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Pan-European Water Use Efficiency and Sustainability Evaluation Based on Stochastic Meta-frontier Analysis

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ABSTRACT

In 2007, the European Union (EU) intended to become a water-efficient community. Yet, despite the EU's commitment to the United Nations (UN) sustainable development goals (SDGs), relevant insights based on scientific research are still sparse. This study presents a pan-European water use performance evaluation, considering differences in production technologies and potential efficiency determinants. The empirical results are obtained by analysing country-level panel data from 2011 to 2020. Our paper provides more instructive and encompassing findings to inform holistic policy formulation and management practices than prior studies that have typically relied on partial-factor indicators with limited explanatory power. We find that European countries are subject to technological and efficiency heterogeneity, and our production function and inefficiency equation estimations attest to the existence of divergent cause-effect relationships, calling for decentralised, customised solutions. Arguably, our comparative benchmarking analysis constitutes the first comprehensive cross-country investigation for Europe of its kind, underscoring the importance of impactful science in fostering the preservation of high civilisation in line with the theme of this special issue.

Keywords: Europe, performance determinants, stochastic meta-frontier analysis, sustainability, water use efficiency

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INTRODUCTION

Water is both an irreplaceable natural and strategic economic resource (Zheng et al., 2018), indispensable for life on Earth and crucial to socio-economic progress (Luo et al., 2018; Yang et al., 2021). Moreover, by ensuring that this vital resource remains available for current and future generations,

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efficient water utilisation is of fundamental importance for the stability and growth of societies. Notably, efficient water use coincides with the overall pursuit of resource sustainability and sustainable development (Bronner et al., 2022; Lombardi et al., 2019; Walker et al., 2019). Thus, we advocate that a thorough understanding of water use efficiency is integral to preserving and advancing human civilisation.

As water quality and availability are considered major concerns in the European Union (EU), the community proposed a set of measures in 2007 to move towards a water-efficient and water-saving economy (European Commission, 2020, 2021). Furthermore, the European Innovation Partnership (EIP) on water was launched in 2012 to "build an economy that is cleaner, greener, and more efficient" (European Commission, 2015). In addition, the EU has embraced the United Nations (UN) sustainable development goals (SDGs) to synchronise corresponding efforts across its member states (Adler, 2011).

In light of the above, we aim to evaluate water use efficiency in a pan-European context to gain insights for corresponding policy formulation and management practices. Our research is motivated by several critical gaps in the relevant literature. Existing research has overlooked regional heterogeneity due to technological differences across Europe. Hence, we apply a meta-frontier framework to account for variations in production technologies. Furthermore, we extend beyond traditional indicators to assess total-factor efficiency, allowing for more encompassing and instructive findings than prior studies that have typically relied on partial-factor measures with limited explanatory power. Additionally, we incorporate neglected aspects such as water quality and the type of resource usage in our analysis.

For our investigation, we employ stochastic frontier analysis (SFA). Originally developed by Aigner et al. (1977), SFA reflects the actual production technology, providing a more accurate depiction of the relevant underlying economic process (Bogetoft & Otto, 2011; Madaleno & Moutinho, 2023) than non-parametric benchmarking methods, particularly data envelopment analysis (DEA). Moreover, whereas DEA is not entirely compatible with statistical analysis because of its deterministic nature, SFA separates inefficiencies from random errors and supports the simultaneous assessment of contextual factors, enabling a more nuanced performance evaluation (Kumbhakar et al., 2021; Madaleno & Moutinho, 2023).

The key significance of our study in this special issue is rooted in the role water plays as a foundational element of humanity. Efficient water utilisation is deeply intertwined with the continuity of advanced civilisation by bolstering natural habitat preservation and human population well-being (Hatfield & Dold, 2019; United Nations, 2021b). In this sense, we seek to make an impactful scientific contribution to help pave the way for a prosperous future. Our paper offers a fresh perspective by focusing on Europe, as opposed to the commonly studied case of China. To our knowledge, the present work is the first comprehensive transnational study on Europe in this field. The units of analysis are countries and regions based on country clusters.

LITERATURE REVIEW

Although cross-national comparisons play a crucial role in understanding sustainability comprehensively, allowing countries to learn from one another, previous research has paid little attention to the issue of regional heterogeneity (Zheng et al., 2018). In particular, the misconception that different production systems use the same underlying technology has been a common feature in previous SFA applications (Alem, 2021). Countries should be classified according to different production frontiers to facilitate policymaking that caters to their respective circumstances (Ganhadeiro et al., 2018; Sarkhosh-Sara et al., 2020; Yu et al., 2018). To this effect, a meta-frontier approach (Battese et al., 2004; Battese & Rao, 2002; O'Donnell et al., 2008) enables the computation of comparable efficiencies for production subject to distinct technologies (Alem, 2021).

Meanwhile, water efficiency can be defined as the economic value of production per unit of water usage (Wudil et al., 2023), and it is often assessed as such, notwithstanding that corresponding partial-factor metrics consider water as a single input, neglecting other inputs (Zheng et al., 2018). In practice, water is one of several key inputs in the production process (Yang et al., 2021). Hu et al. (2006) constructed an index of total-factor water efficiency, and in the ensuing literature, which mostly concerns China, water utilisation efficiency has typically been measured based on a classical production function approach (Ding et al., 2019; Luo et al., 2018; Wang et al., 2018; Zheng et al., 2018).

According to the European Commission (2020), freshwater abstraction varies among EU member states due to country size, available resources, abstraction practices, climate, and economic structure. Indeed, various exogenous factors can affect water use efficiency (Deng et al., 2016; Luo et al., 2018), including socio-economic ones (Ma et al., 2017). Scholars have considered a range of potential determinants, such as living standards, urbanisation, industrial agglomeration, resource endowment, or environmental regulation.

In particular, water resource efficiency can be influenced by differences in living standards between countries that arise from varying levels of economic development (Yu et al., 2018; Zheng et al., 2018). Previous work showed a positive effect of per capita gross domestic product (GDP) on water utilisation efficiency in Chinese provinces (Bao & Chen, 2017), but other researchers discerned no clear link (Ding et al., 2019).

As symbols of modern civilisation, cities often have advanced water supply and sewage treatment facilities, contributing to improved water use efficiency (Bao & Fang, 2010; Ma et al., 2016). While urbanisation can have a positive impact (Bao & Chen, 2017; Zheng et al., 2018), it may also disturb the hydrologic balance (Mays, 2013), with population growth and concentration posing concerns about the sustainable use of natural resources (Sarkhosh-Sara et al., 2020). In addition, inappropriate scaling in management and production during urbanisation can impede efficiency enhancements (Ding et al., 2019).

Furthermore, the volume of water abstraction per inhabitant is affected by the prevalence of water-intensive economic activities such as farming and electricity generation (European Commission, 2020). Given that the agricultural and industrial sectors are major water consumers, efficiency improvements could be achieved by refining crop irrigation methods and optimising industrial water usage (Bai et al., 2017). More generally, water use efficiency can be linked to economic structure (Li & Ma, 2015; Su et al., 2012), where it has been shown that industrialisation exerts both a positive (Zheng et al., 2018) and a negative (Wang et al., 2018) effect.

Resource endowment potentially constitutes another influential factor (O'Donnell et al., 2008), with per capita freshwater resources as a sustainability indicator (European Commission, 2020). On the one hand, when water resources are plentiful, outdated production technology and inadequate water resource management may be more prevalent, evidencing the existence of a 'resource curse' (Ding et al., 2018; Zheng et al., 2018). However, other findings suggest no such relationship (Ding et al., 2019).

Moreover, governmental intervention can affect resource usage, for example, by imposing environmental regulations to steer consumption behaviour, stimulate technological innovations targeting recycling and reuse practices, or promote investment in infrastructure upgrades (Ganhadeiro et al., 2018; Zhang et al., 2017). While some research indicates that corresponding policies influence water use efficiency positively (Ding et al., 2019; Zheng et al., 2018), other results suggest little impact (Wang et al., 2018).

Prior results are inconclusive, and in shedding additional light on these issues, we focus on Europe rather than the usual case of China to bring a new perspective to the literature.

METHODS

General Setup

To reflect varying production technologies, we use cluster analysis to create three groups of European countries. Our technology-related segmentation criteria comprise the Competitive Industrial Performance (CIP) index, resource productivity, energy productivity, and the share of renewable energy in total energy.

Constructing separate production frontiers allows us to assess countries against the best practices in a particular cluster (Jiang et al., 2020). Furthermore, the meta-frontier can be seen as an umbrella encompassing all possible frontiers that may emerge due to differences between countries (Molinos-Senante & Sala-Garrido, 2016). The meta-frontier curve envelopes the cluster frontiers in a basic output-oriented framework, as illustrated in Figure 1.

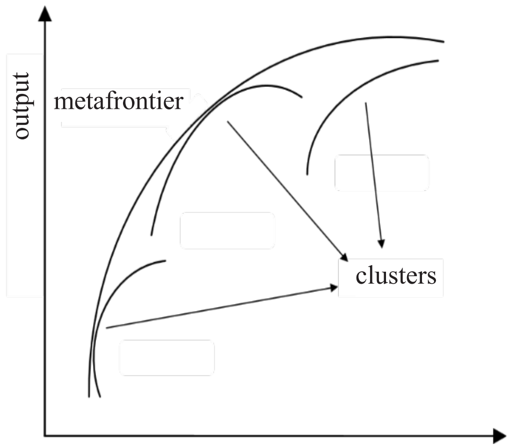

Figure 1. Meta-frontier and cluster frontiers
Source: Authors' work

The discrepancy between each cluster frontier and the meta-frontier can be quantified by employing technology gap ratios (TGRs) that span from 0 to 1 (Jiang et al., 2020). The TGRs provide a measure for the proximity of each cluster frontier, and thus each country, to the meta-frontier (Molinos-Senante & Sala-Garrido, 2016).

Meta-frontier Model

Consider a production process in which each country employs capital stock K, labour force L and water resource W as inputs to produce output Y, which also affects water quality Q as an additional production outcome. Conceptually, the production technology can be defined as:

$$P = \{(K, L, W, Y, Q): (K, L, W) \text{ can produce } (Y, Q)\} \quad [1]$$

Suppose there are G different groups of countries in each region and classified according to their technology level. The group-specific production technologies can be described as:

$$P^g = \{(K, L, W, Y, Q): (L, K, W) \text{ can produce } (Y, Q)\}, \quad [2]$$
$$g = 1, ..., G.$$

Similar to the definitions suggested by Zhou et al. (2012) and Wu et al. (2012) in their energy-related studies, we stipulate the following Shephard sub-vector input distance function for water use (hereafter named Shephard water distance function):

$$D_w(K, L, W, Y, Q) = \sup\{\theta: (K, L, W/\theta. Y, Q) \in P\} \quad [3]$$

Equation [3] quantifies the maximum potential reduction in W. Consequently, $W/D_w(K, L, W, Y, Q)$ represents the hypothetical water usage.

With respect to group technologies, given capital K, labour L, and outcomes Y and Q, the water input requirement set for group g is defined as:

$$WI^g = \{W: (\overline{K}, \overline{L}, W, \overline{Y}, \overline{Q}) \in P^g\}.$$

Referring to Lin and Du (2013) and Zhou et al. (2012), we define the Shephard water distance function for the group technologies as:

$$D_W^g(K, L, W, Y, Q) = \sup\{\theta: (K, L, W/\theta, Y, Q) \in P^g\}, \quad [4]$$
$$g = 1, ..., G.$$

This way, countries adjust their water input to move towards the frontier (Lin & Du, 2013).

The term $W/D_W^g(K, L, W, Y, Q)$ is a theoretical measure of water use based on best practices within a particular group. It represents a country's potential water usage, assuming it utilises the best technology available within its group. The set $\{W/D_W^g(\overline{K},\overline{L},W,\overline{Y},\overline{Q})\}$ represents the lower boundary of the water input set WI^g and is referred to as group g's water input frontier.

Total-factor water efficiency WE, which is the ratio of optimal-to-actual water use (Hu et al., 2006), can be computed as follows:

$$WE = \frac{W/D_W(K,L,W,Y,Q)}{W} = \frac{1}{D_W(K,L,W,Y,Q)} \quad [5]$$

WE is the reciprocal of the Shephard water distance function. It ranges from 0 to 1, where a score of 1 indicates full efficiency.

Accordingly, concerning the group-specific frontiers, WE is defined as:

$$WE^g = 1/D_W^g(K,L,W,Y,Q), g = 1, \dots, G. \quad [6]$$

Further, we assume that the group-specific production technologies belong to a wider technology set P^*. Hence, the production technology of Europe can be defined as follows:

$$P^* = \{P^1 \cup P^2 \cup \cdots \cup P^G\} \quad [7]$$

$$P^* = \{(K, L, W, Y, Q):(K, L, W) \text{ can produce } (Y, Q)\} \quad [8]$$

In this context, the water input requirement set for the common technology can be expressed as $WI^* = \{W:(\overline{K},\overline{L},W,\overline{Y},\overline{Q}) \in P^*\}$. The lower boundary of this set relates to the meta-frontier.

With respect to the wider technology, the Shephard water distance function is stated as follows:

$$D_W^*(K,L,W,Y,Q) = \sup\{\theta:(K,L,W/\theta,Y,Q) \in P^*\} \quad [9]$$

And, regarding the meta-frontier, total-factor water efficiency is:

$$WE^* = 1/D_W^*(K,L,W,Y,Q) \quad [10]$$

Meanwhile, Equation (7) implies that the meta-frontier envelopes the group frontiers. It can be expressed as follows:

$$D_W^*(K,L,W,Y,Q) \geq D_W^g(K,L,W,Y,Q) \Rightarrow WE^* \leq WE^g \quad [11]$$

Moreover, the technology gap ratio TGR, which measures how close group g's frontier is to the meta-frontier, can be defined as:

$$TGR^g(K,L,W,Y,Q) = \frac{W/D_W^*(K,L,W,Y,Q)}{W/D_W^g(K,L,W,Y,Q)} = \frac{WE^*}{WE^g} \quad [12]$$

Based on Equation (12), the following relationship can be established (also see Figure 2):

$$WE^* = WE^g \times TGR^g \quad [13]$$

Next, in accordance with existing literature (Du & Lin, 2017; Zheng et al., 2018), we adopt a translog function to specify the Shephard water distance function for country i and period t, as follows (Equation 14):

where the random variable v_i^t (which accounts for statistical noise) follows the standard normal distribution, and each β is a parameter to be estimated.

Observing that the Shephard water distance function is linearly homogenous in water input (Färe & Primont, 1995), we can write (Equation 15):

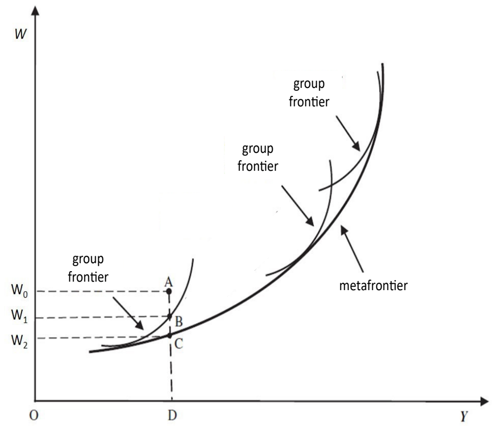

Figure 2. Total-factor water efficiency and technology gap ratio

Note: The curve represents the production isoquant for variables *W* and *Y* when *L* and *K* are fixed. In relation to its group's frontier, country *A*'s water efficiency equals the ratio *BD*/*AD*. With respect to the meta-frontier, it is equal to the ratio *CD*/*AD*. Country *A*'s *TGR* is, therefore, the ratio *CD*/*BD*.

Source: Authors' work

$$\begin{aligned}\ln D_W^t(K_i^t, L_i^t, W_i^t, Y_i^t, Q_i^t) &= \beta_0 + \beta_K \ln K_i^t + \beta_L \ln L_i^t + \beta_W \ln W_i^t \\ &+ \beta_Y \ln Y_i^t + \beta_Q \ln Q_i^t + \beta_{KK}(\ln K_i^t)^2 \\ &+ \beta_{LL}(\ln L_i^t)^2 + \beta_{WW}(\ln W_i^t)^2 + \beta_{YY}(\ln Y_i^t)^2 \\ &+ \beta_{QQ}(\ln Q_i^t)^2 + \beta_{KL} \ln K_i^t \ln L_i^t \\ &+ \beta_{KW} \ln K_i^t \ln W_i^t + \beta_{KY} \ln K_i^t \ln Y_i^t \\ &+ \beta_{KQ} \ln K_i^t \ln Q_i^t + \beta_{LW} \ln L_i^t \ln W_i^t \\ &+ \beta_{LY} \ln L_i^t \ln Y_i^t + \beta_{LQ} \ln L_i^t \ln Q_i^t \\ &+ \beta_{WY} \ln W_i^t \ln Y_i^t + \beta_{WQ} \ln W_i^t \ln Q_i^t \\ &+ \beta_{YQ} \ln Y_i^t \ln Q_i^t + \beta_t t + \beta_{tt} t^2 + \beta_{Kt} t \ln K_i^t \\ &+ \beta_{Lt} t \ln L_i^t + \beta_{Wt} t \ln W_i^t + \beta_{Yt} t \ln Y_i^t \\ &+ \beta_{Qt} t \ln Q_i^t + v_i^t\end{aligned} \qquad [14]$$

$$\begin{aligned}&D_W^t(K_i^t, L_i^t, W_i^t, Y_i^t, Q_i^t) \\ &= W_i^t \times D_W^t(K_i^t, L_i^t, 1, Y_i^t, Q_i^t)\end{aligned} \qquad [15]$$

Then, Equation (14) can be transformed to read:

$$\begin{aligned}-\ln W_i^t = \ln(1/W_i^t) &= \beta_0 + \beta_K \ln K_i^t + \beta_L \ln L_i^t + \beta_Y \ln Y_i^t + \beta_Q \ln Q_i^t \\ &+ \beta_{KK}(\ln K_i^t)^2 + \beta_{LL}(\ln L_i^t)^2 + \beta_{YY}(\ln Y_i^t)^2 \\ &+ \beta_{QQ}(\ln Q_i^t)^2 + \beta_{KL} \ln K_i^t \ln L_i^t + \beta_{KY} \ln K_i^t \ln Y_i^t \\ &+ \beta_{KQ} \ln K_i^t \ln Q_i^t + \beta_{LY} \ln L_i^t \ln Y_i^t \\ &+ \beta_{LQ} \ln L_i^t \ln Q_i^t \\ &+ \beta_{YQ} \ln Y_i^t \ln Q_i^t + \beta_t t + \beta_{tt} t^2 + \beta_{Kt} t \ln K_i^t \\ &+ \beta_{Lt} t \ln L_i^t + \beta_{Yt} t \ln Y_i^t + \beta_{Qt} t \ln Q_i^t + v_i^t - u_i^t\end{aligned} \qquad [16]$$

where $u_i^t \equiv \ln D_W^t(K_i^t, L_i^t, W_i^t, Y_i^t, Q_i^t)$ is a non-negative variable representing water inefficiency. Following the estimation of the parameters in Equation [16], water efficiency can be computed in the following way: $WE_i = \exp(-\hat{u}_i)$.

Moreover, in line with a model specification proposed by Battese and Coelli (1995) that allows for the estimation of a stochastic frontier with an error term that is associated with external variables, assuming $N(\mu_i^t, \sigma_u^2)$, the water efficiency determinants are incorporated in the following inefficiency equation:

$$\mu_i^t = \delta_0 + \sum_p z_{ip}^t \delta_p \qquad [17]$$

where z_{ip}^t refers to the determinants, and each δ is a parameter to be estimated. It should be noted that all parameters in Equations (16) and (17) are computed simultaneously.

The corresponding group-specific and meta-frontier formulations can be derived analogously (Lin & Du, 2013; Zhou et al., 2012). Based on Battese et al. (2004)

and O'Donnell et al. (2008), the following condition (broadly stated in line with the above notation) must be met to ensure that the meta-frontier indeed envelopes the group frontiers: $-\ln W_{it}^{*} \geq -\ln \widehat{W}_{it}^{g}$. The parameters of the meta-frontier can be calculated through optimisation (Battese et al., 2004; O'Donnell et al., 2008), as follows: $Min\left|\ln \widehat{W}_{it}^{g} - \ln W_{it}^{*}\right|$ s.t. $-\ln W_{it}^{*} \geq -\ln \widehat{W}_{it}^{g}$. Subsequently, the TGRs can be obtained through $TGR_{it} = \widehat{W}_{it}^{*}/\widehat{W}_{it}^{g}$. In the final step, the total-factor water efficiency scores related to the meta-frontier can be computed using the following formula: $WE_{it}^{*} = WE_{it}^{g} \times TGR_{it}$.

Sample and Data

Our sample consists of 29 European countries, comprising the 27 EU members: Austria (AUT), Belgium (BEL), Bulgaria (BGR), Croatia (HRV), Cyprus (CYP), Czechia (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Malta (MLT), the Netherlands (NLD), Poland (POL), Portugal (PRT), Romania (ROU), Slovakia (SVK), Slovenia (SVN), Spain (ESP), and Sweden (SWE), as well as the two non-EU members Switzerland (CHE) and the United Kingdom (GBR). The study timeframe covers ten years, from 2011 to 2020. The dataset is based on publicly available data collected and retrieved through database extraction from various sources (see Table 1).

The factors of production considered are labour, capital, and water, while the economic output and environmental outcome variables are total production and water quality, respectively. In addition, the potential determinants of water use efficiency investigated include living standards, urbanisation, economic structure, resource endowment, resource use, and environmental conservation regulation.

A summary of our complete panel dataset is presented in Table 1.

Table 1
Dataset

Categories	Items (description)	Notation	Units	Mean	Max.	Min.	Std. dev.
Clustering (segmentation) criteria							
#1	Competitive Industrial Performance (CIP) index	CIP	Index	16,4	55,0	1,0	10,9
#2	Resource productivity	RP	Purchasing power standards (PPS) per kilogram (kg)	1,97	4,55	0,62	0,92

Table 1 *(Continue)*

Categories	Items (description)	Notation	Units	Mean	Max.	Min.	Std. dev.
#3	Energy productivity	EP	PPS per kg of oil equivalent (KGOE)	8,37	22,22	3,95	2,71
#4	Renewable energy sources	REN	Share of energy from renewable sources, %	20,1	60,0	2,0	11,6
Inputs							
Labour	Total employment	L	Persons employed (thousand)	8.163	45.133	169	10.701
Capital	Total fixed assets	K	Million PPS	1.579.710	10.557.443	27.235	2.237.115
Water	Total freshwater abstraction	W	Cubic metres (million cbm)	7.026	35.069	41	9.613
Outcomes							
Output	Gross domestic product (GDP)	Y	Million PPS	512.716	3.147.495	8.986	712.924
Water quality	Water quality standard of natural bathing sites	Q	Index	76,9	100,0	8,0	16,6
Total-factor water efficiency determinants							
Living standard	Population without sanitation facilities	LST	%	2,8	36,7	0,0	6,2
Urbanisation	Urban population	URB	%	73,3	98,0	53,0	12,6
Economic structure	Gross value added (GVA), agriculture	STR	Share of GDP, %	2,1	6.3	0,2	1,2
Resource endowment	Renewable freshwater resources	END	Thousand cbm per inhabitant	8,3	32,3	0,1	7,7
Resource usage	Freshwater abstraction for public water supply	USE	Share of total freshwater abstraction, %	31,5	96,0	3,0	21,5
Environmental protection	Terrestrial protected area	EPR	%	19,1	37,9	8,3	8,3

Data sources: AQUASTAT, Eurostat, Statistical Review of World Energy of the Energy Institute (EI), Swiss Federal Statistical Office (SFSO), UN Industrial Development Organization (UNIDO), UN Population Division, US Energy Information Administration (EIA), World Database on Protected Areas (WDPA).

Our analysis was conducted using software R.

RESULTS AND ANALYSIS

Factor Analysis

As advocated in the literature (Deng et al., 2016; Ganhadeiro et al., 2018), we perform a factor analysis to avoid potential multicollinearity among certain cluster criteria (Table 2), namely, the Competitive Industrial Performance (CIP) index, resource productivity (RP), and energy productivity (EP), while also reducing dimensionality (Figure 3).

Table 2
Correlation matrix for segmentation criteria

	CIP	RP	EP	REN
CIP	1			
RP	0.49508101	1		
EP	0.37666359	0.4736538	1	
REN	-0.06863821	-0.33122077	0.05008609	1

Source: Authors' work

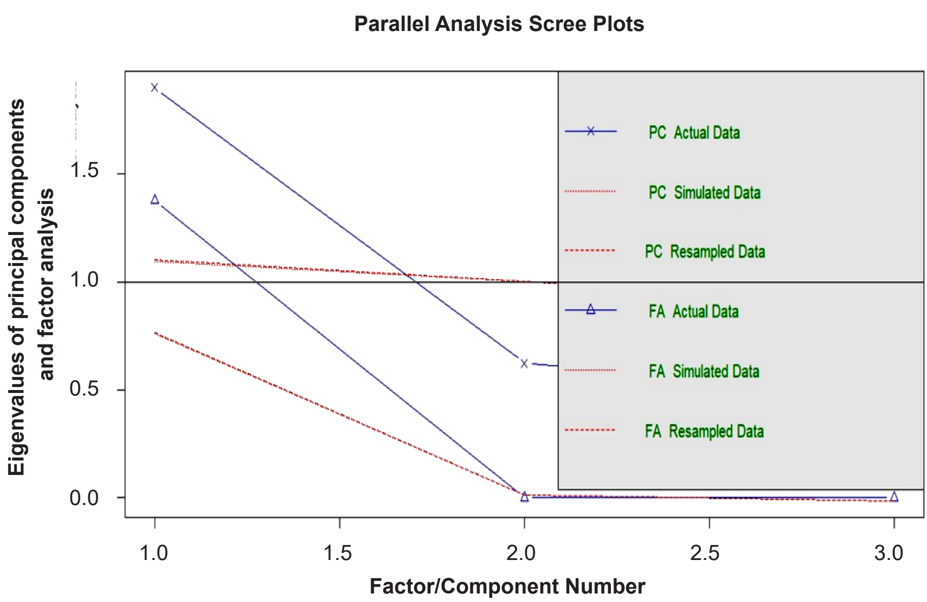

Figure 3. Factor extraction

Note: The factor loadings for CIP, RP, and EP are 0.627, 0.789, and 0.600, respectively.

Source: Authors' work

Cluster Analysis

We apply k-means clustering based on the latent factor (LF) derived from the preceding factor analysis and the REN values (see Table 3).

Table 3
The final set of segmentation criteria after data reduction

Items (description)	Notation	Units	Mean	Max.	Min.	Std. dev.
Latent factor (based on original variables CIP, RP, EP)	LF	Index	35,7	100,0	0,0	21,7
Renewable energy sources	REN	% energy from renewable sources	20,1	60,0	2,0	11,6

Source: Authors' work

As shown in Figure 4, the countries are divided into three groups according to technological characteristics. Groups 1 and 3 have nine constituent countries, while Group 2 contains eleven.

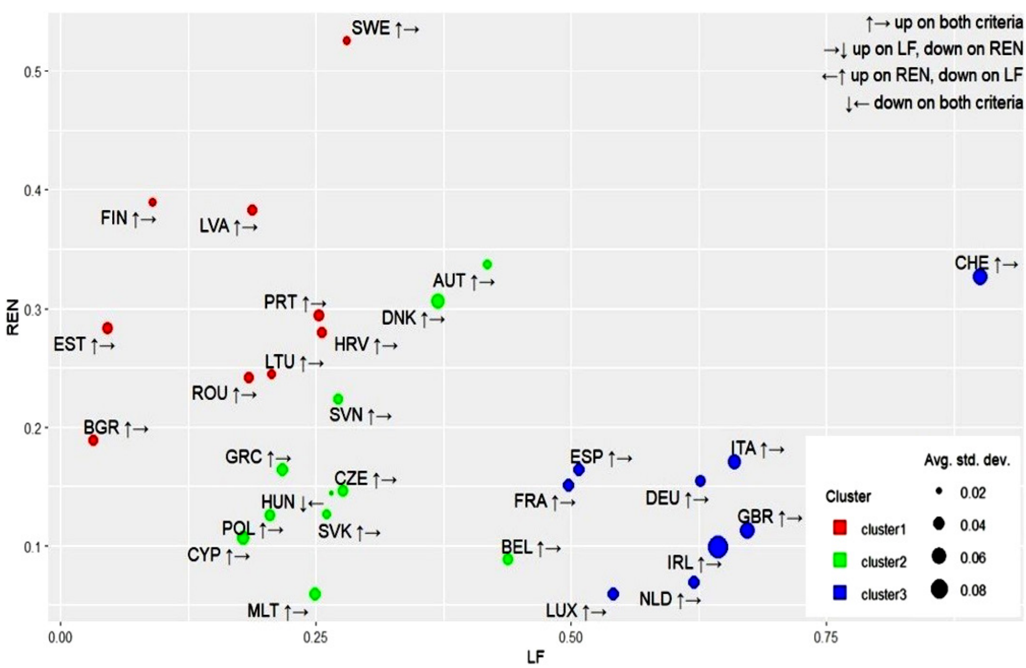

Figure 4. Segmentation (classification of countries)

Note: The impact or weight of each variable on the clustering outcome can be assessed by examining their within-cluster sum of squares. In particular, the standardised within-cluster sum of squares for the factor scores is 0.380 (Cluster 1), 0.176 (Cluster 2), and 0.444 (Cluster 3). For the REN values, the corresponding numbers are 0.715 (Cluster 1), 0.221 (Cluster 2), and 0.064 (Cluster 3).

Source: Authors' work

Figure 5 and the numbers reported in Table 4 reveal that the countries in Cluster 1 are predominantly located in Northern and Eastern Europe. These countries tend to be smaller, less urbanised, less industrialised, and in the process of modernising. Cluster 2 mainly contains medium-sized economies in Central and Southern Europe. Their living standards and extent of urbanisation and industrialisation are generally in the middle range. The countries included in Cluster 3 are primarily situated in Western Europe. On average, they are larger, more advanced, urbanised, and industrialised.

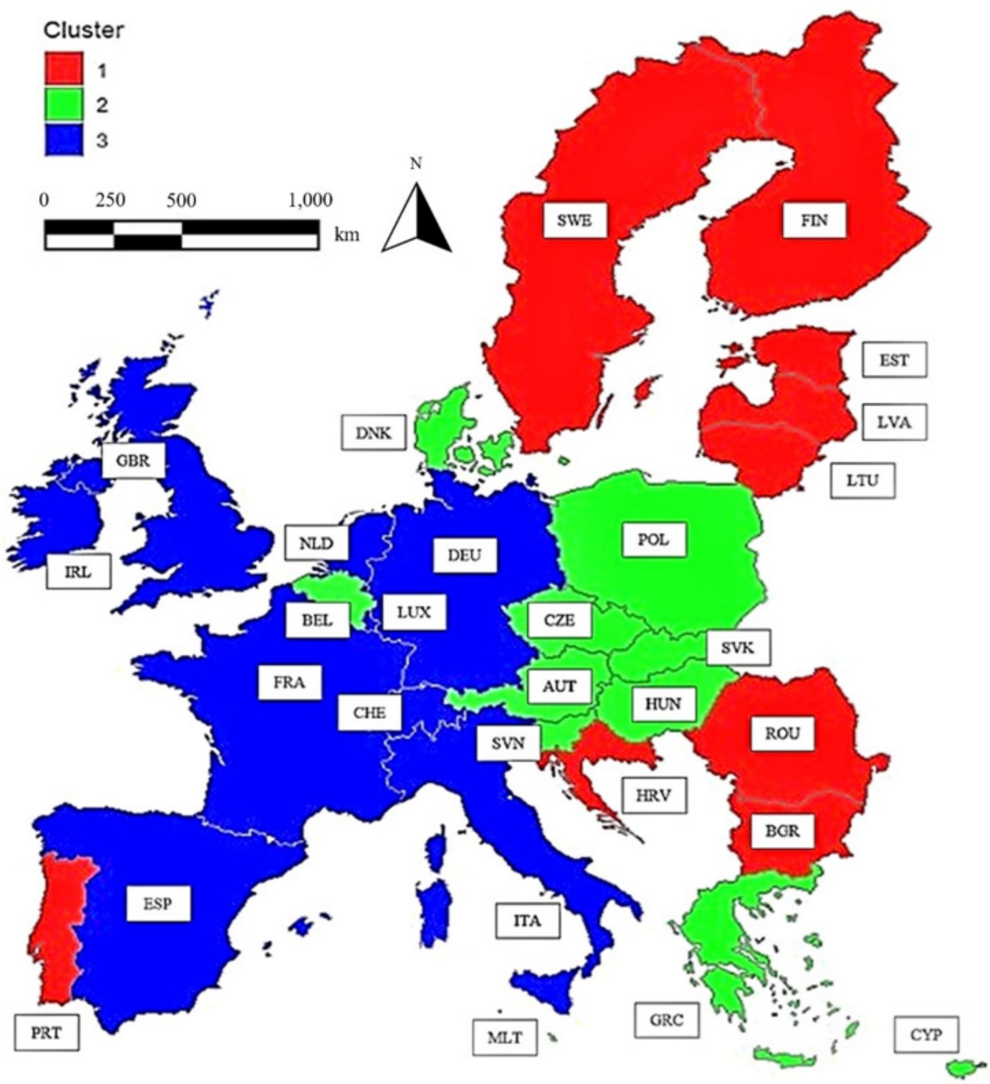

Figure 5. Map
Source: Authors' work

A summary of our panel dataset by cluster is presented in Table 4.

At this stage, it should be noted that we have checked that the relevant data for the production function variables and the performance determinants do not pose concerns regarding multicollinearity.

Table 4
Summary of panel dataset by cluster

Cluster	Mean	Max.	Min.	Std. dev.
Cluster 1 (*90 obs.*)				
Q	73,4	98	8	17,4
Y	153.878	422.627	24.288	119.920
L	3.204	8.829	606	2.466
K	528.872	1.419.057	74.630	389.048
W	3.144	8.880	169	2.730
LST	7,8	36,6	0	9,2
URB	69,3	88	54	10,7
STR	3	6,3	1,4	1
END	15,2	32,3	1,2	8,7
USE	28	78	3	21,3
EPR	20,1	36,7	11,5	9,1
Cluster 2 (*110 obs.*)				
Q	79,4	100	22	17,2
Y	228.418	876.761	8.986	203.119
L	4.177	16.484	169	4.155
K	664.064	1.476.990	27.235	424.049
W	3.438	11.911	41	3.680
LST	0,8	4,2	0	1,1
URB	72,3	98	53	15,1
STR	2	4,2	0,4	1
END	5,7	22,5	0,1	5,5
USE	26,3	52	11	12
EPR	20,6	37,9	8,3	8,7
Cluster 3 (*90 obs.*)				
Q	77,2	100	10	14,6
Y	1.219.030	3.147.495	36.487	922.452
L	17.994	45.133	224	14.227
K	3.749.673	10.557.443	76.506	2.994.167
W	15.294	35.069	43	13.257
LST	0,1	2,6	0	0,3
URB	78,5	92	62	8,6
STR	1,3	3,1	0,2	0,7
END	4,4	15,3	1,2	3,2
USE	41,3	96	11	27,1
EPR	16,2	27,3	8,5	6,1

Source: Authors' work

Stochastic Meta-frontier Analysis

Table 5a reports the computed coefficients for each group, while Table 5b shows the coefficients for the pooled data and the linear optimisation results for the meta-frontier.

Table 5a
Parameter results for group frontiers

	Group 1			Group 2			Group 3		
	Estimates (MLE)	Std. error		Estimates (MLE)	Std. error		Estimates (MLE)	Std. error	
(Intercept)	-158.8796	1.0587	***	-89.4806	14.5490	***	-10.1228	70.7619	
log(K)	24.7208	0.7629	***	13.5038	3.3105	***	50.3681	14.3098	***
log(L)	5.3601	1.3519	***	-38.3953	4.4095	***	-20.9193	17.8607	
log(Y)	-16.5016	0.8874	***	27.7238	4.7521	***	-37.4762	20.6337	.
log(Q)	34.9694	1.0119	***	-3.5260	3.5275		-7.1407	5.8311	
I(0.5 * log(K)^2)	21.9658	1.1256	***	-2.9469	0.5417	***	3.7362	1.6993	*
I(0.5 * log(L)^2)	-1.8491	1.0091	.	-7.2496	1.1918	***	-4.6047	2.3899	.
I(0.5 * log(Y)^2)	14.9808	0.8552	***	-5.7873	1.8688	**	18.0053	4.2013	***
I(0.5 * log(Q)^2)	0.2382	0.3477		0.1396	0.4951		-0.0267	0.1066	
I(log(K) * log(L))	-7.8560	0.8245	***	2.4347	0.7067	***	7.1164	1.9125	***
I(log(K) * log(Y))	-18.7613	0.9880	***	0.2015	1.0688		-12.5825	2.2594	***
I(log(K) * log(Q))	-7.3808	0.7654	***	0.4950	0.3749		-0.3739	0.3960	
I(log(L) * log(Y))	8.8358	1.1408	***	5.1815	1.2054	***	-2.8627	2.4100	
I(log(L) * log(Q))	2.1663	0.6124	***	0.5520	0.5096		-0.9322	0.7533	
I(log(Y) * log(Q))	3.7224	0.8322	***	-0.6817	0.6068		1.5774	0.8535	.
t	-0.2506	0.2905		-0.7417	0.0961	***	0.3983	0.4752	
I(t^2)	0.0021	0.0033		-0.0002	0.0011		0.0002	0.0012	
I(t * log(K))	0.1258	0.0739	.	0.0365	0.0199	.	0.1275	0.0365	***
I(t * log(L))	-0.2872	0.0537	***	-0.1450	0.0281	***	0.0143	0.0608	
I(t * log(Y))	0.1216	0.0714	.	0.1191	0.0343	***	-0.1801	0.0664	**
I(t * log(Q))	-0.1183	0.0558	*	0.0093	0.0218		0.0108	0.0215	
Z_(Intercept)	-0.0755	0.4443		-7.7907	0.7935	***	2.0583	0.7174	**
Z_LST	0.4341	0.6076		11.6312	4.0518	**	-6.7640	4.9136	
Z_URB	1.0659	0.6085	.	6.5442	0.6333	***	-2.0626	0.6242	***
Z_STR	0.1531	0.9986		24.1149	4.2502	***	49.1883	6.2924	***
Z_END	-0.0112	0.0077		-0.0012	0.0060		0.0121	0.0144	
Z_USE	-1.0995	0.2507	***	-2.5542	0.3507	***	-1.4466	0.4467	**
Z_EPR	1.9777	0.6403	**	16.5403	1.2769	***	-1.3808	0.7861	.
sigmaSq	0.0295	0.0081	***	0.0120	0.0023	***	0.0078	0.0015	***
gamma	1.0000	0.1828	***	0.8387	0.0540	***	0.9593	0.0205	***
log-likelihood value	32.5967			129.5798			124.3207		

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Note: A low gamma value suggests that deviations from the frontier are caused by random error. Specifically, when gamma is close to zero, deviations mainly stem from noise. Conversely, if gamma is close to one, deviations are primarily due to technical inefficiency. When gamma equals one, all deviations from the frontier result from inefficiency (Battese & Coelli, 1995; Coelli et al., 2005; Tran et al., 2008).

Source: Authors' work

Table 5b
Parameter results for common ('pooled') frontier and meta-frontier

	Common frontier			Meta-frontier
	Estimates (MLE)	**Std. error**		**Optimisation results (LP)**
(Intercept)	-44.1545	2.8525	***	0.000307
log(K)	11.2289	1.1116	***	0.002256
log(L)	-12.1156	0.4322	***	0.000292
log(Y)	2.4043	1.0205	*	0.002437
log(Q)	1.9831	0.6229	**	0.001410
I(0.5 * log(K)^2)	-0.9810	0.4178	*	-0.014724
I(0.5 * log(L)^2)	-0.7161	0.0939	***	-0.007614
I(0.5 * log(Y)^2)	-0.3872	0.2899		-0.005939
I(0.5 * log(Q)^2)	-0.2448	0.0728	***	0.003151
I(log(K) * log(L))	0.9979	0.0705	***	-0.025507
I(log(K) * log(Y))	-0.3077	0.3482		0.008407
I(log(K) * log(Q))	-0.6501	0.1133	***	0.000426
I(log(L) * log(Y))	0.3781	0.1357	**	-0.019277
I(log(L) * log(Q))	-0.0312	0.0452		-0.003933
I(log(Y) * log(Q))	0.6251	0.0958	***	0.000835
t	-0.0949	0.0855		0.005529
I(t^2)	-0.0028	0.0004	***	0.006275
I(t * log(K))	0.0046	0.0110		-0.010292
I(t * log(L))	-0.0135	0.0103		0.003544
I(t * log(Y))	0.0082	0.0061		-0.007160
I(t * log(Q))	0.0247	0.0086	**	0.010179
Z_(Intercept)	0.4604	0.2479	.	
Z_LST	-1.7977	0.4906	***	
Z_URB	0.3712	0.2413		
Z_STR	24.8108	2.3208	***	
Z_END	0.0154	0.0035	***	
Z_USE	-4.6519	0.1025	***	
Z_EPR	3.5894	0.4110	***	
sigmaSq	0.0996	0.0070	***	
gamma	1.0000	0.0000	***	
log-likelihood value	63.0515			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Note: The log-likelihood ratio (LR) test compares the 'pooled' model, where all regions are combined, to an 'unpooled' model, where each group has its frontier. Based on our calculated statistics, there is strong evidence to suggest that the frontiers of the three regional groups are not the same.

Source: Authors' work

Across the three groups, capital exhibits the most consistent and statistically significant association in terms of the first-order partial elasticities of water productivity. This association is strongest for Group 3, where a percentage increase in capital corresponds to a rise in water productivity of approximately 50%. The estimated elasticity for water quality (34.97) is positive and statistically significant in the first group only (and in the pooled sample).

The results also show the elasticities of water productivity in a nonlinear way. For instance, the percentage change in water productivity with respect to capital varies with the level of capital itself. In the case of Group 2, the relevant second-order elasticity is -2.95, i.e., as the scale of capital increases, its enhancing effect on water productivity lessens. The second-order elasticities of total production follow the same pattern, with a negative value for Group 2 but positive values elsewhere.

Meanwhile, the influence of capital on water productivity diminishes as the level of total production climbs, and vice versa, for Groups 1 and 3. Concerning other statistically significant interaction results, for Group 1, the positive association between water productivity and water quality weakens as the level of capital grows (and vice versa). Conversely, the combined effect of water quality and output on water productivity shows the opposite trend.

Moreover, the estimated time trend can generally be interpreted as the average annual rate of technological change (Alem, 2021). In this study, the corresponding parameter for Group 2 is significant and negative, suggesting technological degradation manifested as a decline in water productivity over time. Significant parameter values for interaction terms involving time imply that technological changes affecting water productivity vary depending on capital, labour, production, or water quality levels.

Regarding the estimation results for the inefficiency equation, Table 5a illustrates that all potential determinants, except resource endowment, influence water use efficiency to some extent. However, the type of water usage consistently shows a statistically significant impact across all groups. Resource endowment also emerges as a statistically significant influence when considering the pooled data in Table 5b. Specifically, the impact of LST on water use efficiency remains inconclusive, with a positive effect observed in Cluster 2 and a negative effect for the common or 'pooled' frontier. The influence of URB is also unclear, showing a highly significant positive effect in Cluster 2 and a highly negative effect in Cluster 3. STR generally positively affects water use efficiency, while END shows a positive effect only in the common frontier. Conversely, USE consistently has a negative effect. EPR predominantly exhibits a positive effect. Here, it should be clarified that a statistically significant positive relationship implies that the determinant in question has a negative impact (and vice versa), given the undesirable nature of inefficiency.

The descriptive statistics of the TGRs calculated for the different groups are reported in Table 6.

Cluster 3 leads in terms of TGR, with an average value of 0.46. Hence, the frontier of Cluster 3 is closer to the meta-frontier compared to the frontiers of the other two clusters. In comparison, Cluster 1 has an average TGR of 0.30. On average, countries in Cluster 1 require over 50% more water than those in Cluster 3 to attain the same production outcome with equivalent labour and capital inputs. Across individual observations, TGR values range from a minimum of 0.05 in Cluster 1 to a maximum of 1.00 in Cluster 3.

Figure 6 displays the frequency distributions for the TGRs.

Table 6
Descriptive statistics for TGRs

	Cluster 1	Cluster 2	Cluster 3
Mean	0.3041	0.3933	0.4598
Std. dev.	0.1940	0.1967	0.2208
Min.	0.0455	0.0753	0.1524
Max.	0.8517	0.9227	1.0000
Obs.	90	110	90

Kruskal-Wallis chi-squared = 25.332, df = 2, p-value = 3.157e-06

Note: We use the Kuskall-Wallis non-parametric test (Kruskal & Wallis, 1952) to assess whether the TGRs differ among groups. Based on the corresponding result, we strongly reject the null hypothesis that TGRs in different groups come from the same population.

Source: Authors' work

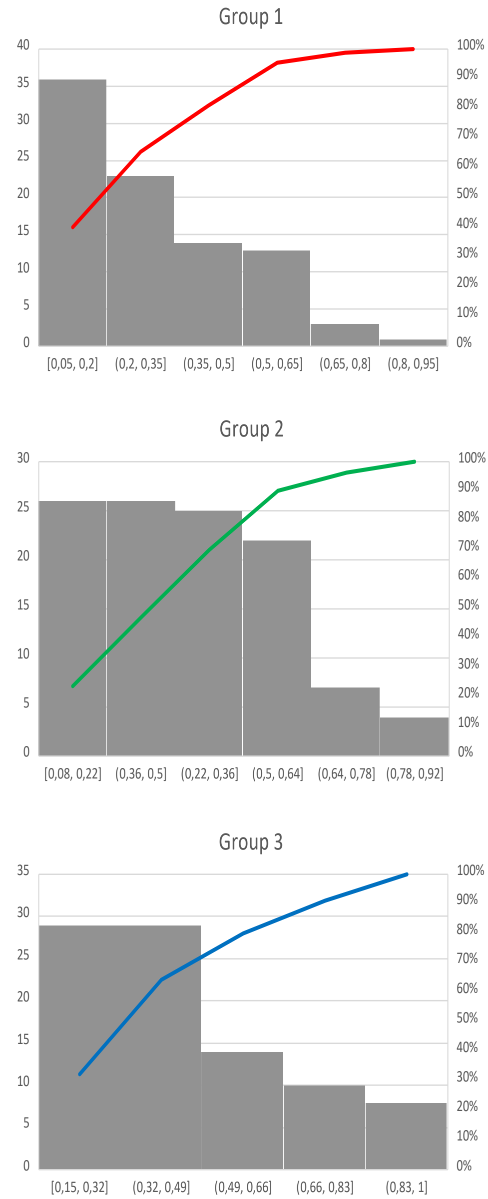

Figure 6. Frequency distributions of TGRs

Source: Authors' work

The three clusters exhibit comparable patterns of variation with respect to their TGRs. Figure 7 depicts the evolution of TGRs for the different groups.

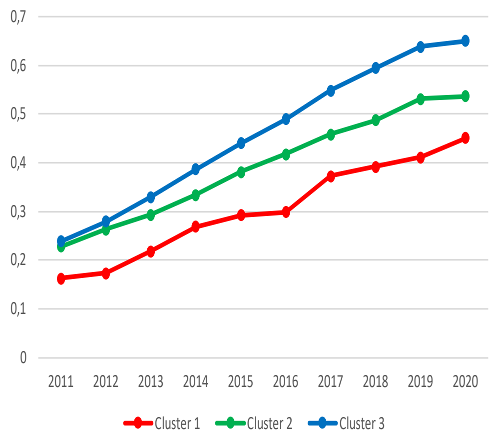

Figure 7. Change in average TGRs over time by cluster

Source: Authors' work

The average TGR of all three clusters trended upward throughout the entire study period, although Cluster 1 almost plateaued midway (Figure 7). Cluster 3 remained steadily ahead of the other two clusters and continuously extended its lead. This divergence, in the form of a widening technology gap, reversed towards the end of the timeframe, with Cluster 1 experiencing sharper growth, whereas Clusters 2 and 3 appeared to flatten out. All clusters peaked in 2020, the final period considered. Cluster 1 reached a TGR of 0.45 (compared to a starting value of 0.16 in 2011), while Clusters 2 and 3 recorded values of 0.54 (2011: 0.23) and 0.65 (2011: 0.24), respectively.

Table 7 provides an overview of the efficiency scores at an aggregated level.

Table 7 illustrates that the countries in Clusters 1, 2, and 3 attained group-specific mean efficiencies of 0.56, 0.66, and 0.67, respectively, compared with the overall European mean efficiency of 0.52, based on the assumption of a common ('pooled') technology, and versus a lower mean meta-frontier efficiency across all clusters of 0.25. The greatest variability (with a standard deviation of 0.37) is observed in Cluster 2.

Taking the meta-frontier technology as a reference, Cluster 1 had an average efficiency score of 0.18, while the average scores for Clusters 2 and 3 were 0.23 and 0.33, respectively. BGR recorded the worst average group-specific performance in Cluster 1, GRC in Cluster 2 and ESP in Cluster 3. In terms of the group frontiers, the best performers on average were LVA (Cluster 1), AUT (Cluster 2) and LUX (Cluster 3). EST posted the lowest average score for the' pooled' frontier and LUX the

Table 7
Descriptive statistics for efficiency scores

	Group-specific frontiers			**Common ('pooled') frontier**	**Meta-frontier**
	Cluster 1	***Cluster 2***	***Cluster 3***		
Mean	0.5567	0.6599	0.6675	0.5199	0.2459
Std. dev.	0.1960	0.3674	0.2544	0.3087	0.2000
Min.	0.2388	0.0875	0.2923	0.0734	0.0193
Max.	0.9956	0.9949	0.9966	0.9998	0.9913

Source: Authors' work

highest. In relation to the average meta-frontier scores, the least and most efficient countries were, respectively, EST and LVA (Cluster 1), GRC and MLT (Cluster 2), and ESP and LUX (Cluster 3).

Figure 8 presents the average efficiency scores of the different groups over time.

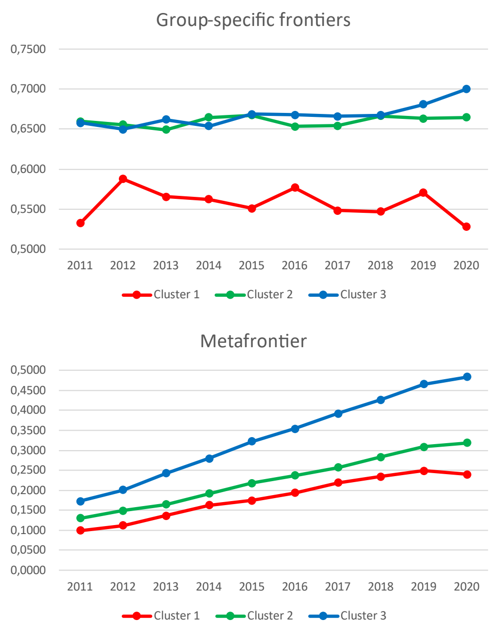

Figure 8. Change in average efficiency scores
Source: Authors' work

Cluster 1's group-specific average efficiency score stayed below those of Clusters 2 and 3 over the entire timeframe. Cluster 1 peaked in 2012 with an average score of 0.59, compared to scores of 0.53 in the first and last years studied. Clusters 2 and 3 had similar scores most of the time, but Cluster 3 reached a maximum score of 0.70 in 2020 (compared to 0.66 in 2011), while Cluster 2 had a score of 0.66 (the same as in 2011). Concerning the meta-frontier, each cluster experienced a continuous upward trend in terms of the average efficiency score, except Cluster 1, which dropped from its highest value of 0.25 in 2019 to 0.24 in the 2020 cut-off period. Cluster 3 had the highest average efficiency every year, while Cluster 1 had the lowest. In addition, Cluster 3's incline was considerably steeper over the entire period than its two counterparts, resulting in a continually diverging score band.

FINDINGS AND DISCUSSION

Although water utilisation is deemed sustainable in the long term in most of Europe, certain regions are at risk of facing water scarcity, necessitating efficiency gains to prevent seasonal water shortages (European Commission, 2020). Moreover, regions with low rainfall, high population density, or intensive agricultural and industrial activity may face sustainability issues in the future, especially considering that water shortages could be exacerbated by climate change impacts on water availability (European Commission, 2020). In addition, recycling and reuse can enhance water system sustainability in Europe (Bronner et al., 2022; European Commission, 2015). While water abstraction exerts the most significant pressure on the quantity of freshwater resources, a large part of the water withdrawn for domestic, agricultural, or industrial use is returned to the environment and its water bodies, albeit often as wastewater with impaired quality (European Commission, 2020). Thus, besides water use efficiency and corresponding changes in consumption practices, a key water management issue in Europe concerns drinking water quality (European Commission, 2021).

By highlighting the existence of heterogeneity among European countries, our results show that the sampled nations operate under different conditions. Figure 9 illustrates the distinct attributes of each group concerning the size of the economy, the standard of living, and the extent of urbanisation and industrialisation. It should be noted that, in the context of sustainable development, hallmarks of humanity's longevity and high civilisation, such as economic prowess, improvements in living standards through built infrastructure, human settlement in cities, and industrialisation, are closely related to the issue of water use efficiency (United Nations, 2021a).

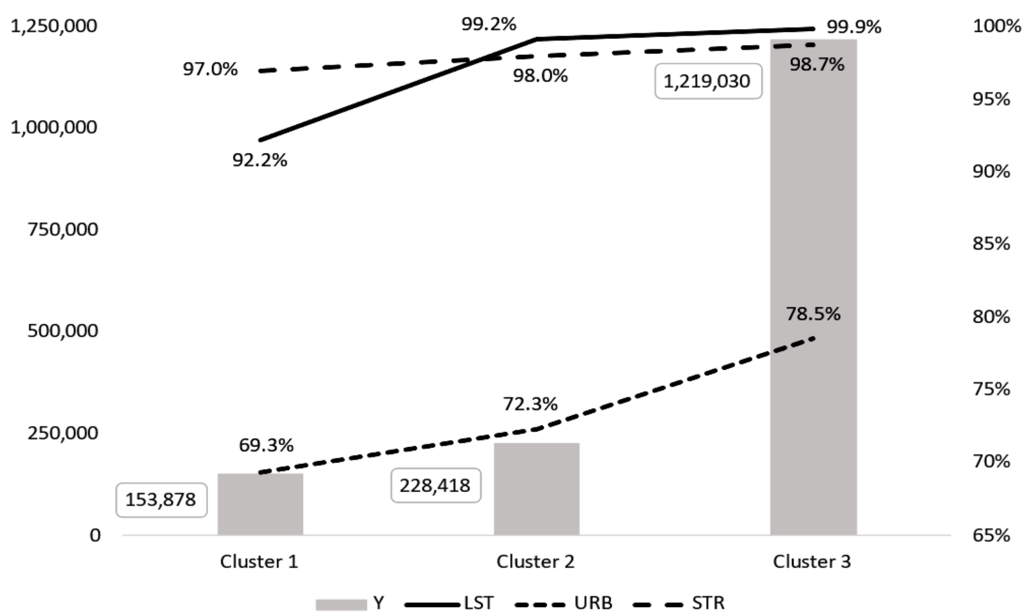

Figure 9. Cluster characteristics

Note: Cluster 1: Smaller, less advanced, less urbanised, less industrialised economies on average. Cluster 2: Middle range for the size of the economy, living standard, urbanisation, and industrialisation. Cluster 3: Larger, more advanced, more urbanised, more industrialised economies on average.

Source: Authors' work

Against the background of the underlying cluster analysis, our results for the TGRs and efficiency scores collectively demonstrate a general positive association between technological progress and water use efficiency. Furthermore, the results for the production function reveal that capital exhibits the most consistent relationship with water productivity. The positive influence of capital tends to diminish with increasing scale and total production. Generally, there is a significant positive linkage between water productivity and water quality. Group 2 appears to have experienced technological degradation along with a decline in water productivity over time. Additionally, we find that all potential contextual determinants influence water use efficiency to some extent. However, only the actual type of water usage has a consistent, statistically significant impact across all groups (Table 8).

Table 8
Influence of contextual factors on water use efficiency

Factor	Current findings	Interpretation and comparison with previous results (where applicable)
LST	The actual effect of LST (living standard in terms of the percentage of the population without sanitation facilities) on water use efficiency is unclear. For Cluster 2, a higher proportion of the population lacking sanitation facilities corresponds to greater inefficiency, which implies that widening the availability of sanitation facilities enhances efficiency. However, this relationship is reversed in the case of the common frontier.	In Cluster 2, expanding the proportion of the population with sanitation facilities can boost efficiency, but this relationship is inverted in the context of the pooled sample. Overall, this aligns with previous work concerning China, which shows that per capita income can affect efficiency (Bao & Chen, 2017), although the results of Ding et al. (2019) refute this claim.
URB	Concerning URB (percentage of the urban population), there is a highly significant negative effect in Cluster 2, indicating that urbanisation is associated with increased inefficiency, and a highly significant positive effect in Cluster 3, suggesting that urbanisation leads to improved water use efficiency.	These contrasting effects highlight the ambiguous impact of urbanisation on water use efficiency. It is akin to the case of China, where urbanisation has been shown to exert a positive influence (Bao & Chen, 2017; Zheng et al., 2018) or constitute an impediment due to an accompanying rise in water consumption and pollution (Ding et al., 2019).
STR	In terms of economic structure, it is observed that STR, i.e., gross value added (GVA) represented by agriculture as a percentage share of GDP, generally exerts a negative effect on water use efficiency. It means that economies with a more substantial agricultural sector tend to be more inefficient, suggesting that the process of industrialisation augments efficiency.	Economies with larger agricultural sectors tend to be less efficient, implying that countries can improve their performance by becoming more industrialised. In comparison, the process of industrialisation, including industrial transformation and upgrading, has been found to have both a positive (Bai et al., 2017; Zheng et al., 2018) as well as a negative (Wang et al., 2018) impact on China.
END	For the pooled data, the resource endowment variable END (the amount of renewable freshwater resources available per inhabitant) exhibits a negative influence. It suggests that an excessive abundance of water resources imposes a detrimental impact on water use efficiency in the case of the common frontier.	Our results substantiate the notion that an overabundance of water resources may engender complacency in water usage, manifesting the existence of a ‘resource curse’. In comparison, resource endowment is regarded as a significant influence in China in some cases (Ding et al., 2018; Zheng et al., 2018) but not in others (Ding et al., 2019).

Table 8 *(Continue)*

Factor	Current findings	Interpretation and comparison with previous results (where applicable)
USE	Considering resource usage as a water use efficiency determinant represents a novel contribution to the existing body of literature. In this context, USE (the percentage share of freshwater abstraction for public water supply in total freshwater abstraction) is consistently associated with reduced inefficiency. Thus, our results suggest that a larger public water sector exerts a positive influence and is linked to increased efficiency.	In Europe, households and manufacturing industries are heavy water users, with the latter often relying on non-public self-supply (European Commission, 2020). It is also noteworthy that, although household water use is generally more uniform due to consistent basic needs, it can far exceed manufacturing water use in service-dominant countries (European Commission, 2020). As such, the proportion of public water supply partly reflects a country's economic structure.
EPR	The environmental protection variable EPR (percentage of terrestrial area under protection) predominantly exhibits a detrimental impact, meaning that an increase in the extent of protected areas is associated with heightened inefficiency.	Expanding land designated for nature conservation (i.e., protecting terrestrial areas) decreases efficiency. With respect to China, while environmental regulation can play an effective role in enhancing water utilisation efficiency in some situations (Ding et al., 2019; Zheng et al., 2018), such intervention may be of little avail in others (Wang et al., 2018).

Source: Authors' work

CONCLUSION

This study presents a first-of-its-kind pan-European assessment of water use efficiency and sustainability, employing cluster analysis and a meta-frontier approach. Moreover, we contribute to existing research by integrating water quality into the evaluation framework and examining the type of resource usage as an efficiency determinant. By aligning with the objectives of this special issue, our research aims to inform responsible, impactful, science-based, and border-transcending resource governance and management. By doing so, we strive to secure the legacy of our shared, thriving civilisation and lay the groundwork for enduring socio-economic progress and a prosperous future.

The results confirm a positive relationship between technological progress and water use efficiency. Our findings also demonstrate a general positive association between water productivity and quality. Our analysis delineates the intricate interplay of essential tenets of high civilisation, including socio-economic factors such as economic scale, living standards, urbanisation, and industrialisation, in shaping water use efficiency. All examined determinants influence efficiency to varying degrees. While some aspects remain inconclusive, we have gained greater clarity on several issues. Specifically, bigger agricultural sectors are less efficient, suggesting that industrialisation can improve performance. Furthermore, an overabundance of renewable freshwater resources can lead to inefficiency, indicating a 'resource curse'. In addition, a larger public water sector increases efficiency, while expanding land for nature conservation decreases it.

Our investigation reveals substantial technological diversity among European countries and varying cause-effect relationships concerning water utilisation efficiency. It underscores the need for decentralised solutions to address pertinent sustainability challenges based on the formulation of water policies and management approaches tailored to specific local circumstances.

Implications and Recommendation

Investigating water use efficiency and its determinants and providing evidence on corresponding technology gaps form a useful scientific basis for tackling resource sustainability challenges. In particular, our results illustrate that European countries operate under different conditions and exhibit considerable technological and efficiency heterogeneity. Considering these varying circumstances, adopting decentralised solutions and tailoring best resource stewardship practices for individual countries or groups of countries is advisable. We are confident that the insights gained can inform water policy formulation, particularly within the UN's SDG 6 framework on 'clean water and sanitation' (United Nations, 2024), thereby enhancing human well-being and advancing the progress of human civilisation.

In the present European context, smaller economies, often at nascent development stages with limited urbanisation and industrialisation, struggle to attain high water use efficiency, whereas larger economies typically fare better. Moreover, our results pertaining to living standards resonate with the idea that public commitment to human well-being, based on sanitation infrastructure investment, acts as a catalyst for the progress of societies as they transition from a lower to a higher state of development (United Nations, 2024). Meanwhile, urbanisation emerges as a double-edged sword with mixed implications for human civilisation, encapsulating a complex rapport between humanity and natural resources. On the other hand, our analysis shows that industrialisation is associated with more efficient water use, speaking to the improvement of resource management systems in the course of modernisation (United Nations, 2021a).

Limitation and Outlook

Continuing research may focus more dedicatedly on comparing Europe and China. Many relevant findings for China exist, while the present paper could signal the beginning of a similar stream of work on Europe. Additionally, future studies may explore considerations of the Environmental Kuznets Curve (EKC). The EKC concept, which proposes that environmental damage initially increases and then decreases with per capita income (Hamaide, 2022), could be applied to Europe, building on previous results concerning China (Ding et al., 2019;

Wang et al., 2018; Zheng et al., 2018). Moreover, although freshwater endowment may serve as a proxy for location-specific climatic and geographic circumstances (European Commission, 2020), it would be beneficial to explicitly consider the ramifications of such conditions, given that efficient water utilisation can support the endurance of human high civilisation by mitigating climate change threats (United Nations, 2021).

Meanwhile, mirroring humanity's complex relationship with natural resources, urbanisation presents a dual narrative, both hindering and enhancing water use efficiency, thereby posing challenges as well as opportunities in preserving human high civilisation. The multifaceted nature of urbanisation underlines the need for further research to unravel the delicate balance between urban growth and sustainable water management in the interest of humanity. In addition, while our findings illustrate the imperative of industrialisation for improving water use efficiency, affirming the transformative potential of evolving economic structures in sustainable development and safeguarding human civilisation, future research could focus on how innovative resource use practices can propel societies forward (Callejas Moncaleano et al., 2021). Moreover, while guiding economic growth towards sustainability is important for protecting our natural habitat and societal well-being, future studies could explore the potential relationship between efficient water utilisation and social equity, the latter being a key factor in maintaining public harmony and preserving cultural values (United Nations, 2021b).

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REFERENCES

Adler, M. (2011). *Well-being and fair distribution: Beyond cost-benefit analysis.* Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195384994.001.0001

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21-37. https://doi.org/10.1016/0304-4076(77)90052-5

Alem, H. (2021). A metafrontier analysis on the performance of grain-producing regions in Norway. *Economies*, *9*(1), 10. https://doi.org/10.3390/economies9010010

Bai, M., Zhou, S., Zhao, M., & Yu, J. (2017). Water use efficiency improvement against a backdrop of expanding city agglomeration in developing countries-A case study on industrial and agricultural water use in the Bohai Bay Region of China. *Water (Switzerland)*, *9*(2), 89. https://doi.org/10.3390/w9020089

Bao, C., & Chen, X. (2017). Spatial econometric analysis on influencing factors of water consumption efficiency in urbanizing China. *Journal of Geographical Sciences*, *27*(12), 1450-1462. https://doi.org/10.1007/s11442-017-1446-9

Bao, C., & Fang, C. L. (2010). Interaction mechanism and control modes on urbanization and water resources exploitation and utilization. *Urban Studies*, 17, 19-23.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, *20*(2), 325-332. https://doi.org/10.1007/BF01205442

Battese, G. E., Prasada Rao, D. S., & O'Donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis*, *21*(1), 91-103. https://doi.org/10.1023/B:PROD.0000012454.06094.29

Battese, G. E., & Rao, D. S. P. (2002). Technology gap, efficiency, and a Stochastic Metafrontier Function. *International Journal of Business and Economics*, *1*(2), 87-93.

Bogetoft, P., & Otto, L. (2011). Benchmarking with DEA, SFA, and R. In *International Series in Operations Research & Management Science* (Vol. 157). Springer. https://doi.org/10.1007/978-1-4419-7961-2

Bronner, M., See, K. F., & Yu, M. M. (2022). Circular water economy performance evaluation based on dynamic network data envelopment analysis. *Journal of Cleaner Production*, *367*, 132474. https://doi.org/10.1016/j.jclepro.2022.132474

Callejas Moncaleano, D. C., Pande, S., & Rietveld, L. (2021). Water use efficiency: A review of contextual and behavioral factors. *Frontiers in Water*, *3*, 685650. https://doi.org/10.3389/frwa.2021.685650

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis* (2nd ed.). Springer.

Deng, G., Li, L., & Song, Y. (2016). Provincial water use efficiency measurement and factor analysis in China: Based on SBM-DEA model. *Ecological Indicators*, 69, 12-18. https://doi.org/10.1016/j.ecolind.2016.03.052

Ding, X., He, J., & Wang, L. (2018). Inter-provincial water resources utilization efficiency and its driving factors considering undesirable outputs: Based on SE-SBM and Tobit Model. China Population, *Resources and Environment*, 28, 157-164.

Ding, X., Zhang, Z., Wu, F., & Xu, X. (2019). Study on the evolution of water resource utilization efficiency in Tibet autonomous region and four provinces in Tibetan areas under double control action. *Sustainability (Switzerland)*, *11*(12), 3396. https://doi.org/10.3390/SU11123396

Du, K., & Lin, B. (2017). International comparison of total-factor energy productivity growth: A parametric Malmquist index approach. *Energy*, 118, 481-488. https://doi.org/10.1016/j.energy.2016.10.052

European Commission. (2015). Innovation in the European water sector. *Science for Environment Policy, Future Brief 10*. http://ec.europa.eu/science-environment-policy

European Commission. (2020). *Eurostat, statistics explained: Water statistics.* https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Water_statistics

European Commission. (2021). *Eurostat, statistics explained: Water supply, sewerage, waste management and remediation statistics.* https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Water_supply,_sewerage,_waste_management_and_remediation_statistics_-_NACE_Rev._2

Färe, R., & Primont, D. (1995). *Multi-output production and duality: Theory and applications.* Springer Netherlands. https://doi.org/10.1007/978-94-011-0651-1

Ganhadeiro, T. G. L., Da Silva Christo, E., Meza, L. A., Costa, K. A., & De Souza, D. P. M. (2018). Evaluation of energy distribution using network data envelopment analysis and Kohonen Self Organizing Maps. *Energies*, *11*(10), 2677. https://doi.org/10.3390/en11102677

Hamaide, B. (2022). Sustainability and the Environmental Kuznets Curve Conjecture: An Introduction. *Sustainability (Switzerland)*, *14*(12), 7372. https://doi.org/10.3390/su14127372

Hatfield, J. L., & Dold, C. (2019). Water-use efficiency: Advances and challenges in a changing climate. *Frontiers in Plant Science*, *10*, 429990. https://doi.org/10.3389/fpls.2019.00103

Hu, J. L., Wang, S. C., & Yeh, F. Y. (2006). Total-factor water efficiency of regions in China. *Resources Policy*, *31*(4), 217-230. https://doi.org/10.1016/j.resourpol.2007.02.001

Jiang, H., Hua, M., Zhang, J., Cheng, P., Ye, Z., Huang, M., & Jin, Q. (2020). Sustainability efficiency assessment of wastewater treatment plants in China: A data envelopment analysis based on cluster benchmarking. *Journal of Cleaner Production*, *244*, 118729. https://doi.org/10.1016/j.jclepro.2019.118729

Kruskal, W. H., & Wallis, W. A. (1952). Use of Ranks in One-Criterion Variance Analysis. *Journal of the American Statistical Association*, *47*(260), 583-621. https://doi.org/10.2307/2280779

Kumbhakar, S. C., Parmeter, C. F., & Zelenyuk, V. (2021). Stochastic Frontier Analysis: Foundations and Advances I. In *Handbook of Production Economics* (pp. 1–40). Springer. https://doi.org/10.1007/978-981-10-3450-3_9-2

Li, J., & Ma, X. (2015). Econometric analysis of industrial water use efficiency in China. *Environment, Development and Sustainability*, *17*(5), 1209-1226. https://doi.org/10.1007/s10668-014-9601-2

Lin, B., & Du, K. (2013). Technology gap and China's regional energy efficiency: A parametric metafrontier approach. *Energy Economics*, *40*, 529-536. https://doi.org/10.1016/j.eneco.2013.08.013

Lombardi, G. V., Stefani, G., Paci, A., Becagli, C., Miliacca, M., Gastaldi, M., Giannetti, B. F., & Almeida, C. M. V. B. (2019). The sustainability of the Italian water sector: An empirical analysis by DEA. *Journal of Cleaner Production*, *227*, 1035-1043. https://doi.org/10.1016/j.jclepro.2019.04.283

Luo, Y., Yin, L., Qin, Y., Wang, Z., & Gong, Y. (2018). Evaluating water use efficiency in China's western provinces based on a slacks-based measure (SBM)-undesirable window model and a malmquist productivity index. Symmetry, *10*(8), 301. https://doi.org/10.3390/sym10080301

Ma, H., Chou, N. T., & Wang, L. (2016). Dynamic coupling analysis of urbanization and water resource utilization systems in China. *Sustainability (Switzerland)*, *8*(11), 1176. https://doi.org/10.3390/su8111176

Ma, H., Ding, Y., & Wang, L. (2017). Measurement and convergence analysis of green water utilization efficiency. *Journal of Natural Resources*, *32*(3), 406-417. https://doi.org/10.11849/ZRZYXB.20160381

Madaleno, M., & Moutinho, V. (2023). Stochastic Frontier Analysis: A review and synthesis. In *Lecture Notes in Economics and Mathematical Systems* (Vol. 692, pp. 55-78). Springer. https://doi.org/10.1007/978-3-031-29583-6_4

Mays, L. W. (2013). Groundwater resources sustainability: Past, present, and future. *Water Resources Management*, *27*(13), 4409-4424. https://doi.org/10.1007/s11269-013-0436-7

Molinos-Senante, M., & Sala-Garrido, R. (2016). Cross-national comparison of efficiency for water utilities: A metafrontier approach. *Clean Technologies and Environmental Policy*, *18*(5), 1611-1619. https://doi.org/10.1007/s10098-016-1133-z

O'Donnell, C. J., Rao, D. S. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics*, *34*(2), 231-255. https://doi.org/10.1007/s00181-007-0119-4

Sarkhosh-Sara, A., Tavassoli, M., & Heshmati, A. (2020). Assessing the sustainability of high-, middle-, and low-income countries: A network DEA model in the presence of both zero data and undesirable outputs. *Sustainable Production and Consumption*, 21, 252-268. https://doi.org/10.1016/j.spc.2019.08.009

Su, S. P., Huang, S. W., Sun, X. X., & Lin, W. X. (2012). Analysis of sustainable use efficiency of provincial water resources. *Chinese Journal* *of Eco-Agriculture*, 20, 803-809. https://doi.org/10.3724/SP.J.1011.2012.00803

Tran, T. B., Grafton, R. Q., & Kompas, T. (2008). Firm efficiency in a transitional economy: Evidence from Vietnam. *Asian Economic Journal*, *22*(1), 47-66. https://doi.org/10.1111/j.1467-8381.2008.00268.x

United Nations. (2021a). *Progress on change in water-use efficiency*. Food and Agriculture Organization of the United Nations, UN-Water. https://www.unwater.org/publications/progress-water-use-efficiency-2021-update

United Nations. (2021b). *The United Nations world water development report 2021: Valuing water.* UN-Water. https://www.unwater.org/publications/un-world-water-development-report-2021

United Nations. (2024). *Sustainable development: Ensure availability and sustainable management of water and sanitation for all.* https://sdgs.un.org/goals/goal6

Walker, N. L., Norton, A., Harris, I., Williams, A. P., & Styles, D. (2019). Economic and environmental efficiency of UK and Ireland water companies: Influence of exogenous factors and rurality. *Journal of Environmental Management*, 241, 363-373. https://doi.org/10.1016/j.jenvman.2019.03.093

Wang, S., Zhou, L., Wang, H., & Li, X. (2018). Water use efficiency and its influencing factors in China: Based on the data envelopment analysis (DEA)-Tobit model. *Water (Switzerland*), *10*(7), 1-16. https://doi.org/10.3390/w10070832

Wu, F., Fan, L. W., Zhou, P., & Zhou, D. Q. (2012). Industrial energy efficiency with CO_2 emissions in China: A nonparametric analysis. *Energy Policy*, *49*, 164-172. https://doi.org/10.1016/j.enpol.2012.05.035

Wudil, A. H., Ali, A., Mushtaq, K., Baig, S. A., Radulescu, M., Prus, P., Usman, M., & Vasa, L. (2023). Water use efficiency and productivity of irrigated rice cultivation in Nigeria: An application of the stochastic frontier approach. *Sustainability (Switzerland), 15*(10), 7824. https://doi.org/10.3390/su15107824

Yang, F., Wang, D., Zhao, L., & Wei, F. (2021). Efficiency evaluation for regional industrial water use and wastewater treatment systems in China: A dynamic interactive network slacks-based measure model. *Journal of Environmental Management*, *279*(2), 111721. https://doi.org/10.1016/j.jenvman.2020.111721

Yu, A., You, J., Zhang, H., & Ma, J. (2018). Estimation of industrial energy efficiency and corresponding spatial clustering in urban China by a meta-frontier model. *Sustainable Cities and Society*, *43*(April), 290-304. https://doi.org/10.1016/j.scs.2018.08.037

Zhang, F., Song, X. N., Xue, H. F., & Dong, H. Z. (2017). Decoupling relationship and dynamic response between industrial water intensity, environmental regulation and technological progress. *China Population, Resources and Environment*, *27*, 193-201.

Zheng, J., Zhang, H., & Xing, Z. (2018). Re-examining regional total-factor water efficiency and its determinants in China: A parametric distance function approach. *Water (Switzerland)*, *10*(10), 1286. https://doi.org/10.3390/w10101286

Zhou, P., Ang, B. W., & Zhou, D. Q. (2012). Measuring economy-wide energy efficiency performance: A parametric frontier approach. *Applied Energy*, *90*(1), 196-200. https://doi.org/10.1016/j.apenergy.2011.02.025