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Evaluating input use efficiency in agriculture through a stochastic frontier production: An application on a case study in Apulia (Italy)

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ABSTRACT

Water is considered the most critical resource for sustainable agricultural development worldwide. Water scarcity has become an issue, especially in arid and semi-arid areas. There is the need to develop efficient management options to reduce water consumption and waste. In order to measure irrigated crop technical efficiency, a stochastic frontier production method – in which the inefficiency component is heteroscedastic – is used with the aim to assess what crop type and production technique revealed highest efficiency. The model is applied to a case study in southern Italy by using 2016 data from the EU Farm Accountancy Data Network. Our results show that the assumption of heteroscedasticity in the one-sided error term in the stochastic frontier is valid: individual farms' characteristics critically influence technical efficiency. Processing tomato is the most efficient crop production system; organic farms tend to have a lower level of technical efficiency compared to conventional farms; and fertigation system is found to increase the level of technical efficiency.

1. Introduction

Achieving efficient food production while ensuring sustainable input use is already a formidable challenge in a context of increasing urbanization and industrialization but it will be further exacerbated by climate change which will affect crop productivity, reducing water availability and changing its seasonal distribution (Lipper et al., 2017). Agricultural food production must grow by 50% before 2050 to meet increasing food demand (FAO, 2017). The agricultural sector is already responsible for 70% of global water demand and water availability is expected to decrease by 40% by 2030 due to increasing pressures (Foley et al., 2011). Water is considered the most critical resource for sustainable agricultural development worldwide (Pereira et al., 2009), especially in the context of climate change given the expected impact of rainfall changes on harvests' reliability and production's efficiency (Zhang et al., 2018). Furthermore, compared to other uses, water used in agriculture tends to have lower returns (Young, 2005).

Efficient agriculture water management through improved water use efficiency or enhanced agricultural water productivity is a critical response to growing water scarcity (Deng et al., 2006), including the need to leave enough water in rivers and lakes to sustain ecosystems and to meet the growing demands of cities and industries (Sharma et al., 2015). This is particularly true in arid and semi-arid areas where, according to the World Water Development report on climate change, water supply has become a major challenge, and important trade-offs exist in the use of water resources (Haddeland et al., 2014). Considerable efforts have been made in order to introduce policies aiming at increasing water efficiency based on enhanced water management (Scott et al., 2014).

This paper focuses on vegetables production in southern Italy. According to the World Bank, irrigated agriculture in Italy in 2013 covered about 19% of useable farmland and used 2/3 of available water resources (Massarutto, 1999). Irrigation is a critical issue in Southern Italy due to: high value of fresh fruits and vegetables production (Guzmán et al., 2009); high water requirements for irrigated crops; decreasing water availability; and climate, which is classified as semi-arid using the FAO UNEP aridity index (Costantini et al., 2013). We look at the specific case of the Sud Fortore Area of Capitanata Consortium in the Apulia region of Italy where parsimonious and efficient water use is necessary (Giuliani et al., 2017) due to high competition for scarce water resource.

In this context, this paper aims at measuring the input-specific technical efficiency of irrigated crop production and identify its determinants, giving emphasis on the use of water as input factor in agricultural production. Water efficiency is proposed as a key element of water resources planning and management under scarcity. We use a stochastic frontier approach developed by Aigner et al. (1977), which estimates the maximum output attainable given a set of inputs (Greene, 1993), both controllable (e.g. inputs used in the production process) and not controllable (e.g. climate change or soil properties).

Despite recent concerns on the stochastic frontier approach on technical efficiency (Parmeter and Kumbhakar, 2014), this method

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has become widely applied in econometric analyses (Pereira and Marques, 2017; Kumbhakar, 1993, 2002; Jaenicke et al., 2003). The stochastic approach adopted allows us to incorporate the one-sided component error which reflects inefficiency, and the two-sided error which captures the random effects outside the control of the production unit, such as climate change. The use of the stochastic frontier approach allows a deeper investigation into the presence and magnitude of firm inefficiency (Parmeter et al., 2017).

The paper is innovative from various points of view. First, only a small number of studies focused on the efficiency (9% of the reviewed studies) through the stochastic approach (Pereira and Marques, 2017) in this context. Second, we look at the input-specific technical efficiency of irrigated crop production in horticulture farms using a unique dataset which reports detailed observations at plot level. We therefore suggest a stochastic model in which the inefficiency component is heteroscedastic in the measurement of technical efficiency in the sampled farms. Third, the heteroscedastic frontier model enables us to consider the effect of farms' characteristics on the efficiency, e.g. crop type, organic production, fertigation use and management type, also drawing some specific indications on water use efficiency. These variables are outside farmers' control and can greatly influence harvest volumes (Van der Vlist et al., 2007; Loureiro, 2009). Overall, this paper can give an important contribution to the current debate on the efficient use of water resource in agriculture.

The rest of the paper is organized as follows. Section 2 presents a literature review on indicators and studies related to water efficiency management. In Section 3 we describe data and method used. Section 4 reports the results and the discussion. Conclusions are reported in section 5.

2. Literature review

The concept of Technical Efficiency (TE) in agriculture production relates to obtaining crop yields by minimizing inputs use giving the existing technology. Coelli et al. (2002) defined TE as "*the ability of the farm to use feasible amounts of inputs to produce a given level of output*". Inputs include: labour, fertilizers, pesticides, machinery, seeds and water for irrigation (Greene, 1993). In the case of single output, the total factor productivity is the ratio of the actual output and the optimal ones as specified by a "production function" (Greene, 1993). The concept of TE through the frontier production function models (Battese, 1992) has been applied in a considerable number of studies in agriculture (Watto and Mugera, 2015; Hong and Yabe, 2017; Khanal et al., 2018). Agricultural technical efficiency evaluation, and in particular water use efficiency assessment at farm level have been studied among researchers by proposing different methodologies and strategies. As regards the irrigation efficiency concept, we refer here to the farm ability to use a certain amount of water in order to produce a given level of output (Coelli et al., 2002).

A first approach to measure technical efficiency of irrigated crops is related to the water use efficiency (WUE) and irrigation water use efficiency (IWUE) indicators. The term water use efficiency (WUE) refers to a non-dimensional output/input ratio. It is used to measure water performance of irrigated or non-irrigated crops, to produce biomass and/or harvestable yields (Pereira et al., 2012). WUE is generally defined in agronomy as crop yield per unit of water used to produce the yield. Usually WUE has unit of kg/m^3 (Howell, 2001). Moreover, to measure water productivity, we referred to the irrigation water use efficiency (IWUE) indicator, that may be generically defined as the ratio between the actual crop yield achieved (Ya) and the water use, expressed in kg/m3. The denominator may refer to the total water use (TWU), including rainfall, or just to the irrigation water use (IWU). In our case, we referred to the latter. These indicators provide useful information for any process or system involving water, for irrigation or other uses, to make a more efficient water use (Molden et al., 2010).

Various studies have focused on indicators related to WUE (Howell, 2001; Molden et al., 2010; Pereira et al., 2012). The concept of water efficiency is also linked to water productivity (WP) which was proposed by Kijne et al. (2003) as a robust measure of the ability of agricultural systems to convert water into food. As a general principle, water productivity is the ratio of the net benefits from crop, forestry, fishery, livestock and mixed agricultural systems to the amount of water needed to produce such benefits (Battese, 1992). It reflects the objectives of producing more food, income, livelihood and ecological benefits at less social and environmental costs per unit of water consumed. The denominator is expressed in terms of water supply or water depletion. More specifically, physical water productivity is defined as the ratio of agricultural output to the amount of water consumed (Perry, 2011), while economic water productivity is defined as the value derived from each unit of water used. The latter has also been used to relate water use in agriculture to nutrition, jobs, welfare and the environment. Unfortunately, considering only WUE indicator could be a misleading measure because it assumes that yield is produced by a single input (water), while it is the effect of the combination of multiple inputs (Coelli et al., 2002; Wang et al., 2010).

Researchers have therefore analysed technical efficiency of irrigation water use by considering different methodologies and approaches, while controlling for the contributions of multiple inputs (Karagiannis et al., 2003; Speelman et al., 2008). Several studies focused on the stochastic frontier analysis (SFA). Villano and Fleming (2006) apply the SFA methods to rice production in the Philippines, while Tang et al. (2015) focused on both technical and allocative efficiency in China. Yigezu et al. (2013) measured efficiency in irrigation water use in Syria by using a SFA model. To determine the efficiency of small farmers in Ethiopia, Battese and Corra (1997) apply SFA with heteroscedastic error terms. The same model specification has been used by Kumbhakar (1993, 2002) to evaluate the efficiency and risk preferences of Swedish dairy farms and Norwegian salmon producers; and by Jaenicke et al. (2003) to compare technical efficiency and risk in different cotton cultivation systems. Dhehibi et al. (2007) applied to citrus production in Tunisia a stochastic production frontier approach, based on Battese and Coelli (1988) inefficiency effect model, obtaining farm-specific estimates of technical and irrigation water efficiency.

Other studies looked at the contribution of multiple inputs and outputs by using the data envelopment analysis (DEA), proposed by Charnes et al. (1989) which is based on non-parametric technical efficiency models.[1] Lilienfeld and Asmild (2007) considered the irrigation system in the irrigation efficiency analysis, concluding that management and field techniques are important components of water use efficiency at the farm level. Gadanakis et al. (2015) provided a

[1] DEA is a deterministic method and thus the results are affected by extreme observations (Ramanathan, 2003) and furthermore, the sensitivity of this method is affected by the number of observations as well as to the dimensionality of the frontier (Pereira and Marques, 2017). Despite numerous studies applied the Data Envelopment Analysis (DEA) to measure productive efficiency (see among others Agovino et al., 2018), in this paper one of the main advantages of the Stochastic Frontier approach compared to the non-parametric techniques is that it easily accommodates the various 'environmental' factors influencing efficiency, the quality of inputs and other contextual variables, thus allowing for a precise measurement of farm efficiency (Laureti et al., 2014).

benchmarking tool to assess water use efficiency at farm level, by using data on 66 horticulture farms across England.

Due to increasing concerns over the impact of agriculture on the environment, it is also important to assess the influence of production practices on various aspects related to water use. Agrochemicals can cause water pollution (Molden, 2013). In order to overcome the problem of environmental degradation, organic agriculture practice has emerged allowing for the reduction of chemical inputs. Even if organic agriculture is perceived as environmentally sustainable, it is important to underline that this definition includes different production systems. Results obtained from Iocola et al. (2018), pointed out that not all the organic vegetable systems are agro-environmentally sustainable. Besides, Seufert et al. (2012) focused on crop yield, concluding that yields from organic systems are on average 25% lower than conventional. Fertilization can have controversial effects as well, causing water pollution. Among other solutions, the use of fertigation could constitute a solution to increase crop production and ensure efficient water use (Mahajan and Singh, 2006; Chaichi et al., 2015). A study conducted by Groenveld et al. (2018) used data at plot level to determine the optimal irrigation rate for fertigated crop: its results can be used to optimize irrigation at different levels of nitrogen concentration.

3. Materials and methods

3.1. Methodology

We looked at production efficiency using a stochastic production frontier as proposed by Aigner et al. (1977). This approach relies on the fact that deviations from the production "frontier" might not be entirely under the control of the farm and external events may lead to inefficiency.

A frontier model for cross-sectional data can be written as follows:

$$y_i = f\left(x_i;\beta\right) \cdot exp\left\{-u_i\right\} \cdot exp\left\{v_i\right\}. \tag{1}$$

where y_i denotes the output for the ith farm (i=1,…, N). $f(x_i;\beta)$ represents the production function, where $\boldsymbol{x}$ is the vector of the inputs used and $\boldsymbol{\beta}$ is the vector of the estimated technological parameters. Assuming a log-linear form for the $f(x_i;\beta)$, the stochastic frontier can be expressed as:

$$\ln \quad y_i = \ln f\left(x_i;\beta\right) + v_i - u_i \tag{2}$$

In this specification, the disturbance term is defined by $\varepsilon_i = v_i - u_i$.

The first term v_i captures the effect of statistical noise. These components are assumed to have a normal distribution with zero mean and constant variance, $iid \sim N\left(0;\sigma_v^2\right)$.

The second term u_i is associated with the technical inefficiency; it is assumed to be independently distributed of v_i and non-negative random variables, $u_i \geq 0$.

The one-sided components u_i are assumed to be heteroscedastic and to follow a half-normal distribution, with the following probability density function:

$$f\left(u_i\right) = \frac{2}{\sqrt{2\pi\sigma_{u_i}^2}} exp\left\{-\frac{u_i^2}{2\sigma_{u_i}^2}\right\} \tag{3}$$

$$\text{where} \;:\; E\left(u_i\right) = \sqrt{\frac{2}{\pi}}\sigma_{u_i} \text{ and } \; Var\left(u_i\right) = \left[\frac{\pi-2}{\pi}\right]\sigma_{u_i}^2. \tag{4}$$

The set of inputs specified in the technical production function $f(x_i;\beta)$ includes factors such as: land, water used and hours of human and machinery. Regarding the specification of an appropriate production output, crop yields obtained during the period have been analysed.

The homoscedasticity assumption of the random effects v is justified since these factors influence the farms' production output with the same degree of dispersion. In the heteroscedastic specification, adopted here, the parameters $\sigma_{u_i}^2 = g\left(z_i;\delta\right)$ vary as a function across units as a vector z_i of variables. For each production unit, inefficiency could derive by an incorrect allocation of inputs and by the effects of other factors z_i which are exogenous to the production process but influence the efficiency level. More specifically, we can assume that exogenous variables, such as farms' specific characteristics (among others: size of the farm, age of the manager, type of soil, management type, organic production process or use of fertigation system, irrigation system, etc …) have an influence on achieving the optimum output. In order to explain the heteroscedasticity assumption, it is worth to note that among sample farms there is a strong heterogeneity on these exogenous dimensions. For this reason, inefficiency changes according to variation among farms, due to the variance of the half normal random variable.

The marginal density function of the composed error term on u and v, f (εi), is a density of a scaled skewed normal distribution (Domınguez-Molina et al., 2003). When there is heteroscedasticity on the one-sided error term, the density function becomes:

$$f_i\left(\varepsilon_i\right) = \frac{2}{\sigma_i}\varphi\left(\frac{\varepsilon_i}{\sigma_i}\right)\left[1-\Phi\left(\frac{\varepsilon_i\lambda_i}{\sigma_i}\right)\right] \quad -\infty<\varepsilon_i<\infty \tag{5}$$

Where $\sigma_i = \left(\sigma_{ui}^2 + \sigma_v^2\right)^{1/2}$, $\lambda_i = \sigma_{ui}/\sigma_v$, φ and Φ are the probability density and the distribution functions of a normal random variable, respectively.

The distributional assumption required for the identification of the inefficiency term implies that this model is usually fit by maximum likelihood (ML). For a sample of n-producers the log-likelihood function $lnL\left(y\middle|\beta,\lambda,\sigma^2,\delta\right) = \sum_{i=1}^{n} \ln\left[f_i\left(\varepsilon_i\right)\right]$, can be written as:

$$lnL\left(y\middle|\beta,\lambda,\sigma^2,\delta\right) = constant - \frac{1}{2}\sum_i ln\left[g\left(z_i;\delta\right)+\sigma_v^2\right] + \sum_i ln\Phi\Big(-$$

Where $\sigma_i^2 = \sigma_v^2 + g\left(z_i;\delta\right)$ and $\lambda_i = \frac{\sqrt{g(z_i;\delta)}}{\sigma_v}$.

A generalization of the log-likelihood (Aigner et al., 1977) can be expressed as:

$$lnL\left(y\middle|\beta,\lambda,\sigma^2,\delta\right) = constant - n\ \ln\ \sigma + \sum_i \ln\left[1-\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right] - \frac{1}{2\sigma^2}$$

In order to obtain the estimates of $\beta, \delta\ and\ \sigma_v^2$ the log-likelihood can be maximized.

We use the functional form suggested by Harvey (1976) in order to implement the Maximum Likelihood (ML). This model is expressed by $\sigma_i^2 = \sigma^2 exp\left(z_i;\delta\right)$. When the vector z includes constant, it can be reduced as $\sigma_i^2 = exp\left(z_i;\delta\right)$. In order to obtain individual technical efficiency, we use the Battese and Coelli (1988) estimator by using $E\left\{exp(-\mu|\varepsilon\right\}$. This measure has necessary value between 0 and 1.

3.2. Data and case study

We use data extracted from the Farm Accountancy Data Network (FADN)[2] dataset for the year 2016. FADN surveys are carried out annually at European level by Liaison Agencies of each state member of European Commission. The overall EU sample covers approximately 80.000 holdings. They represent a population of about 5.000.000 farms in the EU, which covers approximately 90% of the total utilised agricultural area (UAA) and account for about 90% of total agricultural production. The set of units under observation consists of all agricultural holdings of at least 1 ha of UAA or whose production has a value amounting to least 2500 euros. The dataset includes physical, structural, economic and financial data for each farm.

The advantage of using the FADN dataset is that information is available for the following dimensions: time (year), location (country, region), farm typology (type of farm activity, and economic size). For these reasons, the results based on the specific case study discussed in this study may be replicable and generalizable in other agricultural districts with different characteristics in term of crop type, soil typology and other factors related to farm location and climatic conditions. The comparability among different case studies would allow drawing specific policy implications.

We focus on the Sud Fortore Area of the ‘Capitanata Irrigation Consortium’, located in the Northern part of the Apulia region of Southern Italy. The study area is characterised by a semi-arid climate and water scarcity (only 45% of the area is irrigated). The agricultural system in the area is largely affected by weather fluctuations and climate changes. As found by Capitanio et al. (2015), such characteristics have contributed to the development and acceptance of a specific public intervention system aimed at reducing income variability in a context of climatic risk.

The Capitanata Consortium is one of the most important irrigated areas in the Mediterranean region both for expansion of the area cropped and the quantity of water used in agriculture. The ‘Sud Fortore’ district is an intensively cultivated area. Main crops include durum wheat, tomatoes, and other fresh vegetables (e.g. asparagus, leaf beet, cabbage, chicory, spinach). They are often grown in very large farms which use innovative technologies and intensive irrigated methods. The area is characterised by flat cropland, highly productive soils and semi-arid climate with hot and dry summers (annual rainfall is about 550 mm, within 60–80 days per year) and short and temperate winters, (Rinaldi et al., 2011; Bettini, 2016). Irrigation is an essential component of production for many farmers to support crop diversification, and to ensure good and high-quality yields (Pellegrini et al., 2016; Autorità di Bacino della Puglia, 2004). Water is supplied from large artificial reservoirs and wells with pressurized on demand distribution system (Ronco et al., 2017)”. In addition to the effect of irrigation, the production process is significantly influenced by the environmental parameters which nowadays can be effectively monitored by means of ubiquitous computing technologies (Aiello et al., 2011).

To evaluate efficiency of irrigated crop production in the case study, we have selected a sample of 114 horticultural plots covering 1160.77 ha of irrigated land. A map of the analysed area is reported in figure 1. For each farm, we considered the type of crop cultivated in each plot in order to obtain information on the input use at single plot level. We use the parametric approach by considering each plot as a Decision-Making-Units (DMU).

3.3. Model specification

We focus on high water demand crops, such as: processing tomatoes, table tomatoes, broccoli, zucchini, chicory, potato, fennel, pepper, aubergine, green beans and cucumber. These crops represent 92.5% of the total horticultural production in the case study area.

Inputs considered include: irrigated land measured in hectares (ha), water used for irrigation measured on a volume basis (m^3/ha), human labour and machinery measured in number of hours per hectare (hours/ha). Crop output is measured in tonnes per hectare (ton/ha).

Fertilizers, seeds and pesticide are input variables in the production function (Pereira and Marques, 2017). Unfortunately, in order to avoid model misspecification, we cannot include them in the analysis, due to the unavailability of crop and plot-level data, since they are collected at farm level, without distinction on the crop types.

On the contrary, we could include farms’ specific characteristics which are mainly related to water quality. In particular, we control for organic agriculture practices and the use of fertigation system. In our study we also control for crop type and management and its influence on farm technical performance and the optimum output. The irrigation system typology is not considered as a source of inefficiency because all farms use the same irrigation system.

The estimation of the heteroscedastic production frontier is sensitive to model specifications (Wang, 2003; Liu et al., 2006). In this study, in order to explore the issue of heterogeneity, we followed the approach explained by Laureti et al. (2014) in which they used models to account for observed and unobserved factors which generate heterogeneity in the efficiency of teaching activities of Italian universities. With reference to the literature available on the production possibilities structure and after preliminary analysis, the production technology has been specified as a Cobb-Douglas production frontier (Fried et al., 2008). Such a choice of the functional form is connected to the shape, values of the elasticities of factor demand and factor substitution. The Cobb-Douglas production function is widely used because this production function has universally smooth and convex isoquants (Fried et al., 2008). This model relaxes the restrictions on demand elasticities and elasticities of substitution. Furthermore, it is less susceptible to multicollinearity than the possible alternative translog function (Laureti, 2008).

[2] The Farm Accountancy Data Network (FADN) is a European system of sample surveys conducted every year to collect accountancy data from farms, with the aim of monitoring the income and business activities of EU agricultural holdings. The FADN is an important informative source for understanding the impact of the measures taken under the Common Agricultural Policy on different types of agricultural holdings. http://ec.europa.eu/agriculture/rica/publications_en.cfm.

Based on the results provided from a generalised likelihood ratio test, a Cobb–Douglas specification has been chosen. The Cobb–Douglas production function involves the estimation of less parameters than the translog functional form. This facilitates the results interpretation. On the contrary, the presence of quadratic and interaction terms in the translog form complicate results interpretation (Felipe, 1998; Johnes and Johnes, 2009).

As regards the one-sided error term, we choose the half-normal distribution because this model satisfies the scaling property. As noted by Wang and Schmidt (2002) and Alvarez et al. (2006), the scaling property allows to isolate the effect of farms' characteristics and throughout the production process. With the scaling property, u is distributed as $\sigma_{u_i}^2 = exp\left(z_i;\delta\right)$ times a half normal $N^+(0;1)$. The level of efficiency depends on the random variable u and on the $exp(z_i;\delta)$. This property consists of essentially to stretch or shrink the horizontal axis, so that while the scale of the u distribution changes, its underlying shape does not .

4. Results and discussion

4.1. Results

Processing tomato is the main crop production in the case study area (Fig. 2).

Table 1 reports the sample descriptive statistics with reference to the variables chosen as proxies of the main factors of production considered in the production frontier, namely land, labour, capital and water. The indicator related to the irrigated water use (IWU) shows higher value for pepper (62,345.8 m^3/ha) and green beans (57,159.8 m^3/ha), indicating that such crops are most water demanding. However, when considering Water Use Efficiency (WUE), i.e. the ratio between crop yields (kg/ha) and water used for irrigation (m^3/ha), such crops show the lowest level of water efficiency, i.e. 0.22 and 0.44, for green beans and pepper, respectively. On the contrary, processing tomato shows the highest level of water efficiency (5.01), together with the highest production level (93,239 kg/ha).

Table 2 shows the distribution of the sample farms' individual characteristics included in the u term of the heteroscedastic frontier

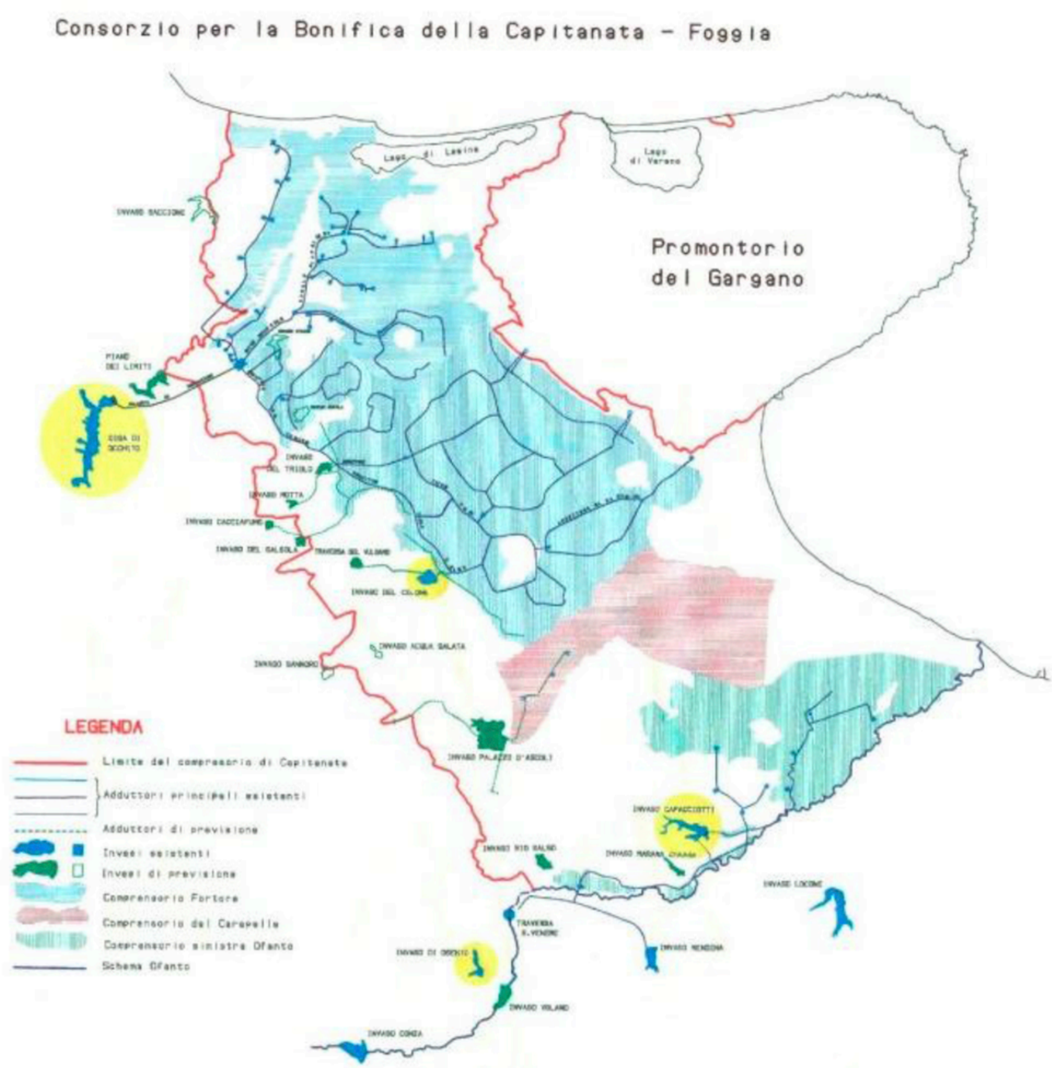

Fig. 1. Map of the Apulia region included in the studied area of the Capitanata Consortium.

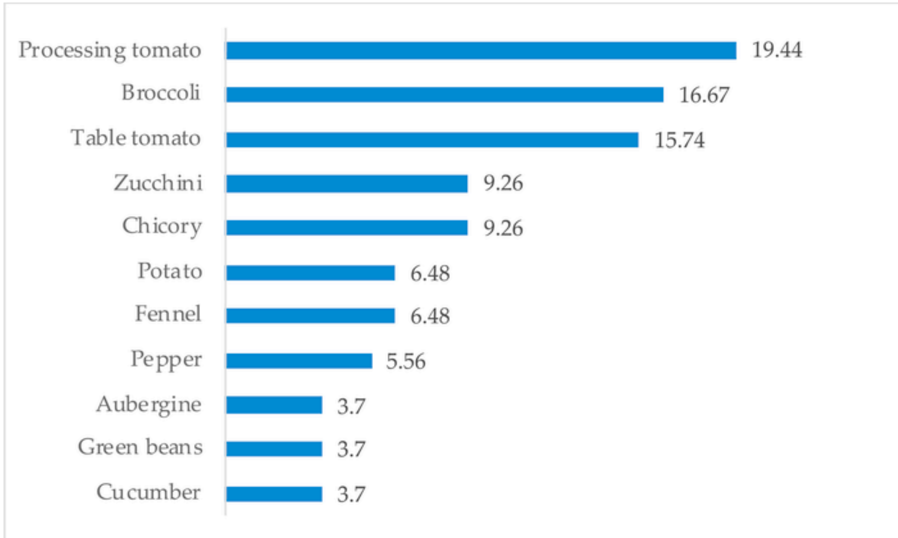

Fig. 2. Horticulture production in the case study area (% of land). Source: authors' elaboration from FADN 2016 data.

Table 1
Inputs and output in horticulture production in the case study area and water use indicators: descriptive statistics by crops.

Crop		IWU	Yield	Irrigated Land	Labour	Machinery	WUE
		m^3/ha	kg/ha	ha	Hours/ha	Hours/ha	Yield/IWU
	n	mean	mean	mean	mean	mean	kg/m^3
Broccoli	18	15,547.0	12,960	11.6	270.3	43.8	0.83
Cucumber	4	30,260.0	41,621	3.2	1886.9	67.7	1.38
Chicory	10	12,381.9	18,308	7.3	346.8	25.2	1.48
Green beans	4	57,159.8	12,799	2.8	3,770.4	137.5	0.22
Fennel	7	6,795.1	15,589	8.7	275.5	24.8	2.29
Aubergine	4	46,420.0	31,950	2.1	523.8	59.7	0.69
Potato	7	10,755.3	26,638	25.7	262.9	43.1	2.48
Pepper	6	62,345.8	27,250	5.2	408.9	47.4	0.44
Processing Tomato	21	18,387.7	93,239	21.0	213.9	68.8	5.07
Table tomato	17	19,276.2	29,164	5.5	621.3	61.8	1.51
Zucchini	10	19,660.5	34,313	2.7	429.2	63.1	1.75
	108	27,180.8	31,257	8.7	819.1	58.4	1.65

Source: authors' elaboration from FADN 2016 data.

Table 2
Sample farms' individual characteristics and crop type.

	Fertigation		Organic farming		Management			Total
	No	Yes	No	Yes	Direct (only family labour)	Direct (with family labour)	Indirect	Total
Broccoli	11.32	5.455	8.255	10	6.485	11.705	0.00	8.33
Cucumber	1.89	5.45	2.91	20	1.85	6.38	0.00	3.70
Chicory	9.43	9.09	8.74	20	7.41	12.77	0.00	9.26
Green beans	1.89	5.45	3.88	0	1.85	6.38	0.00	3.70
Fennel	5.66	7.27	6.8	0	7.41	6.38	0.00	6.48
Aubergine	3.77	3.64	3.88	0	0.00	6.38	14.29	3.70
Potato	0.00	12.73	6.8	0	11.11	2.13	0.00	6.48
Pepper	5.66	5.45	5.83	0	3.7	6.38	14.29	5.56
Processing tomato	18.87	20	18.45	40	22.22	19.15	0.00	19.44
Table tomato	18.87	12.73	16.5	0	16.67	6.38	71.43	15.74
Zucchini	11.32	7.27	9.71	0	14.81	4.26	0.00	9.26
Total	100	100	100	100	100	100	100	100

Source: authors' elaboration from FADN 2016 data.

model in relation to the type of production. in this first exploration of the data, the association among variables are studied through the Chi-squared index. These aspects will be introduced in the model in order to identify which factors may influence the inefficiency component.

Table 2 shows that for some crops (e.g. potato, cucumber and green beans) it is quite common to adopt the fertigation system while the diffusion of organic horticulture production is very limited, with the exception of cucumber production (results are significant as shown from the χ^2 test of independence test (Pearson χ^2 (1) = 3.45, p-value = 0.063). Another heteroscedasticity element, which has been included in the model, has to do with the management type, which is found to be significant for cucumber, green beans and aubergine (75%): the χ^2 test of independence allows us to reject the null hypothesis of independence between variables (Pearson χ^2 (10) = 17.6421, p-value = 0.090).

Before implementing the stochastic frontier specification, we verified the model's specification validity by studying the distribution of the u_i. Through the skew-test, we found that the error distribution is statistically significant left-skewed. After implementing the stochastic frontier efficiency model, we used a LR test in order to test the null hypothesis of no heteroscedasticity in the one-sided error term. The test is carried out by comparing the value of the log-likelihood function with and without the restrictions imposed. Results show that the null hypothesis is rejected (the value of the likelihood ratio (LR) test statistic is 55.68 with a $\chi^2 = 23.684$).

Parameters for the function and inefficiency model were estimated simultaneously. Statistical tests are needed to evaluate suitability of the model. An appropriate testing procedure is the Generalised likelihood-ratio test, which allows us to provide statistical insights into the specification of the Cobb-Douglas production function. The Cobb-Douglas model is a restricted form of the Translog specification – for the frontier function. The results suggest us evidence in favour to the Cobb-Douglas model specification (the value of the likelihood ratio (LR) test statistic is 1.01 with a $\chi^2 = 3.84$).

In the next tables, we show the results of the stochastic frontier efficiency model obtained using STATA 14 software (StataCorp, 2015). The estimate of the ratio (λ) of the standard deviation of the inefficiency component (σ_u) to the standard deviation of the idiosyncratic component (σ_u) gives information on the TE relevance into the production process. The estimated λ indicates that TE is relevant in explaining output variability in the yield production. Table 3 shows the production frontier parameters estimates. Some inputs, e.g. mechanized labour and water volume are found to be strongly significant. Since the Cobb–Douglas coefficients have an elasticity interpretation, the value of the parameters can be taken as a measure of elasticity. The production elasticity estimates indicate that volume of water has the highest contribution to yield production. The coefficients of the inputs indicate the return to scale for the crop system. The magnitude of volume of water is equal to 0.127. The low elasticity coefficient related to the volume of water is an interesting result because this finding implies that the impact on yield is less than proportional compared to the increase of the volume of water. This indiscriminate increase of the volume of water could lead to a less than proportional increase in the yield and therefore to technical inefficiency. Our results suggest also that machinery use is not statistically significant, and volume of water is significant at level of confidence equal to 90%; therefore, we do not derive any implication to production, with respect to other inputs.

Table 3
Production frontier parameters estimates.

	Coefficient	Std. Err.	P-value
Machinery use (hours)	0.058	0.040	0.488
Human labour (hours)	−0.182	0.032	0.043
Irrigated land (ha)	0.127	0.015	0.020
Volume of water (m^3/ha)	0.127	0.026	0.050
Constant	10.208	0.361	0.000
	0.211	0.066	0.001
	0.554	0.043	0.000
	0.380	0.075	0.000

Source: authors' elaboration from FADN 2016 data.

In order to identify the drivers of inefficiency in water use, we included categorical variables that measure farm management type, type of crop grown, use of fertigation and adoption of organic farming. Table 4 shows the impact of introducing the observed heterogeneity indicators into the production model, together with their marginal effects on inefficiency. The results explain that the set of selected covariates explain a significantly variation in the one-sided disturbance across farms: the type of crop grown and the characteristics of the farm play significant roles in shaping efficiency, influencing the variance and the mean of the inefficiency term modelled as a half normal distribution. The direction of the exogenous variables on the inefficiency level are shown in the first column of Table 4.

With reference to the crop type and its impact on the production efficiency, the coefficients refer to processing tomatoes which is the crop selected as benchmark as far as the efficiency level is concerned. The positive sign of the coefficient makes the variance of the processing tomato smaller than the variance of other crops, thus showing a lower inefficiency of processing tomato. Significant differences arise between different crops, in terms of production inefficiency: while cucumber production shows a similar level of efficiency as processing tomato, broccoli, green beans and fennel are much more inefficient productions. As concerns the fertigation, its negative sign (−0.321) makes the variance of the farm adopting fertigation system to be smaller than the variance of the non-adopters indicating that adopting fertigation could increase production efficiency. The coefficient for organic production has a positive sign (0.420), indicating that organic farmers are less efficient than the conventional ones.

The last column of Table 4 also reports the sample means of the marginal effects, allowing us to quantify the effects of exogenous factors on technical inefficiency (Wilson et al., 2001). As suggested by Wang (2002, 2003), by indexing the exogenous factors as $r = 1; \ldots; R$, the marginal effect can be calculated using the estimators: $\frac{\partial[E(u_i|x_i z_i)]}{\partial z_{ir}}$. It can be interpreted as the semi-elasticity of the output with respect the exogenous variables. This is also the partial effect of z_{ir} on y_i. Considering organic production, the average marginal effect of −0.227 indicate that organic farmers are found to be less efficient than the conventional ones by 22.7%, as this is the output loss associated with organic production, all other factors remaining constant.

Table 4
Estimates of variance parameters and marginal effects on inefficiency.

	Coefficient	Std. Err.	P-value	Marginal effect on E (ui)
Crop type				
Ref. processing tomato				
Broccoli	1.915	0.408	0.000	1.035
Cucumber	−0.102	1.034	0.921	−0.055
Chicory	1.421	0.430	0.001	0.768
Green beans	1.640	0.531	0.002	0.886
Aubergine	0.827	0.572	0.148	0.447
Potato	1.270	0.480	0.008	0.687
Pepper	1.255	0.512	0.014	0.678
Table tomato	0.970	0.436	0.026	0.524
Fertigation				
Ref. no	−0.321	0.174	0.065	−0.174
Organic production				
Ref. no	0.420	0.379	0.067	0.227
Management Type				
Ref. direct with prevalence of family extras	0.004	0.183	0.983	0.002
Constant	−0.430	0.396	0.278	

Source: authors' elaboration.

4.2. Discussion

We looked at overall technical efficiency by crop by using the Battese and Coelli (1988) estimator defined as $E\{\exp(-\mu|\varepsilon\}$. It ranges between 0 and 1. The results are reported in Table 5.

Average technical efficiency is estimated to be 0.692. This means that the sampled farms can produce on average 69.2% of the fully efficient production level. Inefficient farms could increase their production by 30.8% with no additional inputs by simply better organizing the inputs into the production process. The first column in Table 5 reports the corresponding values by crop. Most efficient crops are: fennel (99.4%), zucchini (94.2%) cucumber (94.5%) and processing tomato (94%).

Interestingly, farms adopting fertigation are found to have a higher level of technical efficiency (74% vs 63% of the fully efficient production) and are more efficient than the conventional ones by 17.4% (the average marginal effect is equal to −0.174). Fertigation is an efficient method of applying fertilizers through irrigation water as a carrier and distributor of crop nutrients in adequate quantities. The use of fertigation would save labour needed for fertilizer applications and reduce fertilizers loss, maximizing its effects on the yields. At the same time yields are expected to increase due to the synergic effect of water. All this would translate in the improvement of technical efficiency. For example, Badr et al. (2010) evaluate the effect of fertilizer application through drip irrigation of tomato fields. Results indicate distinctive yield performance consequent to the use of fertigation.

Organic farms have a level of technical efficiency lower than farmers adopting a conventional technology (64% vs 69%). Several studies aimed at assessing efficiency differentials between organic and conventional farming exist in the literature. Our results confirm findings e.g. from Madau Fabio (2007) who found that conventional farms were significantly more efficient than organic farms in a sample of Italian cereal farms, due to lower productivity, inefficient subsidies and limited farmers' knowledge; and Tiedemann and Latacz-Lohmann (2013) who show a markedly increased risk of crop failure for organic agriculture with a larger price fluctuation in the smaller market for organic producers with evident effects on efficiency reduction.

Processing tomato shows the highest level of water efficiency compared to other crops (see Table 5). A possible explanation could be found in the diffused use of advanced drip irrigation technology in processing tomato production. Such system maximizes the production capacity of hybrid seeds, therefore improving crop's yields. It also reduces water and energy use, increasing the efficiency in water and fertilizers' use, with direct implications in increasing efficiency (and reducing overall production costs). Processing tomato production is part of a dynamic agri-food chain driven by the economic competitiveness of tomato industry in this area which has strong influence on chain organisation and governance, key variables to explain the economic performances of the sector (Mantino, 2014).

Table 5
Technical efficiency by crop.

	Mean	s.d.	p25	p75
Crop type				
Broccoli	0.261	0.045	0.235	0.288
Cucumber	0.946	0.014	0.933	0.961
Chicory	0.440	0.092	0.379	0.532
Green beans	0.390	0.037	0.363	0.418
Fennel	0.994	0.000	0.994	0.994
Aubergine	0.798	0.153	0.678	0.917
Potato	0.602	0.008	0.598	0.609
Pepper	0.629	0.218	0.497	0.665
Processing tomato	0.940	0.018	0.933	0.952
Table tomato	0.753	0.176	0.598	0.992
Zucchini	0.992	0.000	0.991	0.992
Total	0.692	0.285	0.403	0.956
Use of Fertigation (yes)	0.743	0.251	0.563	0.958
Adoption of Organic farming (yes)	0.644	0.372	0.343	0.923

Source: authors' elaboration.

5. Conclusions

This paper aims at measuring the input-specific technical efficiency of irrigated crop production and identify its determinants, giving special emphasis on water use. It applies a heteroscedastic stochastic frontier model to a sample of 114 horticultural farms located in the Sud Fortore Area of the Capitanata's Consortium in southern Italy.

As concerns the indicators estimated, we found that the most demanding water crops are pepper and green beans; specifically, Water User Efficiency indicator suggests that such crops are the most inefficient ones. On the other hand, processing tomato shows the highest level of water efficiency (5.01), together with the highest production level (93,239 kg/ha).

Regarding the Technical Efficiency model specification, as supported by the data, the assumption of heteroscedasticity in the one-sided error term is valid. The inputs included in the analysis can be interpreted as a measure of elasticity. The low elasticity coefficient related to the volume of water is an interesting result. It implies that the impact on crop yield is less than proportional compared to the water volume increase. An indiscriminate increase of the volume of water used could cause a less than proportional increase in the yield, therefore leading to technical inefficiency. Our results suggest also that human labour and irrigated land are not statistically significant; therefore, we not derive any implication to production, with respect to other inputs.

Model results reveal the existence of comparable technical efficiency scores among farms. In line with most of the literature, organic farming in the study area is found to be less efficient than conventional farming, while fertigation production system is found to be more efficient. The model also indicates to what extent it is possible to increase crop production efficiency by simply modifying the way in which producing factors are organized into the production process.

The results of this study provide a basis for further statistical developments in the estimation of technical efficiency of water use, including the specification of spatial econometric models accounting for spatial autocorrelation and spatial heterogeneity. Also, the study could be extended by considering the various existing irrigation systems and their potential effects on efficiency increase. Last, thanks to the use of FADN dataset and to model's characteristics, the method used could be easily applied to other areas and allow interesting comparisons, with useful implications for farmers, managers of the irrigation Consortia and policy makers.

Author contributions

Ilaria Benedetti is the main and corresponding author. She has conducted the data analysis and drafted the following paragraphs: literature review, methodology, model specifications, and results. Giacomo Branca coordinated the work of the research unit within the SIM project. He conceived and shaped the research idea, and drafted the following paragraphs: introduction, discussion, and conclusions. Raffaella Zucaro has provided support in building the case study and aided in interpreting the results. She has drafted the following paragraph: data and case study. All authors discussed the results and commented on the manuscript, contributing to its revision and finalization.

Conflicts of interest

The authors declare no conflict of interest.

Uncited references

Frija et al., 2009.

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References

Agovino, M., Cerciello, M., Gatto, A., 2018. Policy efficiency in the field of food sustainability. The adjusted food agriculture and nutrition index. J. Environ. Manag. 218, 220–233.
Aiello, G., Cannizzaro, L., La Scalia, G., Muriana, C., 2011. An expert system for vineyard management based upon ubiquitous network technologies. Int. J. Serv. Oper. Inform. 6 (3), 230–247.
Aigner, D.J., Lovell, C.A.K., Schimdt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econom. 6, 21–37, 1977.
Alvarez, A., Amsler, C., Orea, L., Schmidt, P., 2006. Interpreting and testing the scaling property in models where inefficiency depends on firm characteristics. J. Prod. Anal. 25, 201–212.
Autorità di bacino della Puglia (AdBP), 2004. Piano di Bacino: Stralcio Assetto Idrogeologico (PAI). Relazione di piano.
Badr, M.A., Hussein, S.A., El-Tohamy, W.A., Gruda, N., 2010. Nutrient uptake and yield of tomato under various methods of fertilizer application and levels of fertigation in arid lands. Gesunde Pflanz. 62 (1), 11–19.
Battese, G.E., 1992. Frontier production functions and technical efficiency: a survey of empirical applications in agricultural economics. Agric. Econ. 7 (3–4), 185–208.
Battese, G.E., Coelli, T.J., 1988. Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. J. Econom. 38, 387–399.
Battese, G.E., Corra, G.S., 1977. Estimation of a production frontier model: with application to the pastoral zone of eastern Australia. Aust. J. Agric. Econ. 21, 169–179.
Bettini, O., 2016. Italian Processed Tomato Overview, Global Agriculture Information Network Report. Rome.
Capitanio, F., Adinolfi, F., Santeramo, F.G., 2015. Environmental implications of crop insurance subsidies in Southern Italy. Int. J. Environ. Stud. 72 (1), 179–190.
Chaichi, M.R., Nurre, P., Slaven, J., Rostamza, M., 2015. Surfactant application on yield and irrigation water use efficiency in corn under limited irrigation. Crop Sci. 55 (1), 386–393.
Charnes, A., Cooper, W.W., LI, Shanling, 1989. Using data envelopment analysis to evaluate efficiency in the economic performance of Chinese cities. Soc. Econ. Plan. Sci. 23 (6), 325–344.
Coelli, T., Rahman, S., Thirtle, C., 2002. Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: a non-parametric approach. J. Agric. Econ. 53, 607–626.
Costantini, E.A.C., Fantappié, M., L'Abate, G., 2013. Climate and pedoclimate of Italy. In: The Soils of Italy. Springer, Dordrecht, pp. 19–37.
Deng, X.P., Shan, L., Zhang, H., Turner, N.C., 2006. Improving agricultural water use efficiency in arid and semiarid areas of China. Agric. Water Manag. 80 (1–3), 23–40.
Dhehibi, B., Lachaal, L., Elloumi, M., Messaoud, A., 2007. Measuring irrigation water use efficiency using stochastic production frontier: an application on citrus producing farms in Tunisia. Afr. J. Agricul. Resourc. Econ. 1 (2), 1–15.
Domınguez-Molina, J.A., Gonzalez-Farias, G., Ramos-Quiroga, R., 2003. Skew-normality in stochastic frontier analysis. Comunicacion Tecnica 1–13.
FAO, 2017. The Future of Food and Agriculture: Trends and Challenges, Rome.
Felipe, J., 1998. On the interpretation of coefficients in multiplicative-logarithmic functions: a reconsideration. Appl. Econ. Lett. 5, 397–400.
Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Balzer, C., 2011. Solutions for a cultivated planet. Nature 478 (7369), 337, 2011.
Fried, H.O., Lovell, C.K., Schmidt, S.S., Schmidt, S.S., 2008. The Measurement of Productive Efficiency and Productivity Growth. Oxford University Press.
, .
Gadanakis, Y., Bennett, R., Park, J., Areal, F.J., 2015. Improving productivity and water use efficiency: a case study of farms in England. Agric. Water Manag. 160, 22–32.
Giuliani, M.M., Nardella, E., Gagliardi, A., Gatta, G., 2017. Deficit irrigation and partial root-zone drying techniques in processing tomato cultivated under mediterranean climate conditions. Sustainability 9 (12), 2197.
Greene, W., 1993. The econometric approach to efficiency analysis. In: Fried, H.O., Lovell, C.A.K., Schmidt, S.S. (Eds.), The Measurement of Productive Efficiency: Techniques and Applications. Oxford University Press, pp. 68–119.
Groenveld, T., Yair, Y., Kohn, Gross A., Lazarovitch, N., 2018. Optimization of nitrogen use efficiency by means of fertigation management in an integrated aquaculture-agriculture system. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2018.12.031.
Guzmán, I., et al., 2009. Technical efficiency in the fresh fruit and vegetable sector: a comparison study of Italian and Spanish firms. Fruits 64 (4), 243–252.
Haddeland, I., Heinke, J., Biemans, H., Eisner, S., Flörke, M., Hanasaki, N., Konzmann, M., Ludwig, F., Masaki, Y., Schewe, J., et al., 2014. Global water resources affected by human interventions and climate change. Proc. Natl. Acad. Sci. U.S.A. 111, 3251–3256.
Harvey, A.C., 1976. Estimating regression models with multiplicative heteroscedasticity. Econometrica 44 (3), 461–465.
Hong, N.B., Yabe, M., 2017. Improvement in irrigation water use efficiency: a strategy for climate change adaptation and sustainable development of Vietnamese tea production. Environ. Dev. Sustain. 19 (4), 1247–1263.
Howell, T.A., 2001. Enhancing water use efficiency in irrigated agriculture. Agron. J. 93 (2), 281–289.
Iocola, I., Campanelli, G., Diacono, M., Leteo, F., Montemurro, F., Persiani, A., Canali, S., 2018. Sustainability assessment of organic vegetable production using a qualitative multi-attribute model. Sustainability 10 (10), 3820.
Jaenicke, E.C., Frechette, D.L., Larson, J.A., 2003. Estimating production risk and inefficiency simultaneously: an application to cotton cropping systems. J. Agric. Resour. Econ. 28, 540–557.
Johnes, G., Johnes, J., 2009. Higher education institutions' costs and efficiency: taking the decomposition a further step. Econ. Educ. Rev. 28 (1), 107–113.
Karagiannis, G., Tzouvelekas, V., Xepapadeas, A., 2003. Measuring irrigation water efficiency with a stochastic production frontier: an application to Greek out-of season vegetable cultivation. Environ. Resour. Econ. 26, 57–72.
Khanal, U., Wilson, C., Lee, B., Hoang, V.N., 2018. Do climate change adaptation practices improve technical efficiency of smallholder farmers? Evidence from Nepal. Clim. Change 147 (3–4), 507–521.
Kijne, J.W., Barker, R., Molden, D., 2003. Water productivity in agriculture: limits and opportunities for improvements. In: Comprehensive Assessment of Water Management in Agriculture Series, vol 1, CABI International, UK.
Kumbhakar, S.C., 1993. Production risk, technical efficiency, and panel data. Econ. Lett. 41, 11–16.
Kumbhakar, S.C., 2002. Specification and estimation of production risk, risk preferences and technical efficiency. Am. J. Agric. Econ. 84, 8–22.
Laureti, T., 2008. Modelling exogenous variables in human capital formation through a heteroscedastic stochastic frontier. Int. Adv. Econ. Res. 14 (1), 76–89.
Laureti, T., Secondi, L., Biggeri, L., 2014. Measuring the efficiency of teaching activities in Italian universities: an information theoretic approach. Econ. Educ. Rev. 42, 147–164.
Lilienfeld, A., Asmild, M., 2007. Estimation of excess water use in irrigated agriculture: a data envelopment analysis approach. Agric. Water Manag. 94, 73–82 https://doi.org/10.1016/j.agwat.2007.08.005.
Lipper, L., McCarthy, N., Zilberman, D., Asfaw, S., Branca, G. (Eds.), October 2017. Climate Smart Agriculture - Building Resilience to Climate Change. Springer http://www.springer.com/us/book/9783319611938.
Liu, Y., et al., 2006. Model Selection in Stochastic Frontier Analysis: Maize Production in Kenya. Michigan State University, East Lansing.
Loureiro, M.L., 2009. Farmers' health and agricultural productivity. Agric. Econ., vol 40(4), 381-388. In: Include Heteroscedasticity in the Error Term Due to the Fact that in the Data There Are Different Types of Farms in Terms of Size, Location, and Specialization.
Madau Fabio, A., 2007. Technical efficiency in organic and conventional farming: evidence form Italian cereal farms. Agric. Econ. Rev. 8, No 1.
Mahajan, G., Singh, K.G., 2006. Response of greenhouse tomato to irrigation and fertigation. Agric. Water Manag. 84 (1–2), 202–206.
Mantino, F., 2014. Localised Agri-food Systems in Italy: strategies for competitiveness and role of institutional factors. In: Paper Prepared for Presentation at the EAAE 2014 Congress 'Agri-Food and Rural Innovations for Healthier Societies' August 26 to 29, 2014 Ljubljana, Slovenia.
Massarutto, A., 1999. Agriculture, Water Resources and Water Policies in Italy.
Molden, David, 2013. Water for Food Water for Life: A Comprehensive Assessment of Water Management in Agriculture. Routledge.
Molden, D., Oweis, T., Steduto, P., Bindraban, P., Hanjra, M.A., Kijne, J., 2010. Improving agricultural water productivity: between optimism and caution. Agric. Water Manag. 97 (4), 528–535.

Parmeter, C.F., Kumbhakar, S.C., 2014. Efficiency analysis: a primer on recent advances. Found. Trends® Econometr. 7 (3–4), , 191-385.
Parmeter, C.F., Wang, H.J., Kumbhakar, S.C., 2017. Nonparametric estimation of the determinants of inefficiency. J. Prod. Anal. 47 (3), 205–221.
Pellegrini, G., Ingrao, C., Camposeo, S., Tricase, C., Conto, F., Huisingh, D., 2016. Application of water footprint to olive growing systems in the Apulia region: a comparative assessment. J. Clean. Prod. 112, 2407–2418.
Pereira, H., Marques, R.C., 2017. An analytical review of irrigation efficiency measured using deterministic and stochastic models. Agric. Water Manag. 184, 28–35, 2017.
Pereira, L.S., Cordery, I., Iacovides, I., 2009. Coping with Water Scarcity: Addressing the Challenges. Springer Science & Business Media, Dordrecht, 382.
Pereira, L.S., Cordery, I., Iacovides, I., 2012. Improved indicators of water use performance and productivity for sustainable water conservation and saving. Agric. Water Manag. 108, 39–51, 2012.
Perry, C., 2011. Accounting for water use: terminology and implications for saving water and increasing production. Agric. Water Manag. 98, 1840–1846.
Ramanathan, R., 2003. An Introduction to Data Envelopment Analysis: a Tool for Performance Management. SAGE Publications.
Rinaldi, M., Garofalo, P., Rubino, P., Steduto, P., 2011. Processing tomatoes under different irrigation regimes in Southern Italy: agronomic and economic assessments in a simulation case study. J. Agrometeorol. 3 (3), 39–56.
Ronco, P., Zennaro, F., Torresan, S., Critto, A., Santini, M., Trabucco, A., Marcomini, A., 2017. A risk assessment framework for irrigated agriculture under climate change. Adv. Water Resour. 110, 562–578.
Scott, C.A., Vicuña, S., Blanco-Gutiérrez, I., Meza, F., Varela-Ortega, C., 2014. Irrigation efficiency and water-policy implications for river basin resilience. Hydrol. Earth Syst. Sci. 18 (4), 1339.
Seufert, V., Ramankutty, N., Foley, J.A., 2012. Comparing the yields of organic and conventional agriculture. Nature 485, 229–232.
Sharma, B., Molden, D., Cook, 2015. Water Use Efficiency in Agriculture: Measurement, Current Situation and Trends, Managing Water and Fertilizer for Sustainable Agricultural Intensification. International Water Management Institute (IWMI), C 3, Paris.
Speelman, S., D'Haese, M., Buysse, J., D'Haese, 2008. L. A measure for the efficiency of water use and its determinants, study at small-scale irrigation schemes in North-West Province, South Africa. Agric. Syst. 98 (1), 31–39.
StataCorp, 2015. Statistical Software: Release, vol 14, StataCorp LP, College Station, TX.
Tang, J., Folmer, H., Xue, J., 2015. Technical and allocative efficiency of irrigation water use in the Guanzhong Plain, China. Food Policy 50, 43–52.
Villano, R., Fleming, E., 2006. Technical inefficiency and production risk in rice farming: evidence from central Luzon Philippines. Asian Econ. J. 20, 29–46.
Van der Vlist, A.J., Withagen, C., Folmer, H., 2007. Technical efficiency under alternative environmental regulatory regimes: the case of Dutch horticulture. Ecol. Econ. 63 (1), 165–173.
Wang, H.J., 2003. A stochastic frontier analysis of financing constraints on investment: the case of financial liberalization in Taiwan. J. Bus. Econ. Stat. 1, 406–419.
Wang, H.J., Schmidt, P., 2002. One-step and two-step estimation of the exogenous variables on technical efficiency. J. Prod. Anal. 18, 129–144.
Wang, J., Huang, J., Zhang, L., Huang, Q., Rozelle, S., 2010. Water governance and water use efficiency: the five principles of WUA management and performance in China. J. Am. Water Resour. Assoc. 46, 665–685, 2010.
Watto, M.A., Mugera, A.W., 2015. Econometric estimation of groundwater irrigation efficiency of cotton cultivation farms in Pakistan. J. Hydrol.: Reg. Stud. 4, 193–211.
Wilson, P., Hadley, D., Asby, C., 2001. The influence of management characteristics on the technical efficiency of wheat farmers in Eastern England. Agric. Econ. 24, 329–338.
Yigezu, Y.A., Ahmed, M.A., Shideed, K., Aw-Hassan, A., El-Shater, T., Al-Atwan, S., 2013. Implications of a shift in irrigation technology on resource use efficiency: a Syrian case. Agric. Syst. 118, 14–22 https://doi.org/10.1016/j.agsy.2013.02.003.
Young, R.A., 2005. Determining the Economic Value of Water: Concepts and Methods. Resources for the Future, Washington, DC.
Zhang, S., Zhang, J., Jing, X., Wang, Y., Wang, Y., Yue, T., 2018. Water saving efficiency and reliability of rainwater harvesting systems in the context of climate change. J. Clean. Prod.