

# Estimating Scale Efficiency Of Platinum-Mining Companies' Environmental Performance: A South African Perspective

Pieter W Buys, North-West University, South Africa  
Merwe Oberholzer, North-West University, South Africa  
Toy Prinsloo, Wilmar Oils and Fats (Pty) Ltd, South Africa

## ABSTRACT

*The purpose of the study is to develop a data envelopment analysis (DEA) model to estimate the relative scale efficiency of platinum-mining companies' environmental performance. South African platinum-mines were used to demonstrate the model, which uses environmental performance indicators as the input variables in order to generate mineral extraction and financial performances as the output variables. The input variables considered were greenhouse gas emissions, water usage and energy usage, while the output variables were platinum production, return on equity and return on assets. The contribution of the study is that a DEA model was developed that could identify relatively efficient companies that could act as benchmarks with regard to environmental issues in the mining sector. A further contribution is that the study concluded that platinum-mining companies tend not to achieve economies of scale, where the companies that are relatively larger in size tend to operate on a scale that is too large and companies that are physically relatively smaller in size tend to operate on a scale that is too small.*

**Keywords:** Economies of Scale; Energy Usage; Environmental Performance; GHG Emissions; Platinum-Mining; Scale Efficiency; Water Usage

## INTRODUCTION

In recent times, the concept of Corporate Social Responsibility (CSR), including the social and environmental accounting aspects thereof, has received much attention in academia and the business media (Yang, 2011). Many organizations are being impacted by CSR and its requirements, in some form or another. As a result, a growing number of companies are publishing various types of social responsibility and sustainability reports (Yang, 2011; Brown & Fraser, 2006). The debate around social responsibility and sustainability was initiated by the World Commission on Environment and Development's *Brundlandt Commission Report* entitled "Our Common Future" in 1987, which identified three key dimensions of sustainable development, namely environmental, economic and social sustainability (Talbot & Venkataraman, 2011; WCED, 1987). According to Vitezić (2011) CSR may be measured through these three dimensions by testing its relationship against financial performances. Further developments in social responsibility reporting include the Global Reporting Initiative (GRI), which provides voluntary guidelines for organizations to report on their social responsibility performances (GRI, 2002), with the key aim of enhancing the quality of sustainability reporting (Ambe, 2007).

A key aspect of sustainability is the concept of climate change, and its interaction with organizational performances. The United Nations Framework Convention on Climate Change defines the concept as the change that is attributed (directly or indirectly) to such human activity that alters the composition of the earth's atmosphere (IPCC, 2007). It is generally accepted that a key contributing factor to climate change is the increased levels of man-made greenhouse gases (GHG) in the earth's atmosphere, which in turn results in the earth's surface getting warmer. Human activities result in four long-lived GHGs, namely carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>), nitrous oxide (N<sub>2</sub>O)

and halocarbons, which are a group of gases containing fluoride, chlorine and bromine. According to IPCC (2007), the main contributing sources of GHGs due to human activities include:

- CO<sub>2</sub> emissions: Burning of fossil fuels and deforestation;
- CH<sub>4</sub> emissions: Fully-vented septic systems, livestock enteric fermentation, manure management and paddy rice farming;
- N<sub>2</sub>O emissions: Fertilisers in agricultural activities; and
- Halocarbon emissions: Refrigeration systems, fire suppression systems and manufacturing processes.

Even though South Africa contributes only around one percent of the global GHG (and then especially CO<sub>2</sub> specific) emissions, its emissions are considered very high in relation to its population and economy (DEAT, 2007). In a South African study on economic growth and carbon emissions, Odhiambo (2011) found that there is a distinct unidirectional causal flow from economic growth to GHG emissions. As such, South African decision-makers face the challenge of addressing high GHG emissions while attempting to stimulate a developing economy. Furthermore, according to Kiker (2000), the availability and quality of water are major concerns that will have a very big impact on the South African economy and it is anticipated that the problem will only worsen. External influences on the environment are important since they have a direct impact on a major threat to mankind's continued existence on the planet, namely the threat of climate change (Yarnal, 2010; Morrissey & Reser, 2007). The effect of this can be seen in the temperature increases of the world's atmosphere and its oceans, the havoc created by extreme weather patterns in various regions, and the widespread melting of sea ice and the associated rise in global sea levels (IPCC, 2007; Turpie *et al.*, 2002), which in turn may have far-reaching negative economic and social impacts (Turpie *et al.*, 2002).

Therefore, these environmental changes are likely to have an influence on not only on the physical environment of the planet's inhabitants, but also on the global economies, including the mining industry. As the *de facto* standard on social reporting (GRI, 2002), the GRI reporting guidelines for the mining sector require disclosure on eight environmental performance indicators, namely the usage and consumption of materials, energy and water, as well as its biodiversity, emissions/effluents/waste, products/services, compliance and transport (GRI, 2010). As an industry, mining companies around the world have a responsibility to improve their environmental performances, including decreasing their contribution to the levels of GHG being released into the atmosphere. Within the context of the largely resource-based South African economy, the mining industry is a major contributor to the country's welfare and growth. According to the Chamber of Mines of South Africa, the industry contributes up to 20 percent of the country's direct corporate tax receipts, while also directly contributing to approximately nine percent to the country's GDP, and a further ten percent being indirectly contributed to the GDP (Anon, 2010). Furthermore, within the context of environmental performances, this specific study is centred on the platinum-mining industry, to the exclusion of the other key gold- and coal-mining companies, primarily because sufficient data for analysis were only available from companies in the platinum sector. Considering the aforementioned, the primary question under consideration in the article is whether platinum-mining companies achieving economies of scale (scale efficiency) with regard to their environmental impact are opposed to generating production volume and economic gains for their shareholders.

Data envelopment analysis (DEA), as an efficiency measurement technique, lends itself to aggregate organizational performances into a single measure where multiple inputs and multiple outputs are used (Coelli *et al.*, 2005); within this context making it possible to estimate the relative efficiency of an organization's environmental performance. The technique has been used *inter alia* by Lee *et al.* (2008) who analyzed the managerial efficiency of 96 listed Taiwanese manufacturing companies who received ISO 14000 certificates; Munksgaard *et al.* (2005) who investigated the emissions of nations, cities and households; Wier *et al.* (2005) who evaluated the sustainability of household usages; Yu and Wen (2010) who researched China's urban environmental sustainability; and Kuo *et al.* (2010) who applied DEA in an analytical network process for a well-known international camera manufacturer. No empirical link could be found where DEA was used to estimate the scale efficiency of environmental performance in the mining sector. Therefore, the primary purpose of this article is to develop a model that is able to estimate the scale efficiency, which indicates the degree to which the mining companies are achieving economies of scale with regard to their environmental performances. Within the context of the South African platinum-mining sector, the DEA model included both the constant return to scale (CRS) and variable return to scale (VRS) DEA approaches.

The organization of the article is therefore as follows: Firstly, a theoretical and contextual framework will be provided by high-lighting the aspects of environmental performance and the DEA technique used to evaluate the effectiveness of such performances. This is followed by sections explaining the method of the study, the data, sample, the applied DEA model and the empirical results. Finally, the study is summarized and concluded.

## **ORGANIZATIONAL PERFORMANCE**

Due to the inherent interaction between the mining industry and the natural environment, environmental changes (and the related proposed legislation and accords) will have a major impact on not only how mines are operated, but also on their economic performances – i.e. the impact moves from the environment to the mine. However, it goes further than this and the mines are also being evaluated on their impact on the environment – i.e. the impact moves from the mine to the environment. The risks facing the mining industry are therefore not just the regulatory requirements and the reduction of GHG emissions, but also reputational risks related to sustainability concerns, including the risk that customers will switch to alternative products, higher insurance premiums and physical risks due to extreme weather conditions (CDP, 2008). Corporate reputation is very often considered as a key mediator in the relationship between the organization's CSR and its financial performances (Vitezić, 2011; Griffin, 2008). Since such reputational risks may be exacerbated by the organization's possible failure to reduce emissions and by less than adequate responses to the challenges presented by climate change (CDP, 2008), many organizations consider the risk to its reputation as a key issue facing their operations. Within the context of this study, a mining company with commendable environmental performances is the one with relatively low GHG emissions, combined with low water and energy usage.

### **Environmental performance**

The focus in this article falls on three sub-performance indicators, namely the GHG emissions (measured in tons), the water usage (measured in m<sup>3</sup>) and the energy usage (measured in GJ). This is because these indicators are quantifiable and all the mining companies included in this study reported their performances in relation hereto. Since the overproduction of GHG is a major contributing factor to global warming, the first input variable in estimating environmental performance is therefore centered on GHG emissions. The second input variable in evaluating environmental performance is that of water usage. With South Africa being a climatically sensitive and water-stressed country, the effects of climate change will have a very big impact on crops and other agricultural activities (SECCP, 2009). Furthermore, the International Council of Mining and Metals considers the impact of climate change and then especially the impact of GHG as the most important issue facing the mining industry (IPCC, 2007); and due to the mining industry's strong dependence on water, it is very vulnerable to the effects of climate change. Many organizations and industry leaders are expecting that GHG emission regulations and carbon taxes are on the horizon within the South African context. These regulatory burdens will have direct and indirect implications on the price increases on the third input variable of environmental performance considered in this study, namely energy usage (CDP, 2008).

### **Corporate performance**

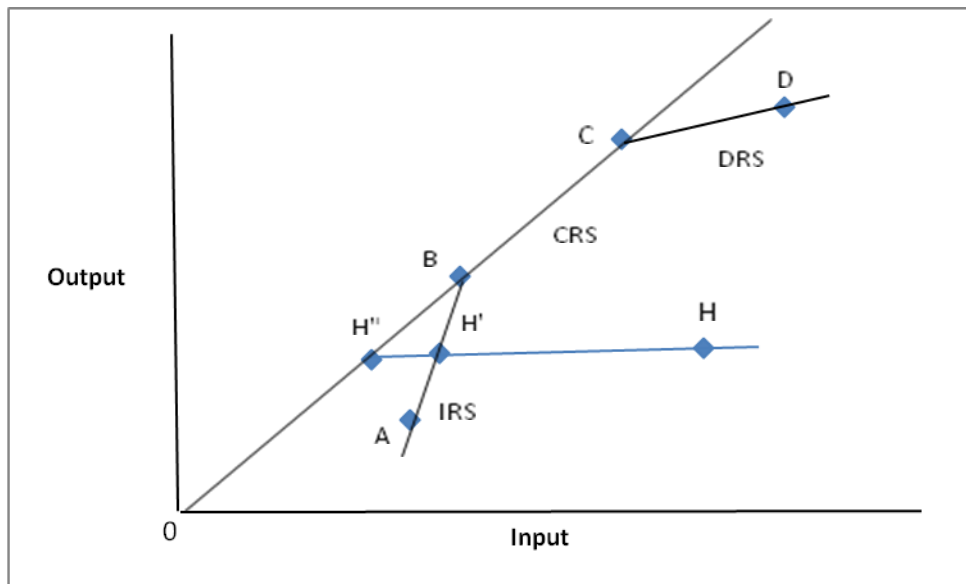
When considering other research projects into sustainability and social responsibility performance, such as Cowton (2004), Guerard (1997) and Hamilton *et al.* (1993), key performance indicators used were typically based on the return on the investment. Even though no evidence was found in support of a 'correct' performance indicator for purposes of this study, consideration is given to the company's ability to generate both earnings and investment returns. Therefore, two commonly used financial ratios were used as the first two output variables, namely i) the return on assets (ROA), which indicates the company's profitability in relation to the assets employed and is calculated by dividing earnings with the total assets (Hornegren *et al.*, 2008; Correia *et al.*, 2007), and ii) the return on equity (ROE), which is determined by dividing the earnings after interest and tax with the equity's book value, which would, according to Correia *et al.* (2007) and De Wet (2004), consist of the issued ordinary share capital, plus the share premium and reserves. Furthermore, the chosen outputs of the DEA model should also be in line with the efficiency being measured. In this study, a key focus considered is the extraction of platinum and the financial gains there from. Therefore, the third output variable to be considered in the DEA model is the production of platinum in terms of ounces.

**DEA AS A MEASURE OF EFFICIENCY**

According to Ray (2004), DEA is a non-parametric linear programming technique that measures the relative efficiency of a comparative ratio of outputs to inputs for a particular decision-making unit (DMU). The traditional measurement of efficiency (or productivity) assumes only a single output divided by a single input (Cronje, 2002). A key advantage of using DEA as a relative efficiency measure is found in the fact that it can accommodate multiple inputs, multiple outputs and other factors in a single model (Halkos & Salamouris, 2004). Furthermore, it provides the ability to identify inefficient organizations and potential improvement areas for these organizations, as well as highlighting efficient organizations that could be used as benchmarks by less efficient organizations (Avkiran, 1999).

The fundamental assumption of DEA is that if a producer (DMU) is capable of producing  $Y(A)$  units of output with  $X(A)$  inputs, then other producers should also be able to do the same – if they were operating efficiently. The fundamental objective of the DEA modelling exercise is to find the “best” virtual producer for each real producer and then to compare the producer to its best virtual producer in order to determine its efficiency. The best virtual producer is found by means of linear programming (Anderson, 1996). Analyzing the efficiency of a number of DMUs requires a formulation of a linear programming problem for each DMU.

The focus of this study is on scale efficiency, which estimates whether an organization operates on a scale that maximizes productivity. This should be preceded by estimating technical efficiency, which is an indication of how well inputs are converted into outputs (Avkiran, 1999; Coelli *et al.*, 2005). According to Avkiran (1999), analysts typically choose between using constant return to scale (CRS) or variable return to scale (VRS). The CRS implies a proportionate rise in outputs when inputs are increased, or in other words, an organization’s efficiency is not influenced by the scale of its operations (Avkiran, 1999). This is a significant assumption, since CRS may only be valid over a limited range and its use should be justified (Anderson, 1996). Furthermore, Avkiran (1999) states that VRS implies a disproportionate rise or fall in outputs when inputs are increased, or in other words, if an organization grows in size, its efficiency will not remain constant, but it will either rise or fall. Using CRS, an organization is automatically considered fully scale efficient, while using the VRS approach the degree of scale efficiency should be estimated, i.e. where a firm is too small in its scale operations, which falls within the increasing return to scale (irs) part of the production function, and an organization too large if it falls within the decreasing return to scale (drs) part of the production function. These inefficient organizations can be improved by keeping the same input mix, but changing the size of operations (Coelli *et al.*, 2005).



**Figure 1: CRS and VRS efficiency frontiers (Source: Adapted from Zhu (2004))**

To illustrate, Figure 1 assumes the observed data consists of a single-input, single-output with five DMUs, namely A, B, C, D and H. OBC is the CRS frontier. A, D and H are not on the efficiency frontier and therefore they are considered non-efficient. H, for example, should move from an input-orientated view, horizontally to point H' to become fully efficient. The less restricted VRC frontier is indicated by ABCD. Under this approach, H only needs to move horizontally to point H'. The DEA equation is as follows (Zhu, 2004):

$$\min \theta - \varepsilon \left( \sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right)$$

subject to

$$\sum_{j=1}^n \lambda_j \chi_{ij} + s_i^- = \theta \chi_{io} \quad i = 1, 2, \dots, m;$$

$$\sum_{j=1}^n \lambda_j \gamma_{rj} - s_r^+ = \gamma_{ro} \quad r = 1, 2, \dots, s;$$

CRS       $\lambda_j \geq 0 \quad j = 1, 2, \dots, n.$

VRS : Add  $\sum_{j=1}^n \lambda_j = 1$

The input-orientated formula calculates input minimization (where  $\theta$  indicates the efficiency score). Each observation,  $DMU_j$  ( $j = 1, \dots, n$ ), uses  $m$  inputs  $X_{ij}$  ( $i = 1, 2, \dots, m$ ) to produce  $s$  outputs  $Y_{rj}$  ( $r = 1, 2, \dots, s$ ), where  $DMU_o$  represents one of the  $n$  DMUs under evaluation, and  $X_{io}$  and  $Y_{ro}$  are the  $i$ th input and  $r$ th output for  $DMU_o$ , respectively. In order to take any slack into consideration, the inclusion of the non-Archimedean  $\varepsilon$  effectively allows the minimization over  $\theta$  to pre-empt the optimization involving the slacks,  $s_i^-$  and  $s_r^+$ . [For a more detailed discussion on the DEA methodology, see Ray (2004), Zhu (2004) and Coelli *et al.* (2005).]

**RESEARCH METHOD**

In order to properly estimate the scale efficiency of platinum-mining companies' environmental performance, the sample for this study within the South African context was selected as follows:

- South African mining companies that are listed on the Johannesburg Securities Exchange (JSE Ltd) situated in Johannesburg, South Africa;
- South African mining companies that subscribe to the South African Business Council for Sustainable Development hosted by the National Business Initiative (NBI) ([www.nbi.org.za](http://www.nbi.org.za)); and
- South African mining companies that reported on their environmental performances based on the GRI reporting guidelines and submitted such reports to GRI, and are available on the GRI database.

Initially, there were ten mining companies that met the basic requirements, of which four were in the platinum-mining sector, and a further three companies each in the coal-mining and the gold-mining sectors. Since this study focuses on the platinum-mining sector, the gold- and coal-mining companies are excluded. The combination of the four platinum-mining companies and the five years under consideration provided a total of 20 data points. This approach was also used by Oberholzer and Van der Westhuizen (2010) where, in a similar case, each data point was regarded as a DMU. Since Avkiran (1999) states that the observations should be at least three times as large as the sum of the chosen variables. Therefore in the context of this article a minimum number of 18 data points are required (three times the total number of variances, being three input plus three output variables) in the DEA model, which means that the sample size of 20 data points meet this basic requirement.

Because few mining companies reported on environmental-related issues prior to 2005, only data from 2005 onwards were included in this study. Documentary data from internal company sources (such as the annual

reports) and sustainability reports were used to acquire the physical data needed for this study. The McGregor BFA (2010) database supplied the financial data used in this study.

### **DEA MODEL**

The successful application of the assessment of comparative efficiency of the DMUs depends on the selection of appropriate input and outputs variables (Min *et al.*, 2009), which can be related to each other. Therefore, one variable may be a function of another variable, for example both labor costs and the number of employees may be used as inputs, and both production units and sales revenue may be used as outputs (Ray, 2004). It is also important to note that the input and output variables are not opposed to each other, but rather complementary to each other (Li & Liang, 2010). The input variables should be the resources that lead to the key business drivers, while the output variables should be the key business drivers that are critical to the success of the business (Avkiran, 1999). The following therefore summarizes the DEA model that was specified:

Input variables:	$x_1 = \text{GHG emissions (tons)}$
	$x_2 = \text{Water usage (m}^3\text{)}$
	$x_3 = \text{Energy usage (GJ)}$
Output variables:	$y_1 = \text{Return on equity (ROE)}$
	$y_2 = \text{Return on assets (ROA)}$
	$y_3 = \text{Production of platinum (in oz)}$

### **Input variables**

The input variables used in the DEA model are GHG emissions, water usage and energy usage. As mentioned, these quantifiable environmental performance indicators were reported by all the companies included in the sample. It may be argued that GHG emissions are not a typical input, but rather a negative output of a mine. In addressing this argument to some extent, the approach used by Seinfeld and Zhu (1999) was adopted by developing a two-stage DEA model whereby the outputs of the first stage automatically form the inputs of the second stage. It is important to note that because management has some control over the input variables, the three input variables are considered to be discretionary. When the input variables are non-discretionary (fixed), Cook and Seinfeld (2009) suggest that some of the assumptions of the original model be relaxed. In respect of the remaining environmental performance indicators, as per the GRI requirements, it can be argued that materials are accommodated to some extent, since the production volume of platinum is taken as an output variable, with the assumption that materials consumed are directly related to the platinum volume extracted. The other aspects of biodiversity, products/services, compliance and transport are due to their nature not only difficult to quantify, but also inherently difficult to assess in terms of quality.

### **Output variables**

An important goal for these mining companies is to create wealth for their shareholders, which implies a profitability motif. In this study, such profit is measured by using ROA and ROE as the first two input variables for the model. These ratios are also part of the Du Pont analysis, which has the strength that the company's performance is aggregated relative to investments and capital structure (Correia *et al.*, 2007). As stated, the chosen outputs should also be in line with the efficiency that will be measured. In this article, the key focus considered is the production of platinum and the financial gains there from. Therefore, the third output variable is the production of platinum in terms of ounces.

## **EMPIRICAL RESULTS AND DISCUSSION**

Table 1 reveals the data of the three input variables and the three output variables for Mining Company 1 (M1) to Mining Company 4 (M4) for the period 2005 to 2009. Mining Company 3 (M3) made a loss in 2009, and this resulted in negative ROE and ROA values. Since DEA models require positive data (Zhu 2004; Charnes *et al.*, 1978; Banker *et al.*, 1984), these two negative values were adjusted to zero. This is based on the practice used by Halkos and Salamouris (2004), where the performances of the remaining companies are still in a better position than

the adjusted one. The alternative would have been to follow the practice used by Mercan *et al.* (2003) and Luo (2003), who simply omitted all the negative data. As a result of experience, ROE and ROA values are often very volatile in nature and extreme values are not a rare phenomenon. The existence of some outliers could have given biased results. The method used to identify outliers is recommended by Wegner (2007), where data values that lie more than 1.5 (Quartile<sub>3</sub> – Quartile<sub>1</sub>) away from either the lower quartile or the upper quartile were omitted. Fortunately, in this instance all the data fall within these limits and is therefore used.

**Table 1: Input variables and output variables of M1 to M4 for the period 2005 to 2009**

Mining company / year	Input variables			Output variables		
	Water usage (m <sup>3</sup> )	Energy used (GJ)	GHG (Tons)	Prod (Oz)	ROE (%)	ROA (%)
M1 / 2005	25,525,000	23,795,000	4,942,000	4,258,382	21.38	17.58
M1 / 2006	27,787,000	26,009,000	5,325,000	4,595,151	41.89	35.89
M1 / 2007	30,148,000	25,896,000	5,227,000	4,192,011	43.35	35.16
M1 / 2008	28,362,000	25,398,000	5,581,000	4,302,554	49.77	27.74
M1 / 2009	34,151,000	23,701,000	5,580,000	4,395,394	10.67	4.75
M2 / 2005	33,386,356	14,804,720	2,869,768	1,848,000	37.12	29.63
M2 / 2006	30,886,478	15,561,130	3,059,365	1,846,000	31.37	29.80
M2 / 2007	33,278,000	15,659,787	3,112,487	2,026,000	21.94	22.30
M2 / 2008	39,131,000	16,134,719	3,222,898	1,907,000	40.53	36.49
M2 / 2009	35,900,000	16,388,000	3,391,195	1,704,000	14.70	16.80
M3 / 2005	9,500,000	5,813,000	1,489,000	1,704,249	3.33	2.69
M3 / 2006	10,858,464	7,384,000	1,775,000	1,809,744	4.66	5.52
M3 / 2007	11,795,482	7,434,000	1,673,000	1,477,529	5.63	6.54
M3 / 2008	9,256,244	6,555,000	1,659,000	1,366,307	1.98	2.96
M3 / 2009	8,885,360	6,613,000	1,594,827	1,268,918	0	0
M4 / 2005	11,667,000	1,953,000	596,856	325,214	15.56	16.79
M4 / 2006	14,701,000	1,968,120	601,513	361,599	35.21	39.10
M4 / 2007	15,725,000	2,297,880	722,538	324,296	55.69	63.01
M4 / 2008	14,442,000	2,136,960	671,939	292,989	51.41	57.26
M4 / 2009	15,079,000	2,188,247	756,729	302,474	7.57	10.08

Source: McGregor database (<http://mcgregorbfa.co.za>) and various company annual reports

Figure 2 is helpful to illustrate the physical measures as presented in Table 1 and puts the relative values in perspective. The physical measures were standardized, because water usage, energy usage, GHG emissions and production volumes are measured in terms of m<sup>3</sup>, GJ, tons and ounces, respectively. The average annual volumes of each mining company were used, and therefore the physical size of the four companies' production is indicated relative to each other. Note that ROE and ROA are excluded, since they are already relative values and not physical measures. Figure 2 exhibits that M1 has the highest inputs but also the highest output (production), with M2 having the second highest physical size. Its inefficiency is also clear, especially when the extremely high water usage and the low production output are considered. In turn, M3 is, except for water usage, in the third place regarding physical size, followed by M4.

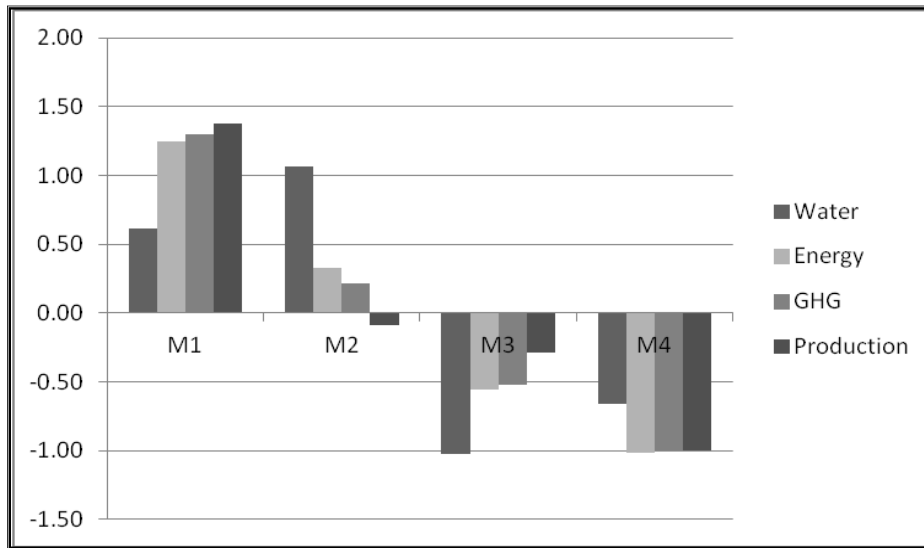


Figure 2: Standardized values of physical elements

The next step was to aggregate the data in Table 1 and Figure 2 into a single measurement. Figure 3, which summarizes the technical efficiencies (in Table 2), indicates the result of the average input-orientated technical efficiency of the four mining companies, where the three input variables, namely water usage, energy usage and GHG emissions were used opposed to the three output variables, namely production of platinum, ROE and ROA. The figure shows the results according to CRS and VRS approaches. As mentioned earlier, it was expected that the efficiency estimates of CRS would be lower than the less restricted VRS estimates. Nevertheless, Figure 3 indicates with regard to both CRS and VRS, that on average, M1 is the most technically efficient and M2 is the least technically efficient, with M3 and M4 in-between. The results imply, for example, that M1 could reduce its inputs according to both the CRS and VRS approaches by 8.1 percent and 1.2 percent respectively, without reducing its outputs.

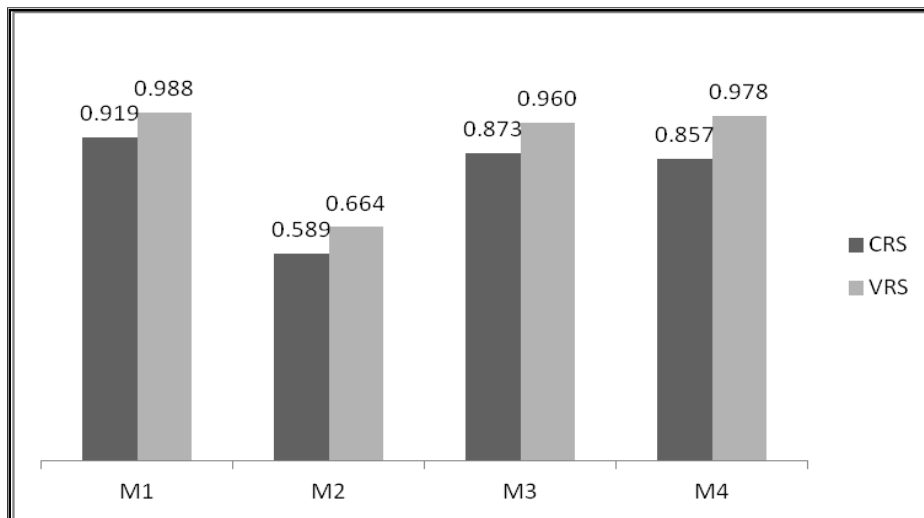


Figure 3: Average input-orientated technical efficiency (2004-2009)



Table 2 below presents a detailed report of the input-orientated VRS and CRS envelopment analyses. Firstly, it exhibits that the VRS technical efficiency (TE) was eleven times on the efficiency frontier, i.e. fully efficient with a score of 1. It can be seen that both M1 and M4 operated four times on the efficiency frontier and M3 operated three times on the efficiency frontier. According to the CRS technical efficiency, the companies were six times on the efficiency frontier. Furthermore, M1 was twice fully efficient and M3 and M4 were once and three times fully efficient, respectively. Regarding the return to scale (RTS), M1 operated three times and M2 operated all five times at a decreasing return to scale, implying that they were operating on a scale that was too large, while M3 and M4 were operated mainly on an increasing return to scale, implying that they were operated on a scale that was too small.

**Table 2: Input-orientated envelopment efficiencies and return to scale (RTS)**

Mining company / Year	VRS TE	CRS TE	RTS
M1 / 2005	1.000	0.964	Decreasing
M1 / 2006	1.000	1.000	Constant
M1 / 2007	0.938	0.911	Decreasing
M1 / 2008	1.000	1.000	Constant
M1 / 2009	1.000	0.721	Decreasing
Average	0.988	0.919	
M2 / 2005	0.752	0.656	Decreasing
M2 / 2006	0.677	0.600	Decreasing
M2 / 2007	0.687	0.615	Decreasing
M2 / 2008	0.707	0.608	Decreasing
M2 / 2009	0.497	0.468	Decreasing
Average	0.664	0.589	
M3 / 2005	1.000	1.000	Constant
M3 / 2006	0.966	0.952	Increasing
M3 / 2007	0.836	0.789	Increasing
M3 / 2008	1.000	0.829	Increasing
M3 / 2009	1.000	0.796	Increasing
Average	0.960	0.873	
M4 / 2005	1.000	0.731	Increasing
M4 / 2006	1.000	1.000	Constant
M4 / 2007	1.000	1.000	Constant
M4 / 2008	1.000	1.000	Constant
M4 / 2009	0.892	0.555	Increasing
Average.	0.978	0.857	

Source: Data elaborated using software of Zhu (2004)

## CONCLUSION

The purpose of the article was to estimate the scale efficiency, which indicates the degree that the platinum-mining companies are achieving economies of scale with regard to their environmental performances. South African platinum-mining companies were used to demonstrate the DEA model. The study used both the constant CRS and VRS DEA approaches to estimate the technical and scale efficiencies. The input variables used were GHG emissions, water usage and energy usage. The output variables were platinum-production volume, ROA and ROE.

It was found that firstly, regarding both the CRS and VRS approaches, M1 is on average technically the most efficient organization, while M2 is technically the least efficient organization, with M3 and M4 in-between. According to the CRS and VRS approaches, the mining companies were operated in total six times and 11 times on the efficiency frontier, respectively. The study also found, as expected, that the efficiency estimates of the less-restricted VRS approach are higher than the efficiency estimates of the CRS approach. Furthermore, M1 and M2 operated mainly on a decreasing return to scale, implying that they were operating on a scale that was too large, while M3 and M4 mainly operated on an increasing return to scale, implying that they were operating on a scale that was too small. An analysis of the data also revealed that M1 is physically the largest organization, followed by M2, M3 and M4, respectively. Although the CRS approach is based on the assumption that mines are able to linearly

scale their inputs and outputs without changing their efficiency, its value is that it helped to arrive to the conclusion that these mines did not achieve economies of scale. Say, for example, a company can achieve economies of scale by producing 100 ounces of platinum within a specific period. If they are producing on an increasing return to scale, they may, for example, require 50 percent of the inputs to produce only ten percent of platinum, namely ten ounces. On the opposite side, if they are producing on a decreasing return to scale, they may require, for example, three times as much input only to double the outputs.

The practical implication hereof is that platinum-mining companies can firstly measure their impact on the environment relative to their rivals and achieving economies of scale will also be helpful to relatively reduce the environmental impact. The value of the study is found in the fact that this is the first effort to develop a DEA model to estimate the degree that mining companies are achieving economies of scale with regard to environmental impact. The limitations of the study are that only a limited number of companies were included, because not all the companies submitted sustainability reports according to GRI guidelines. Further research should be done to refine the DEA model and also to consider other variables. As time passes and more mining companies adhere to the GRI sustainability reporting, similar studies should be extended to other mining sectors.

#### **AUTHOR INFORMATION**

**Professor Pieter W Buys** is currently the Research Program Leader at the North-West University (South Africa) and holds two PhDs (Accountancy and Management Accountancy), two Masters Degrees (MComm and MBA), and he is also a US Certified Management Accountant (CMA). He has worked in the ERP and business consulting industry in Canada, the USA and South Africa for more than 15 years. He has published more than 28 articles in peer-reviewed and professional publications. His current research revolves around corporate social responsibility and corporate resilience. E-mail: Pieter.Buys@nwu.ac.za

**Professor Merwe Oberholzer** is currently Professor in the School of Accounting Sciences at the North-West University (South Africa) and holds a PhD in Management Accountancy. He has taught extensively in the Chartered Accountancy and Chartered Management Accountancy programs. His academic research output includes more than 30 peer-reviewed articles and conference presentations. His current research focuses on DEA modelling in the context of social responsibility and corporate resilience. E-mail: Merwe.Oberholzer@nwu.ac.za

**Mr Toy Prinsloo** currently works as Management Accountant at Wilmar Oils and Fats (Pty) Ltd in the Industrial Sector (South Africa). He holds a Masters degree in Management Accountancy from the North-West University (South Africa) and is a passed finalist at the Chartered Institute of Management Accountants (CIMA).

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