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Water use efficiency and public goods conservation: A spatial stochastic frontier model applied to irrigation in Southern Italy

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ABSTRACT

Water used for irrigation is essential for global food production. Increased water scarcity, due to climate change, is a constraint to agricultural development, especially in arid and semi-arid areas. This increases pressure on agriculture which often manages water inefficiently and competes with other sectors for water use. Enhancing farmers' production efficiency may lead to substantial water savings and conservation. Public sector is called to play a role in water governance and to introduce appropriate multilevel regulatory and incentive measures for better water management. This work applies a spatial stochastic frontier model to the case of high water-demanding fruit and vegetable crops in the Apulia region of Southern Italy, where water is scarce due to semi-arid climate and erratic rainfall. Using cross-sectional data from the EU Farm Accountancy Data Network, this work incorporates firm specific heterogeneity into technical efficiency analysis and implements an autoregressive specification of the inefficiency component. Results support the hypothesis that spatial heterogeneity exists in on-farm efficiency of irrigated crop production and is adequately captured by the spatial stochastic frontier model approach. Technical efficiency of farms with similar structural and management characteristics greatly varies across crops and geographical areas, because of the different natural resource endowment and agro-climatic factors. Policies providing incentives to on-farm adoption of modern water-saving technologies and measures to promote small family farm activities could effectively contribute to water conservation goal, but they should be well-articulated to account for agriculture spatial diverseness.

1. Introduction

Water used for irrigation is essential for global food production and is the most critical resource for agricultural development worldwide in arid and semi-arid areas [1]. Water scarcity is already affecting agriculture production [2] even in temperate areas of Europe [83], and is expected to increase in the future, due to climate change [3]. A shift towards sub-tropical climate has been recorded during the last twenty years in the Mediterranean region, determining temperature and vegetation stress rise in coastal areas [4] and increased demand for irrigation [5]. In Italy, where significant variability exists as concerns local water availability [82], annual rainfall over the last sixteen years has decreased by 5%. A generalized increase in both minimum and maximum temperatures is also recorded [6] and significant rainfall reduction is projected [7].

Agricultural sector is responsible for about 70% of global freshwater withdrawals [8]. Growing water competition increases pressure on agriculture which often gains the lowest economic return per unit of resource used [9]. Farmers often employ water in excess with respect to real crop requirements, stressing global water resources [10]. Water savings could be achieved in agriculture [11] but major improvements in irrigation technology and management would be required [12]. Introducing knowledge-intensive management solutions and enhancing technical efficiency (TE) in water use for crop production, e.g. by increasing yields per unit of water consumed (output-oriented measures) or decreasing water used to produce a given yield (input-oriented measures), may lead to substantial water savings [13].

Water from surface watercourses and aquifers used for irrigation are common pool resources whose consumption is non-excludable but rival: farmers cannot be prevented from freely accessing it; and the quantity of water consumed by one user is not available anymore for other users [14]. Water sustaining agriculture ecosystems is non-rival and non-excludable and is close to a public good [15]. Also, water is for the most part a non-tradable good because of its physical attributes, social attitudes and legal-political considerations [16]. Regular markets fail to account for such common and public characteristics of water and for the

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related social externalities. Public sector is therefore called to play an important role in water governance and introduce appropriate multi-level regulatory and incentive measures to promote sustainable resource management and water savings in response to global challenges [15, 17–19]. Water suppliers and planning agencies are increasingly exploring efficiency options for managing demand [20] and design rules and enforcement mechanisms for the sustainable management of common resources [21].

In this context, we investigate about the dependence from spatial characteristics of the on-farm production TE. Results will: support policy makers to properly articulate water policy instruments and applicative levels; provide water suppliers with useful information for enhanced resource management; and help farmers to take informed decisions in response to the policy incentives. Using cross-sectional data from the EU Farm Accountancy Data Network (FADN) for the growing season 2016, we apply a spatial stochastic frontier model (SSFM) to the case of high water-demanding fruit and vegetable production in Apulia, a semi-arid region of Southern Italy which has been recently facing droughts whose frequency and duration have recently taken on worrying dimensions [22].

This paper is innovative as concerns the methodology used for measuring efficiency. The analysis is developed under the hypothesis that spatial heterogeneity exists in crop production efficiency. Traditional stochastic frontier models (SFM) do not control for the spatial autoregressive dependence while omitting this term leads to inconsistent parameter estimates [23]. We incorporate firm specific heterogeneity into TE analysis by using an autoregressive specification of the inefficiency component. We consider several potential sources of spatial dependence in efficiency, including soil quality, climatic conditions, socio-economic aspects and other location-specific attributes which are usually important in agriculture production. In addition, the methodology can be easily applied to other EU countries given the common base of data used in the analysis.

The paper is structured as follows. The policy and research framework are illustrated in section 2. The literature review is reported in section 3. Section 4 presents the methodological approach and the empirical strategy. Section 5 describes the case study, data used in the empirical analysis and model specification. Results are presented and discussed in Section 6. Conclusions and policy implications are drawn in Section 7.

2. Policy and research framework

The international community has recognized that "managing water as an economic good is an important way of achieving efficient and equitable use, and of encouraging conservation and protection of water resources" [24]. EU has advocated innovative technologies and good practices that are less water-intensive and increase water-use efficiency; and the inclusion of economical water use into the system of conditions for the award of EU subsidies [25].

European policies made substantial steps in this direction. The Water Framework Directive (WFD) acknowledges the need to consider the full value of water and promotes the application of economic-based instruments like adequate incentive water pricing and cost recovery of water services. Also, member countries are expected to set water efficiency objectives by the year 2020 (Directive 2000/60/EC) [75]. Under pillar I of the Common Agricultural Policy (CAP), the decoupled subsidy offers opportunities towards improved water management and water-saving irrigation techniques [26]. The cross-compliance mechanism contributes to a sustainable water usage by obliging farmers to meet specific agri-environmental targets in order to receive their direct payment support. Under pillar II, Rural Development Programme promotes resource efficiency and the shift toward a climate-resilient economy in the agriculture and food sectors. EU funds support actions to boost knowledge-intensive production technologies for the improvement of water usage farms' performance.

Several technology options exist. Improved plant physiology and enhanced agronomic practices make water application more efficient and allow producers raising the output achievable with the same amount of inputs, therefore increasing food produced per unit of water resource [27]. Modern and automated irrigation management for effective water conveyance, allocation and distribution efficiently reduce water losses and increase water productivity. Smart irrigation based on real-time weather forecasts and recorded soil moisture condition achieves parsimonious water use and efficiency improvements, and has already demonstrated potential for further water savings [28–33].

In Italy, irrigation water management is based on decentralized institutional arrangements, relying on river basin authorities which oversee water allocation, and local water management authorities (irrigation Consortia) which deal with water withdrawals and distribution, control and enforcement, planning and building infrastructure. Rotational delivery and 'contributive' payments system are applied, where farmers pay a contribution to the irrigation Consortium for water usage, often based on the area irrigated rather than the amount of water consumed. Such payment system is not contributing to efficient water use [26]. The WFD encourages a shift towards 'volumetric' payment mechanisms based on real volumes consumed and a proper pricing structure. This should create incentives for water suppliers towards the implementation of more efficient irrigation management systems and for farmers regarding the adoption of on-field efficient water-saving management solutions. Such demand-side approach raises water-use efficiency and has high payoffs on investments [34]. However, policy-makers should be provided with adequate information about farms' TE levels in order to send the right policy incentive [35]. Farmers relatively more technically efficient are better equipped and more willing to adopt efficient irrigation as well. There is the need to examine what structural and spatial characteristics may influence TE. Even when considering the same water-saving technology, policies should adequately consider the heterogeneity existing among farms.

We bring a contribution in this respect. We look at TE of irrigated fruit and vegetable production in a semi-arid region where water is key for agriculture production and where the impact of introducing water-savings irrigation technologies would be more evident. We consider selected structural characteristics of farms such as production specialization category, farm management type, and farm size. In addition, we look at spatial characteristics like the geographical and agro-ecological conditions under which the farms operate. We highlight the spatial heterogeneity existing in TE levels of the sampled farms. Our results will be useful for policy makers to adequately calibrate the measures aimed at reducing water waste and enhancing sustainability of agriculture production.

3. Literature review: water use efficiency measurement at farm level

A simple approach to measure TE of irrigated crops is based on the use of one-dimensional indicators which consider the impact of each single input on production. A largely adopted indicator is Water Use Efficiency (WUE), defined as the ratio between crop yield achieved (Ya) and the total water used by the crop. It is expressed in kg of output produced per m^3 of water used [36]. However, WUE use is debated since it implicitly assumes that crop yields depend only on water, while it is the effect of the combination of multiple inputs [37,38].

Much research has been conducted to overcome such critiques and to control for the yield contributions of multiple inputs. TE has been extensively analysed by using non-parametric approaches, including the Data Envelopment Analysis (DEA). This method determines a maximal performance measure, i.e. technical efficiency, for each firm relative to all other firms in the observed population without imposing a specific functional form. The primary relationship between the frontier estimate and each firm is that all units lie on or below that frontier. To this aim, certain assumptions concerning the technological structure of the frontier are necessary such as convexity, disposability and returns to scale. The framework of DEA is a deterministic one, in that it assumes all deviations from the frontier are the result of inefficiency. Nevertheless, a stochastic model can be constructed once a data generating process is defined. Therefore, statistical analyses may be carried out and sampling properties of DEA estimators can be established although it might be complicated to perform due to the complexity and multidimensional nature of DEA estimators [39]. In our research context, the non-parametric method is applied to irrigation districts in Southern Spain by [40]; Eco-efficiency of an eventual water pricing reform in some irrigated agricultural areas in Southern Italy was assessed by using various DEA models [76] while a comparative study was developed in Italy and Portugal funding interesting insights concerning the efficiency of different governance structures [41]. However, since DEA is basically a deterministic method, the results may be influenced by extreme values, number of observations and frontier dimensionality [42,43].

With the aim of analyzing technical efficiency of irrigation water use, several studies have applied the parametric approach introduced by [44, 45]. The SFM considers the presence of two random error terms: inefficiency in production and random effects beside farms' control. The production frontier itself is stochastic since it varies randomly across farms due to the presence of the random error component.The Battese and Coelli [47] specification was used on a sample of citrus farms in Tunisia [46] while[48] focused on out-of-season vegetable growing farms located in Crete. Factors influencing farms' TE in Spain during the period 2000–2004 were analysed by [49] with reference to the olives for oil production sector while irrigation water use efficiency in Northern China is explored by [50] founding that farmers' income loss due to higher water prices can be offset by increasing irrigation water use efficiency. SFM was also used to estimate the cost frontier function of a sample of water utilities and determine their efficiency scores and the economies of scale and density [51]. A SFM, in which the inefficiency component is heteroscedastic, was used by [52]. Contrastingly to the present study, they used a small sample of farms located in the 'Capitanata' irrigation district (northern part of Apulia region), characterised by homogeneous agro-climatic conditions and which was selected as case study. Moreover, the authors focused on tomatoes for processing crop – which is the most common and water-demanding crop in the study area – to assess what type of production technique revealed the highest efficiency levels.

Our study contributes to the existing literature by using a SSFM which allows us to control for the spatial heterogeneity across farms, thus disentangling farm efficiency from farm heterogeneity. It also looks at a wide agriculture area characterised by a variety of agro-climatic conditions and cultivated crops, expanding the results of previous works. This represents the novelty of the analysis conducted here. Traditional SFMs do not control for the spatial dependence inherent in agricultural production processes. Therefore, omitting this term would lead to biased parameters estimation and misleading inference [23]. Yet, the literature on spatial stochastic frontier modelling with cross-sectional specific effects is rather sparse. Only a relatively small number of studies estimate spatial stochastic frontiers, even if the interest on spatial dependence has been increasing over the last years. A spatial autoregressive stochastic frontier model (SAR) for cross-sectional data was suggested by [53]. Subsequently, the Kelejian and Prucha's model was extended by [54] to a panel of Indonesian rice farms where spillovers affect farm-level efficiency. The inclusion of spatial dependence into TE analysis by using an autoregressive specification into the inefficiency term was suggested by [55] and [73] . A similar spatial error autoregressive specification on a representative sample of Italian wine producers based on FADN data was applied by [56]. The effect of spatial interdependence on public service efficiency among nearby municipalities was studied by [57] using the same approach and considering a cost frontier. The concept of efficiency spillovers was introduced by [58] integrating SAR and a half-normal SFM using Maximum Likelihood methods. The comparison of spatial dependency effects on TE measures obtained considering two neighborhood structures (residential and rural) for different agro-ecosystems (irrigated and rain fed ecosystems) was carried out by [59,60].

4. Methods

A traditional SFM for cross-sectional data can be written as follows:

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

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 inputs and $\boldsymbol{\beta}$ is the vector of the technological parameters to be estimated. Assuming a log-linear form for the $f(x_i;\beta)$, the stochastic frontier can be expressed as:

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

The composed error term $\varepsilon_i = v_i - u_i$ is the sum of a symmetric, normally distributed variable v_i (the idiosyncrasy) and the absolute value of a normally distributed variable (the inefficiency) which is assumed to be independently distributed from v_i:

$v_i \sim N(0;\sigma_v^2)$, $u_i = |U_i|$ where. $U_i \sim N(0;\sigma_u^2)$

Following the contribution of [61] it is possible to recover observation specific estimates of the inefficiency u_i or technical efficiency (TE), $TE_i = \exp(-u_i)$. The estimator for the normal-half normal case is given by:

$$TE_i = E(exp\{-\hat{u}_i\}|\varepsilon_i) = \left[\frac{1-\Phi(\sigma_* - \mu_{*i}/\sigma_*)}{1-\Phi(-\mu_{*i}/\sigma_*)}\right] exp\left\{-\mu_{*i} + \frac{1}{2}\sigma_*^2\right\} \tag{3}$$

where Φ is the CDF of the standard normal distribution, $\mu_* = \frac{\sigma_u^2}{\sigma^2}$ and $\sigma_*^2 = \frac{\sigma_u^2\sigma_v^2}{\sigma^2}$.

As in the case of agricultural production process there are potential sources of spatial dependence which may influence TE levels, we applied a SSFM by using an autoregressive specification of the inefficiency component following the approach suggested by [55,56] based on the use of maximum likelihood methods. Spatial dependence refers to the correlation between the farms' technical inefficiencies and the inefficiency levels of 'neighboring farms'. The Spatial Stochastic Frontier Model (SSFM) can be specified as follows:

$$\ln y_i = \ln f(x_i;\beta) + v_i - u_i \ \ln y_i = \ln f(x_i;\beta) + v_i - \left(1-\rho\sum\nolimits_i w_{i.}\right)^{-1}\tilde{u}_i \tag{4}$$

where ρ is the spatial parameter weighting the spatially-dependent error vector (0<ρ<1). If $\rho = 0$ the proposed model turns to be equivalent to the classical SFM; $\ln y_i$ denotes the log of output of farm i, $f(x_i;\beta)$ refers to the production function;

$v_i \sim N(0;\sigma_v^2)$, $u_i = |U_i|$ where $U_i \sim N\left(0;\left(1-\rho\sum\limits_i w_{i.}\right)^{-2}\sigma_{\tilde{u}}^2\right)$ and $\tilde{u}_i \sim N(0,\sigma_{\tilde{u}}^2)$

u_i and v_i are identically and independently distributed of each other and of the regressors. Denoting $\left(1-\rho\sum\limits_i w_{i.}\right)$ as $\delta(\rho)$, the marginal density function can be written as follows:

$$f(\varepsilon) = \int_0^\infty f(u,\varepsilon)du = \frac{2}{\sigma}\phi\left(\frac{\varepsilon}{\sigma}\right)\left[1-\Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right]$$

where ϕ and Φ are the density and the CDF of the standard normal distribution, respectively, $\sigma = \sqrt{\sigma_v^2 + (\delta(\rho))^{-2}\sigma_{\tilde{u}}^2}$ and $\lambda = \frac{(\delta(\rho))^{-1}\sigma_{\tilde{u}}^2}{\sigma_v}$.

To estimate the TE measure for each farm, we used a slightly modified version [55] of the estimator suggested by [61] introduced in eq. (3).

Before proceeding to estimate empirical models for measuring

Table 1
Farm distribution (% over total farms in the region) and WUE ratio in the Apulia region (year 2016).

Farm characteristics	%	WUE	Farm characteristics	%	WUE
Crop type:			*Specialization level*		
Asparagus	8.38	0.045	Polycultures	6.59	0.085
Broccoli	8.39	0.051	Specialized in fruits and vegetables	6.59	0.056
Artichokes	10.18	0.086	Specialized in arable crops	86.83	10.31
Chicory	5.39	0.032	*Management type:*		
Watermelon	4.19	0.026	With prevailing extra family labor	49.7	0.150
Green beans	1.2	0.007	With prevailing family labour	43.71	0.336
Fennel	3.59	0.080	With only family labour	6.59	0.038
Aubergines	3.59	0.021	*Legal status:*		
Melon	7.19	0.177	Cooperatives	2.99	0.100
Olive	8.98	0.199	Individual farm/simple partnership	95.81	0.090
Potato	1.80	0.027	General partnership	1.20	0.046
Sweet pepper	3.59	0.021	*Farm size*		
Peas	0.60	0.033	Big	58.68	0.145
Tomato	17.37	0.200	Medium	29.94	0.014
Spinach	2.40	0.053	Small	11.38	0.002
Grapes	7.78	0.075	*Organic farms:*		
Zucchini	5.39	0.032	Yes	1.20	0.046

Source: Our elaboration from FADN 2016 data.

teaching efficiency, further discussion is required concerning the functional form with which we choose to work. In order to describe the agricultural production process, a flexible functional form may be used to model complex features of the production function (pf), such as elasticities of substitution, which are functions of the second derivatives of production. A widely used flexible functional form is the translog model, which is often interpreted as a second-order approximation to an unknown functional form [62]:

$$\ln y = \beta_0 + \sum_{n=1}^{N} \beta_k \ln x_n + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \gamma_{kl} \ln x_k \ln x_l + \varepsilon \quad (5)$$

A useful characteristic of this formulation is that the Cobb-Douglas (CD) pf is a special case of translog since it can be obtained by setting all $\gamma_{kl} = 0$. Another interesting feature is the assumption that the function is continuous and twice continuously differentiable. Then, by Young's theorem it must be true that $\gamma_{\mathrm{kl}} = \gamma_{\mathrm{lk}}$. The CD pf has universally smooth and convex isoquants [63] and relaxes the restrictions on demand elasticities and elasticities of substitution. Furthermore, it is less susceptible to multicollinearity than the possible alternative translog function [64]. The CD pf can be written as follow:

$$\ln y = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_k \quad (6)$$

The translog functional form may be preferred to the CD form due to the restrictive elasticity of substitution and the scale properties of the latter. On the other hand, the presence of quadratic and interaction terms in the translog form do not make the results simple to interpret [65,66]. Therefore, models (2) and (4) were estimated by using both functions. Based on statistical tests and overall significance, we decided that the preferred functional form for describing the agricultural process in the fruit and vegetable sector of the Apulian agriculture is the Cobb–Douglas production function.

A key aspect when estimating spatial models is the specification of the spatial matrix $\boldsymbol{W}$ which captures the spatial arrangement of the cross-sectional units and also the strength of the spatial interaction between the units. This matrix is specified prior to estimation and is based on some measure of geographical or economic proximity. To remove dependence on extraneous scale factors, $\boldsymbol{W}$ is a $n \times n$ row-standardized matrix of spatial weights and $\mathbf{w}_u$ is the spatially-dependent unilateral error vector, u. Each row-normalized weight can be interpreted as the fraction of all spatial influence on unit i attributable to unit j. Moreover, all the diagonal elements of $\boldsymbol{W}$ are set to zero.

We used *k-Nearest Neighbour Weights* matrices based on the centroid distances, d_{ij}, between each pair of farms i and j. More specifically, let centroid distances from each farm i to all farms $j \neq i$ be ranked as follow: $d_{ij(1)} \leq d_{ij(2)} \leq \ldots \leq d_{ij(n-1)}$. Then for each $k = 1,\ldots,n-1$, the set $N_k(i) = \{j(1), j(2), \ldots, j(k)\}$ contains the k closest units to i. For each given k, the k-nearest neighbour weight matrix, $\boldsymbol{W}$, has spatial weights of the standard form:

$$w_{ij} = \begin{cases} 1, & j \in N_k(i) \\ 0, & otherwise \end{cases}$$

To explore the sensitiveness of the estimates of pf parameter and efficiency levels to the assumptions regarding the spatial-weight matrix, we estimate equation (4) by using different neighborhood criterions for defining alternative spatial weight matrices. Indeed, one major issue in the K neighbours' rule, is the sensitivity of choice of the neighborhood size k. If k is very small, the local estimate tends to be very poor, due to the influence of the data sparseness and the noisy, ambiguous or mislabeled points. We can increase k and consider a large region around to smooth the estimate. However, a large value of k easily decreases the estimate, and results in the dramatic degradation of the performance, because more outliers are introduced from the other classes [67].

5. Case study, data and model specifications

About 10% of Italian farms and more than 21% of total arable land of Southern Italy are in the Apulia region. Irrigation is practiced on about 19% of the cultivated land in the region [68]. Water is a critical resource for agriculture due to the semi-arid climate conditions and the extensive cultivation of high water-demanding fruit and vegetable crops which account for 44% of the regional gross production [74]. We focus here on high water-demanding crops, such as tomatoes, broccoli, zucchini, chicory, potatoes, fennel, peppers, eggplants, green beans and cucumbers.

We use data of 167 family farms operating in Apulia. Data are extracted from the EU-FADN dataset[1] for the year 2016. Data includes from physical and structural information, to economic and financial facts. They are available over the following dimensions: time (year), location (country, region), farm typology (type of farm activity, and economic size). In the FADN dataset, physical and economic-financial data are reported for each holding and are included in different tables, namely: general information on the holding (including sampling structure and weights), crops production, water use, environment (latitude,

[1] See https://ec.europa.eu/agriculture/rica/.

Table 2
Summary statistics for input and output variables used in model specifications.

	Mean	C.V.	Min	Max
Crop yield (kg/ha)	4815	3.97	0.10	136,492
Irrigated land (ha)	5.51	1.32	0.08	51
Irrigation activity (hours_day/ha)	13.68	0.62	1.10	24
Human labour (hours/ha)	664	1.36	0.10	4960
Mechanized labour (hours/ha)	100	1.50	0.10	968

Source: Our elaboration from FADN 2016 data.

longitude, soil characteristics), revenue, costs, balance sheet and financial situation. We merged the available files in order to obtain a unified dataset containing information regarding all the farms in the fruit and vegetable sector: general information on the holding, crops production and water based on the univocal farm code identifier.

To estimate the SFM referring to equation (2) and SSFMs referring to equation (4), we consider as output the harvest obtained expressed in ton per hectare and as inputs: hectare of irrigated land (LAND), hours of irrigation per day per hectare (WATER), hours of human labor per hectare (LAB_H) and hours of machinery labor per hectare (LAB_M). Table 1 reports the descriptive statistics related to farms characteristics and the above mentioned WUE indicator, determined as the ratio between crop yields (kg/ha) and water used for irrigation (m3/ha) by considering farm characteristics. Table 2 reports variables used as inputs and outputs.

"Specialization level" refers to farms' techno-economic characterization defined within the FADN classification and glossary.[2] This classification includes technical aspects related to the production orientation. Table 1 shows that most farms (87%) are specialized in arable crops (such as cereals and horticulture), showing similar features in terms of technical characterization. Tomatoes and artichokes are the main crops produced in the sample (17% and 10% of farms, respectively). Green beans are found to reach the lowest level of WUE ratio (0.007) while tomatoes for processing show the highest level (0.200). Most farms (about 96%) are individual farm/simple partnership units where family labor is the most important workforce source. The descriptive statistics for output (yield) and input variables (hectares of irrigated land, hours of irrigation, hours of human labor, hours of machinery labor) are reported in Table 2.

6. Results

Table 3 reports the estimation results obtained from SFM, based on equation (2); and from SSFMs, based on equation (4), at various distance-based neighbours (from K = 1 to K = 7).[3] We estimated models (2) and (4) by using the translog and CD production functions. Estimation results for the Translog production functions are reported in Table A1 in the Appendix. Based on generalized likelihood-ratio test we decided to use the CD production function (LR = 2.72 with a $\chi2 = 3.84$). Moreover, in order to evaluate the correct specification of the model, we compared the OLS with the SFM. Based on the LR test, the SFM based on eq (2) is preferred to the OLS regression model (LR-Test: 13.664, p-value: 0.000). The parameter estimates for SFM and SSFM models are similar, indicating that they both estimate similar empirical structures characterizing yield production of fruit and vegetable farms. In addition to the estimation of coefficients, the SFM model estimates the variances of the two error components σ_u^2 and σ_v^2. By using the estimator from [61] we obtain TE measures for both model specifications. As expected, the average values of TE are significantly higher for the model that does not accommodate spatial dependence. Indeed, the SFM based on equation (2) shows the highest average inefficiency error in relation to the random error (the λ parameter is equal to 0.794). This result may suggest

Table 3
Results from the Cobb-Douglas SFM and SSFM with *k* nearest points as neighbours.

	SFM	SSFM					
		K = 1	K = 2	K = 3	K = 4	K = 5	K = 7
Intercept	5.377***	5.784***	5.784***	6.286***	6.231***	5.665***	5.517***
	(0.830)	(0.785)	(0.785)	(0.779)	(0.886)	(0.845)	(0.861)
LN(LAND)	0.407***	0.428***	0.428***	0.393***	0.434***	0.423***	0.417***
	(0.107)	(0.108)	(0.108)	(0.108)	(0.110)	(0.110)	(0.111)
LN(WATER)	−0.561**	−0.615**	−0.615**	−0.652***	−0.684**	−0.610**	−0.586**
	(0.199)	(0.196)	(0.196)	(0.196)	(0.209)	(0.203)	(0.206)
LN(LAB_H)	0.483***	0.505***	0.505***	0.444***	0.500***	0.498***	0.488***
	(0.127)	(0.128)	(0.128)	(0.123)	(0.125)	(0.128)	(0.128)
LN(LAB_M)	−0.344*	−0.348*	−0.348*	−0.228	−0.302*	−0.340*	−0.341*
	(0.152)	(0.152)	(0.152)	(0.150)	(0.151)	(0.152)	(0.152)
σ_u^2	1.757	2.086	2.086	1.244	1.736	1.744	1.694
	(1.573)	(1.339)	(1.339)	(1.127)	(1.261)	(1.413)	(1.342)
σ_v^2	2.783***	2.636***	2.636***	2.694***	2.725***	2.781***	2.802***
	(0.607)	(0.533)	(0.533)	(0.497)	(0.528)	(0.574)	(0.564)
$\sigma_{u\_sem}^2$		0.004	0.101	0.111	0.011	0.001	0.001
σ^2	4.541	4.699	4.727	4.048	4.471	4.526	4.498
$\lambda = \sigma_u / \sigma_V$	0.794	0.771	0.791	0.462	0.637	0.627	0.605
ρ		0.047	0.129	0.139	0.107	0.043	0.027
Moran I	0.065***	−0.054	−0.053	−0.039	−0.049	−0.021	−0.006
Efficiency	0.446	0.425	0.423	0.491	0.446	0.447	0.452
Log-likelihood:							
SSFM	−339.586	−338.422	−338.422	−333.020	−337.414	−339.275	−339.473
OLS	−339.900	−339.866	−339.866	−339.866	−339.866	−339.866	−339.866
AIC	693.173	707.595	698.233	698.133	706.933	710.633	711.016

Source: Our elaboration from FADN 2016 data.

[2] See: https://ec.europa.eu/agriculture/rica/diffusion_en.cfm#sg.

[3] Results are obtained using R statistical software (https://www.r-project.org), by using SSFM R-package [55].

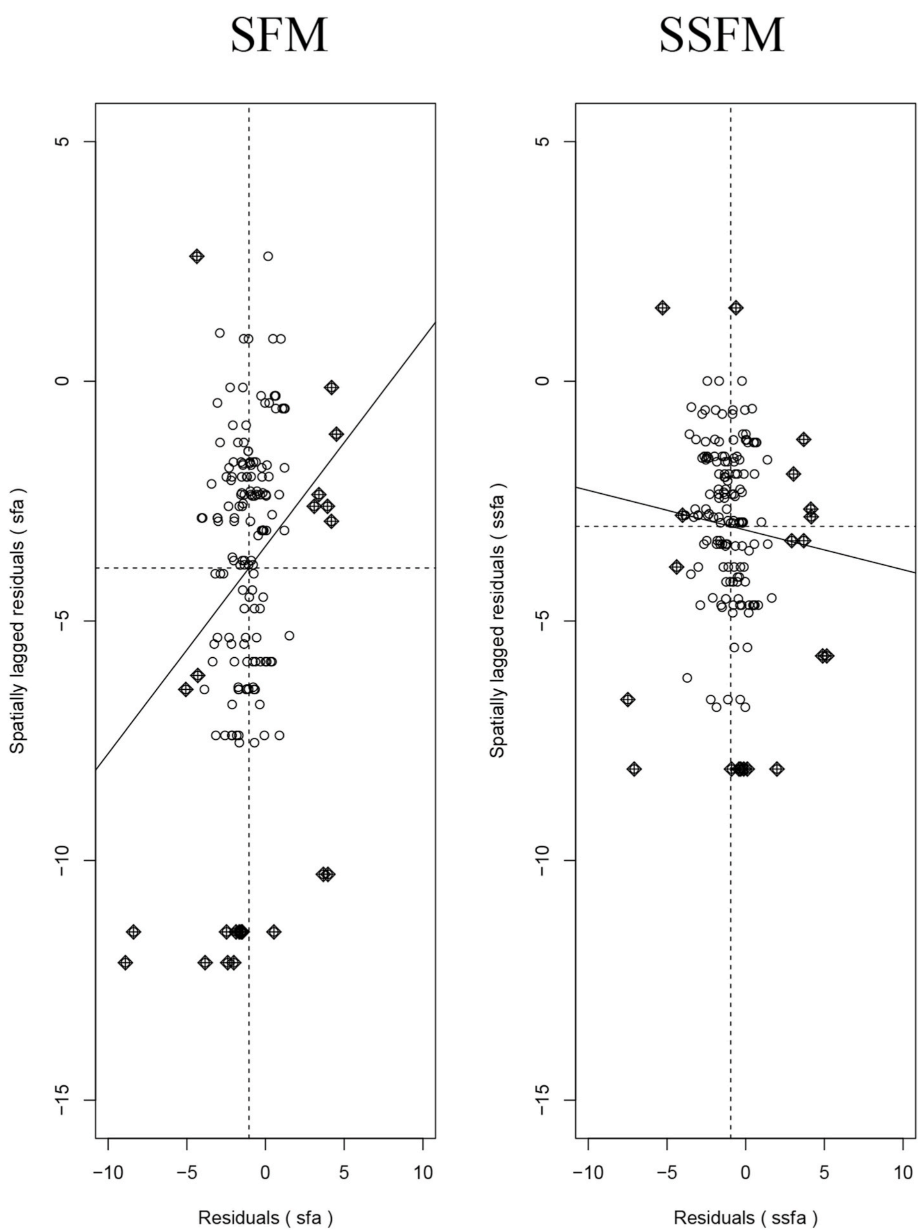

Fig. 1. Moran scatterplots for SFM and SSFM
Source: Our elaboration from FADN 2016 data.

that, from a methodological point of view, measuring the level of efficiency without considering the spatial dependence inherent in agricultural production may be misleading and the effect of spatial dependence is incorporated into the TE.

The presence of spatial dependence is confirmed by analyzing the Moran's I statistics calculated on SFM residuals which show a positive and significant global autocorrelation (Moran I statistic: 0.066, p-value: 0,009). This justifies the adoption of a SSFM. Indeed, when the spatial parameter ρ is included in the model specification, the Moran's I is not significant anymore, supporting the hypothesis that spatial heterogeneity in TE is captured by SSFM. Autocorrelation among residuals are tested with graphs that allow us to assess the similarity among observed values to its neighbours[4] and are reported in Fig. 1. The linear regression line reflects the overall pattern of association between W_y and y. The upper right and lower left quadrants represent positive spatial association. The upper left and lower right quadrants correspond to negative association. Points in the scatterplot that are extreme with respect to the central tendency reflected by the regression slope may be outliers because they do not follow the same process of spatial dependence as most observations. The diamonds points in the plots are points of high influence. The points in the plot are closer to each other (i.e. clustered in space) in the SSFM case than in the SFM one.

In the SSFM estimation we construct various distance spatial weight matrix W by choosing a different number of k nearest points as neighbours, thus obtaining asymmetric neighbours with all areas having k neighbours. Our study confirms the sensitiveness of the efficiency estimates to different model specifications and assumptions regarding the choice of the neighbourhood size k. In order to select the most suitable model we used the Akaike Information Criterion (AIC). Table 3 shows that the best specification is obtained when consider $k = 3$ neighbours.

Following model specification in eq. (4), in the SSFM model with k =

[4] The horizontal axis is the response axis and it is the value of the observations, the vertical axis is the spatial lag of the corresponding observations on the horizontal axis X.

Table 4
Technical efficiency measures by farm characteristics.

Farm characteristics	Mean (TE)	Min (TE)	Max (TE)	Std. Dev. (TE)
Specialization level				
Polycultures	0.501	0.439	0.533	0.033
Specialized, fruit and vegetable	0.489	0.351	0.589	0.072
Specialized, arable crops	0.489	0.136	0.724	0.092
Management type				
Prevailing extra family labour	0.484	0.136	0.699	0.097
Prevailing family labour	0.497	0.316	0.724	0.082
Exclusively family labour	0.488	0.351	0.555	0.059
Organic farms				
Yes	0.511	0.456	0.566	0.078
No	0.490	0.136	0.723	0.088
Legal status				
Cooperatives	0.484	0.399	0.606	0.079
Individual farm/simple partnership	0.490	0.136	0.724	0.089
General partnership	0.511	0.456	0.566	0.078
Farm size				
Big	0.485	0.136	0.717	0.098
Medium	0.487	0.294	0.724	0.079
Small	0.524	0.439	0.665	0.046

Source: Our elaboration from FADN 2016 data.

3 neighbours, the lambda ratio (λ) assumes the smallest value; and the variance of the spatial dependence($\sigma^2_{u\_sem}$) assumes the highest value. These results emphasize the importance of spatial dependence across neighbourhoods. The coefficients related to hectares of land, hours of human labour and hours of irrigation per hectare are significant: the first two have a positive sign, while the latter has a negative sign. Such coefficients can be directly interpreted as elasticities thanks to the CD specification. While an increase in land and labor availability would expand crop yields more than proportionally, probably as a result of economies of scale; water use increase would lead to a less than proportional crop yield enhancement which in turn will be a source of technical inefficiency. The coefficients in the SSFM are lower than those in the SFM, suggesting that the elasticity values in the SFM may be overestimated. Returns to scale are lower than 1, indicating decreasing returns to scale technology.

Turning to the TE estimates, average fruit and vegetable production in the Apulia region is relatively inefficient (0.491) even if TE varies by considering farm characteristics, such as crop type, farm size and legal status, management type and farms' specialization degree[5] (Table 4). Small farms are the most efficient units in our sample (the average efficiency level amounts to 0.524). By looking at various farm characteristics, high heterogeneity degree emerges. For example, general partnerships are more efficient than cooperatives and individual farms or simple partnerships. Artichokes (TE amounts to 0.628), peppers (0.537), eggplants (0.503) and tomatoes (0.503) are among the most efficient crops. Organic agriculture is found to be more efficient than traditional agriculture (0.512 vs 0.490).

The impact of spatial dependence on TE is shown in Fig. 2, which reports the spatial distribution of TE for the farms located in various municipalities included in the analysis, both for the SFM and SSFM. High TE levels are illustrated by dark blue colour while low TE levels are marked in light blue colour. TE results confirm that SSFM can capture the heterogeneity among production units through spatial autocorrelation. TE varies greatly across municipalities within the same province. For example, most efficient farms are those located in the municipality of Lesina (0.549), Brindisi (0.522) and Martano (0.519); while the lowest efficiency level is found among farms located in Cerignola (0.471), Muro Leccese (0.420) and Orta Nova (0.377) municipalities.

The efficiency level greatly varies across areas when we consider farms' structural characteristics, too. Family-managed farms with prevailing family labour in the municipality of Leverano show an average level of efficiency higher than overall mean (0.529 vs. 0.490). In the

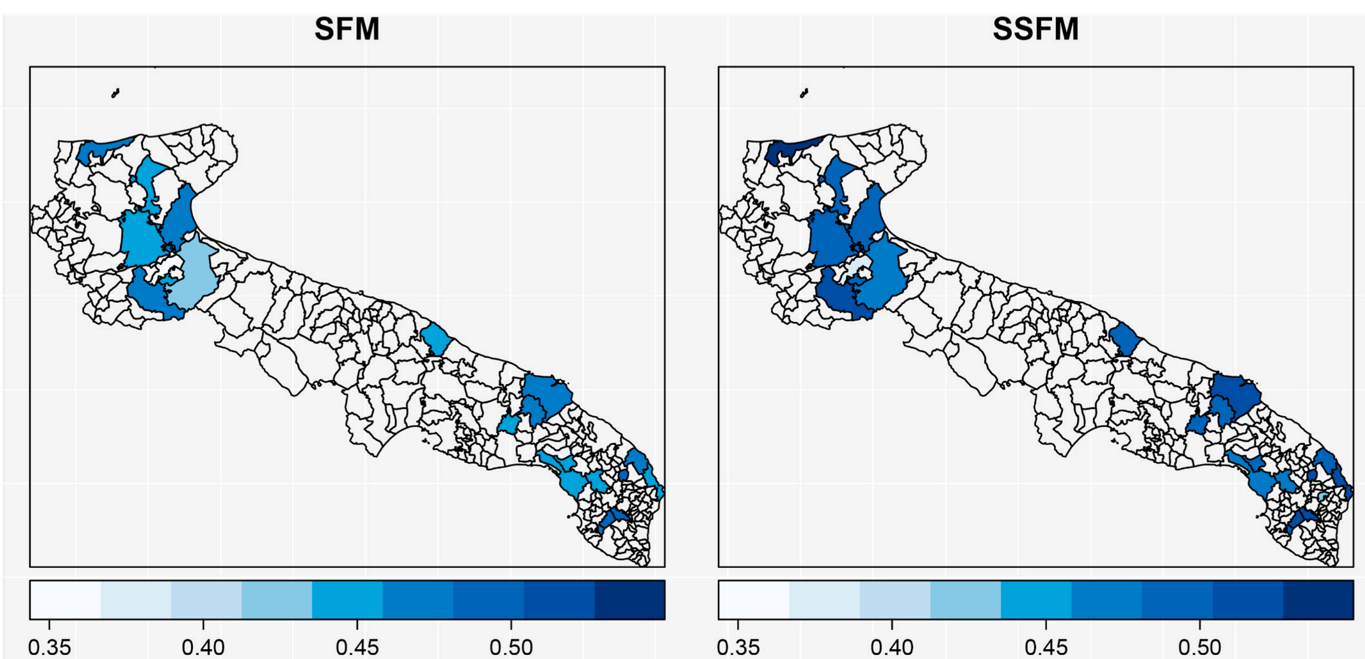

Fig. 2. Technical efficiency of SFM and SSFM in Apulia (Italy), by municipality
Source: our elaboration from FADN 2016 data.

[5] For the farm's characteristics, we calculated the ANOVA tests. The results indicate that there are significant differences in the level of TE achieved (p-value = 0.000).

same area, Martano and Nardò municipalities show higher efficiency levels when considering direct family management with exclusive use of family labour (0.530 and 0.500, respectively); and higher efficiency level is found in Casarano, where farms are mostly specialized in arable crops. As concerns farm sizes, bigger farms in the Brindisi municipality have an efficiency level above the average.

7. Conclusions and policy implications

Water is a critical resource for sustainable agriculture production in arid and semi-arid areas. Focusing on high water-demanding fruit and vegetable production in a water-scarce area of Southern Italy, a spatial error stochastic frontier model for cross-sectional data is estimated, with emphasis on water resource use. A sample of 167 family farms from the FADN dataset is considered. Results support the hypothesis that spatial dependence exists in TE of irrigated crop production and is adequately captured by the spatial stochastic frontier model approach. Technical efficiency of farms with similar structural and management characteristics greatly varies across geographical areas due to the diverse natural resource endowment and agro-climatic factors. Differences in TE among crops occur as well.

Important implications for water policy exist. Multilevel governance in the water sector implies that evidence-based policies should be articulated considering multiple implementation levels and scales, from local on-farm management and landscape water authorities (e.g. Consortia) to sub-national (e.g., administrative Regions), national (e.g., Ministry of Agriculture) and supra-national EU Institutions.

At farm level, different crops have different inputs use efficiency levels. Policies supporting research on plant physiology, enhanced crop-specific agronomic practices, and resilient cropping systems can improve inputs productivity and contribute to natural resources conservation and planning. For example, the EU promotes the diffusion of crops more suitable to water scarcity and more efficient in water use [69]. Organic farming is also more efficient than traditional cultivation, with relevant side effects on water conservation improvements. EU and member states already support organic farming through subsidies from pillar II of the CAP, contributing indirectly to water savings.

At landscape level, 'volumetric-based' payments are expected to provide incentives towards a reduction of water waste and to increase on-farm water-use efficiency. However, to transmit the right incentive, the payment system should be well designed and account for structural and spatial farms heterogeneity. A mixed method of charging, which allows a water volume-based charge plus a fixed hectare-based charge may favour the transition from the current payments system. Water managers have the opportunity to express their needs for better protection of water resources in the framework of the rural development and WFD policy. Also, under existing governance rules of landscape water management authorities, increasing water payments would result in additional investments to expand irrigated area. This would probably have a positive effect on TE since expansion of irrigated land and associated labour use is expected to increase yields more than proportionally.

At national and European level, the presence of spatial dependence on farm TE suggests that implementation of policies aimed at improving efficiency in the use of water and other inputs should be appropriately differentiated depending on the agro-climatic conditions and predominant soil properties in the area. In this respect, small family-farming sector – the predominant business model in European agriculture and active in diversified cropping systems – would generate most social benefits from increased efficiency. Agriculture income support policies would indirectly contribute to water resource conservation and can be accounted for contributing to the agriculture sustainability goal. CAP measures under pillar I implemented over the 2014-20 period have transferred substantial funds to family farms and have ensured the survival of many farms that would have otherwise gone out of business [70]. Rural development policies contained in pillar II of the CAP have been effective in addressing the specific challenges facing Europe's family farms [70] and could be strengthened to promote further increases in resource efficiency. For example, modernization of farm holdings investment measures could be tailored towards the adoption of more efficient irrigation technologies, including smart-irrigation options.

By providing a wide range of policy mechanisms and payments, EU policy sets distinct incentives to farmers regarding water use. The coordination between the different authorities involved in the water use planning process is key to harmonize implementation and enhance water conservation. For example, representatives from the authorities in charge of Rural Development planning need to be represented in the river basin authorities and vice versa. Training and knowledge-sharing programmes that educate farmers on more water efficient practices could complement incentive-based measures.

Even if the results discussed in this paper refer to the specific Apulia region case-study, the model used relies on data extracted from the EU-FADN dataset. The work is therefore replicable and generalizable to other EU agricultural contexts with diverse characteristics in terms of crop type, soil typology and other factors related to farm location and agro-climatic conditions. The comparability among different case studies would allow drawing contextualized policy implications. Our results provide also a basis for further statistical developments in the TE estimation of farm production, in particular the model specification addressing both spatial dependence and heteroskedastic TE to estimate efficiency determinants, similarly to what [71,72] did in the context of the Japanese manufacturing industry.

CRediT authorship contribution statement

Tiziana Laureti: Conceptualization, Supervision, Methodology, Writing - review & editing, Visualization. **Ilaria Benedetti:** Data curation, Methodology, Software, Visualization, Validation, Writing - original draft. **Giacomo Branca:** Conceptualization, Funding acquisition, Investigation, Writing - original draft, Validation.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seps.2020.100856.

Appendix

Table A1
Results from the Translog SFM and SSFM

	SFM	SSFM (K = 3)
Intercept	6.592*	6.619***
	(2.680)	(1.891)
LN(LAND)	1.241*	1.244*
	(0.545)	(0.543)
LN(WATER)	−2.319*	−2.325*
	(1.183)	(1.215)
LN(LAB_H)	0.595	0.589
	(0.781)	(0.786)
LN(LAB_M)	−0.319	−0.321
	(0.850)	(0.864)
LN(LAND) LN(WATER)*	−0.393**	−0.392*
	(0.151)	(0.153)
LN(LAND) LN(LAB_H)*	0.013	0.012
	(0.131)	(0.133)
LN(LAND) LN(LAB_M)*	(0.156)	0.153
	0.137	(0.142)
LN(WATER) LN(LAB_H)*	−0.226	−0.229
	(0.191)	(0.191)
LN(WATER) LN(LAB_M)*	0.250	0.250
	(0.247)	(0.250)
LN(LAB_H) LN(LAB_M)*	0.211	0.210
	(0.166)	(0.172)
$LN(LAND)^2$	0.141	0.138
	(0.161)	(0.162)
$LN(WATER)^2$	0.719	0.714
	(0.460)	(0.483)
$LN(LAB\_H)^2$	−0.006	−0.010
	(0.226)	(0.229)
$LN(LAB\_M)^2$	−0.558*	−0.559*
	(0.245)	(0.250)
σ_u^2	0.002	−0.044***
	(0.163)	(0.001)
σ_v^2	3.108***	3.106***
	(0.345)	(0.350)
$\sigma_{u\_sem}^2$		0.044
σ^2	3.109	3.061
$\lambda = \sigma_u/\sigma_V$	0.022	0.000
ρ		0.105
Moran I	0.052	−0.018
Efficiency	0.969	1.000
Log-likelihood:		
SFA	−331.658	−331.658
OLS	−331.657	−331.657
AIC	697.316	697.315

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