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The evaluation of productivity in South African deciduous fruit industry: evidence from stone and pome fruits

Lindikaya W. Myeki[1,2] · Omphile Temoso[3] · Bonani Nyhodo[4]

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Abstract

This study examines the total factor productivity (TFP) of the South African deciduous fruit sector over an 8-year period (2014–2021), using industry-level data for five fruit types (apples, pears, plums, apricots, and peaches). TFP growth was estimated using the Färe-Primont (FP) index and decomposed into technical change (TECH) and efficiency change (TFPE). The results show that the TFP of the industry increased by 27% (3.53% per year) due to a 35% (4.38% per year) increase in technical change, while TFPE decreased by 6% (−0.81% per year). The TFPE breakdown into technical efficiency (OTE) and scale-mix efficiency (OSME) reveals that 6% decrease in OSME was entirely responsible for TFPE slowdown, while OTE remained unchanged. While both sub-sector contributions were significant, stone fruit grew at a faster rate (32%, or 4.05% per year) than the pome sub-sector (21%, or 2.74% per year). Overall, entire industry, sub-sectors, and fruit types show that TECH was key to TFP growth, whereas TFPE slowed it. Investments in efficiency support programmes have the potential to enhance sector growth.

Keywords Productivity · Horticulture · Deciduous Fruit · Färe-Primont index · South Africa

1 Introduction

The objective of this study is to provide an overview of the productivity trends and their sources in the deciduous fruit industry in South Africa. This is accomplished by estimating the total factor productivity (TFP) growth of the industry over a period of 8 years (2014–2021), considering differences between sub-sectors and fruit types.

Deciduous fruits are described as fruit trees that lose their leaves during the winter season. These fruits amongst the others consist of apples, pears, nectarines, plums, peaches, apricots, and cherries (Hortgro 2019; Mjonono 2020). The first two fruits are classified as pome fruits, while the rest as stone fruits (Mjonono 2020; Theron 2012). These classifications or subsectors (pome and stone) are the foundation of the deciduous fruit industry in South Africa. This industry began in South Africa's Western Cape province in the late 1800s in response to increased demand for fresh produce from passing ships and international markets (Theron 2012). However, it is worth noting that the establishment of the Deciduous Fruit Exchange in 1926, which was renamed the Deciduous Fruit Board in 1939, the Universal Fruit Trade Co-operative in 1987, Unifruco in 1989, the Deciduous Fruit Producers' Trust in 1997, and Hortgro in 2013 are also significant historical events in the industry (Theron 2012).

According to Hortgro, the deciduous fruit industry body, South Africa's deciduous fruit industry consists of 1158 producers working on 53,692 hectares of land, with 1.26 permanent jobs per hectare and an annual revenue of R15.7 billion (Hortgro 2019). Apples are the most significant fruit in terms of planted area and production, followed by table grapes, pears, peaches, plums, and apricots. The country is self-sufficient in deciduous fruits and only imports a small amount for niche markets or off-season demand (USDA 2018). The apple, pear, and table grape sub-sectors are expected to expand into new production areas due to

✉ Lindikaya W. Myeki
lindikayam@yahoo.co.za

[1] Department of Agricultural Economics, University of the Free State, Bloemfontein 9301 Free State, South Africa

[2] Department of Agricultural Economics, University of the Free State, Bloemfontein, South Africa

[3] UNE Business School, University of New England, Armidale 2351 NSW, Australia

[4] Agri-trust Division, National Agricultural Marketing Council, Pretoria 0001 Gauteng, South Africa

favourable weather conditions and high-yielding cultivars (USDA 2022). As a result, the deciduous fruit sector is identified as a strategic sector for job creation, reducing inequality, contribute to alleviation of poverty, and lowering food imports and food prices in the National Development Plan (NDP) and Agricultural Action Plan (APAP) (DALRRD 2013). This significant contribution would only be possible if the industry productivity could be improved.

The deciduous industry, like many others, faces both challenges and opportunities. These include increased market globalisation, trade liberalisation, industry deregulation, advances in information technology, changes in consumer taste and preference, a surplus of deciduous fruit in traditional South African markets, and increased global competition, all of which have impacted the industry since the late 20th century (Mashabela and Vink 2008; Hortgro 2019). Other challenges include rising farm input costs, higher shipping rates, inefficiencies in infrastructure such as power outages, inefficient port operations, and deteriorating road networks (USDA 2022). To maintain and improve on this position, continuous productivity and efficiency analysis is required, as it will aid in policy interventions and identification of areas for investment at various levels of the industry value chain. Simply put, the deciduous fruit industry's productivity growth analysis is too important to leave to chance.

Van Schalkwyk and Groenewald (1992) and Thirtle et al. (1993) published the first studies on agricultural productivity in South Africa in the early 1990s. These studies used a variety of datasets, study sites, and methods, resulting in varying productivity estimates. For example, Van Schalkwyk and Groenewald (1992) used regional-level data to estimate productivity for the grain industry using a Cobb-Douglas production function. Throughout the study, certain regions saw sustained productivity growth, while others saw little progress. Thirtle et al. (1993) used a TFP index to estimate production efficiency in South African commercial agriculture from 1947 to 1991 and the result reveal that TFP increased at a 1.3% annual rate during the period. Both studies helped pave the way for later research. For example, Liebenberg and Pardey (2010) looked at agricultural productivity patterns using data from 1910. Thirtle et al. (2005) estimated the technological, efficiency, and productivity changes of both commercial and smallholder agricultural sub-sectors.

Despite shedding light on national and regional agricultural productivity, the previous studies had several limitations. This includes relying on partial measures of productivity such as yield per hectare, labour productivity, and land productivity. Partial productivity measures often underestimate or overestimate productivity growth (Coelli et al. 2005). This is because partial productivity measures assume that the agricultural systems being evaluated have identical production scales and that there are no interactions between production factors (Minviel and Veysset 2021; Temoso et al. 2023). Most importantly, earlier empirical research failed to provide details on industry, sub-sector, and product-specific productivity growth estimates.

A few studies (Conradie et al. 2009; Conradie et al. 2019; Myeki et al. 2019) have attempted to address the limitations in previous studies by focusing on industry-level productivity. Conradie et al. (2009), for example, examined the productivity of table and wine grapes for districts in the Western Cape province. However, the study was limited to district-level analysis in one province and did not provide overall industry (country-level) performance. Furthermore, because the study was completed more than 10 years ago, it does not provide the most up-to-date picture of productivity growth in that industry.

Myeki et al. (2019) focused on regional TFP analysis for the table grape industry using the Malmquist index. However, their study, just like most of South Africa's agricultural productivity studies, relied on output and input quantity indices such as the Malmquist that do not satisfy a set of basic axioms from index theory (O'Donnell 2018). In addition, since these indices do not disaggregate efficiency into finer components, they do not account for the role of mix-efficiency change in productivity growth (O'Donnell 2018). O'Donnell (2018) defines mix efficiency as the ability of a manager to effectively exploit economies of output (input) substitution, which are the benefits gained by substituting one output (input) for another.

To the best of our knowledge, no study has looked at productivity growth in the South African deciduous industry, including differences in productivity between subsectors and fruit types and breaking down TFP growth into finer components to identify its main sources. Similarly, international studies on the productivity of the deciduous fruit industry or its sub-industries are scarce, and those that do exist frequently use partial productivity indicators (e.g., Aydin and Aktürk 2018, who studied energy use efficiency for peach and cherry production in Turkey; and Bhat et al. 2021, estimating yield and land productivity for the apple industry in India).

This study aims to address this gap by estimating the South African deciduous fruit TFP growth and its sources from 2014 to 2021 using the FP index. Particularly, the first objective of this study is to assess the TFP growth trends for the South African deciduous fruit industry during the 2014 to 2021 period. The second objective is to determine the contribution of each fruit type and subsector to the overall deciduous fruit industry's productivity. Third, it is to identify the primary sources of productivity growth for the entire sector and its subsector, i.e., whether technical change or efficiency changes - technical, scale, and mix efficiency changes were the key sources.

As a result, our contributions to the literature are as follows: First, we present new empirical evidence on productivity estimates for the South African deciduous fruit industry, focusing on various fruit types and subsectors. Second, we use the FP index to decompose agricultural TFP into technical change and finer components of efficiency change measures such as technical, scale, and mix efficiencies. As noted in O'Donnell (2014 2018), the index is called the Färe-Primont TFP index because the component output and input indexes used to derive it can be traced back to Färe and Primont (1994 p. 36 38). O'Donnell (2014) show that the FP index is better than the Malmquist and Tornqvist indexes, which were previously used in South African agricultural studies, for three reasons: it is considered a proper index because it satisfies basic rules of index theory, such as transitivity and proportionality; its values are consistent with measurement theory, implying that patterns in the numbers always mirror patterns in the quantities; and it allows for reliable spatial and temporal TFP comparison.

This method has been used in several studies to measure agricultural TFP, including Rahman and Salim (2013) for comparing agricultural regions in Bangladesh, Temoso et al. (2015) for comparing agricultural regions in Botswana, and Dakpo et al. (2018) for comparing beef farms in France. Martinez-Cillero et al. (2019a) compared beef farms in Ireland; Myeki et al. (2022) compared African countries; and Temoso et al. (2023) compared agricultural districts in Botswana.

Third, by breaking down TFP growth into different components (technological change, scale, technical and mix efficiency changes), our findings can give policymakers information they can use to make targeted policies and investments that could help the South African deciduous fruit industry grow. As highlighted by O'Donnell (2018), increasing funding for research and development can be used to advance technical change, while expanding education, training, and extension programmes can enhance technical efficiency. Changes in key variables that influence managerial behaviour, such as minimum wages, taxes, and/or subsidies, can enhance scale and mix efficiencies (O'Donnell 2018, p. 383).

The rest of the article is organised as follows: Section 2 presents the methodology of the study, with special attention given to the empirical model, data, and variable descriptions. Section 3 deals with the results and the discussion in Section 4. Sections 5 and 6 present the policy implications and conclusions of the study, respectively.

2 Methodology

2.1 Model

The South African deciduous fruit industry uses a variety of inputs (land, labour, trees, etc) to produce a variety of outputs (apples, apricots, peaches, pears, and plums, etc). Various types of production units at various aggregation levels, such as firms, industries, and countries, are commonly studied in the efficiency and productivity literature (Coelli et al. 2005). Our primary focus is on the five fruit types (apples, peaches, pears, and so on) that can be divided into two major sub-sectors, pome and stone, and contribute to the deciduous industry.

To account for the multiple outputs and inputs in our data, we used the Färe-Primont (FP) TFP index. This method is appropriate in situations such as ours, where peaches, apples, and other deciduous trees are grown in the same orchard using the same resources such as land, labour, and water. This is related to the concept of technical jointness. The concept of technical jointness in agricultural production refers to the idea that specific agricultural production processes and inputs (such as land, labour, and trees) can yield benefits for multiple agricultural activities (such as apples, peaches, and pears) at the same time (Paul and Nehring 2005). In essence, the use of shared resources or techniques across various aspects of agricultural production results in the emergence of synergies or economies of scale. Synergies are related to economies of scope and input and output mix efficiency, whereas economies of scale are related to scale efficiency (Paul and Nehring 2005; Coelli et al. 2005; O'Donnell 2018). According to Paul and Nehring (2005), when there is a complementary relationship between overall output and input, any change in one output or input influences the contributions of other outputs or inputs, affecting performance.

The assumption of technical jointness, on the other hand, ignores the specific needs of each crop, as well as the farm's, farmer's, market, regulations, and location. These variables can have a significant impact on productivity, requiring the use of tailored practices to optimise results for each deciduous fruit variety on a farm (Paul and Nehring 2005). Despite these potential limitations, we believe the FP index is the best approach for our analysis in this situation as it can handle multiple inputs and outputs and decompose productivity into finer components, including measures related to economies of scale (scale efficiency) and synergies (input and output mix efficiency).

According to O'Donnell (2011 and 2018), the FP index, which is based on two indices originally proposed by Färe and Primont (1994 p. 36–38) for firms (in our context, fruit types: apples, apricots, peaches, pears, and plums), can be measured by considering the ratio of aggregate output to aggregate input. If $X_{it} = (X_{Iit}, \ldots X_{Nit})$ and $Q_{it} = (Q_{Iit}, \ldots, Q_{Mit})$ are input and output quantity vectors for the fruit type i in period t then the TFP is:

$$TFP_{it} = \frac{Q_{it}}{X_{it}} \tag{1}$$

In case of more than one period and fruit type, for instance the deciduous fruit or sector i in period t relative to fruit type h in period s, this can be expressed as:

$$TFP_{(it,hs)} = \left(\frac{TFP_{hs}}{TFP_{it}}\right) = \left(\frac{Q_{hs}/X_{it}}{Q_{it}/X_{hs}}\right) = \left(\frac{Q_{hs,it}}{Q_{it,hs}}\right) \quad (2)$$

However, this Eq. (2) may differ for a given index methodology. For instance, within the context of FP index proposed by O'Donnell (O'Donnell 2014), it is expressed as:

$$TFP_{it,hs} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{TFPE_{it}}{TFPE_{hs}}\right) \quad (3)$$

The first ratio on the right-hand side of Eq. (1) computes technical change (TFP_t^*), described as the change in maximum productivity possible for all sampled deciduous fruits using the production technology in period t. The second ratio is a measure of overall efficiency change ($TFPE_{it}$). The later can be decomposed further into several measures of efficiency change, thus leading to:

$$TFP_{(it,hs)} = \left(\frac{OTE_{hs}}{OTE_{it}}\right)\left(\frac{OSE_{hs}}{OSE_{it}}\right)\left(\frac{RME_{hs}}{RME_{it}}\right) \quad (4)$$

OTE represents the output-oriented technical efficiency change, which refers to maximum radial expansion of all deciduous fruit industry outputs to reach the production frontier without changing input vector and output mix. In the same Eq. (3), the output-oriented scale efficiency (OSE) refers to productivity improvements through exploitation of economies of scales, also computed holding input vector and output mix constant. Residual mix efficiency (RME) measures productivity increases associated with a deciduous fruit moving from a point of maximum productivity in the mix invariant frontier to a maximum productivity point in the unrestricted frontier (O'Donnell 2014). The OSE and RME can be combined into OSME. Hence in the section for findings, we present OTE and OSME as the finer components of efficiency change.

2.2 Estimation procedure

According to O'Donnell (2018), it is possible to estimate proper indices such as Färe-Primont, Geometric Young and Lowe through the utilisation of both parametric methods such as stochastic frontier analysis (SFA) and non-parametric methods such as data envelopment analysis (DEA). In this study, the DEA method was employed to estimate the FP index using the DPIN 3.0 software.

The DEA approach was chosen because of its ability to incorporate multiple inputs and outputs simultaneously without the need for pricing information (Hjalmarsson et al. 1996; O'Donnell 2018). It avoids the statistical issues that arise when estimating technologies with multiple inputs and outputs, such as endogeneity (Bogetoft and Otto 2010; O'Donnell 2018). Also, unlike the SFA, DEA does not depend on specific functional forms or make assumptions about production technology (Bogetoft and Otto 2010). This property enables DEA to handle situations with small sample sizes better than SFA and other econometric-based approaches (OECD 2022). Also, because DEA uses linear programming methods, it makes it easier to identify the "best practice" for every DMU and to measure changes in efficiency, technology, and TFP growth for each DMU in the sample, such as sectors (Hjalmarsson et al. 1996; Bogetoft and Otto 2010; OECD 2022).

While the DEA method has been demonstrated to be useful, including in our study, it has some limitations. One of its shortcomings is a failure to account for statistical noise, which implies an inability to distinguish between inefficiency and noise; any deviations from the frontier are interpreted as instances of inefficiency (Hjalmarsson et al. 1996; Coelli et al. 2005). Due to its non-parametric and non-stochastic nature, DEA, unlike parametric methodologies such as SFA and growth accounting, lacks statistical tests to validate estimates (Hjalmarsson et al. 1996; Bogetoft and Otto 2010). This includes the inability to generate parameters that can be used to identify the most important factors in production by estimating elasticities and testing for jointness and interaction terms for complementary and substitutability properties (Paul and Nehring 2005). Furthermore, DEA models cannot account for omitted inputs via error terms, nor can they account for the direct influence of farm-related characteristics on production, such as soil quality, plant age, and farmers' experience and education, which can lead to measurement errors and under- or over-estimation of efficiencies. (Hjalmarsson et al. 1996; O'Donnell 2018; OECD 2022).

Despite such limitations, we believe a DEA-based TFP index is the best method for addressing our objectives given the small sample size and multiple inputs and outputs nature of our dataset. Our findings can be used as a baseline for future research on deciduous fruit productivity using a larger sample size and a broader range of farm characteristics such as soil quality, weather, and plant age incorporated into the models. To address DEA limitations such as accounting for missing variables and measurement errors, SFA and other approaches could be used.

Following O'Donnell (2011) and O'Donnell (2018), the DEA model specification is discussed below. According to O'Donnell (2011) the key assumption for using DEA is that the output distance functions representing the technology available at the time take the form of:

$$D_0(x_{it}, q_{it}, t) = \left(q_{it}'\alpha\right)/\left(\gamma + x_{it}'\beta\right) \quad (5)$$

D_0 represents the output distance function while x and q signify the input and output vectors for individual fruit types i in period t. The output-oriented problem entails determining the unknown parameters in Eq. (5) to reduce technical efficiency.

This yields the following equation:

$$D_0(x_{it}, q_{it}, t)^{-1} = OTE^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x'_{it} : \gamma l + X'\beta \geq Q'\alpha;\ q'_{it} = 1;\ \alpha \geq 0;\ \beta \geq 0\} \quad (6)$$

where Q is a J x M_t matrix of observed value of fruit production, X is K x M_t matrix of observed inputs, t is an M_t x 1 unit vector, and M_t denotes the number of observations used to estimate the frontier in period t (O'Donnell 2010).

The DPIN 3.0 software computes productivity and efficiency indices using a variant of this linear programming problem. It begins by solving the following linear programming problem to obtain the Färe-Primont aggregates:

$$D_0(x_0, q_0, t_0)^{-1} = \min_{\alpha,\gamma,\beta}\{\gamma + x'_0 : \gamma l + X'\beta \geq Q'\alpha; q'_0 = 1; \alpha \geq 0; \beta \geq 0\} \quad (7)$$

the Färe-Primont aggregated output and inputs are solved as follows:

$$Q_{it} = (q'_{it}\alpha_0)/(\gamma_0 + x'_0\beta_0) \quad (8)$$

$$X_{it} = (x'_{it}\eta_0)/(q'_0\phi_0 - \delta_0) \quad (9)$$

The values of β_0, γ_0, $\varnothing_0$, and η_0 are determined by solving Eqs. (8) and (9). The DPIN 3.0 employs sample mean vectors to serve as representatives of the output and input vectors in Eqs. (8) and (9). The technology represented in this LP is derived under the assumption of no technical change and permits the technology to demonstrate variable returns to scale (VRS). When considering the scenario where technology is assumed to demonstrate constant returns to scale (CRS), it is observed that DPIN 3.0 establishes that the values of sets $\gamma = \delta = 0$ (O'Donnell 2011).

2.3 Data and variable selection

The data used for this study was acquired from the Hortgro in '*Key Deciduous Fruit Statistics, 2014–2021*.' As a representative of the industry, Hortgro focuses on production, research and technology, communication, markets, and transformation. The annual publications outline various issues in the deciduous fruit industry under two classifications, namely pome fruit and stone fruit. The information includes, but is not limited to, total area planted, on-farm employment, crop enterprise budgets, exchange rate trends, monthly inflation trends, historical prices, fuel prices, the value of the industry, production volume and sales, number of trees, cultivars, and export markets. The information is collected through a statutory measure called records and returns, making it official and reliable data. The approach to the data collection process is similar to that of Myeki et al. (2019), who estimated Malmquist TFP growth for five table grape regions.

2.3.1 Outputs

While non-parametric methods allow for multiple inputs and outputs, the existing literature on productivity analysis in South Africa (Conradie et al. 2019; Myeki et al. 2019) has largely used a single output. The total production of the five fruits - apples, apricots, peaches, pears, and plums - in tonnes was used as an output variable in this study. The quantity-based output variable is typically preferred in agricultural productivity because it avoids the aggregation issues that arise when using value- equivalents outputs expressed in constant prices (Rahman and Salim 2013). However, it is important to note that the quantity-based variable has some limitations, especially in situations with a high degree of variety and product differentiation, making it difficult to account for quality differences that can bias productivity measures as well as the policy implications.

2.3.2 Inputs

three production input variables were considered: (i) *land*, which is defined as the area under cultivation per type of deciduous fruit, measured in hectares (ha); (ii) *number of trees*, which is defined as the total number of trees by type of deciduous fruit; and (iii) *labour*, which is defined as the number of people engaged in "on-farm employment" by type of deciduous fruit.

The descriptive summary for both output and input variables over the study period is presented in Table 1. The first observation is that there are clear differences in production inputs (land, trees, and labour) and outputs (apples, pears, plums, apricots, and peaches). The pome fruit sector, which includes pears and apples, had an average output of 506,918 tons. This was generated from 14,775 hectares of land, 27 million trees, and 17,198 labourers. On the other hand, the stone fruit sector recorded an average output of 215,940 tonnes using 7270 hectares of land, 8 million trees, and 7972 labourers. Based on the results for each type of fruit in Table 1, it is also clear that the industry is very diverse.

We did not, however, include other input variables for the South African deciduous industry in our study due to lack of data, including water, fertiliser, herbicides, and other variables. Our results could be skewed by the missing input variables. Future research should therefore consider these elements to spot any potential variations in the findings of our current study.

Table 1 Summary statistics of inputs and output variables, 2014–2021

Fruit	Parameters	Production	Land	Trees	Labour
Apples	Mean	935,443	24,282	32,948,308	27,855
	Std	112,959	771	3,145,018	1164
	Min	792,324	22,925	28,172,967	26,697
	Max	1,164,105	25,272	36,736,869	30,165
Apricots	Mean	427,234	12,513	16,718,441	13,296
	Std	21,123	272	962,617	566
	Min	402,738	12,211	15,527,878	12,361
	Max	461,201	12,913	18,014,902	14,068
Peaches	Mean	181,094	6643	6,410,167	7485
	Std	21,890	782	783,876	490
	Min	155,864	5478	5,480,028	6897
	Max	211,610	7462	8,007,034	8059
Pears	Mean	78,393	5269	21,454,086	6542
	Std	12,438	168	33,030,422	399
	Min	62,557	5000	8,833,830	5904
	Max	101,969	5486	103,181,194	7059
Plums	Mean	39,493	2655	1,852,073	3134
	Std	10,907	281	147,426	817
	Min	21,578	2187	1,604,338	1969
	Max	58,214	2962	2,021,719	4650

Table 2 TFP changes and its components by deciduous sub-sectors, 2014–2021

Industry	Period	TFP	TECH	TFPE	OTE	OSME
Deciduous	2014	1.00	1.00	1.00	1.00	1.00
	2015	1.15	1.13	1.01	1.00	1.01
	2016	1.07	1.13	0.95	1.00	0.95
	2017	1.08	1.14	0.95	0.99	0.96
	2018	0.99	1.14	0.87	0.90	0.97
	2019	0.98	1.14	0.86	0.90	0.96
	2020	0.99	1.15	0.86	0.94	0.92
	2021	1.27	1.35	0.94	1.00	0.94
Pome	2014	1.00	1.00	1.00	1.00	1.00
	2015	1.05	1.13	0.92	0.97	0.95
	2016	1.06	1.13	0.93	0.99	0.94
	2017	1.11	1.14	0.98	1.00	0.98
	2018	0.98	1.14	0.86	0.88	0.97
	2019	1.00	1.14	0.88	0.91	0.96
	2020	1.07	1.15	0.93	0.95	0.98
	2021	1.21	1.35	0.90	0.98	0.92
Stone	2014	1.00	1.00	1.00	1.00	1.00
	2015	1.21	1.13	1.07	1.02	1.05
	2016	1.08	1.13	0.96	1.01	0.95
	2017	1.06	1.14	0.93	0.99	0.94
	2018	1.00	1.14	0.87	0.92	0.96
	2019	0.96	1.14	0.84	0.89	0.96
	2020	0.93	1.15	0.81	0.94	0.87
	2021	1.32	1.35	0.98	1.01	0.96

3 Findings

3.1 Productivity and efficiency growth for the deciduous fruit industry

This section examines the TFP growth and components of the South African deciduous fruit industry from 2014 to 2021. A value less than one in Table 2 indicates that there has been no growth in the corresponding measure relative to the base year (2014), whereas a value greater than one indicates growth. Over an 8-year period (2014–2021), TFP for the deciduous fruit sector increased by 27% (3.53% per year), owing to a greater increase in technical change (TECH of 35 or 4.38% per year), while overall efficiency slightly declined (TFPE drop of 6 or −0.81% per year). The breakdown of TFPE into OTE and OSME reveals that the 6% (−0.81% per year) decrease in OSME was entirely responsible for TFPE slowdown. TFP fell slightly in three of the 8 years (2018, 2019, and 2020).

In terms of sub-sector performance, TFP growth of the pome fruit increased by 21% (2.74% per year) over an 8-year period, with an increase in TECH of 4.38% per year being the main source of growth, while TFPE declined by 1.57% per year. The negative growth in TFPE is primarily due to a slowdown in OSME (−1.25% per year), while the decline in OTE (−0.35% per year) was moderate. When the two sub-sectors are compared, the results show that stone fruit was the most productive sub-sector of the industry, with TFP growth of 4.04% per year (32%). The main driver of this TFP growth was TECH, while TFPE fell slightly. Furthermore, OTE only increased by 1%, which was insufficient to compensate for the 8% decline in OSME.

Figure 1 adds to the previous findings in Table 2 by showing a positive correlation between TFP growth and its components. This finding has conventional significance on several levels. The correlation coefficient of 0.90 indicates a strong positive relationship between TFPE and TFP, which is significant at the 1% level of significance. TFPE has a higher correlation coefficient than TECH, implying that it explains most of the variation in TFP growth across fruit types and time. In terms of has a stronger correlation than OTE. Again, this implies that variation in OSME, rather than OTE, explains the overall efficiency variations TFPE.

3.2 Productivity and efficiency growth by fruit type

Figure 2 shows the results of TFP and its components by five types over an 8-year period. Peaches had the highest TFP growth of 58% (6.77% per year), with both TECH of 4.38% per year and TFPE of 2.29% per year contributing. Most of the increase in TFPE was due to a strong increase in

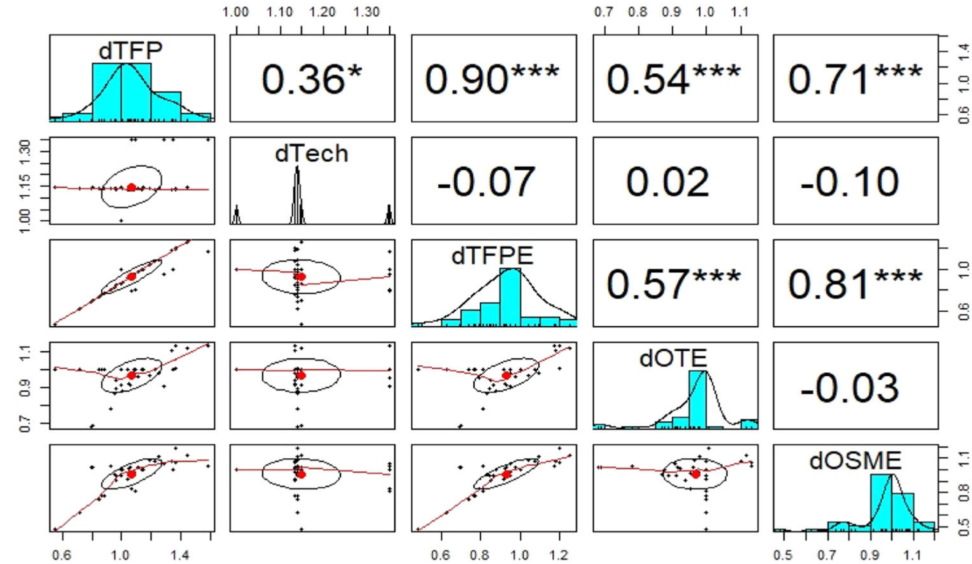


Fig. 1 Summary of relationship between TFP and its components. Note: dTFP is productivity growth, dTech is technical change, dTFPE is efficiency change. The dOTE is technical efficiency change and dOSME is scale-mix efficiency change. *$p < 0.05$, **$p < 0.01$, *** $p < 0.001$

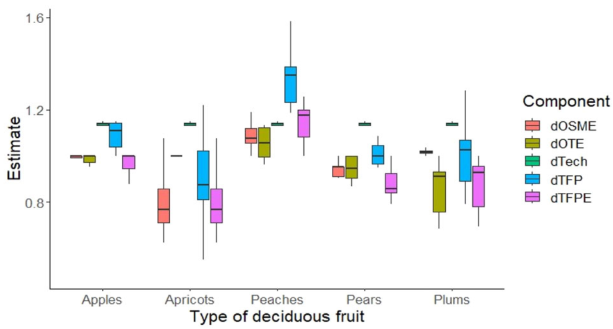


Fig. 2 Summary of TFP, Technical and Efficiency changes by type of deciduous fruit, 2014–2021. Note: dTFP is total productivity growth, dTech is technical change, dTFPE is total factor efficiency change. The dOTE is technical efficiency change and dOSME is scale mix efficiency change

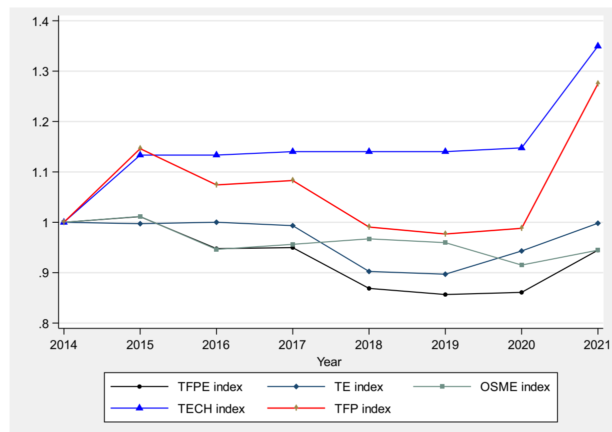


Fig. 3 Annual trend of TFP, technical and efficiency changes, 2014–2021

technical efficiency (OTE of 1.79% per year) and a slight increase in scale-and-mix efficiency (OSME of 0.49% per year).

Apple came in second place with a 35% increase in TFP growth (4.38% per year), with the entire increase due to an increase in TECH. Given the lack of efficiency contribution for this fruit type, the results imply that there is potential to increase its TFP by increasing both technical and scale-and-mix efficiency. Plums ranked third with TFP growth of 3.62% per year (28%), primarily due to TECH, while TFPE declined by 0.73% per year (5%). Although OSME was positive (0.66% per year), it was insufficient to offset the 1.38% per year decline in OTE.

Apricots had the second lowest TFP growth of the five fruit types, at 1.28% per year, owing to technical change, while TFPE declined by 2.96% per year. The drop in TFPE was also entirely due to a drop in OSME, while OTE remained unchanged. Pears were the least productive deciduous fruit. TFP for pears increased by 0.93% per year (4.38% per year) due to technical changes, while TFPE decreased by 3.30% per year. The breakdown of TFPE for this fruit type reveals that the slowdown was primarily caused by OSME, which fell by 17% (2.6% per year), and OTE, which fell by 5% (0.72% per year). As a result, there is an opportunity to boost productivity by improving both technical and scale-mix efficiencies.

3.3 Trends in the deciduous fruit industry TFP and its components

Figure 3 depicts the trends in TFP and its components for the deciduous industry, with 2014 serving as the baseline. This analysis can aid in understanding the dynamics of productivity over time and how various environmental and macroeconomic factors, such as drought and COVID-19, may have affected it.

The results show that between 2014 and 2016, TFP increased by 7.4% due to a 13.3% increase in TECH, while TFPE decreased by 5.2%. TFP fell by 8% between 2016 and 2018, owing primarily to TFPE. Despite a slight increase in OSME, the 9.8% decrease in OTE during this period led to a fall in overall efficiency. TFP growth fell by 0.3% between 2018 and 2020, owing to a 5.2% decline in OSME, which offset an increase in OTE (4.1%) and a marginal increase in TECH (0.7%). The industry recovered in the final sub-period (2020–2021), registering a 28.7% increase in TFP due to a significant increase in TECH (20.2%) and TFPE (8.7%). During this period, OTE increased by 5.5% and OSME increased by 3.0%, demonstrating the significance of both components for TFPE. As a result, this was the only time when the industry was both technically efficient and scale-and-mix efficient.

Figure 4 shows the same analysis as in Fig. 3, but with a focus on specific types of deciduous fruits. Except for the 2016–2018 sub-period, TFP growth for apples was positive throughout the study period. TFP growth in apples during this period was due to technical inefficiency (a 9.9% drop in OTE), which could not be offset by increases in scale-and-mix efficiency (OSME of 2.3%) and TECH (0.7%). Apart from the negative TFP growth in 2016–2018, overall TFP growth in apples was positive, especially during the 2018–2020 and 2020–2021 sub-periods, with 14.7 and 20.2% growth, respectively. Throughout the study period, the primary source of apple growth was technological change.

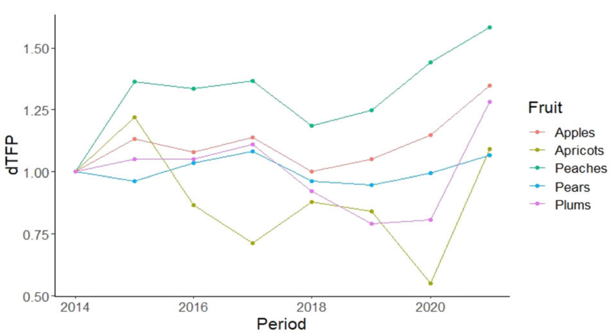
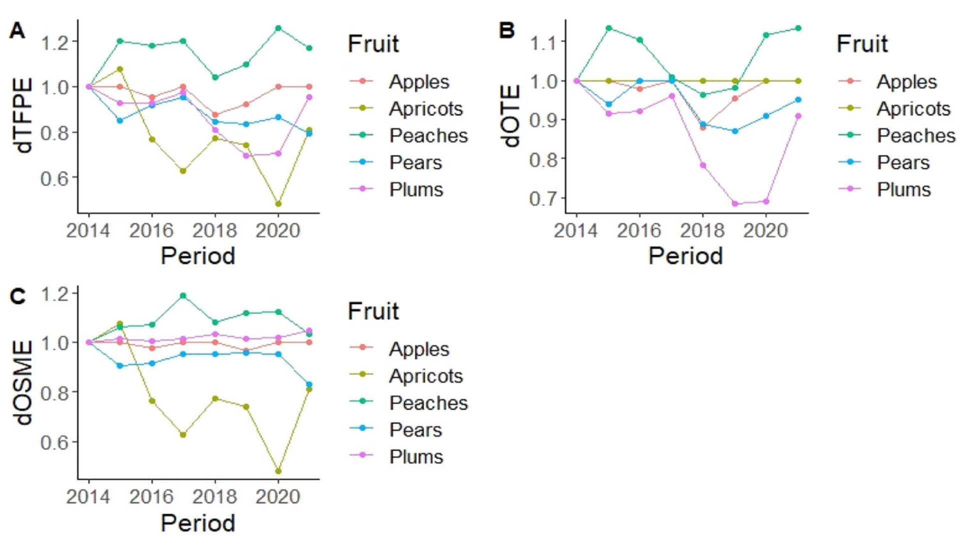


Fig. 4 Annual trend of TFP and technical changes by type of deciduous fruit, 2014–2021. Note: dTFP represents productivity growth

TFP growth in pears was positive throughout the study period, except for the subperiod 2016–2018, when it fell by 11.7%, with OTE (8.8%) accounting for this drop. Apart from the 2016–2018 subperiod, both apples and pears, which fall under pome fruit subsector, saw positive TFP growth during the study period. Apart from the period between 2018 and 2020, when the contribution of TFPE was greater than that of TECH, technical change has been the primary driver of this sub-sector's growth (Fig. 5).

The results show that the TFP of peaches increased throughout the study period, apart from the 2016–2018 sub-period, when it decreased by 15.1%. TFP slowed during that sub-period because of a 13.9% decrease in OTE. TFP growth trends for plums were mixed, with the first sub-period (2014–2016) experiencing a slight growth of 5.1% but the following two sub-periods experiencing a negative growth trend. TFP increased by 47.6% in the final sub-period, 2020–2021, with both TECH and TFPE making significant contributions. Apricots also had a mixed performance, with negative TFP growth of 13.3% in the initial years (2014–2016), followed by some growth (1.4%) in the 2016–2018 period, then a huge dip of 33% in 2018–2020, and a massive increase of 54.3% in the final sub-period.

Fig. 5 Efficiency, Technical and Mix-Efficiency changes by type of deciduous fruit, 20142021. Note: dTFPE in (**A**) represent the efficiency change which is further decomposed into technical efficiency change represented by dOTE in (**B**) and OSME in (**C**) signifying the scale-mix efficiency change



4 Discussion

The purpose of this study was to assess the productivity (TFP) growth of the South African deciduous fruit industry and its sources from 2014 to 2021. According to the results, the industry's TFP increased by 27%, or 3.53% per year. This result suggests a high potential for contributing to food security, job creation, poverty alleviation, and hunger alleviation in support of the country's National Development Plan (NPC 2012), Agriculture Policy Action Plan (DALRRD 2013), and Economic Reconstruction and Recovery Plan (Mosala et al. 2022). Technical change was the primary driver of TFP growth, increasing by 35% (4.38% per year), implying that R&D investment and the adoption of improved technologies may have played a critical role in TFP growth in the deciduous fruit industry. This study supports previous findings (Alene 2010; Headey et al. 2010; Pratt and Yu 2008) and suggests that the industry should continue to invest in R&D and new technology adoption to ensure long-term and profitable production. Modern inputs, irrigation practices, environmental protection, and climate-smart agriculture practices can all be part of this research and development.

The results of finer TFPE decomposition show a marginal decrease in technical efficiency (an OTE drop of 0.03%) and scale and mix inefficiencies (an OSME drop of 0.81%). These efficiency components slowed TFP growth during the study, but not significantly enough to cancel out the positive contribution of technological change (TECH). These can be addressed through a variety of channels. According to O'Donnell (2018, p. 382), providing educational and training services aimed at informing managers about the availability and appropriate use of technologies via agricultural extension programmes can help to improve OTE. The potential for improving OSME lies in changing the production environment as well as adjusting relative output and input prices through wage, tax, and/or subsidy changes (O'Donnell,2018).

We also aimed to investigate TFP and its components for each sub-sector and type of deciduous fruit. The results show that the stone fruit sub-sector grew faster than the pome sub-sector. In terms of TFP growth by fruit type, peaches grew at the fastest rate, owing to increased technological change. Apples were the second-most productive fruit, owing to technological change. This finding is consistent with the findings of Feng and Huo (2015), who examined green productivity growth in China using the Malmquist-Luenberger index. Their research suggested that environmentally friendly apple production technology be promoted, and fertiliser consumption rates be reduced to promote green productivity. Furthermore, Bhat et al. (2021) reported an increase in Indian apple production from 1975 to 2015.

Pears, plums, and apricots had lower rates of TFP growth than apples and peaches. These findings indicate that productivity varies within the deciduous industry, which can be attributed to differences in sub-sectors and fruit types. Previous research, on the other hand, has only looked at certain aspects of productivity, such as yield, and has not examined TFP and how it varies across sub-sectors and types of fruits (Abd El-Hamied and El-Amary 2015; Aydn and Akturk 2018). This statement implies that more research is needed in this area.

The TFP trend results demonstrate that the South African deciduous fruit industry grew from 2014 to 2016. This could be attributed to the 2014–2015 production season, which saw the return of normal growing conditions after hail and rainfall damage in late December 2013 (USDA 2014). Similarly, despite a declining trend, growth was positive in 2016–17 due to increases in new plantings, young orchards entering full production, and high-yielding varieties (USDA 2016). TFP growth fell below 1% from 2017/18 to 2019/2020 because of the drought, which caused a sharp drop in dam levels and water restrictions, particularly in the Western Cape province (USDA 2017). However, TFP growth was positive in the 2020–2021 period, including at the sub-sector level. This is due to favourable weather conditions, new production areas, and higher-yielding cultivars, all of which are expected to remain important growth drivers in the short term (USDA 2022). However, rising shipping costs (Sihlobo and Kirsten 2021), rising input costs, and local port inefficiencies (Zalk 2019) are likely to impede this growth.

TFP growth for peaches follows an S-curve, with technical change following suit, implying that technological change, rather than efficiency change, has been the industry's primary driver. Rising per capita consumption, increased demand in the local processing industry and export markets, and currency depreciation are all indicators of rising demand during this period, which may also explain TFP growth (DALRRD 2014, 2019a). Apples show a W-shaped trend, with an increase in 2015, a decline in 2016, an increase in 2017, a sharp decline in the 2018/19 production season, and an increase in the 2019/2020 production season. According to DALRRD (2019b), this could be attributed to unfavourable weather conditions (drought and heat waves) in certain apple-producing areas.

Pears experienced negative TFP growth from 2016–17 to 2020–21, which could be attributed to the effects of the 2015–16 drought. Plums TFP trend was relatively stable for the first four years but then followed a V-curve, possibly due to drought (Pienaar and Boonzaaier 2018). The negative TFP growth in apricots, particularly in the sub-periods 2014–2016 and 2018–2020, could be attributed to the use of old cultivars as well as the drought effect (Human 2018; Pienaar and Boonzaaier 2018). Positive TFP growth rates averaged 1.4% from 2016 to 2018, owing to increased planted area, normal weather conditions, yield improvements, and available irrigation water following improved 2020 winter rainfall (USDA 2021).

Overall, our findings indicate that the industry experienced positive TFP growth during the 2019–2021 period, which coincided with COVID-19. These findings could be explained by the fact that the effects of COVID-19 on productivity may manifest with a lag; in other words, they may not be detected in current data. Another possibility is that other factors are at work, specifically the South African government's unprecedented policy response to COVID-19. For example, the agricultural sector was declared an essential sector during the period and thus was not subject to pandemic-related lockdown regulations. Furthermore, because harvesting was nearly complete when the pandemic began, its impact on production was expected to be minor or non-existent (USDA 2020). However, lower apple and pear exports were expected during the period due to the impact of COVID-19 on global demand, bottlenecks or closures at some ports, limited container availability, and constrained shipping capacity (USDA 2020). However, there is currently no evidence indicating that the COVID period had a full impact on the productivity of the industry.

5 Conclusion and policy implications

The study adds to available body of literature pursuing an understanding of productivity in agricultural industries for contribution to the country's economy. It has analysed systematically, the total factor productivity (TFP) growth of South African deciduous fruit industry using Färe-Primont index approach. Our findings indicate that the TFP of the deciduous fruit industry increased by 27% (3.53% per year) during the study period, indicating that the industry has been productive and has the potential to contribute to food security, job creation, poverty alleviation, reduction of hunger, and farm income generation. However, this productivity varies depending on the sub-sector and type of deciduous fruit examined.

TFP decomposition results show that technical change has been the primary driver of TFP growth, while efficiency change has made a minor contribution. The preceding observation has important policy implications regarding the role of technological change in increasing TFP. Thus, investing in R&D and technology, including the development of novel genetic resources and drought-resistant cultivars, as well as climate smart technologies and processes, will ensure the industry's long-term productivity while mitigating the negative effects of climate change as manifested by phenomena such as drought, hail, frost, and heat waves.

Our results also show that efficiency growth was minimal or negative in some of the sub-periods, implying that addressing this has the potential to boost overall TFP growth. This can be accomplished by addressing technical inefficiencies that have slowed the industry's overall efficiency growth through programmes that remove barriers to the adoption of improved technologies and enhance education and training services to advise managers on proper technology use (Rahman and Salim 2013; Temoso et al. 2015; O'Donnell 2018). The differences in TFP growth and its sources by sub-sector and fruit type suggest that policy formulation in the industry should take such sub-sector and fruit type heterogeneity into account rather than a one-size-fits-all policy.

As discussed in Section 3, it is possible that other key factors in the South African deciduous industry that were not included in this study due to data limitations could have influenced the results. Consequently, these limitations must be considered when interpreting our findings. In addition, we suggest that improved data collection, capture, and reporting by industry stakeholders will be crucial, as it will permit more precise analyses that contribute to the development of more targeted policies and strategies. Future analyses can incorporate additional production factors, such as fertiliser, water, machinery, soil quality, plant age, and farmer experience and education, if data quality is improved. With additional information, econometric methods such as SFA, which address the limitations of DEA analysis, can be evaluated. In addition, the analysis should be expanded to include different geographic levels, such as the district level, to support the country's policy direction, which employs the district development model as a mode of service delivery.

To summarise, prior to this study, no clear evidence of productivity growth for the deciduous industry, its sectors, or fruit types had been reported using frontier methodology. This study established a baseline for future research while also providing indirect monitoring and evaluation of South Africa's deciduous fruit industry in relation to the aspirations of the National Development Plan (NDP) Vision 2030 as well as the economic reconstruction and recovery plan. Future research should include assessing factors affecting the growth rate of the industry, its sectors, and types of fruit as data availability and collection improve. Other variables not covered here, as well as the concept of green productivity growth, should be considered.

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