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Effects of weather on productivity growth of South African table grape industry: a comparison between index approaches

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Abstract

The current literature on productivity growth analysis in South Africa often overlooks two key factors, namely the weather effects and pollution-related issues. This study aims to address the first of these gaps by utilising a decade's worth of panel data from the Table grape industry in the country. We conduct a comparison between Färe-Primont Index that ignores environmental change and statistical noise, and; Proper Index. The latter offers a measure of sustainable productivity, decomposing into technical change, technical efficiency, scale efficiency, mix efficiency, environmental change (weather effects), and statistical noise. In simpler terms, the Färe-Primont Index results in conventional growth (TFP), while the Proper Index leads to sustainable TFPI growth (TFPI). Our findings reveal that ignoring weather effects and statistical noise leads to an increase in TFP. However, accounting for these factors results in a decline in TFPI. Despite this decline, weather effects had an average 0.11% positive impact on TFPI growth. We conclude that weather effects posed a lesser challenge to TFPI growth during the observed period compared to technical change (−4.80%) and scale-mix inefficiency (−0.76%). Therefore, we recommend that the table grape industry prioritise investment in research and innovation as a strategy to improve technical change and improve infrastructure such as irrigation systems, roads, and storage facilities to reduce costs, increase the scale of production, and thus improve scale efficiency. Government policies, such as funding for technology adoption and encouraging diversification, can improve mix efficiency. Future studies should strive to address the second gap in the literature by focusing on pollution-related issues.

Keywords Weather · Productivity · Efficiency · Table grapes · South Africa

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1 Introduction

Weather and climatic variations have a substantial impact on agricultural productivity in many countries, including South Africa. This is due to the fact that climate factors such as rainfall and temperature impact the long-term linkages between agricultural inputs and outputs and can cause productivity to deviate from its long-run trends (Sheng et al., 2021). Dating back from 1990, the national average temperature in South Africa has increased twice as fast as global temperatures (MacKellar et al., 2014). According to Meque et al. (2022) extreme weather events are becoming more common, with frequent heat waves, dry spell durations lengthening significantly, and rainfall intensity increasing. Weather changes in the country are affecting ecosystems, the environment, and economic livelihoods (Gu & Adler, 2023). They are also likely to become increasingly common in the future. Given the importance of weather in agricultural production, changes in temperature and rainfall have led to the emergence of empirical studies concerned with the consequences of environmental change on agricultural productivity. Evidence (Chambers & Pieralli, 2020; Ortiz-Bobea et al., 2018) exists elsewhere regarding this specialty research topic, however, it is scarce in South Africa, owing in part to a lack of applicability for approaches that account for the influence of weather on agricultural productivity.

The available research on effects of weather and economics of agricultural productivity growth pays attention to three specific areas (Wang et al., 2018). One strand seeks to uncover the impact on agricultural productivity by investigating association between weather and agricultural output. The second strand focuses on understanding the adaptive response of various actors within agricultural value chains, while the third addresses the impacts and adaptation. Linked to these strands, Myeki et al. (2023a) reports another stream of literature concerned with consideration of undesirable output (i.e., pollution, greenhouse gas emissions) in productivity analysis. However, our study can be classified under the first strand and much of empirical evidence exist in the United States (U.S). For instance, Njuki et al. (2018) utilise a proper index approach to decompose U.S. agriculture TFP growth into weather effects reported as environmental change, technological progress, technical efficiency, and scale and mix efficiency changes, and found that environmental change have had a negative impact on agricultural productivity growth.

Using panel data from South African table grape industry over a 10-year period (2010–2020), we compare Färe-Primont index that ignores environmental change, with Proper Index, which decomposes productivity into technical change, technical, scale and mix efficiency changes, environmental change, and statistical noise. The proper index is the most recent approach, novel to O'Donnell (2018, 2022), and Njuki et al. (2018). This study is centred around three key research questions. Firstly, we aim to understand if the inclusion or exclusion of weather effects (environmental change) variables leads to any differences in productivity measurement. Secondly, we seek to determine the impact of environmental change on the productivity growth of the industry throughout the study period. Lastly, we explore how these effects vary across different table grape-producing regions. This approach allows us to comprehensively examine the intricate relationship between environmental change and productivity in the context of table grape production.. We acquired panel data from the key industry statistics published annually on the official website of the country's table grape industry. Our analysis focuses on five table grape producing regions, Berg River Valley, Hex River Valley, Olifants River, Orange River and Northern Provinces. We focus on this particular industry because it has been long identified in the national development plan (NDP) vision 2030 as an important contributor towards redressing unemployment, food insecurity, and inequality. In addition, our analysis provides an indirect evaluation for expenditure of statutory levy funds by table grape industry in the country. In its context, table grapes refers to grapes intended for consumption while they are fresh, as opposed to grapes grown for wine production, juice production or drying into raisins (SAGTI, 2021). The weather effects or environmental change is measured by average annual temperature and rainfall.

By undertaking this analysis, the paper makes three unique contributions to the available body of knowledge on productivity growth of table grape industries. First, unlike previous research which has consistently applied the Malmquist index, despite being criticised by O'Donnell (2018), for failing to satisfy the entire axioms of index number theory, we employ the proper or proper index approach of Njuki et al. (2018) and O'Donnell (2022) which overcomes the aforesaid drawbacks. Second, the proper index approach provides the most exhaustive breakdown of TFP into technical change, environmental change, scale-mix efficiency changes and technical efficiency change; such analysis remains non-existent in global table grape industries. Third, the paper lays the foundation for future research not only for table grape industries located in the Southern Hemisphere but also in other parts of the world. Policy insights emanating from this paper are relevant to global table grape industries given importance of sustainable development worldwide.

Next, we examine existing literature for the purpose of establishing research gaps and the merit of the study in Sect. 2 followed by the discussion of methodology, data and estimation in Sect. 3. The finding and their discussion are presented in Sect. 4. Section 5 provides the conclusion and policy insights while the list of references is presented in Sect. 6.

2 Literature review

2.1 The role of weather on economic performance

Scholars have long studied climate change and its effects on economic sectors and welfare (Neumann, 2021). Due to its climate dependence, agriculture is particularly interesting (Department of Environmental Affairs, 2011). Much of this research examines how climate change affects agricultural production, yield, and productivity (D'Agostino & Schlenker, 2016). These studies employ agronomic, agro-economic, or Ricardian models. Agronomic models emphasise the biological and physical aspects of farming. They predict crop yields using soil type, weather, and farming practices. These models explain how these variables affect agricultural output (Lobell & Gourdji, 2012). David Ricardo's models offer unique perspectives. They examine how climate variables affect land values. Agro-economic models take a holistic approach by combining agricultural and economic factors. They consider farmers' behaviour, market conditions, and policy effects. This comprehensive view clarifies agriculture's economic dynamics.

Many studies within agro-economic models primarily focus on the relationship between production economics and environmental climate. Researchers have extensively studied this relationship using various methods, including traditional econometric models (non-frontier methods), such as ordinary linear regression (OLS), time series modelling, and dynamic panel data models (Lobell & Gourdji, 2012). These include Dell et al. (2012) who examined temperature shocks and economic growth. The study found that historical temperature fluctuations have an impact on economic growth in poor countries, with higher temperatures slowing growth rates and having other effects on agricultural and industrial output. Fomby et al. (2013) examined the response of gross domestic product to natural disasters using dynamic generalized method of moments panel estimator. They concluded that natural disasters have different effects across multiple dimensions, with developing countries suffering the most, and that the timing of the growth response varies depending on the disaster type and economic activity sector. Loayza et al. (2012) reports that not all disasters induce the same growth response, with severe disasters often having worse effects than moderate ones.

2.2 Establishing resonance between weather and agricultural productivity

There are also several studies on this topic which are specific within the context of agriculture (D'Agostino & Schlenker, 2016; Fisher et al., 2012; Bareille & Chakir, 2023; Khurshid et al., 2023; Tol, 2024). For instance, the results of Panel Error Correction model used by Sheng et al. (2021) reveal that farmers in Australia were taking corrective action concerning weather-induced loss in productivity. However, the weight of these studies in agriculture adopt frontier approach, and these are discussed in the rest of this section. We also learn towards the frontier approach because it provides the most comprehensive decomposition of productivity growth for policy.

The effect of weather and climate on productivity continues to receive a growing attention in agriculture. Njuki et al. (2020), for example applies multiplicative TFP index to ascertain the impact of of weather changes (temperature and rainfall) on productivity of Wisconsin dairy farms, O'Donnell (2022) employs stochastic production frontier model to breakdown proper productivity index into measures of technical progress, environmental change, technical efficiency change, scale-and-mix efficiency change, and changes in statistical noise. The findings reveal that the impact of weather on productivity is negligible. Using the same model, Njuki et al. (2018) found that weather contributed to 0.012% decline in productivity. A notable observation is that much of the research on the effects of weather on productivity focuses on developed countries. This implies more ground to cover in agricultural industries of developing countries such as South Africa.

2.3 Effects of weather on table grape productivity

A number of grape-related studies (Naya & Navarro, 2022; Moreira et al., 2011; Coelli & Sanders, 2013; dos Santos et al., 2020) conducted in different parts of the world to investigate productivity growth are restricted to technical efficiency. Some do pay attention to allocative efficiency (Aparicio et al., 2013) and cost efficiency (Fernandez & Morala, 2009). They commonly apply data envelopment analysis (Jiao et al., 2015) and stochastic frontier (Moreira et al., 2011; Conradie et al., 2006; Tóth & Gál, 2014; Piesse et al., 2018), consistently reporting room for improvement of efficiency. These studies, however, do not examine technical change, scale-mix efficiency, or weather effects. This shows that existing research does not give significant weight to a comprehensive measure of productivity. According to recent agricultural productivity research (Temoso et al., 2023; Myeki et al., 2023b), a technically efficient farm or region may not be productive in terms of productivity. As a result, eliminating technical inefficiencies may not necessarily result in increased productivity. Instead of focusing just on technical efficiency change, these recommendations stress the need to assess total factor productivity and its more detailed parts, such as technical change, scale, and mix efficiency changes.

The majority of available literature on grapes also concentrate on effects of weather or climate and partial factor productivity measures such as labour and land. Anastasiou et al. (2023) reports that rainfall and temperature changes negatively affect both the yield and quality of table grapes in Southern Greece. According to Bock et al. (2013), high temperature tend to reduce the length of growing cycle for grapes, while Bois et al. (2017) maintains that variation in rainfall increases exposure to pests and diseases. Naude and Naude (2019) discovered that the excessive heat due to high temperature negatively affect the grape growing cycle for table grapes in South Africa, resulting in reduced yield. Heat waves a have also been found to reduce labour productivity for grapes in U.S. (Castillo et al., 2021). While these studies lay foundation for further exploration of weather effects on productivity, their estimates of productivity only take into account single output and input rather than TFP.

2.4 Study's contribution

The few that have attempted to analyze productivity include Conradie et al. (2009) using Tornqvist-Theil index on panel data of various table grape producing districts in Western Cape, South Africa, and Sellers-Rubio et al. (2016) focusing on cross-country Malmquist TFP analysis for wineries in Europe. Both methodologies employed in these studies are deemed inappropriate by O'Donnell (2018) due to theoretical flaws. In addition, they fail to account for statistical noise and the effects of environmental change. Our study seeks to address this major research gap and contribute toward the on-going debate on food uncertainty arising from negative effects of weather on productivity by applying the recent complete or proper index approach pioneered by O'Donnell (2018, 2022) to table grape industry in South Africa.

Moreover, by breaking down TFP growth into distinct components, our findings can assist policymakers in establishing targeted policies and investments that will benefit the South African table grape fruit industry (Myeki et al., 2023b). According to O'Donnell (2018), increasing R &D funding can be used to advance technical change, while expanding education, training, and extension programmes can improve technical efficiency, and changes in key variables influencing managerial behaviour, such as minimum wages, taxes, and/or subsidies, can improve scale and mix efficiencies (O'Donnell, 2018).

3 Materials and methods

3.1 Sample characteristics

The data information for this research cover five table grape producing regions in South Africa from 2010 to 2020. As mentioned earlier in the introduction, the choice of table grape industry stems from its identification as priority industry to unlock job creation and contribute to food security (NPC, 2012). The availability of data was key criterion for choosing this industry. This data is publicly available from the official annual key industry statistics publication in the website of SAGTI. Mtshiselwa (2020) asserts that the industry collects this data from approximately 450 table grape growers using the levy funds. Other activities funded through industry levy funds include market access and development, information and knowledge management, transformation and training, and research and technical transfer.

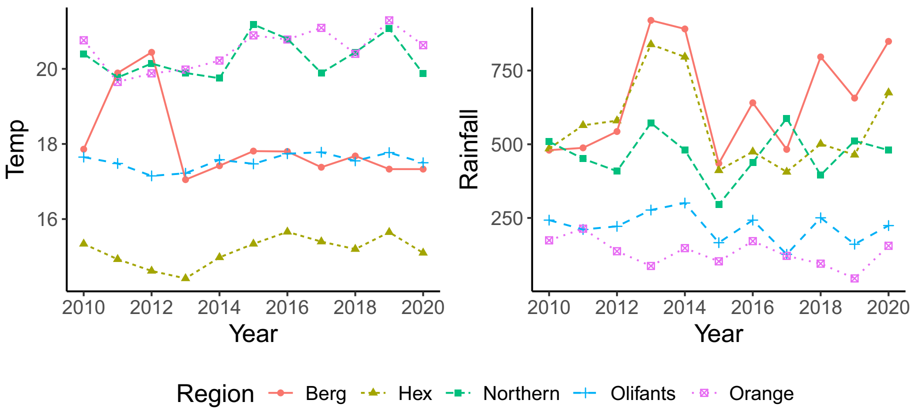

Fig. 1 Weather patterns for South African table grape regions, 2010–2020. *Note*. North represents Northern provinces

The table grapes data for the 2020/2021 production season shows that China was the largest producer at 11.2 million metric tonnes compared to the previous season, followed by India (2.9 million metric tonnes), Turkey (1.9 million metric tonnes), and South Africa, which ranked 11 among the global producers of table grapes(NAMC, 2022). Nonetheless, among the world exporters of table grapes, South Africa was ranked 4th after Peru, Chile and China—with the European Union (EU-27) absorbing over 50% of its total table grapes exports followed by the United Kingdom at 22%, Canada at 7% and the Middle East at 6%. The rest of the table grape exports from South Africa were destined for Africa, Russian and Far East. Hex River Valley and Orange River were the top table grape-producing regions over the reported season in South Africa. The variation in output for each table grape region can be attributed to several factors, such as experience and technology adoption rates. However, weather is one of the major factors affecting grape production (see Fig. 1. For instance, the Orange River region is situated in the most dry province in the country, hence exhibiting a high mean annual temperature and low mean annual rainfall. On the other hand, Northern Province is the most humid region, hence the high mean annual rainfall compared to other regions. During 2015, a year considered the worst drought in South Africa, the region received its lowest level of rainfall due to the high temperature. This climate variation for each region allows for table grape production throughout the year in South Africa.

A graphically representation of sampled table grape for the study is depicted in Fig. 2. The Hex River Valley, Berg River Valley, and Olifants River are located in Western Cape province and account for 62% of total table grapes produced in the country (see Fig. 2). Again, Hex River Valley, Berg River Valley are regarded as the oldest table grape region while Olifants is the smallest among the five. The Orange region is located in the most dry province in the country but largely benefits from irrigation water provided by Orange River. The farmers forming the Northern Provinces region are scattered along the borders of Gauteng, North-West and Mpumalanga province while occupying some parts of Limpopo province. The geographic location of table grape regions implies climatic variance leading to differences in productivity levels but also permitting table grape supply from November to May.

Fig. 2 Map obtained from (SAGTI, 2017) showing nine provinces of South Africa and five table grape regions

3.2 Selection of variables

For the purpose of our analysis, we identified and selected five variables supported by available literature. Previous research (Conradie et al., 2006; Moreira et al., 2011) employs table grape production and we also follow suit. However, in our context the grape production volume is measured in 4.5 kg equivalent cartoons. In accordance with Coelli and Sanders (2013) and Sellers-Rubio et al. (2016), this output variable is matched by Land, described as number hectares (ha) under table grape production, Labour composed of total number of employees (n), that is permanent and seasonal employees, and Other cost (R) is measured in rands and includes amongst others water, electricity, crop insurance, maintenance and fuel. Initially, we were provided with two main towns for each table grape producing region by a designated chairperson in one of the regions. Subsequently, ezGeocode was implemented to collect latitude and longitude coordinates for each of the main towns, enabling us to retrieve precise data from DSSAT.[1] The temperature is measured in degrees Celsius (°C) while rainfall is in millimeters (mm) per year. The descriptive summary of these variables is presented in Table 1.

The *p*-values for output, land and weather effects (temperature and rainfall) are significant indicating evidence of heterogeneity among table grape regions. This can be attributed to several factors such as age of the region, climate and size. This also indicates the importance of designing region-specific policy interventions rather than taking an umbrella approach.

3.3 Estimation procedure

The selection of appropriate model for productivity analysis largely remains subjective to researchers' intuition. But O'Donnell (2018) recommend TFP indices that satisfy the entire axioms (such as monotonicity, linear homogeneity, identity, commensurability, proportionality, and transitivity) of economic index number theory. These are often referred as proper indices. Based on O'Donnell (2018, 2022), Njuki et al. (2018, 2020), we follow the

[1] through the guidance of the following link: https://www.youtube.com/watch?v=96hvSiP6ANI

Table 1 Descriptive summary of output and input variables, 2010–2020

Variable	Region					p-value
	Berg ($N = 11$)	Hex ($N = 11$)	Northern ($N = 11$)	Olifants ($N = 11$)	Orange ($N = 11$)	
Output	(2,487,233)	19,699,212	5,343,822	3,067,497	17,761,663	< 0.001
	(2,487,233)	(2,041,422)	(1,441,838)	(791,979)	(2,061,422)	
Land	4144	5786	1546	1089	5231	< 0.001
	(703)	(842)	(628)	(261)	(667)	
Labour	33,112	32,304	32,035	30,240	27,459	0.2
	(6676)	(6513)	(6459)	(6097)	27,459(5536)	
Othercosts	195,065	(68,915)	190,901	176,950	(73,567)	> 0.9
	(73,708)	(68,915)	(72,063)	(66,903)	(73,567)	
Temperature	18.00	15.15	20.29	17.54	20.51	< 0.001
	(1.11)	(0.39)	(0.53)	(0.21)	(0.52)	
Rainfall	653	563	466	220	132	< 0.001
	(183)	(148)	(83)	(52)	(48)	

Source Author's calculation (2024). The output, land, labour costs and other costs are measured in 4.5 kg equivalent cartoons, hectares, and in South African rands, respectively. Temperature is measured in degrees celsius while rainfall is in millimeters per year. All the values are expressed as means, inside parentheses are standard deviations. p-value were derived from Kruskal-Wallis rank sum test

Cobb–Douglass stochastic frontier framework,[2] to decompose proper TFP index ($TFPI_{hs,it}$) into measures of technical progress index ($\frac{OTI_t^*}{OTI_s^*}$), environmental change index ($\frac{OEI_{it}}{OEI_{hs}}$), technical efficiency change index ($\frac{OTEI_{it}}{OTEI_{hs}}$), scale-and-mix efficiency change index ($\frac{OSMEI_{it}}{OSMEI_{hs}}$), and changes in statistical noise index ($\frac{SNI_{it}}{SNI_{hs}}$); expressed as:

$$TFPI_{hs,it} = \frac{OTI_t^*}{OTI_s^*} \times \frac{OEI_{it}}{OEI_{hs}} \times \frac{OTEI_{it}}{OTEI_{hs}} \times \frac{OSMEI_{it}}{OSMEI_{hs}} \times \frac{SNI_{it}}{SNI_{hs}} \tag{1}$$

The index presented in Eq. (1) measures the productivity of firm i in period t relative to firm h in period s, I stands for index and O indicates that the model adopts an output orientation approach. The OTI is output-oriented technology index, representing research and development (R &D) activities (O'Donnell, 2022, 2018). The OEI is output-oriented environment index,signifying changes in variables that are physically involved in the production process but beyond the control of table grape production managers, while $OTEI$ is output-oriented technical efficiency index and represents the managerial capacity or capacity utilization in table grape production (O'Donnell, 2018; Njuki et al., 2018) and $OSMEI$ represent the output-oriented scale and mix efficiency index translated as the potential benefits associated with changing the scale of operations and output mix in table grape production.

2

$$\ln q_{1it} = f^t\left(x_{it}, q_{it}^*, z_{it}\right) + v_{it} - u_{it}$$

where f^t is the approximating function, x q and z are respectively fixed vectors of inputs, outputs and environmental variables. The t is a fixed reference period for individual (i) table grape region, u_{it} is the inefficiency term, and v_{it}, accounts for functional form errors and other sources of statistical noise.

Table 2 Estimates of Cobb–Douglass Stochastic Frontier with inefficiency effects

Variables	Parameters	Estimates	SE	z-value	Sig
Constant	β_0	−2.78	1.19	2.34	0.02 *
Year	t	−0.05	0.02	−3.22	0.00**
Ln (temperature)	z1	0.09	0.03	2.91	0.00**
Ln (rainfall)	z2	0.34	0.20	1.64	0.10
Ln (land)	β_1	1.02	0.03	37.21	0.00***
Ln (labour)	β_2	−0.01	0.14	0.07	0.94
Ln (other cost)	β_3	0.35	0.17	2.05	0.04**
Sigma-Square	σ^2	0.11	0.06	1.88	0.06*
Gamma	γ	0.93	0.06	15.53	0.00***
Mu	μ	−0.65	0.43	−1.52	0.13
Log-likelihood function	LLF	31.95	–	–	–
Mean efficiency	θ	0.89	–	–	–

If the environmental change index and statistical noise index are discarded, the index collapses to Färe-Primont productivity index, novel to O'Donnell (2011) as follows:

$$TFP_{hs,it} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}}\right)\left(\frac{OSME_{it}}{OSME_{hs}}\right) \tag{2}$$

The first term on the right-hand side of Eq. (2) measures the change in maximum TFP over time. Thus, it is a measure of technical change. The second and third terms measure the technical, and scale-mix efficiencies. The specific details of fundamental assumptions regarding the method and models employed in this study are presented in O'Donnell (2011, 2012). But just to mention a few, the Stochastic Frontier Analysis (SFA) is a parametric approach that is based on a specific error-term distribution and production function. It estimates a model with deterministic and stochastic components and assesses technical, scale, and mix efficiency. Conventional econometric methods, such as Ordinary Least Squares (OLS), assume linearity, independence, homoscedasticity, and normality for errors. It is not necessary for OLS validity, but it is useful for defining finite-sample properties. For the purpose of our study, they were estimated using R software, specifically the packages developed by (O'Donnell, 2018). The results are presented in the next section.

4 Results

4.1 Estimates of Cobb–Douglass stochastic frontier

The estimates of parameters for Cobb–Douglass stochastic production frontier model are presented in Table 2. The coefficient of land is statistically significant at 0.001% level of significance. This indicates a direct impact of land and other costs on table grape production. However, land carries more contribution to output compared to other variables. This finding has serious implications for investor attraction strategy and land reform policy within the industry. In addition a unit increase in investment spending by incurring other costs is associated with 0.35%. The coefficient for variable year (t) suggest that the industry

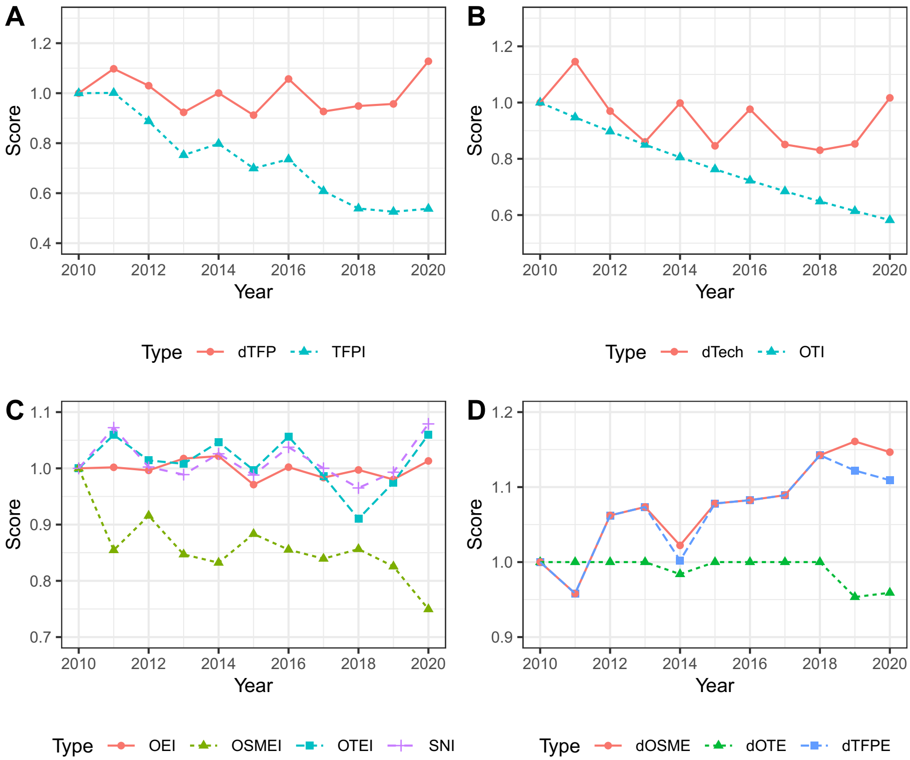

Fig. 3 The estimates of TFPI (TFP) for table grape industry, illustrated by four panels. Panel A provides a comparison of TFP estimated using the conventional approach (labelled dTFPI) with the proper index (labelled TFPI). A similar thing applies to Panel B, where dTech is estimated using the conventional approach while OTI is from the proper index. On the other hand, Panel C presents TFP components from the proper index, while Panel D presents the conventional approach

experienced an annual regress in technical change at a rate of 0.05%. In the inefficiency effects model, the positive for environmental variable is interpreted as negative and vice-versa. So, the coefficient of variable temperature is statistically significant at 0.01% indicating that a unit increase in temperature is associated with 0.09% decrease in table grape output. As expected, variable rainfall is statistically insignificant, a possible explanation for this could be the fact that these regions are not dependent of rainfall for table grape production.

Sigma-Square is positive indicating that the output differs due to factors which are within the controls of table grape regions. Variable gamma is analogous to R^2 and show strong goodness of fit for our analysis. Finally, the mean technical efficiency of 0.89 suggest that there is room to improve on efficiency without changing the inputs by 11%.

4.2 The TFP estimates for South African table grapes

Over the study period, we observed a negative TFPI annual growth rate of 4.29%, with Orange River and Hex River experiencing the largest decline of 6.62% per annum, whilst Olifants River experienced the smallest decline of −1.24% per annum. Technical regress

Table 3 Regional productivity growth estimates, 2010–2020

Region	TFPI	OTI	OEI	OTEI	OSMEI	SNI
Berg	−4.60	−4.80	0.48	1.69	−3.45	1.58
Hex	−6.62	−4.80	0.28	0.72	−4.03	1.20
Northern	−2.38	−4.80	−0.05	−0.75	4.55	−1.13
Olifants	−1.24	−4.80	−0.06	0.33	2.10	1.34
Orange	−6.62	−4.80	−0.09	0.74	−2.98	0.45
Region	TFP	TECH	TFPE	OTE	OSE	OME
Berg	0.56	0.15	0.41	0.00	0.54	0.00
Hex	0.15	0.15	0.00	0.00	0.00	0.00
Northern	3.96	0.15	3.80	−2.06	−0.31	0.00
Olifants	4.46	0.15	4.30	0.00	−0.42	0.00
Orange	0.58	0.15	0.43	0.00	0.28	0.00

(OTI) estimated at an average of 4.80% contributed to the overall decline in TFP for industry see the comparison of panel A and B in Fig. 3. This suggest that growth was curtailed by regress in innovation of new techniques, systems and processes to transform inputs to output. However, this finding matches those presented earlier in Table 2 regarding the coefficient of variable year (t). This observation is similar to the finding regarding OEI at an average of 0.14%, suggesting that weather effects had the smallest impact on productivity compared to other constituents. This is evident in panel C of Fig. 3, where the trend of environmental index is almost flat over the study period. We discover an average growth of productivity (dTFP) at 4.14% per annum when environmental index and statistical noise are discarded. This implies a huge gap between the two index approaches, which continues to expand over time as depicted in Panel A of Fig. 3. Regardless of the index approach the overall findings show that changing the scale of operation and output mix promote productivity in the table grape industry in South Africa (see Panel C and D). But technical change consistently inhibits growth over the study period.

We also analyse the results in Fig. 3 by focusing on different subperiods. The pre-drought period (2010–2016) witnessed significant decline in TFPI by 22.6% followed by 16.8% during drought period. Cumulatively, this suggests an average of 39.5% decline in productivity (TFPI). But this is contrary to an average TFP growth of 0.3%, estimated using conventional index (dTFP), arising from 4.0% in pre-drought period and −12.1% during drought period. As anticipated, the adverse effects of weather conditions (OEI) led to an average decrease of 0.5% in TFPI during the drought period. This demonstrates the significant impact that environmental factors can have on productivity.

4.3 Estimates for Table grape regions

In this section, we conduct a detailed spatial analysis of Total Factor Productivity (TFP) growth and its components across the five table grape-producing regions. We delve into the specifics of productivity growth within the table grape industry, taking into account the effects of weather conditions, and present our findings for each region in Table 3. From a Färe-Primont index perspective the efficiency change (TFPE) emerged as growth promoter for the regions except in Hex River Valley. This is quite different when viewed from Proper

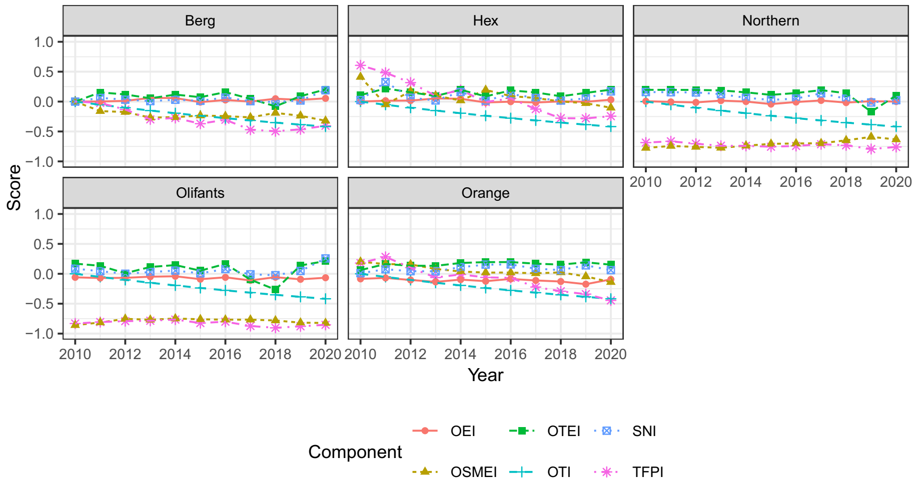

Fig. 4 Annual TFPI comparisons for selected regions with Berg River Valley in 2010

index perspective. For instance, Hex River Valley and Orange River Valley were the worst performing regions with TFPI averaging −6.62% per annum for both regions. These were followed by Berg River Valley at average of −4.60% per annum. This inhibition of growth was influenced by OTI, averaging −4.80% in all the regions. However, the OSMEI was the single most TFPI constituent sustaining growth in Northern Provinces and Olifants River Valley. Contrary to our expectation, OEI was found to promote growth in Berg River Valley and Hex River Valley. However, the inhibiting effect of OEI was very small compared to other components of TFPI in Northern Provinces, Olifants River Valley and Orange River Valley. Expect for Hex River Valley, the table grape region showed improvement in managerial capacity evident from the results of OTEI. Overall the findings suggest that the growth (TFPI) was undermined by the decline in technological innovation (OTI).

Figure 4 compares the results of Proper index approach for selected regions between 2010 and 2020 with values for Berg River in 2010. It is clear from the results that Hex River Valley (0.61%) and Orange River Valley (0.18%) were more productive in 2010 compared to Berg River Valley during the same period. The improvement in scale-mix efficiency was the driving factor. This finding was expected because Hex River Valley and Orange River Valley are regarded as older regions and are likely to consist of farmers with high experience, greater adoption rates for new technology, and fewer mistakes committed in the production process. However, the opposite is also true when Berg River Valley in 2010 is compared to Olifants River Valley (−0.83%) and Northern Provinces (0.18%) during the same period. The former is the smallest table grape region whereas the latter (Northern Provinces) tends to be very humid which is not the best climate for table grapes to thrive. The overall findings suggest that OSMEI and OTI were the main contributing factors driving the annual productivity change for table grape regions. While climate variability (OEI) along with water rights remain a challenge in table grape industry, it appears that they are a less problem compared to aforesaid contributing factors. Using the results for Orange River and Berg River in 2020, we can compare them directly as follows: on average, the farmers in Orange River were less productive than those in Berg River farmers. The deterioration of production environment arising from climate variability and less technological innovation were drives of decline in productivity growth.

5 Discussion

This study sought to assess total factor productivity growth in the South African table grape industry, including its various components. It also investigated the effect of weather on this growth. We carried out the analysis using two index approaches for comparison: conventional and proper indexes. Both approaches provide different estimates of productivity, but the weather contributed positively at an average of 0.11% per annum. This corroborates Njuki et al. (2020) discovering 0.13% contribution of observed and unobserved environmental factors to productivity changes in U.S. dairy farms, but contrary to Lachaud et al. (2017), reporting an inhibiting effect of weather ranging from 0.02 and 22.7% in Latin American and Caribbean countries between 1961 and 1999. The weather effects on productivity of each table grape region are heterogeneous, with Berg River and Olifants River experiencing the largest effect. This observation was also discovered by O'Donnell (2022) regarding the weather effects on agricultural productivity of various states in America.

Our findings of Proper index show that productivity declined over the study period, supporting Sellers-Rubio et al. (2016) regarding their Malmquist productivity rate of wineries in Spain and Italy between 2005 and 2013. Similar to Conradie et al. (2019) we discovered that the decline in productivity was due to regress of technical change. But this is opposed to Sellers-Rubio et al. (2016) who finds efficiency change to exact an inhibiting effect on growth. However, the same study (Sellers-Rubio et al., 2016) confirms our findings from the perspective of Färe-Primont index. Nonetheless, the findings of Proper index illustrating the decline of productivity are worrisome given that the table grape industry continues to benefit from statutory levy funds, earmarked for promotion of productivity.

Regardless of index method employed our study consistently found positive influence of scale-mix efficiency on productivity of table grapes. This finding aligns with Tozer and Villano (2013) who maintains that residual mix efficiency may indicate that most farmers modified their input mixtures to account for varying seasonal conditions. As oppose to some table grape efficiency studies (dos Santos et al., 2020; Aparicio et al., 2013; Coelli & Sanders, 2013), we discovered that managerial effects also contributed positively (except in Northern Provinces) to the productivity growth in table grape industry over the study period. But this varies according to table grape region and period. For instance, the results of pre-drought period (2010–2016) derived from proper index approach show significant decline in productivity growth due to technical change. On the other hand, Färe-Primont results show an increase of 4% due to a rise in efficiency change. The findings for the latter can be attributed to high demand for seedless varieties from Africa, Far East and Russia coupled with strong returns and successfully implementation of transformation initiative by the industry (SAGTI, 2021, 2017, 2015).

During the drought period (2016–2018) the industry experienced the greatest decline in total factor productivity. These findings from 2015 confirm the negative impact of the worst drought in a century, which affected the bunch weight, berry size, and colour development. The drought was at its peak, resulting in Level 6 water restrictions in Western Cape, which led to a decrease in TFP in 2017 and 2018 (SAGTI, 2019). However, in the post-drought period, the industry began to experience an increase in TFP, with technological advancement playing the largest role. This period coincided with the arrival of winter rains, which allowed the vines to recover sufficiently from the drought's effects. The 2019/2020 season was unaffected by COVID because the pandemic arrived after farmers had completed harvesting, resulting in an increase in TFP (SAGTI, 2020).

Region-wise, the proper index results reveals significant decline in TFP for all table grape regions during the whole period. Several factors can be ascribed to this finding. For instance, SAGTI (2011) reports flood problem in early producing regions (Northern Provinces and Orange River), increase in oil price due to political instability in North Africa and Middle East, rising cost of electricity and local currency gaining more strength as factors that emerged from the beginning of the period of study (2010/2011 production season). Despite improvement in the next season, the intakes decreased by 9% compared in 2012/2013 season due to rain and hail storms, which affected the product during the season (SAGTI, 2014). For the next three production season the industry was plagued by drought (SAGTI, 2018, 2019). Because the Northern provinces are located outside of the Cape provinces, they were not affected by drought, hence the positive gain in productivity (SAGTI, 2018). However, in post-drought period most regions have been recovering. Taken together, these finding suggest that the industry needs to invest on measures that counteract the climate change crisis. The alternative method (Färe-Primont) show that older regions (Berg River and Hex River Valley). This can be attributed to the fact that older regions are likely to be characterised by farmers with high experience and advanced technology adoption, hence the high performance. During the drought, all five regions experienced negative TFP, with the older regions bearing the brunt of the impact. Western Cape water restrictions and high tariffs contributed to high production costs. Overall, the drought had an impact on the quantity and quality of grapes, including berry size, weight, and colour development SAGTI (2017, 2018, 2019); hence inhibiting TFP growth.

Despite, the small sample size due to data constraints, the outcome of the study provides empirical evidence concerning the impact of weather effects on productivity in South Africa. It also illustrates the importance of taking various types of heterogeneity into consideration when analysing productivity. These types of heterogeneity include the level of R &D support (Salim & Islam, 2010), environmental conditions for production, trade experience (Khan et al., 2017), and prices of inputs and outputs (O'Donnell, 2012). The study should be replicated in other agricultural industries in South Africa while incorporating the effect of emissions.

6 Conclusion

This paper was undertaken to evaluate productivity growth using comparison of two index approaches with special emphasis on weather effects. We employed panel dataset for five table grape regions over a period of ten years. The results highlight that varying methodologies can lead to different productivity estimates. However, the results strongly support the necessity of separating environmental and noise effects when evaluating productivity growth. The most notable observation was a decline in productivity throughout the study period, attributed to a regression in innovation and technology. This observation suggests two potential implications. Firstly, the industry may lack sufficient funding for research and development. Secondly, the allocation of existing research funds may not be appropriate. In this instance, the government should provide more financial support for the industry to drive research and innovation. This could also be matched by creation of enabling economic environment that enables investor confidence to the industry. On the other hand, in instances where growth has been achieved it was ascribed to improved scale of operation, output mix and input management. The research has also shown that productivity estimates vary with time, geographic location, weather and prevailing economic conditions. This implies that accounting for heterogeneity in productivity analysis is important to produce meaningful results that can effectively aid policy design. As a result, the understanding gained here should assist table grape industry to customise formulating policy and sustainable development strategies towards better regional impact. Notwithstanding the relatively limited sample and period of study arising from data constraints, the study has successfully uncovered the impact of weather effects on productivity and significance of considering various types of heterogeneity. Therefore, regulating the impact of economic activities on natural environment, investment in new technologies such as drought-resistant cultivars and water-saving techniques, as well as promoting their adoption, would be crucial for the future of the grape industry.

Future research should, consider farm-level data to better comprehend the factors that influence regional productivity, and link satellite monitoring data with orchard-level data to assess the impact of climate change.

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Data availability The dataset used for this study will be made available upon request.

Declarations

Conflict of interest The authors declared no conflict of interest.

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