be reduced (in an input-oriented model) or each output must be increased (in an output-oriented model) relative to its current level in order to achieve efficiency. Slack movements, or simply "slack," represent the amount of an input that is not used or the amount of an output that is not produced relative to the efficient frontier after proportional adjustments have been made. In essence, if after proportional adjustment of all inputs (or outputs) to reach the frontier, there are still some inputs that are oversupplied or some outputs that are undersupplied relative to the projection on the frontier, these represent slacks. Both of these values provide valuable information for decision makers to develop strategies to achieve effective DMU.

After the columns of Proportional Movements and Slack Movements, the number of which corresponds to the number of inputs plus outputs of the model, follow columns of projections to the efficiency frontier for each input and output. These projections provide very important information for decision makers. They show the target values of each input (in the case of the input-oriented task) and each output (in the case of the output-oriented task) that the DMU must reach in order to become efficient.

Analyzing the results of the DEA task to assess the eco-efficiency of the EAEU countries, several conclusions can be drawn. First, the Republic of Belarus and the Kyrgyz Republic have the highest eco-efficiency throughout the period (Figure 11). The eco-efficiency of the Republic of Armenia increases monotonically and reaches its maximum values at the end of the observation period.

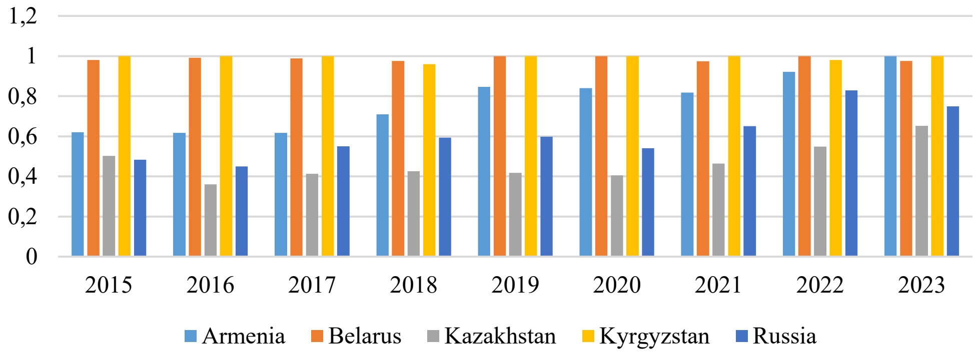

Fig. 11. Eco-efficiency of EAEU countries

Kazakhstan has the lowest eco-efficiency. Its eco-efficiency increases slightly until 2023, but still remains the lowest among the EAEU countries. Russia's eco-efficiency is also low, especially in 2015-2017.

An analysis of the projected input values calculated for all countries at the end of the observation period (as shown in Table 1) reveals the necessary reductions in emissions, water consumption, and waste generation for each identified inefficient country to achieve efficiency.

Tab. 1. Projections of inputs to the efficiency frontier (targets) for inefficient countries in 2023

Country	Real pollutions	Projection (target)	Real waste	Projection (target)	Real water consumption	Projection (target)
Belarus	489.5	452.68	50.4	40.27	1434.6	1398.84
Kazakhstan	2257.5	1473.40	1033.9	340.89	24365.8	15903.16
Russia	16952.0	12700.47	9278.8	1325.24	69131.6	51793.51

It is important to note that in conventional DEA models, more than one object is usually efficient. In order to strictly (uniquely) rank objects by eco-efficiency, it is necessary to use advanced super-efficiency models, which are not available in the free version. To get around this limitation, the following approach to ranking objects can be proposed 1) count the number of cases in which object X was identified as a benchmark (note that only efficient objects can be benchmarks); 2) rank objects by the number of cases in which it acted as a benchmark.

In the problem considered with this approach, the ranking of efficient objects will look as shown in Figure 12.

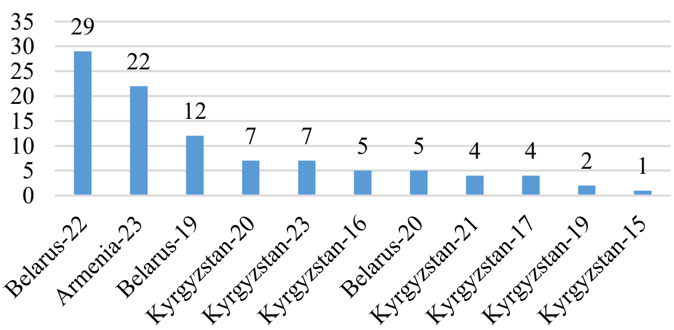

Fig. 12. Ranking according the benchmarks

All of the DMUsshown in Figure 12 are efficient, judging by their scores. However, Belarus-22 is a benchmark for 29 inefficient YMCAs, Armenia-23 is a benchmark for 22 inefficient DMUs, and Kyrgyzstan-15 is a benchmark for only one inefficient object. This fact allows us to rank the efficient objects among themselves, giving preference to those that are benchmarks for a larger number of inefficient objects. Although complete elimination of rank repetition was not achieved in this analysis, distinguishing effective units using this methodology is demonstrably straightforward.

5. CONCLUSIONS

In recent years, the interest in eco-efficiency assessment of various objects and systems has been growing steadily, both in the scientific community and in the policy and business communities. Therefore, the ability to use relatively easy-to-use software to solve eco-efficiency measurement problems is important.

The article systematizes various approaches to the construction of DEA problems for eco-efficiency assessment, which are focused on different structures of the studied objects, types of problems by the type of data (panel or simple sampling), by the formulation and solution of the optimization problem.

The possibilities of the free version of the MaxDEA program are demonstrated on the example of solving the problem of eco-efficiency assessment of the countries of the Eurasian Economic Union. A model of the "black box" type, traditional for DEA methodology, was used, and the inputs were considered to be atmospheric emissions, waste generation, and water consumption. The outputs were GDP and population. Note that with this formulation of the DEA problem and the choice of inputs and outputs, we are dealing with structural eco-efficiency, which is most influenced by the structure of the economy and its resource efficiency.

The results of the calculations of efficiency coefficients on the basis of panel data using the window method show that the Republic of Belarus and the Kyrgyz Republic have the highest eco-efficiency throughout the period of observation. The eco-efficiency of the Republic of Armenia increases monotonically and reaches its maximum values at the end of the observation period. This result is logically well explained by the fact that the Republic of Armenia has experienced a period of rapid economic growth in recent years. Kazakhstan and Russia have the worst eco-efficiency scores, which also correlates well with the fact that the economies of these countries are oriented towards the extraction and export of natural resources.

For all inefficient countries in 2023 (namely Belarus, Kazakhstan and Russia), the targets for atmospheric emissions, waste generation and water consumption are calculated, the achievement of which will help the countries to become eco-efficient. The article also shows ways to circumvent some of the limitations of the free version of the MaxDEA package, such as the ability to rank efficient objects without using advanced super-efficiency models.

Another direction for the study of the eco-efficiency of the EAEU countries could be the construction of a DEA model with a more complex structure, for example, a two-stage model in which the eco-efficiency of the production system is considered first and the eco-efficiency of the pollution treatment system is considered in the second stage. However, attempts to use such models in practice are faced with insufficient comparable statistical data to select indicators as inputs and outputs of DEA models.

Conflicts of interest

The authors declare no conflict of interest.

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