

The role of commercial agriculture in meeting sustainable development goals in South Africa: Evidence from municipal-level total factor productivity analysis

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ABSTRACT

Improving agricultural productivity is critical, both locally and globally, particularly in the pursuit of the Sustainable Development Goals (SDGs) of eradicating poverty (SDG 1), increasing food production for food security (SDG 2), and promoting efficient use of agricultural resources and sustainable farming practices (SDG 12). This study examines and compares total factor productivity efficiency (TFPE) in the South African commercial agricultural sector, along with its drivers, using local municipal-level data. We used the Färe-Primont index to assess municipalities' TFPE levels, considering both traditional (economic) factors (labour, land, and operating expenses) and environmental variables (temperature, rainfall, and soil moisture index). Our TFPE index results are not only lower, but they show more variation across municipalities than the economic TFPE index, which is commonly used in agricultural productivity research. This implies that ignoring environmental variables may bias analysis; therefore, future studies should consider including environmental factors in their analyses. We then used hierarchical clustering to group municipalities with similar TFPE levels and components, followed by fractional regression to identify the drivers of efficiency levels. The cluster analysis results reveal that the best-performing municipalities are in cluster 4, comprising municipalities from the Western Cape Winelands specialising in horticulture production, municipalities near urban areas with better market proximity, those engaged in the global value chain, and those with a high proportion of farmers who own most of their farmland. Furthermore, the fractional regression results show that age, gender, race, market proximity, land use types, and production diversification are significant drivers of TFPE and its components. Our study offers insights into the divergent agricultural TFPE performance among municipalities and the underlying factors causing these disparities. The findings can inform the development of targeted strategies, particularly at the local level, aimed at enhancing agricultural productivity and making significant contributions to achieving the SDGs.

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1. Introduction

Improving agricultural total factor productivity (TFP), which refers to the efficiency with which agricultural output such as crops and livestock are produced relative to inputs such as labour and capital

(O'Donnell, 2018; Zelenyuk, 2023), is critical to meeting the Sustainable Development Goals (SDGs), particularly SDGs 1, 2, and 12 (World Bank, 2022; FAO, 2022). Agricultural TFP can contribute to SDG 1 (end poverty) by increasing agricultural income, SDG 2 by increasing food production, and SDG 12 by improving agricultural resource utilisation efficiency and encouraging the adoption of sustainable farming practices (FAO, 2022; Sachs, 2022). Despite some progress towards the SDGs between 2015 and 2019, Sachs et al. (2023) demonstrated that all SDGs fall far short of their respective targets. The 2020 pandemic, combined

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with other concurrent crises, such as the Russia-Ukraine war, has slowed global progress towards SDG targets (Sachs et al., 2023; FAO, 2022; United Nations, 2022). According to recent data, one out of every ten people on the planet is hungry, and one-third of people struggle to obtain consistent and sufficient food (United Nations, 2022; Sachs et al., 2023). To tackle these problems, it is necessary to enhance agricultural productivity at both local and global levels (World Bank, 2022; FAO, 2022).

This paper assesses South African commercial agricultural TFP using municipal-level data to identify areas that require attention to boost sector productivity and contribute to the achievement of the SDGs. TFP measurement has received a lot of attention in the literature (Zelenyuk, 2023), particularly in agricultural economics and policy (Fuglie, 2018; Kryszak et al., 2023). Agricultural TFP analysis necessitates information on various farming activities and locations (FAO, 2022). However, current literature relies on traditional productivity measures, which have a significant drawback as they only consider inputs and outputs from market transactions, neglecting by-products from agricultural activities and impact of environmental factors such as precipitation and temperatures (Dakpo et al., 2016; Bureau and Antón, 2022). Soil quality, water availability, and climate all have different effects on agricultural output, risk, and performance (Senay et al., 2023), but they are often ignored. However, failing to account for these factors can lead to systematic bias in productivity calculations and incorrect policy recommendations (Bureau and Antón, 2022). In many countries, the inability to consider environmental factors in TFP measurements stems from the scarcity of such data, especially at the subnational level, making it challenging to compare TFP across regions and production systems (FAO, 2022). South Africa is one of the few exceptions, particularly in Sub-Saharan Africa, in that detailed municipal-level data on agricultural indicators, including conventional inputs such as labour and operating expenses, as well as environmental variables such as precipitation, temperature and soil moisture, for the entire country is available. As a result, access to this data motivated the research questions in this study.

South Africa provides an interesting case study for our research objectives for several reasons. First, the country, like many other developing and emerging economies, prioritises agricultural productivity and efficiency improvement to meet its National Development Plan (NDP) vision 2030 and SDG targets for food security, job creation, and poverty reduction (DALRRD, 2013; Nhemachena et al., 2018). However, unlike many African countries, South Africa's agricultural sector is more diverse and commercialised. In contrast to subsistence agriculture, which focuses on production for household consumption, commercial agriculture involves crops and livestock production for business purposes, often requiring vast agricultural land and significant investment (Temoso et al., 2016). The sector aims to maximise profits using modern technology and high-yield varieties. Grains, oilseeds, fruits, sugar, citrus, wine, and vegetables, as well as cattle, dairy, hogs, sheep, poultry, and egg industries, are among the sector's key agricultural outputs (Statistics South Africa, 2022). Agricultural output is often targeted for export, supplying raw materials, and contributing to food production. Value-added activities include meat processing, fruit preservation, dairy products, and sugar refining. Land, labour, capital, and finance are the four key drivers of production in the sector (Statistics South Africa, 2022). The sector's GDP contribution in 2020 was just 2.4%, with agricultural exports exceeding imports, totalling 9.5 billion US dollars in 2020.¹

The sector is critical not only to the South African economy, accounting for 80% of agricultural output and 3% of national economic activity (Statistics South Africa, 2022), but also to the economies of its southern African neighbours, where it accounts for 43.1% of agricultural

GDP (Liebenberg and Pardey, 2012). As a result, increasing South African agricultural productivity is critical to ensuring food security in the country as well as for countries such as Botswana, Namibia, Lesotho, and Eswatini, which rely heavily on food imports from the country.

Second, as discussed by the OECD (2022), South African agricultural productivity growth has slowed in recent years compared to advanced economies, averaging 0.9% per year between 2007 and 2016. Declining agricultural productivity jeopardises the country's international competitiveness, given that one-third of agricultural products are exported (Arndt and Pratt, 2020; OECD, 2022). According to Sihlobo (2021), apart from the impact of COVID-19 on the South African agricultural sector, its ability to realise its full productivity potential has been hampered by a lack of substantive support for commercial agriculture as well as various policy inconsistencies. Consequently, empirical evidence on agricultural TFP and its determinants, particularly at the subnational level, is necessary to identify areas for improvement.

Third, while South African agricultural productivity and efficiency have previously been studied (Van Schalkwyk and Groenewald, 1992; Thirtle et al., 1993; Schimmelpennig et al., 2000; Townsend and Thirtle, 1998; Conradie et al., 2009; Mkhabela et al., 2010; Piesse et al., 2018; Greyling et al., 2023; Matthews et al., 2023; Myeki et al., 2023), research gaps persist (Vink et al., 2022). Previous research, for instance, was confined to municipalities in specific provinces, such as the Western Cape (e.g., Conradie et al., 2009; Matthews et al., 2023), and focused on sub-sectors like grapes and wine (Conradie et al., 2019b), pome and stone fruits (Myeki et al., 2023), and maize (Greyling et al., 2023). This implies that agricultural productivity for a major part of municipalities in the country remains unknown. Therefore, further research is necessary to provide a more current and comprehensive understanding of agricultural TFP performance in the country's diverse production environment.

Given the preceding context, this study contributes to the literature first by examining agricultural TFP in South Africa using the 2017 Census of Commercial Agriculture (CoCA), which covers all aspects of commercial agriculture at national, provincial, district, and local levels (Statistics South Africa, 2020). According to Statistics South Africa, (2020), South Africa can be divided into nine provinces and 52 district municipalities. The district municipalities are classified as either metropolitan or district municipalities. The district municipalities are further categorised into local municipalities. Since our data is available at the local municipality level, this enables us to conduct a more disaggregated analysis while also facilitating aggregation to higher levels, such as the district municipality and provincial levels. Importantly, this approach allows for a more thorough comparison across a broader range of municipalities, while also considering location-specific factors such as temperature, precipitation, infrastructure, and market proxies that can influence agricultural TFP and efficiency. Thus, providing insights for strategy and policy to tailor the implementation of the district development model at the local level for agricultural development.

Second, unlike previous South African studies that used TFP indices such as Fisher, Malmquist, and Törnqvist, we used the Färe-Primont TFP index. This index has been used in other countries to assess livestock productivity (Martinez-Cillero et al., 2019; Temoso et al., 2023), and regional agricultural productivity (O'Donnell, 2010; Rahman and Salim, 2013; Temoso et al., 2015; Myeki et al., 2022; Asante et al., 2023). The Färe-Primont TFP index is preferred because it follows basic index theory rules, is consistent with measurement theory, and allows valid space and time comparisons (O'Donnell, 2018). Färe-Primont TFP divides productivity into technical, scale, and mix efficiencies (O'Donnell, 2018). According to O'Donnell (2018, p.382), technical efficiency is a measure of how well production technologies are selected and applied (i.e., how well a manager "picks books or recipes from the library" and "follows the instructions"), whereas scale efficiency is a measure of how well a manager has captured economies of scale, which are the benefits gained by changing the scale of operations. Mix efficiency is a measure of how well the manager has captured economies of output substitution,

¹ International Trade Administration (ITA, 2024). South Africa - Country Commercial Guide <https://www.trade.gov/country-commercial-guides/south-africa-agricultural-sector>.

where economies of output substitution are the benefits derived from substituting one output for another (e.g., producing less of output 1 to produce more of output 2) (O'Donnell, 2018; Temoso et al., 2023).

Third, we investigated the factors influencing TFP and efficiency levels in South African commercial agriculture using fractional regression models. These include factors such as participation in the global value chain, land use types, production diversity, and farmer characteristics. The results of this study can be used for benchmarking in terms of successful practices and technologies in high-performing regions that can be implemented in low-performing regions, thus promoting knowledge sharing and the dissemination of best practices across agricultural systems (Temoso et al., 2023). Furthermore, the findings can help inform regional strategies to meet the NDP 2030 and SDG targets, as well as the strategic implementation of initiatives such as the Agriculture and Agro-Processing Master Plan (AAMP), the Comprehensive Agriculture Support Programme (CASP), and the District Development Model (DDM), which emphasises district-level development model for effective implementation.

The remainder of the paper is structured as follows. Section 2 describes the commercial agricultural production systems in South Africa. Section 3 discusses the empirical method and data variables. Section 4 reports and interprets the findings. Policy implications and conclusions are presented in Section 5.

2. South African commercial agriculture

2.1. Commercial agriculture in South Africa and sustainable development goals

The South African NDP 2030 seeks to create 250,000 primary jobs and 130,000 secondary jobs through the expansion of commercial agriculture (National Planning Commission (NPC, 2012). To reach these objectives, the District Development Model (DDM) has been implemented as a decentralised strategy to address societal, geographical, and financial challenges (Parliament of South Africa, 2020). The DDM considers the localization of the SDGs, implementing global objectives at multiple tiers, including national, regional, and community-based tiers, while taking unique circumstances and preferences into account (Parliament of South Africa, 2020). The local and district municipalities play a crucial role in this process (Parliament of South Africa, 2020).

An empirical analysis of the current state of commercial agriculture in South Africa and its determinants is critical for developing effective policies and strategies to promote the growth of the sector. This is especially important, given the importance of the sector to the South African economy, food security, and poverty alleviation, as well as the need to extend such policies to the local level. Therefore, the results of this study may be useful for a variety of stakeholders, including governments, academia, and others, as a tool for tracking progress towards SDG goals and ensuring accountability to commitments, as well as a management tool to facilitate the implementation of developments required to meet set targets (Nhemachena et al., 2018).

2.2. Literature review

The productivity and efficiency of agriculture have long been a focus of South African researchers (Van Schalkwyk and Groenewald, 1992; Thirtle et al., 1993; Schimmelpfennig et al., 1995; Conradie et al., 2009; Piesse et al., 2018; Greyling et al., 2023; Matthews et al., 2023). For instance, Thirtle et al. (1993) determined TFP in commercial agriculture from 1947 to 1991 using the Törnqvist-Theil Divisa index and concluded that it increased at a relatively sluggish annual rate of 1.3%. According to Liebenberg and Pardey (2012), the average annual growth rate of agricultural TFP was 1.48% during the study period. Using the stochastic frontier analysis (SFA) and data from 1961 to 2014, Arndt and Pratt (2020) evaluated the performance of South Africa's agricultural sector. According to their results, productivity remained constant

between 1961 and 1980, declined between 1981 and 1994, increased from 1995 to 2004, and gradually remained at 1.5% from 2005. Myeki et al. (2023) used industry-level data from 2014 to 2021 to assess productivity in the deciduous fruit sector and concluded that technical change was the primary driver of growth. In terms of sub-sectors, stone fruit productivity accounted for most of the sector growth, while pome fruit had a moderate contribution. In these studies, only national-scale data was used. However, using aggregate data frequently misses regional disparities caused by varying agroclimatic and regional endowments (Temoso et al., 2023).

Several studies have been conducted in South Africa to understand regional disparities in agricultural productivity and efficiency. van Schalkwyk and Groenewald (1992) examined productivity growth in five regions during the apartheid era and concluded that agricultural productivity increased during this period. Conradie et al. (2009) studied TFP in 31 agricultural magisterial districts in the Western Cape province from 1952 to 2002. According to the study, TFP growth was significantly higher in districts focused on irrigated and exported fruit. Piesse et al. (2018) compared the efficiency of the established and emerging South African wine regions and found land, labour, and pesticides were the most important inputs, while fertiliser, machinery, and electricity contributed marginally to the output.

Conradie et al. (2019a) investigated how environmental change affected livestock efficiency for Karoo sheep and goat farmers from 2012 to 2014. According to the study, efficiency decreased over time, with farms at the bottom of the distribution performing significantly worse. Using data for Karoo sheep farmers covering all eleven Northern Cape districts, Conradie et al. (2021) found irrigation development to have slowed TFP growth during the period. Greyling et al. (2023) examined maize production, yield, and average price in South Africa from 1918 to 2015, concluding that changing agricultural policies had a significant impact on production, productivity, and climate risk. Matthews et al. (2023) studied production technologies and efficiency in four sheep-producing districts in South Africa. They concluded that significant differences between groups existed, which they attributed to natural resource endowments and institutional arrangements, indicating the need for public-private partnerships to revitalise rural areas.

Although various studies have studied TFP and efficiency in South African agriculture, none of the studies used recent data from all nine provinces or comprehensively examined all main sectors. As a result, our research is based on the CoCA 2017 dataset (the most recent commercial agriculture data available in South Africa), which covers broader sub sectors of commercial agriculture at the national, provincial, district, and municipal levels (Statistics South Africa, 2020). CoCA benefits from being tied to the NDP, MTSF, and SDGs (Statistics South Africa, 2020).

3. Method of analysis

This section provides an overview of the empirical models used in the study. First, the Färe-Primont index that was used to estimate commercial agricultural TFP, and efficiency is presented. We also discuss the hierarchical cluster analysis that was used to group municipalities based on their efficiency scores. Then, a fractional regression analysis, which was used to identify key drivers of agricultural TFP and its components, is discussed. This section also includes the data and sources used, as well as their descriptive statistics.

3.1. Färe-Primont TFP index

As previously stated, we estimated TFP and its components using the Färe-Primont TFP index approach (O'Donnell, 2014), which can be specified as follows for a given local municipality i for a given period:

$$TFP_i = \frac{Y_i}{X_i} \quad (1)$$

where $Y_i = Y(y_i)$ is an aggregate output; $X_i = X(x_i)$ is an aggregate input; and $Y(\cdot)$ and $X(\cdot)$ are nonnegative, nondecreasing and linearly homogeneous aggregator functions. The index number associated with measuring firm i 's TFP in comparison to firm h 's TFP during the same period can be expressed as:

$$TFP_{hi} = \frac{Y_i/X_i}{Y_h/X_h} = \frac{Y_{hi}}{X_{hi}} \quad (2)$$

where $Y_{hi} = Y_i/Y_h$ is an output quantity index and $X_{hi} = X_i/X_h$ is an input quantity index. O'Donnell (2018) demonstrates that these functions are suitable candidates for an input and output aggregator function due to their homogeneity and monotonicity. As a result, the corresponding Färe-Primont TFP index value is as follows:

$$TFP_{hi} = \frac{D_O(x_0, y_i)}{D_O(x_0, y_h)} \frac{D_I(x_h, y_0)}{D_I(x_i, y_0)} \quad (3)$$

The TFP index derived from equation (3) serves as a basis for calculating various economically significant productivity components. O'Donnell (2018) shows that the TFP index can be used to calculate total factor productivity efficiency (TFPE) by dividing observed TFP levels (TFP_{it}) by the maximum TFP achieved in a specific production environment and period (TFP_t^*). Thus, TFPE is represented as $TFPE_{it} = TFP_{it}/TFP_t^*$. TFPE can be decomposed into three components: technical efficiency, scale efficiency, and mix efficiency. According to O'Donnell (2018), TFPE can be viewed as a measure of how well managers have optimised outputs while taking previously established inputs and environmental factors into account.

TFPE can be decomposed into finer components through both output- and input-oriented decompositions. However, in the current study, we only present output-oriented measures. This choice aligns with the predominant approach in many other countries, including South Africa, where most farmers seek to maximise output to increase agricultural productivity from a given set of inputs rather than the opposite (Coelli and Rao, 2005). Moreover, as highlighted by Temoso et al. (2015), inputs, such as land are fixed in many agricultural contexts, leading to a preference for an output orientation. Thus, in the short run, farmers tend to have fixed basic production inputs such as land, labour, and capital and may have more flexibility in choosing the type and number of outputs they can produce. The output oriented TFPE components can be represented as follows:

$$TFPE = OTE_i \times OSE_i \times RME_i \quad (4)$$

Where OTE is the output-oriented technical efficiency, which is the maximum number of outputs that can be produced with a given number of aggregate inputs or how well production technologies are selected and applied (i.e., how well a manager selects books or recipes from the library and follows instructions) (O'Donnell, 2018). OSE is output-oriented scale efficiency, a metric that measures how well a manager has captured economies of scale, or the benefits gained by changing the scale of operations. RME is residual mix efficiency, which is the component that remains after accounting for technical and scale efficiency effects, or a producer who is efficient in terms of technical and scale efficiency but inefficient in terms of mixing inputs and outputs. RME is associated with economies of scope, which provide a measure of the difference between TFP at the mix-invariant optimal scale and TFP at maximum productivity.

3.2. Using data envelopment analysis (DEA) to estimate the Färe-Primont TFP index

We utilise the *DPIN version 3.1* developed by O'Donnell (2011) to estimate the Färe-Primont TFPE index and associated efficiency measures using data envelopment analysis (DEA). DEA is a nonparametric method that employs linear programming to empirically assess the

relative efficiency of multiple similar entities or decision-making units (DMUs) (Cooper et al., 2007). The DMU is responsible for converting inputs to outputs. The mathematical procedure is based on calculating efficiency frontiers for the set of DMUs, which allows for the distinction between efficient and inefficient entities while encouraging feasible improvements for efficient operational performance (Cooper et al., 2007, 2011). The efficiency frontier is assumed to include all units, defining the production possibility set. The DMUs along the frontier are taken as the benchmark, whereas those below are inefficient. DEA uses the formulated model to project each DMU on the efficiency frontier and calculate the maximum improvements that can be made to the DMU's inputs and/or outputs (Cooper et al., 2007, 2011).

Following O'Donnell (2011), the main assumption underpinning the use of DEA is that the (local) input/output distance function representing the technology available for a given period is represented by:

$$D_O(x_i, y_i) = (y'_i \alpha) / (y_i + x'_i \beta) \quad (5)$$

The standard output-oriented DEA problem requires determining values for the unknown parameters in equation (5) to minimise them, $OTE_i = D_O(x_i, y_i) = Q(q_i)/Q(\bar{q}_i)$ thus resulting in the following LPs:

$$D_O(x_i, y_i)^{-1} = OTE_i^{-1} = \min_{\alpha, \beta} \{ \gamma + x'_i \beta : \gamma I + X' \beta \geq Y \alpha; y'_i \alpha = 1; \alpha \geq 0; \beta \geq 0 \} \quad (6)$$

where Q is a $J \times M$ matrix of observed outputs; X is a $K \times M$ matrix of observed inputs; I is an $M \times 1$ unit vector; and M denotes the number of observations used to estimate the frontier (O'Donnell, 2011, p. 8). The program uses variants of these two LPs to compute productivity indices and measures of efficiency. The program uses sample mean vectors as representative input and output vectors, respectively. The representative technology in these LP is the technology obtained under the assumption of no technical change and allows the technology to exhibit variable returns to scale.

We utilised the Färe-Primont index to estimate two models. The first model incorporated conventional input factors like land, labour, and other costs, excluding environmental variables such as precipitation, temperature, and soil moisture. This model focuses solely on economic sustainability. The second model incorporated conventional variables along with three environmental factors: precipitation, temperature, and soil moisture. This model considers the economic and environmental sustainability of commercial agriculture. Table 4 compares the results, but the subsequent analyses and discussion will concentrate on the second model, which encompasses both economic and environmental sustainability.

3.3. The second-stage DEA analysis: a fractional regression model

Following the decomposition of TFP and its components, a fractional regression model (FRM) was used to investigate the potential impact of contextual factors on technical, scale, mix, and total factor productivity efficiencies (i.e., OTE, OSE, RME, and TFPE) in commercial agriculture. According to Ramalho et al. (2010), the academic literature is split on which regression model is useful when the proportion of full frontier values equal to one is high and can assess the impact of contextual variables on both inefficient and efficient decision-making units. FRM model accounts for the specific distribution of the dependent variable, typically following a Beta or a Beta-like distribution (Ramalho et al., 2010; Asante et al., 2023). One common approach is to use a link function that transforms the mean of the response variable, such as a logit or a log link. Furthermore, within their theoretical framework, regression analysis with robust variances is a valid form of inference.

The fractional regression model is shown below: $E(y|x) = M(x)\theta$ where $M(\cdot)$ is nonlinear function that satisfies $0 < M(\cdot) \leq 1$ (for more details refer to Ramalho et al., 2010).

We included several contextual factors, as in previous agricultural

economics studies. Among these are gender, race, share of agricultural income from various activities such as horticulture, livestock, field crops, and farmer age.

4. Data and sources

4.1. Study area

We used information from the South African Census of Commercial Agriculture (CoCA), published by Statistics South Africa (Statistics South Africa, 2020). CoCA is a national commercial agriculture census that provides financial performance data for all VAT-registered farmers as well as production performance data for all farmers who responded to the census. Stats SA conducts a census every five years to collect agricultural data from individuals or businesses involved in commercial farming in South Africa. The overarching goal of CoCA is to collect basic quantitative data on commercial agriculture in South Africa for policy formulation and food security (Nortjé, 2020). Crop farms, horticulture farms, livestock farms, and farms engaged in mixed agricultural activities are included in the data. The most recent available data, which covers the 2017 production year and was published in 2020, covers the local and district municipality, provincial, and national levels; therefore, this study's analysis is limited to 2017 cross-sectional data.

Our geographical unit of analysis is the local municipalities, and their distribution across the country are shown in the map in Figs. 1 and 2. A local municipality is the third and most local tier of government in South Africa. South Africa has 205 local municipalities. Our study focuses solely on the 150 local municipalities that engage in commercial agriculture, as not all municipalities practice this activity. Multiple local municipalities make up a district municipality; there are 52 district municipalities. The responsibility for municipal affairs in South Africa is shared between the district and local municipalities.

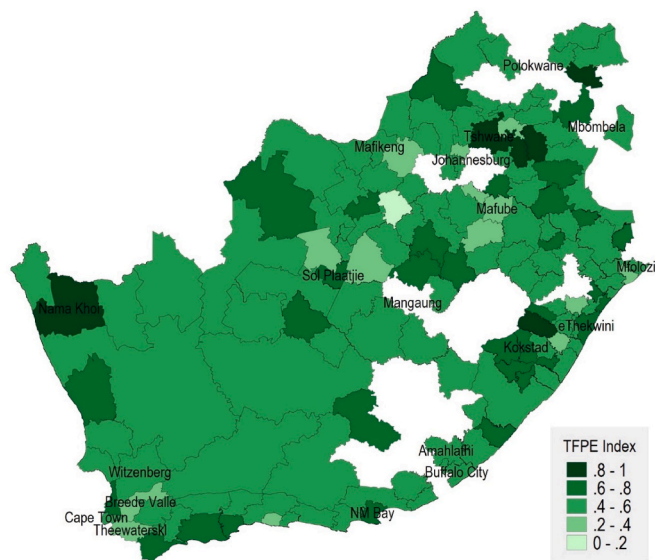


Fig. 1. South African local municipalities TFPE index for commercial agriculture estimated using conventional inputs only.

Note: white spaces represent local municipalities with missing data.

Source: Authors

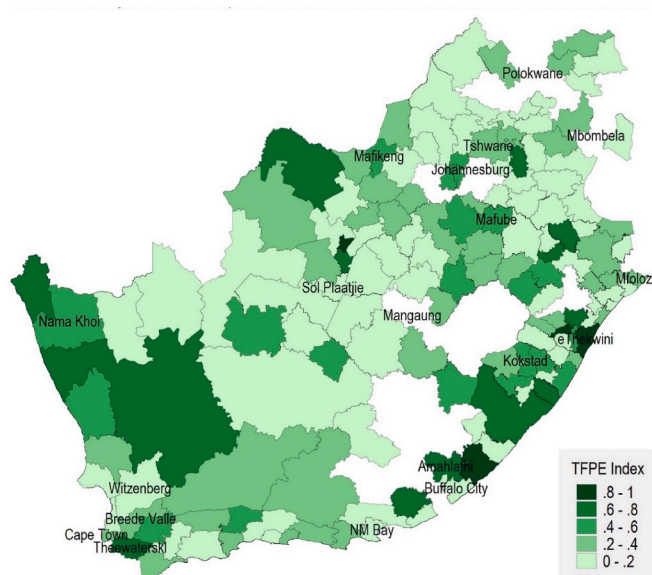


Fig. 2. South African agricultural municipalities economic and Environmental TFPE Performance, 2017.

Note: white spaces represent local municipalities with missing data.

Source: Authors

4.2. Production output variables

Table 1 lists the variables used in the analysis. As shown, the number of farming units (*FarmUnits*) per local municipality varied across the 150 municipalities, ranging from 9 to 175 farming units. South Africa is estimated to have 40,122 commercial farms, with the Free State province housing one out of every four farmers (Statistics South Africa, 2020). According to Statistics South Africa. (2020), livestock farming accounted for the greatest proportion of farming units (33.9%), followed by mixed farming (31.1%), and field crop production (21.1%). Mixed farming involves producing both crops and livestock on the same farm, whereas field crop and livestock farming systems are specialised (Statistics South Africa, 2020).

The output variables considered for this study were income from field crops, horticultural crops and products, animals and animal products, and other agricultural products. As shown in Table 1, income from animals and animal products was nearly twice as large as that from field crops and horticulture. Nonetheless, field crops and horticultural production are important components of South African commercial agriculture and contribute to food security and job creation. The main field crops are maize, soybeans, sunflower seeds, wheat, and sugarcane (Statistics South Africa, 2020).

4.3. Production factors – conventional (economic) and environmental variables

Among the input variables considered in the study are the commonly included factors of production variables in the production economics literature: employment costs (*EmployCosts*), expenditure excluding employee remuneration (*ExpenseTotal*), and land (grazing land, arable land, forest/woodland, and others). The total number of full-time employees (*FT_Labour*) in each municipality ranged from 245 to 15,124, while employment costs (*EmployCosts*) ranged from 4654 to 1.45 million Rands (347–108,209 US dollars). Grazing land was the most

² International Monetary Fund (IMF). Representative Exchange Rates for Selected Currencies for December 2017. https://www.imf.org/external/np/fin/data/rms_mth.aspx?SelectDate=2017-12-31&reportType=REP.

Table 1
Descriptive statistics of commercial agricultural production in South Africa.

Variables	Description	Mean	Min	Max
FarmUnits	Number of commercial farms in each local municipality	230	9.00	175
Outputs				
Field crops	Income earned from various types of field crops by local municipality including cereals, oil seeds, legumes, sugarcane, and fodder crops (000' rands)	427.5	0.00	205.8
Horticulture	Income from various types of horticulture, including wine, fresh export fruit, canned fruit, citrus, and subtropical fruits and vegetables (000' rands)	406.2	0.00	489.2
Livestock	Income from animals and animal products including livestock, poultry, game, aquaculture, and all other animals (000' rands)	898.5	0.00	8235
Other outputs	Other agricultural income (000' rands)	8.86	0.00	28.8
Inputs				
FT Labour	Total full-time farm labour (000)	2.6	0.25	15.1
PT Labour	Total part-time workers (000)	1.8	0.00	23
Arable land	Size of the arable land area in hectares (000' ha)	46	0.00	30.9
Grazing land	Size of the grazing land area (000' ha)	141.5	0.00	2,194,
Forest/woodland	Size of the forest/woodland area (000' ha)	3.97	0.00	38.6
Other land	Size of the other land area (000' ha)	4.72	0.00	252.7
ExpenseTotal	Expenditure excl. employees' remuneration (000' Rands)	1563	18	10,500
EmployCosts	Employment costs (000' Rands)	213	4.7	1451
Environmental factors				
Precipitation	Mean precipitation in each district (millimetres)	629	148	1153
Temperature	Mean temperatures in each district (degrees Celsius)	17	13	23
Soil moisture index	The soil moisture index (SMI) ranges from 0 to 1, and it is based on the difference between current soil moisture and the permanent wilting point.	0	0.424	1
Exogenous factors				
share_FemManager	Proportion of farm owners or managers that are female in each local municipality (%)	9	0	34
share_raceW	Proportion of farm owners or managers that are white in each local municipality (%)	84	0	100
Share_65plus	Proportion of farmers aged 65+ in each local municipality (%)	15	0	38
shareYouth	share of young farmers aged 15–34 years	13	0	33
share_FT	Share of labour that are full-time in each local municipality (%)	66	22	100
share_hortic	Share of income from horticulture in each local municipality (%)	21	0	98
share_crops	share of income from field crops in each local municipality (%)	48	0	100
share_animal	share of income from livestock in each local municipality (%)	30	0	100
Share_other income	Share of income from other agricultural activities in each municipality (%)	1	0	39
HHI	Hirschman-Herfindahl index measuring the area's	60	29	100

Table 1 (continued)

Variables	Description	Mean	Min	Max
	agricultural income diversification/specialisation (%)			
HHI_landuse	Hirschman-Herfindahl index measuring the land use diversification/specialisation (%)	61	26	100

Note: In 2017, the average exchange rate for South African currency to the US was 13.4 South African Rand (ZAR) to one US dollar (USD)².

Table 2
Average TFP levels and components by province in 2017.

Province	Statistics	TFPE	OTE	OSE	RME	OSME
Eastern Cape	Mean	0.167	0.876	0.856	0.216	0.189
	min	0.016	0.506	0.550	0.027	0.016
	max	0.605	1.000	1.000	0.605	0.605
Free State	Mean	0.213	0.896	0.869	0.255	0.239
	min	0.003	0.576	0.419	0.004	0.003
	max	0.513	1.000	1.000	0.627	0.624
Gauteng	Mean	0.255	0.849	0.942	0.284	0.274
	min	0.033	0.586	0.830	0.063	0.052
	max	0.894	1.000	1.000	0.894	0.894
KwaZulu-Natal	Mean	0.192	0.854	0.897	0.240	0.221
	min	0.015	0.541	0.465	0.015	0.015
	max	0.778	1.000	1.000	0.778	0.778
Limpopo	Mean	0.292	0.867	0.952	0.322	0.315
	min	0.035	0.500	0.756	0.075	0.056
	max	0.646	1.000	1.000	0.646	0.646
Mpumalanga	Mean	0.217	0.798	0.896	0.279	0.261
	min	0.006	0.289	0.550	0.023	0.020
	max	0.577	1.000	1.000	0.577	0.577
North West	Mean	0.220	0.857	0.959	0.252	0.247
	min	0.020	0.564	0.634	0.032	0.020
	max	0.578	1.000	1.000	0.578	0.578
Northern Cape	Mean	0.210	0.770	0.937	0.279	0.260
	min	0.037	0.404	0.657	0.065	0.058
	max	0.590	1.000	1.000	0.678	0.665
Western Cape	Mean	0.345	0.921	0.923	0.384	0.368
	min	0.029	0.642	0.594	0.033	0.029
	max	1.000	1.000	1.000	1.000	1.000
South Africa (Mean)	Mean	0.234	0.862	0.909	0.278	0.263
	min	0.003	0.289	0.419	0.004	0.003
	max	1.000	1.000	1.000	1.000	1.000

Note: average TFPE (total factor productivity efficiency), OTE (output-oriented technical efficiency), OSE (output-oriented scale efficiency), OME (output-oriented mix efficiency) and OSME (output-oriented scale-and-mix efficiency) levels with their standard deviations in brackets.

common land use across municipalities, followed by arable land, other land, and finally forest/woodland use. The total expense excluding labour costs ranged from 4654 to 10.5 million Rands (347–746,269 US dollars). However, one of the limitations of the conventional input variables is that they only capture information useful for assessing the economic productivity and sustainability of agriculture, not the environmental one. This approach assumes that production decisions are based on known characteristics of production environments, which may not be realistic, especially in sectors such as agriculture which depends on natural resources such as precipitation and soils (O'Donnell, 2022; Bureau and Antón, 2022).

Building on other agricultural productivity and sustainability studies that investigated the effects of temperature and precipitation on various agricultural output and yields (Temoso et al., 2015; Tozer and Villano, 2013; and O'Donnell, 2022), we incorporated three environmental variables as key production factors: precipitation, temperatures, and soil moisture. These variables correspond to the annual precipitation, average surface temperatures, and soil moisture levels in a specific municipality. The Soil Moisture Index (SMI) is a measure of soil moisture content, ranging from 0 to 1, based on the difference between current

soil moisture and the permanent wilting point (Saha et al., 2018). SMI is crucial for crop growth and development, as it affects seed germination and root development in rain-fed agricultural areas, impacting crop yield, whilst insufficient levels of SMI can lead to water stress and reduced biomass production (Champagne et al., 2012; Saha et al., 2018). Conversely, excessive soil moisture can cause seed decay and crop damage.

The data for annual precipitation and mean temperatures is from the University of East Anglia Climatic Research Unit website (Harris et al., 2021). The soil moisture data was accessed from the website of Center for International Earth Science Information Network (CIESIN) - Columbia University.³

According to O'Donnell (2022), incorporating environmental factors such as precipitation and temperature in economic analysis is based on the idea that they can impact agricultural productivity by influencing the outputs achievable with fixed inputs. More importantly, as pointed out by Conradie et al. (2019a), it is critical to include these variables in the context of South Africa because agricultural production is vulnerable to the risks posed by reduced precipitation and increased temperatures associated with climate change. From a policy point of view, integrating environmental aspects into productive efficiency can provide policy-makers with helpful information on production systems that can lead to improving the design of new policies (Dakpo et al., 2016; Bureau and Antón, 2022).

4.4. Contextual factor variables

Several explanatory variables were used in the second-stage regression analysis to explain the variation in TFPE and its components across municipalities. Among these are the income shares generated by livestock, horticulture, field crops, and other agricultural activities; the proportion of white farmers; farmers' age (older farmers over 65 and youth farmers between the ages of 18 and 34); and farmers' gender, all sourced from the CoCA data (Statistics South Africa, 2020). We also included two variables sourced from the Agri-Hubs Toolkit data: the number of supermarkets per local municipality as a proxy for access to local markets, and the value of import and export duty expenditure per municipality as a proxy for local global value chain participation. Agri-Hubs is a networked innovation system of agro-production, processing, logistics, marketing, training, and extension services, located in a district municipality. The network aims to enable a market-driven combination and integration of various agricultural activities and rural transformation services.⁴

5. Results and discussion

5.1. TFPE and its components

Appendix A presents estimated TFPE scores and components at the local municipal level, based on a comprehensive model that considers both economic and environmental variables. Figs. 1 and 2 show the spatial distribution of TFPE scores estimated using the economic TFPE model and the comprehensive TFPE model, respectively. The two figures show significant differences, with the comprehensive TFPE index results (Fig. 2) demonstrating more spatial variation across municipalities than the economic TFPE index (Fig. 1). As shown in Table 4, the economic TFPE (model 1), which is widely used in agricultural productivity research, produces significantly higher TFPE scores than the comprehensive TFPE index (model 2). The differences are most likely due to the economic TFPE model's failure to account for regional disparities caused

by differences in agroclimatic conditions and endowments (Temoso et al., 2023). According to an OECD study (Bureau and Antón, 2022), when assessing agriculture's sustainable productivity, environmental variations across different regions must be considered and accounted for to identify productivity drivers and barriers. Thus, for this study, our discussion and policy implications will centre on the comprehensive TFPE results.

We assessed the relative performance of municipalities using the comprehensive TFPE index results shown in Appendix A, using Witzenberg as a benchmark (TFPE index value of 1). The findings suggest that Witzenberg municipality farmers operated on South Africa's commercial agriculture frontier and were able to maximise their productive output with available technology. These results can be attributed to *Partners in Agri Land Solutions* (PALS), a private land reform and development initiative launched in Witzenberg municipality in 2014, as well as the municipality's fertile soils and an ideal climate for agricultural production (Kriel, 2018). Mfolozi municipality had the lowest TFPE of 0.003 in comparison to the frontier region (Witzenberg municipality). We expected this result given Mfolozi's limited commercial agricultural activity. Section 5.2 delves deeper into this municipality.

A pairwise correlation matrix (Table 3) was used to determine components influencing TFPE differences amongst the municipalities. The results show that TFPE has a statistically significant and positive correlation with all three variables (OTE, OSE, and RME). The RME correlation coefficient had the greatest magnitude of the three variables, indicating that it had the most influence on the spatial variation in TFPE. These findings suggest that farmers in lower-performing municipalities relative to the frontier (Witzenberg municipality) were unable to achieve scope economies by adjusting their optimal input and output combinations during the production process (Temoso et al., 2023).

5.2. Spatial analysis of TFP and efficiency across municipalities, clusters, and provinces

Table 2 shows the TFPE levels in each province based on a comprehensive Färe-Primont TFP index that incorporates both economic and environmental inputs (or Model 2 in Table 3). The Western Cape province had the highest TFPE (0.345). The province is one of South Africa's largest commercial agriculture hubs, specialising in horticulture and winter field crops such as barley and wheat, which are export oriented (Conradie et al., 2009). It is distinguished by favourable and distinct agroclimatic conditions, including a distinct winter rainfall pattern (Vink and Kirsten, 2003). Limpopo (TFPE: 0.292) and Gauteng (TFPE: 0.255) were ranked second and third, respectively. Gauteng is one of the most urbanised provinces in the country, with good infrastructure including the largest commercial livestock feedlots, the largest grain logistical hub, which allows farmers better access to markets (DALRRD, 2015). Kwa-Zulu Natal (KZN) had the lowest average TFPE (0.192), which may be attributed to the province's near-exclusive commercial production of a single field crop, sugarcane.

To identify groups of local municipalities with similar TFPE and efficiency scores, we used the Ward agglomeration algorithm for hierarchical clustering. This method groups the closest points and then distributes points to the closest group after computing the distance between starting observations (Caliński and Harabasz, 1974; Kassambara,

Table 3

Pairwise Pearson correlation between technical efficiency, scale efficiency and overall (TFPE) efficiency based on the Färe-Primont index model.

	TFPE	OTE	OSE	RME
TFPE	1			
OTE	0.3615 ^a	1		
OSE	0.4087 ^a	−0.1534	1	
RME	0.9776 ^a	0.2388 ^a	0.3781 ^a	1

^a $p < 0.05$.

³ Center for International Earth Science Information Network (CIESIN) <https://sedac.ciesin.columbia.edu/data/set/water-wsim-gldas-v1/docs>.

⁴ Agri-Hubs Toolkit <https://old.dalrrd.gov.za/About-Us/Agriparks/Agri-Hub-Toolkit>.

Table 4

Comparison of TFPE and its components by cluster using conventional approach and comprehensive approaches and their characteristics.

Model 1 - Conventional TFP estimates excluding environmental variables					
Cluster	1	2	3	4	p. overall
	N = 57	N = 18	N = 51	N = 23	
TFPE	0.47 (0.09)	0.80 (0.09)	0.52 (0.08)	0.55 (0.10)	<0.001
OTE	0.60 (0.10)	0.96 (0.06)	0.93 (0.08)	0.87 (0.09)	<0.001
OSE	0.96 (0.04)	0.98 (0.03)	0.94 (0.07)	0.77 (0.08)	<0.001
RME	0.80 (0.09)	0.85 (0.07)	0.59 (0.08)	0.82 (0.08)	<0.001
Model 2 - Comprehensive TFP estimates including environmental variables					
	N = 65	N = 38	N = 28	N = 18	
TFPE	0.13 (0.09)	0.11 (0.06)	0.36 (0.08)	0.66 (0.15)	<0.001
OTE	0.96 (0.06)	0.61 (0.09)	0.90 (0.11)	0.98 (0.05)	<0.001
OSE	0.86 (0.16)	0.93 (0.07)	0.95 (0.06)	0.99 (0.02)	<0.001
RME	0.16 (0.10)	0.18 (0.09)	0.43 (0.06)	0.68 (0.13)	<0.001
*** A two-sample t-test with equal variances between Models 1 and 2 shows a mean difference of 0.264, a t-value of 12.4, and a p-value of 0.000. This implies that conventional (economic) TFPE produces larger scores than comprehensive TFPE model estimates.					
Characteristics of the local municipalities by cluster					
Cluster	1	2	3	4	South Africa (mean)
FarmUnits (No. per municipality)	208	82	343	378	233
IncPerFarm (average per farms and municipality)	6146	5429	9913	16520	8121
share_crops (proportion)	0.33	0.33	0.32	0.13	0.30
share_horticulture (proportion)	0.17	0.24	0.25	0.40	0.23
share_other crops (proportion)	0.02	0.02	0.00	0.00	0.01
share_animal products (proportion)	0.49	0.41	0.43	0.47	0.46
LandUse_Owned (proportion)	0.78	0.72	0.75	0.84	0.77
HHI (Index)	0.56	0.63	0.58	0.57	0.58
HHI_landuse (Index)	0.64	0.65	0.57	0.44	0.60
Supermarkets (Per municipality in Rand)	9.57	5.58	31.68	50.06	18.66
ImpExpDuty (Per municipality in Rand)	967	79	7973	15965	4194

Note: TFPE, OTE, OSE, and RME are total factor productivity efficiency, output-oriented technical efficiency, scale efficiency, and residual mix efficiency, respectively. The presented values are averages, and those in brackets are standard deviations. N is the number of observations in each cluster. Overall, it is an indicator of whether the group differences amongst the four clusters are statistically significant.

2017). Cluster analysis can help with resource allocation by identifying municipalities with similar characteristics or needs (Makhura et al., 1998). Such analysis can help identify needy districts and aid in the implementation of the recently adopted district development model (DDM) and the Agriculture and Agro-Processing Master Plan (AAMP).

Table 4 provides descriptive statistics for the TFPE and components for the four local municipality clusters. The first panel (Model 1) displays the estimated TFPE scores determined using economic variables, while the second panel (Model 2) displays the estimated TFPE scores calculated using both economic and environmental variables. The bottom panel describes the characteristics of the four local municipality clusters identified with Model 2. Models 1 and 2 produce a mean difference of 0.264 in TFPE scores, with Model 1 indicating higher scores. A two-sample t-test with equal variances confirms the statistical significance of this difference: a t-value of 12.4 and a p-value of less than 0.05, indicating a significant difference. Similarly, as we pointed out earlier, Figs. 1 and 2 also show significant differences, with Fig. 1 (Model 1) demonstrating less spatial variation than Fig. 2 (Model 2). Overall, we can conclude that Model 2, which incorporates both economic and environmental production factors, produced more varied and lower TFPE scores than the purely economic TFP index model. Our analysis

emphasises the significance of considering environmental factors in agricultural productivity and sustainability, particularly in identifying regional performance differences that may be attributed to environmental factors.

We used the hierarchical clustering algorithm to group municipalities based on their TFPE scores. Fig. 3 depicts the density distribution of TFPE scores by cluster, and the results show that clusters 3 and 4 have more right-skewed TFPE scores than clusters 1 and 2. In other words, on average, municipalities in this cluster were closer to South Africa's commercial agriculture frontier than clusters 1 and 2. As discussed earlier, the map (Fig. 2) also shows that there are spatial differences in productive performance among South African municipalities. These findings confirm the existence of productivity heterogeneity among South African local municipalities. This highlights the critical importance of considering these factors in research and policy development.

As shown in Table 4 in the middle panel (Model 2), **cluster 1** includes 65 municipalities with a mean TFPE score of 0.13 due to OSE of 0.086, OTE of 0.96, and RME of 0.16. The key sectors for this cluster are animal and animal products (*share_animal*) and crops (*share_crops*), which contributed 49% and 33% of total gross farm income, respectively. Furthermore, the cluster had the second-fewest number of supermarkets (*IncPerFarm*), the average number of farm units per municipality (*FarmUnits*) and import and export expenditures (*ImpExpDuty*). This cluster performed 13% less than the national average (0.87), making it the least technically efficient cluster.

Cluster 2, which consists of 38 municipalities, has the lowest average TFPE score (0.11) of the clusters. Despite being technically efficient, the cluster has OSE (0.79) and RME (0.02). As shown in Table 4, this cluster also has the fewest farming units per municipality, the lowest average farm income, the fewest supermarkets per municipality, and the lowest import and export duties. It also has the lowest percentage of land ownership (78%). Agriculture growth in some municipalities, particularly in Zululand district municipality, is hampered by a lack of organised institutions that provide financial support, market access, and market channels (DALRRD, 2015). Improving scale and mix efficiency through land reform programmes, government subsidies, and improved extension and training services can boost overall efficiency in this cluster.

Cluster 3 is made up of 28 municipalities with an average TFPE of 0.36, placing it second. This cluster was technically and scale-efficient but mix-inefficient (RME: 0.43). Farmers in this cluster can potentially increase their overall efficiency by up to 57% by deriving economies of scope by changing their input and output mixes optimally (O'Donnell, 2018; Martinez-Cillero et al., 2019). This cluster is made up of several urban municipalities, including eThekweni, Johannesburg, Mbombela, and Nelson Mandela Bay. According to Table 4, this cluster has the second-highest number of supermarkets per municipality and the second-highest expenditure on import and export duties per municipality. In terms of contribution to gross farm income, the key sectors for this cluster are animal and animal products, field crops, and horticulture, which contributed 43%, 32%, and 25%, respectively. These indicators suggest that farmers in cluster 3 have greater access to formal markets (supermarkets, exports, and imports), are closer to urban areas with improved infrastructure, which could explain their high performance.

Cluster 4 consists of 18 municipalities with an average TFPE score of 0.66, making it the best-performing cluster. This cluster includes municipalities in the Western Cape Winelands (Witzenberg, Stellenbosch, Drakenstein, and Breede Valley), urban municipalities like Tshwane and Cape Town, and municipalities near large urban areas like JB Marks and Lesedi. According to Table 4, all three TFPE components for the cluster were relatively high: OTE (0.98), OSE (0.99), and RME (0.68). These findings imply that, on average, farmers in this cluster performed well in terms of OTE (improved farmer management abilities and farming practices) and OSE (improved farm productivity by increasing farm output size). However, the RME score of 0.68 indicates that farmers in

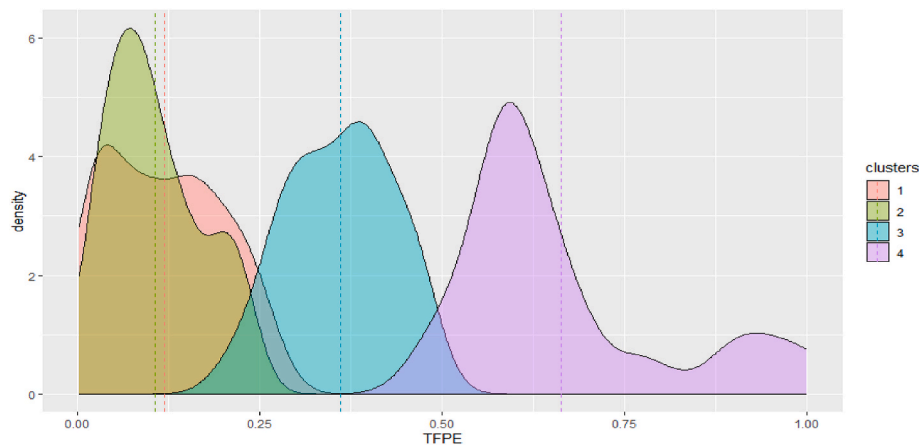


Fig. 3. Distribution of TFPE for local municipalities by cluster.
Source: Authors based on their estimated TFPE scores

this cluster can potentially increase their output by up to 32% by optimising their input and output ratios in the production process (Martinez-Cillero et al., 2019). As evidenced by the HHI indicator in Table 4, this cluster is more specialised than the others. The main sources of income for the cluster were livestock income (*share_animal*: 47%) and horticultural income (*share_hortic*: 40%).

In summary, clusters 3 and 4 in South Africa are home to the most productive municipalities, which also have better market access, own their farmland, and pay more in export and import duties. The results are consistent with previous studies in South Africa (e.g., Makhura et al., 1998; Conradie et al., 2009). Conradie et al. (2009), for example, found significant TFP performance for municipalities surrounding Cape Town. We also found Cluster 4 to be specialised in horticultural output, such as deciduous fruit and wine grapes, which are important South African exports (DALRRD, 2015). Furthermore, the farmers in this cluster paid a significant amount in import and export duty (*ImpExpDuty*), indicating that they are more involved in the global value chain. According to Edwards et al. (2018), firms that import and export routinely outperform firms that do not trade in terms of productivity, employment, wages, and capital intensity in production. Furthermore, farmers in the best-performing cluster own most of their farmland (*share_landown* of 84%) than the average farmer in the country (77%). As a result, the findings support international evidence on the beneficial role of secure land tenure on agricultural productivity (Place and Hazell, 1993; Place, 2009).

Municipalities in clusters 1 and 2 had lower TFPE levels, and therefore they can improve their performance by benchmarking against those in clusters 3 and 4 to identify successful practices and technologies. Infrastructure improvements and increased access to agricultural product distribution channels can boost productivity, while exporting can also help producers integrate into global markets.

5.3. Determinants of TFPE and its components

This study also investigated factors influencing total factor productivity efficiency (TFPE) levels among the local municipalities using fractional regression and TFPE components from the Färe-Primont index. The results are presented in Table 5. We found a negative and statistically significant effect of *log_youth* (the proportion of younger farmers in a given local municipality) on OSE but no effect on OTE or RME. This implies that, on average, younger farmers are less scale-efficient than their older counterparts. This is consistent with earlier research by Gaviglio et al. (2021) carried out in Italy claiming young farmers are inefficient at scaling up due to limited access to resources and a lack of farming experience. Consequently, empowering the youth could contribute to the transformation of the agricultural sector and the

Table 5
Fractional regression results of TFP and its components, 2007 (n = 150).

Variable	TFPE	OTE	OSE	RME
<i>log_youth</i>	0.0282 (0.0398)	−0.0254 (0.0414)	−0.0583** (0.0296)	0.0398 (0.0397)
<i>log_Age65</i>	−0.0212 (0.0484)	0.00519 (0.0447)	−0.0395 (0.0279)	−0.00593 (0.051)
<i>log_IncPerFarm</i>	0.205*** (0.0253)	0.115*** (0.0328)	0.0546*** (0.0163)	0.190*** (0.0266)
<i>log_landUseOwn</i>	−0.0404 (0.116)	0.199* (0.118)	−0.158** (0.0666)	−0.0469 (0.107)
<i>log_RaceWhite</i>	0.632*** (0.137)	0.125 (0.148)	−0.0792 (0.0854)	0.705*** (0.127)
<i>log_Female</i>	−0.0932*** (0.0293)	−0.0195 (0.0328)	−0.00227 (0.013)	−0.0977*** (0.0277)
<i>log_HHIOutput</i>	−0.138 (0.141)	0.0336 (0.131)	0.133* (0.0754)	−0.237 (0.145)
<i>log_HHILandUse</i>	−0.235 (0.148)	−0.104 (0.135)	0.0779 (0.085)	−0.23 (0.153)
<i>log_Supermarket</i>	0.0591*** (0.0146)	−0.00188 (0.012)	0.0162* (0.00955)	0.0622*** (0.0145)
<i>log_GVCratio</i>	0.0161*** (0.00605)	−0.00504 (0.00535)	0.00292 (0.00372)	0.0178*** (0.00554)

Note: Conditional mean marginal effects (dy/dx) for factor levels are the discrete change from the base level. FRM is fractional regression model results with robust standard errors. ***, ** and * denotes the 1%, 5% and 10% level of significance, respectively.

acceleration of productivity growth, particularly as South African commercial farmers are getting older.

We found that the gender variable (*log_female*) has a negative effect on TFPE and RME. This suggests that female-dominated municipalities are inefficient. Previous research in Southern Africa (e.g., Temoso et al., 2023) suggests that male farmers are more efficient due to access to resources and farm management experience. The findings may also reflect structural issues in South African agriculture, where male farmers dominate, and female farmers account for only 9% of the farming population (Statistics South Africa, 2020). Women in South African agriculture face significant barriers to accessing land, credit, and other production factors, as well as market opportunities. This is also true globally, as reported by the FAO (2023) report, where women have less access to land, inputs, services, finance, and digital technology in agricultural systems than men. As a result, reducing gender disparities in access to assets and resources is critical for increasing productivity and closing gender gaps (FAO, 2023).

The results further show that white farmers in South Africa are more efficient in terms of mix (RME) and overall efficiency (TFPE) than non-whites. This is because white farmers have traditionally owned larger

and more secure land and have better access to credit (Arndt and Pratt, 2020). As a result, policies that promote racial inclusivity along with access to land, credit, and agrarian reform are critical to addressing overall efficiency.

We also assessed the effect of farm output specialisation and land use specialisation on municipalities' efficiency. The findings indicate that only farm output specialisation ($\log HHI_{Output}$) had a positive and statistically significant effect on scale efficiency (OSE). Furthermore, we found that municipalities specialising in horticulture and livestock were the most productive. This implies that a higher degree of specialisation is more efficient than a diverse approach. Nonetheless, enhancing diversity might be essential for advancing sustainable agricultural and production through minimizing inputs and conserving resources to reduce ecological and environmental risks, a goal that is in line with SDG 12 (Sachs, 2022).

We also investigated the effect of land ownership on productivity, focusing on the proportion of farmers who own their land ($\log landUseOwn$). This indicator is also linked to the NDP land reform goal of ensuring that women own 20% of commercial agricultural land and SDG goal 5.a.1 (b) of women owning or having rights to agricultural land, regardless of tenure (Statistics South Africa, 2019). According to Arndt and Pratt (2020), in South Africa, there is a significant disparity in land ownership, with only a small percentage of the population owning a significant amount of land. In our results, we found that while land-ownership improves municipal OTE, it has a negative impact on OSE. The OTE's findings are consistent with previous research demonstrating the importance of land tenure in productivity and efficiency (Place, 2009).

To assess the effect of access to agricultural markets, we used the number of supermarkets per municipality as a proxy for the local market, as well as participation in the global value chain using expenditure on import and export duty per municipality. The findings show that both variables have a positive effect on municipal TFPE. This is consistent with the findings of Edwards et al. (2018) and Rao et al. (2012). Edwards et al. (2018) showed that firms that engage in global trade consistently have higher levels of productivity, employment, wages, and capital intensity. Rao et al. (2012), on the other hand, emphasised the importance of supermarkets in bridging the gap between agricultural farmers and consumers. This connection improves market access and farm productivity, especially for farmers who sell perishable goods via supermarkets.

6. Conclusion and policy implications

The purpose of this study was to determine the total factor productivity efficiency (TFPE) of South Africa's commercial agriculture sector. To achieve this, we used the 2017 agricultural census data covering 150 local municipalities, as well as a Färe-Primont index that considers both economic and environmental production factors. This model generated TFPE scores that are lower and more variable than the widely used economic TFPE index in agricultural productivity research. This demonstrates that models that ignore environmental variables may bias productivity analysis and do not provide clear differentiation between regions. As a result, our initial recommendation is that future studies should consider environmental factors in their analyses to gain a more comprehensive understanding of agricultural productivity, especially when the goal is to identify regional disparities that can be attributed to environmental and natural endowment factors.

Our TFPE results provide a unique regional comparative analysis for the entire country, allowing for the identification of frontier and laggard municipalities. The results show that South Africa's commercial agriculture had an average TFPE of 0.234, but there are significant differences at the provincial and municipal levels. The differences were primarily due to differences in scale and mix efficiencies rather than technical efficiency. This contradicts previous South African studies that identified technical efficiency as the main cause. One of the reasons for the difference between our study and previous studies is that they used

methodologies that did not decompose TFP into finer components. However, recent agricultural productivity studies (e.g., O'Donnell, 2022; Myeki et al., 2022; Temoso et al., 2023) have shown that focusing solely on technical efficiency can be misleading because it ignores other important components of productivity, such as mix and scale efficiency.

The distribution of municipalities into distinct clusters based on hierarchical clustering and TFPE levels reveals important insights into regional agricultural performance and suggests targeted strategies for improvement. The results show that the most productive municipalities, Cluster 4, are characterised by a high level of specialisation, a strong export orientation, and proximity to urban areas. Other characteristics include good soils and better access to irrigation, well-developed infrastructure, formal markets, and global value chains. However, because this cluster is more specialised, particularly in horticulture production, investing in integrated livestock crop farming systems or intercropping systems may be a viable strategy for improving overall agricultural performance while contributing to UN SDG Goal 12.

The least productive municipalities, Cluster 2, were in remote rural areas with limited access to infrastructure and a lack of input and output markets. To improve productivity and achieve the SDGs, these municipalities may need to benchmark with municipalities in Clusters 3 and 4 to identify areas for improvement and develop strategies. Farmers in the best-performing clusters, for example, owned most of their land, had better access to formal markets, and were involved in global value chains. As a result, the least-performing clusters can improve their performance by improving land ownership and distribution, improving access to formal markets such as supermarkets and input markets, and assisting producers to access export markets. These could be accomplished by utilising existing strategies and policies, such as the *Agri-Park* programme, which seeks to integrate agricultural activities with rural transformation services for capacity building, storage, processing, and extension.

We also investigated the factors that influence agricultural TFPE and its components across municipalities. The findings indicate that age, gender, race, market access, land use, and agricultural output diversification were important determinants. Thus, to increase productivity in the least productive municipalities, policies can be aimed at addressing scale and mix inefficiencies by adjusting input and output prices through mechanisms such as taxes and subsidies. Improving land rights and ownership could motivate landowners to invest and optimise the utilisation of their land (Banerjee, 2000). These recommendations are in line with South Africa's NDP 2030 and Comprehensive Agricultural Support Programme (CASP), which aim to enhance the involvement of marginalised groups, especially black farmers, by facilitating the transfer of agricultural land to promote inclusive land ownership and stimulate engagement in commercial agriculture, ultimately boosting industry output and contribution to the country's economic development goals (NPC, 2012; SA South Africa Government, 2018).

Our study has two major limitations. First, because our analysis relied on cross-sectional data, we were unable to investigate temporal trends in productivity and its components. As a result, future research should use panel data to examine the dynamic trends and causal effects of policy changes on agricultural productivity and its components. Second, while there are various methods for incorporating environmental factors into production modelling, such as those that consider both desirable (e.g., crop and livestock output) and undesirable (e.g., greenhouse gases and pollution) outputs, as well as those that investigate the direct impact of environmental factors on agricultural output and productivity (Dakpo et al., 2016; O'Donnell, 2022), our study only considered the latter. As a result, future research should also use models that consider undesirable outputs at the local municipality level, such as greenhouse gases and pollution, as well as their impact on productivity and sustainability. This is critical for addressing climate change issues in agriculture (Bureau and Antón, 2022). Furthermore, it is important to undertake a sensitivity analysis of the TFPE to changes in foreseeable future climate conditions caused by climate change, considering various

scenarios of changing climate conditions.

CRedit authorship contribution statement

Omphile Temoso: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lindikaya W. Myeki:** Writing – review & editing, Writing – original draft, Validation, Investigation. **Comfort Motlhabane:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Bright O. Asante:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation. **Renato A. Villano:** Writing – review & editing,

Writing – original draft, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. : South African Municipal-level Agricultural TFP levels and its components

Region	TFPE	OTE	OSE	RME	Cluster
Bela-Bela	0.136	0.820	0.998	0.166	1
Bitou	0.029	1.000	0.877	0.033	1
Blue Crane Route	0.104	1.000	0.688	0.151	1
Buffalo City	0.206	0.820	0.998	0.251	1
Bushbuckridge	0.021	1.000	0.930	0.023	1
City of Johannesburg	0.313	1.000	1.000	0.313	1
Dawid Kruiper	0.154	1.000	1.000	0.154	1
Dipaleseng	0.328	1.000	0.990	0.331	1
Dr Nkosazana Dlamini Zuma	0.151	0.826	0.743	0.246	1
Emadlangeni	0.031	1.000	0.577	0.053	1
Emakhazeni	0.080	1.000	0.709	0.113	1
Emalahleni	0.016	1.000	0.605	0.027	1
Ephraim Mogale	0.227	1.000	0.922	0.246	1
Govan Mbeki	0.321	1.000	0.965	0.333	1
Greater Kokstad	0.103	1.000	0.465	0.221	1
Greater Tubatse/Fetakgomo	0.081	0.933	0.927	0.094	1
Impendle	0.016	1.000	0.748	0.021	1
Inkosi Langalibalele	0.155	0.866	0.993	0.181	1
Inxuba Yethemba	0.161	0.953	0.603	0.281	1
Kannaland	0.034	1.000	0.594	0.056	1
Kgetlengrivier	0.171	0.876	0.989	0.198	1
Knysna	0.025	1.000	0.606	0.041	1
Kopanong	0.178	1.000	0.811	0.219	1
KwaDukuza	0.106	1.000	1.000	0.106	1
Letsemeng	0.218	0.878	0.998	0.249	1
Mafikeng	0.020	0.938	0.600	0.035	1
Magareng	0.079	1.000	0.877	0.090	1
Maluti a Phofung	0.285	1.000	0.906	0.315	1
Mamusa	0.244	0.914	0.998	0.268	1
Mandeni	0.037	1.000	1.000	0.037	1
Mantsopa	0.114	0.876	0.768	0.169	1
Maruleng	0.256	1.000	1.000	0.256	1
Matatiele	0.037	1.000	0.419	0.088	1
Matzikama	0.209	1.000	0.848	0.247	1
Merafong City	0.051	1.000	0.959	0.053	1
Metsimaholo	0.102	0.959	0.920	0.116	1
Mfolozi	0.003	1.000	0.741	0.004	1
Midvaal	0.138	1.000	0.812	0.170	1
Mkhambathini	0.090	0.846	0.966	0.110	1
Mossel Bay	0.056	1.000	0.598	0.094	1
Mpofana	0.196	1.000	0.940	0.209	1
Musina	0.271	1.000	1.000	0.271	1
Nama Khoi	0.020	1.000	0.634	0.032	1
Ndwedwe	0.027	0.958	0.961	0.030	1
Oudtshoorn	0.243	1.000	1.000	0.243	1
Overstrand	0.159	1.000	0.913	0.175	1
Phumelela	0.287	1.000	0.657	0.436	1
Rand West City	0.193	1.000	1.000	0.193	1
Renosterberg	0.056	1.000	0.952	0.059	1
Saldanha Bay	0.070	1.000	0.693	0.101	1
Senqu	0.085	1.000	0.976	0.087	1
Siyancuma	0.196	0.883	0.944	0.235	1
Siyathemba	0.158	1.000	0.929	0.170	1
The Msunduzi	0.144	0.906	0.895	0.178	1
Thembelihle	0.138	1.000	1.000	0.138	1
Tswaing	0.245	0.922	0.991	0.268	1
Umdoni	0.051	0.920	0.994	0.056	1

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Region	TFPE	OTE	OSE	RME	Cluster
uMhlathuze	0.027	0.778	1.000	0.034	1
uMlalazi	0.115	0.833	0.946	0.146	1
uMngeni	0.167	0.816	0.951	0.215	1
uMshwathi	0.188	0.908	0.930	0.223	1
uMuziwabantu	0.015	1.000	1.000	0.015	1
Umzimkhulu	0.017	1.000	0.699	0.024	1
uPhongolo	0.238	0.964	1.000	0.247	1
Walter Sisulu	0.098	1.000	0.550	0.178	1
Alfred Duma	0.059	0.541	0.966	0.113	2
Amahlathi	0.096	0.601	0.980	0.163	2
Ba-Phalaborwa	0.035	0.628	0.756	0.075	2
Blouberg	0.138	0.652	0.974	0.217	2
Cape Agulhas	0.204	0.751	0.996	0.272	2
Chief Albert Luthuli	0.098	0.629	0.831	0.187	2
Dannhauser	0.031	0.625	0.920	0.053	2
Dikgatlong	0.083	0.671	0.961	0.128	2
Dr Beyers Naude	0.053	0.578	0.869	0.106	2
Dr Pixley Ka Isaka Seme	0.136	0.626	0.774	0.281	2
eDumbe	0.064	0.555	0.956	0.121	2
Emfuleni	0.097	0.734	0.860	0.154	2
Greater Taung	0.036	0.564	0.928	0.068	2
Hessequa	0.231	0.702	0.999	0.329	2
Kagisano/Molopo	0.101	0.651	0.973	0.159	2
Lephalale	0.143	0.651	0.999	0.219	2
Makana	0.037	0.651	0.889	0.065	2
Masilonyana	0.226	0.692	0.963	0.340	2
Matjhabeng	0.193	0.732	0.989	0.267	2
Mkhondo	0.152	0.628	0.937	0.258	2
Mogalakwena	0.074	0.500	0.892	0.166	2
Mohokare	0.098	0.586	0.979	0.171	2
Molemole	0.179	0.701	0.940	0.271	2
Mthonjaneni	0.006	0.289	0.852	0.023	2
Ndlambe	0.135	0.652	0.991	0.209	2
Newcastle	0.063	0.506	0.986	0.126	2
Okhahlamba	0.212	0.632	0.999	0.337	2
Ramotshere Moiloa	0.101	0.576	0.972	0.180	2
Ratlou	0.033	0.640	0.830	0.063	2
Raymond Mhlaba	0.085	0.647	0.980	0.134	2
Richmond	0.083	0.593	0.937	0.150	2
Sakhisizwe	0.055	0.550	0.872	0.114	2
Sol Plaatjie	0.109	0.404	0.983	0.275	2
Swellendam	0.216	0.642	0.997	0.338	2
Thaba Chweu	0.069	0.646	0.744	0.143	2
Thabazimbi	0.151	0.580	0.998	0.260	2
Tokologo	0.202	0.613	0.976	0.337	2
Ubuhlebezwe	0.048	0.604	0.978	0.082	2
Bergrivier	0.393	0.837	0.945	0.496	3
City of Matlosana	0.336	0.786	0.999	0.428	3
City of Mbombela	0.458	0.948	0.999	0.484	3
Dihlabeng	0.427	1.000	0.937	0.456	3
Ditsobotla	0.327	0.867	0.998	0.378	3
Ekurhuleni	0.449	1.000	0.925	0.486	3
Elias Motsoaledi	0.406	1.000	1.000	0.406	3
eThekwini	0.370	0.704	0.981	0.536	3
George	0.279	0.890	0.819	0.383	3
Kai !Garib	0.469	1.000	1.000	0.469	3
Kou-Kamma	0.212	0.748	0.891	0.318	3
Lekwa-Teemane	0.263	0.810	0.948	0.343	3
Mafube	0.396	0.959	0.930	0.444	3
Mangaung	0.281	0.749	0.910	0.413	3
Maquassi Hills	0.384	1.000	1.000	0.384	3
Modimolle/Mookgophong	0.287	0.664	0.998	0.433	3
Moqhaka	0.438	1.000	1.000	0.438	3
Msukaligwa	0.241	0.759	0.806	0.394	3
Nala	0.383	1.000	1.000	0.383	3
Naledi	0.352	0.780	0.997	0.453	3
Nelson Mandela Bay	0.384	1.000	1.000	0.384	3
Ngwathe	0.329	0.828	0.985	0.403	3
Nketoana	0.374	1.000	0.909	0.411	3
Nkomazi	0.476	1.000	1.000	0.476	3
Phokwane	0.221	0.860	0.874	0.294	3
Setsoto	0.467	1.000	0.875	0.534	3
Tswelopele	0.398	1.000	1.000	0.398	3
Victor Khanye	0.419	1.000	0.876	0.478	3
Breede Valley	0.940	1.000	1.000	0.940	4
Cederberg	0.566	1.000	0.954	0.593	4

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Region	TFPE	OTE	OSE	RME	Cluster
City of Cape Town	0.692	1.000	1.000	0.692	4
City of Tshwane	0.894	1.000	1.000	0.894	4
Drakenstein	0.607	0.939	0.914	0.707	4
Greater Tzaneen	0.583	1.000	1.000	0.583	4
JB Marks	0.578	1.000	1.000	0.578	4
Kouga	0.513	0.823	0.994	0.627	4
Langeberg	0.487	0.919	0.952	0.557	4
Lekwa	0.634	1.000	1.000	0.634	4
Lesedi	0.646	1.000	1.000	0.646	4
Mogale City	0.578	1.000	1.000	0.578	4
Stellenbosch	0.590	0.887	0.982	0.678	4
Steve Tshwete	0.662	1.000	1.000	0.662	4
Sundays River Valley	0.577	1.000	1.000	0.577	4
Swartland	0.605	1.000	1.000	0.605	4
Theewaterskloof	0.778	1.000	1.000	0.778	4
Witzenberg	1.000	1.000	1.000	1.000	4

References

- Arndt, C., Pratt, A.N., 2020. South African Agricultural Productivity in the Global Context: Comparisons Using FAO Data. SA-TIED Working Paper #96 | March 2020.
- Asante, B.O., Villano, R.A., Temoso, O., 2023. Drivers of integrated crop–livestock farming system's efficiency for smallholder farmers in the forest-savanna transition agro-ecological zone of Ghana. *Environ. Dev. Sustain.* 1–23.
- Banerjee, A.V., 2000. Prospects and strategies for land reform. In: *Annual World Bank Conference on Development Economics 1999*. World Bank, pp. 253–274.
- Bureau, J.C., Antón, J., 2022. Agricultural Total Factor Productivity and the Environment: A Guide to Emerging Best Practices in Measurement.
- Calinski, T., Harabasz, J., 1974. A dendrite method for cluster analysis. *Commun. Stat. Theor. Methods* 3 (1), 1–27.
- Champagne, C., Berg, A.A., McNairn, H., Drewitt, G., Huffman, T., 2012. Evaluation of soil moisture extremes for agricultural productivity in the Canadian prairies. *Agric. For. Meteorol.* 165, 1–11.
- Coelli, T.J., Rao, D.P., 2005. Total factor productivity growth in agriculture: a Malmquist index analysis of 93 countries, 1980–2000. *Agric. Econ.* 32, 115–134.
- Conradie, B., Genis, A., Greyling, J., Piesse, J., 2021. District-level agricultural total factor productivity for the Karoo, South Africa: 1952–2002. *Agrekon* 60 (2), 128–144.
- Conradie, B., Piesse, J., Stephens, J., 2019a. The changing environment: efficiency, vulnerability, and changes in land use in the South African Karoo, 2012–2014. *Environ. Devel.* 32, 100453.
- Conradie, B., Genis, A., Thirtle, C., 2009. District-level total factor productivity in agriculture: Western Cape Province, South Africa, 1952–2002. *Agric. Econ.* 40 (3), 265–280.
- Conradie, B., Piesse, J., Vink, N., Thirtle, C., 2019b. South African wine grape production, 2005–2015: regional comparisons of scale and technical efficiencies and total factor productivity. *Agrekon* 58 (1), 53–67.
- Cooper, W.W., Seiford, L.M., Zhu, J. (Eds.), 2011. *Handbook on Data Envelopment Analysis*. Springer.
- Cooper, W.W., Seiford, L.M., Tone, K., Zhu, J., 2007. Some models and measures for evaluating performances with DEA: past accomplishments and future prospects. *J. Prod. Anal.* 28, 151–163.
- Dakpo, K.H., Jeanneaux, P., Latruffe, L., 2016. Modelling pollution-generating technologies in performance benchmarking: recent developments, limits and future prospects in the nonparametric framework. *Eur. J. Oper. Res.* 250 (2), 347–359.
- DALRRD, 2015. *AGRI PARK Technical Report Summaries* (6 November 2015). Government of South Africa, Pretoria.
- DALRRD, 2013. *National Policy on Food and Nutrition Security*. (Notice 37915), vol. 637. Government Gazette, 22 August 2014.
- FAO, 2022. *Tracking Progress on Food and Agriculture-Related SDG Indicators 2022*. <https://doi.org/10.4060/cc1403en>. Rome.
- FAO, 2023. *The Status of Women in Agrifood Systems – Overview*. Rome.
- Fuglie, K.O., 2018. Is agricultural productivity slowing? *Global Food Secur.* 17, 73–83.
- Gaviglio, A., Filippini, R., Madau, F.A., Marescotti, M.E., Demartini, E., 2021. Technical efficiency and productivity of farms: a periurban case study analysis. *Agric. Food Econ.* 9 (1), 1–18.
- Greyling, J., Pardey, P.G., Senay, S., 2023. Distortionary Agricultural Policies: Their Productivity, Location and Climate Variability Implications for South Africa during the 20th Century.
- Harris, I.C., Jones, P.D., Osborn, T., 2021. *Cru TS4.05: Climatic Research Unit (CRU) Time-Series (TS) version 4.05 of high-resolution gridded data of month-by-month variation in climate (Jan. 1901–Dec. 2020)*. NERC EDS Centre Environm. Data Anal. 2021 <https://catalogue.ceda.ac.uk/uuid/c26a65020a5e4b80b20018f148556681>.
- Kassambara, A., 2017. *Practical Guide to Cluster Analysis in R: Unsupervised Machine Learning*, vol. 1. Sthda.
- Kriel, G., 2018. Witzenberg PALS Is Serious about Land Reform. *Farmers' Weekly*, 2018 Available from: <https://www.farmersweekly.co.za/agri-business/empowerment/witzenberg-pals-serious-land-reform/>.
- Kryszak, Ł., Świerczyńska, K., Staniszewski, J., 2023. Measuring total factor productivity in agriculture: a bibliometric review. *Int. J. Emerg. Mark.* 18 (1), 148–172.
- Liebenberg, F., Pardey, P.G., 2012. A Long-Run View of South African Agricultural Production and Productivity.
- Makhura, M.T., Goode, F.M., Coetzee, G.K., 1998. A cluster analysis of commercialisation of farmers in developing rural areas of South Africa. *Dev. South Afr.* 15 (3), 429–448.
- Martinez-Cillero, M., Thorne, F., Wallace, M., Breen, J., 2019. Technology heterogeneity and policy change in farm-level efficiency analysis: an application to the Irish beef sector. *Eur. Rev. Agric. Econ.* 46 (2), 193–214.
- Matthews, N., Conradie, B., Piesse, J., 2023. Technological differences in South African sheep production: a stochastic meta-frontier analysis. *Agrekon* 62 (1), 19–30. <https://doi.org/10.1080/03031853.2022.2149577>.
- Mkhabela, T., Piesse, J., Thirtle, C., Vink, N., 2010. Modelling efficiency with farm-produced inputs: dairying in KwaZulu-Natal, South Africa. *Agrekon* 49, 102–121.
- Myeki, L.W., Bahta, Y.T., Matthews, N., 2022. Exploring the growth of agricultural productivity in AFRICA: a fare-primont index approach. *Agriculture* 12 (8), 1236.
- Myeki, L.W., Temoso, O., Nyhodo, B., 2023. The evaluation of productivity in South African deciduous fruit industry: evidence from stone and pome fruits. *J. Prod. Anal.* 1–12.
- National Planning Commission (NPC), 2012. *National development plan 2030: our future-make it work*. https://www.gov.za/sites/default/files/gcis_document/201409/ndp-2030-our-future-make-it-workr.pdf. (Accessed 15 June 2023).
- Nhemachena, C., Matchaya, G., Nhemachena, C.R., Karuaihe, S., Muchara, B., Nhlengethwa, S., 2018. Measuring baseline agriculture-related sustainable development goals index for Southern Africa. *Sustainability* 10 (3), 849.
- Nortjé, C., 2020. *Census 2017: an overview of commercial agriculture*. *Oilseeds Focus* 6 (2), 46–47.
- O'Donnell, C.J., 2010. Measuring and decomposing agricultural productivity and profitability change. *Aust. J. Agric. Resour. Econ.* 54 (4), 527–560.
- O'Donnell, C.J., 2011. *DPIN version 3.1: a program for decomposing productivity index numbers*. School of Economics. University of Queensland, Australia.
- O'Donnell, C.J., 2018. *Productivity and Efficiency Analysis*. Springer Singapore, Singapore.
- O'Donnell, C.J., 2022. Estimating the effects of weather and climate change on agricultural productivity. *Q Open* 2 (2), qoac018.
- OECD, 2022. *Agricultural Policy Monitoring and Evaluation 2022: Reforming Agricultural Policies for Climate Change Mitigation*.
- Parliament of South Africa, 2020. *Overview of the District Development Model – A Framework for Co-operative Service Delivery*. Accessed from link.
- Piesse, J., Conradie, B., Thirtle, C., Vink, N., 2018. Efficiency in wine grape production: comparing long-established and newly developed regions of South Africa. *Agric. Econ.* 49 (2), 203–212.
- Place, F., 2009. Land tenure and agricultural productivity in Africa: a comparative analysis of the economics literature and recent policy strategies and reforms. *World Dev.* 37 (8), 1326–1336.
- Place, F., Hazell, P., 1993. Productivity effects of indigenous land tenure systems in sub-Saharan Africa. *Am. J. Agric. Econ.* 75 (1), 10–19.
- Rahman, S., Salim, R., 2013. Six decades of total factor productivity change and sources of growth in Bangladesh agriculture (1948–2008). *J. Agric. Econ.* 64 (2), 275–294.
- Ramvalho, E.A., Ramalho, J.J., Henriques, P.D., 2010. Fractional regression models for second stage DEA efficiency analyses. *J. Prod. Anal.* 34, 239–255.
- Rao, E.J., Brümmer, B., Qaim, M., 2012. Farmer participation in supermarket channels, production technology, and efficiency: the case of vegetables in Kenya. *Am. J. Agric. Econ.* 94 (4), 891–912.
- Sachs, 2022. *From Crisis to Sustainable Development: the SDGs as Roadmap to 2030 and beyond*. Sustainable Development Report 2022. Cambridge University Press, Cambridge et al. <https://dashboards.sdindex.org/>.

- Sachs, J.D., Lafortune, G., Fuller, G., Drumm, E., 2023. Implementing the SDG Stimulus. Sustainable Development Report 2023. SDSN, Dublin: Dublin University Press, Paris. <https://doi.org/10.25546/102924>, 2023. <https://s3.amazonaws.com/sustainabledevelopment.report/2023/sustainable-development-report-2023.pdf>.
- Saha, A., Patil, M., Goyal, V.C., Rathore, D.S., 2018. Assessment and impact of soil moisture index in agricultural drought estimation using remote sensing and GIS techniques. *Multidiscipl. Dig. Publ. Inst. Proc.* 7 (1), 2.
- Schimmelpfennig, D., Thirtle, C., van Zyl, J., Arnade, C., Khatri, Y., 2000. Short and long-run returns to agricultural R&D in South Africa, or will the real rate of return please stand up? *Agric. Econ.* 23 (1), 1–15.
- Senay, Senait D., Greyling, Jan C., Pardey, Philip G., Verhoef, Helene, 2023. Data Note: Spatializing South African Agricultural Censuses, 1918–2017, Agrekon. <https://doi.org/10.1080/03031853.2023.2253878>.
- Sihlobo, W., 2021. South Africa's agricultural policy in 2021. SA Weekly Agricultural Viewpoint from. <https://agbiz.co.za/content/open/18-january-2021-agri-market-viewpoint>. (Accessed 25 April 2023).
- South Africa (SA) Government, 2018. Land reform. Key Issues from. <https://www.gov.za/issues/land-reform>. (Accessed 1 August 2023).
- Statistics South Africa (StatsSA), 2019. Sustainable Development Goals: Country Report 2019. Statistics South Africa, Pretoria. Statistics.
- Statistics South Africa (StatsSA), 2020. Census of Commercial Agriculture, 2017—Financial and Production Statistics. Report No. 11-02-01 (2017).
- Statistics South Africa (StatsSA), 2022. Statistical Release P0351, Mid-year Population Estimates. Statistics South Africa, Pretoria.
- Temoso, O., Ng'ombe, J.N., Bahta, S., Hadley, D., 2023. Total factor productivity growth in livestock production in Botswana: what is the role of scale and mix efficiency change in beef production? *Agrekon* 1–14.
- Temoso, O., Villano, R., Hadley, D., 2015. Agricultural productivity, efficiency, and growth in a semi-arid country: a case study of Botswana. *African J. Agricult. Resour. Econ.* 10 (311–2016-5636), 192–206.
- Temoso, O., Villano, R., Hadley, D., 2016. Evaluating the productivity gap between commercial and traditional beef production systems in Botswana. *Agric. Syst.* 149, 30–39.
- Thirtle, C., Von Bach, H.S., van Zyl, J., 1993. Total factor productivity in South African agriculture, 1947–91. *Dev. South Afr.* 10 (3), 301–318.
- Tozer, P.R., Villano, R., 2013. Decomposing productivity and efficiency among Western Australian grain producers. *J. Agric. Resour. Econ.* 312–326.
- United Nations, 2022. Department of economic and social affairs. The Sustainable Development Goals: Report 2022. UN. UNDESA from <https://unstats.un.org/sdgs/report/2022/The-Sustainable-Development-Goals-Report-2022.pdf>. (Accessed 14 October 2023).
- Van Schalkwyk, H.D., Groenewald, J.A., 1992. Regional analyses of South African agricultural resource use and productivity. *Agrekon* 31 (3), 116–127.
- Vink, N., Kirsten, J., 2003. Agriculture in the National Economy. *The Challenge of Change: Agriculture, Land and the South African Economy*, pp. 3–20.
- Vink, N., Conradie, B., Matthews, N., 2022. The economics of agricultural productivity in South Africa. *Ann. Rev. Resour. Econom.* 14.
- World Bank, 2022. Food Security Update.2022. International Bank for Reconstruction and Development/The World Bank 1818 H Street NW, Washington DC from. <https://thedocs.worldbank.org/en/doc/40ebbf38f5a6b68bfc11e5273e1405d4-0090012022/related/Food-Security-Update-LXX-September-29-2022.pdf>. (Accessed 13 July 2023).
- Zelenyuk, V., 2023. Productivity analysis: roots, foundations, trends and perspectives. *J. Prod. Anal.* <https://doi.org/10.1007/s11123-023-00692-1>.