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EFFICIENCY OF VEGETABLE PRODUCTION IN ALBANIA: A STOCHASTIC FRONTIER APPROACH

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Abstract

In this research we at assessing technical efficiency (TE) of vegetable production in Albania. We use a regional approach, that is we try to assess TE based on regional data, for each of 12 regions of Albania. We use Stochastic Frontier Approach to obtain estimates of TE. We found a high level of TE of roughly 0.9 for vegetable production, with variation from region to region. A major factor of this result is assumed to be the low input base the Albanian farmers use; so farmers seem to operate in the irrational range of input use, where production elasticity is higher than one. This also reveals a serious problem, the need of farmers for policies to support more farm inputs like water, fertilizer, etc. The study confirms role of land and as an extremely major production factor, which is more usual in cases when use of other inputs is limited. Efficiency of vegetable production is significantly and positively dependent on farm capital used, irrigation, amount of labor used and climatic conditions, or intensity of production systems. Size of farms *affects negatively the efficiency, meaning that smaller farms are more efficient. We couldn't assess the effect a number of other factors, such as availability and quality of extension service, access to farm credit, education and age of farmers, because of no data. And we urge that an assessment of technical efficiency based on a survey to collect farm level data.*

Keywords: Technical efficiency, SFA, efficiency score, vegetable production, agriculture land, factor of production

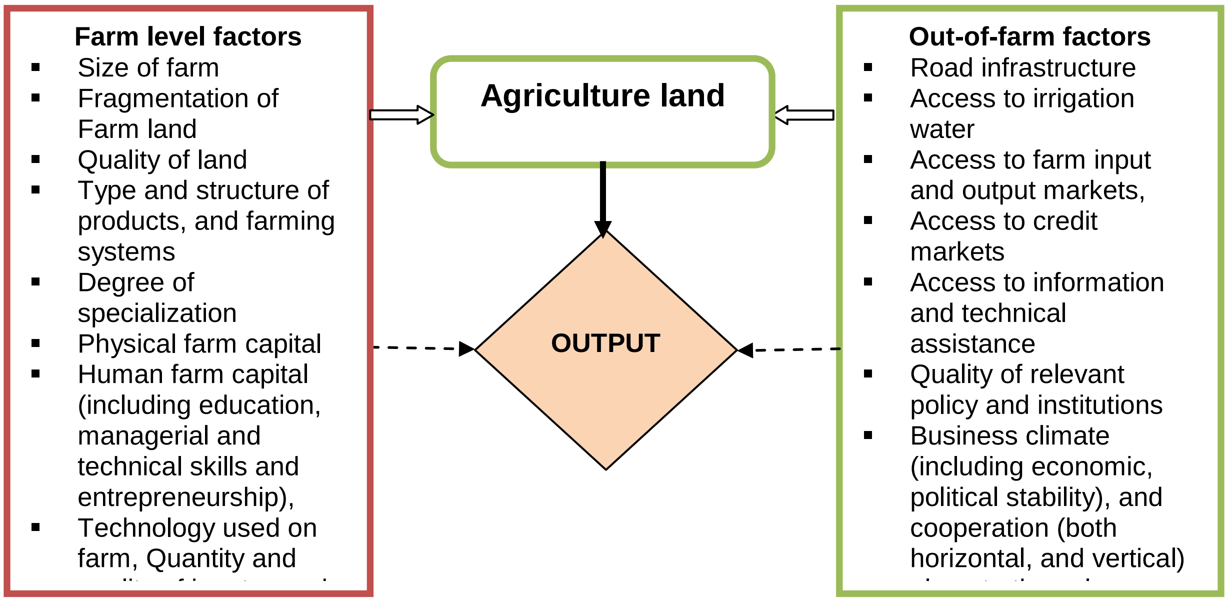
INTRODUCTION

This research is about economic efficiency (EE). Economic efficiency comprises both technical and the allocative efficiency. Our research is concerned with technical efficiency of land used for vegetable production in Albania. Our key question is how efficiently is vegetables production in Albania? If we consider as fixed land already used over years for vegetable production, its efficiency is closely related with the use of other agricultural inputs as well and non agricultural factors. Agricultural land is a primary factor of production, and it is a passive factor of production; all economic agricultural activity is based on land, and vegetables cannot be produced on land by themselves. Labor and capital are active factors of production; capital could be fixed or working and it is man-made. In a general setting, factors influencing efficiency of agriculture land use could be farm-level factors or out-of farm factors. In Albania there is gap of knowledge about level of technical efficiency in agricultural production, vegetables in particular.

Research problem and objective

Our research problem is concerned with the need to know the level of efficiency of land used in the production of vegetables in Albania. Associated with this, we also need to know how different are in terms of efficiency different regions of Albania, or which are most efficient and which ones are less efficient. Also, which years have been more efficient and which ones have been less efficient. This would be an indicator of relative lost production capacity on a national scale and regionally over years comprised by our research. So, objective of our research would be assessment of the level of efficiency of land used for vegetables production in Albania. This could help drawing of conclusions and recommendations about efficiency of actual input base and technology in vegetable production. Figure 1 explains interaction of output with land and other output factors, based on our experience and also theory:

Figure 1: Interaction between farm output, land and other farm output factors

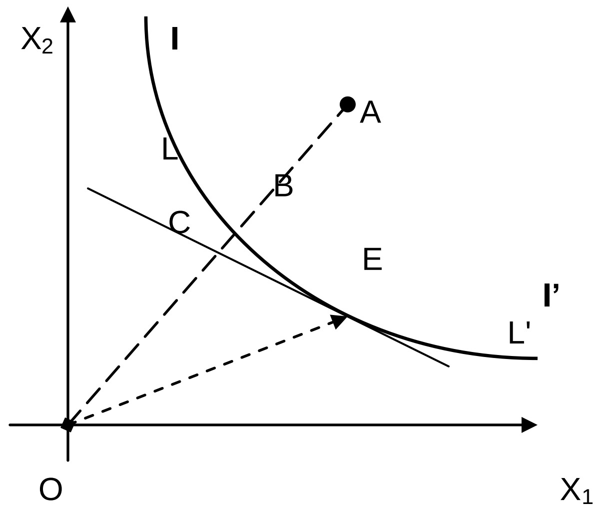


CONCEPTUAL FRAMEWORK

A farm is economically efficient if it is able to produce an amount of output at minimum cost for given level of technology (Farrell, 1957). Technical efficiency is the ability of a firm (farm) to produce maximum output from a given set of inputs, or to produce a given amount of output with minimum inputs. Allocative efficiency is the ability of the firm to produce at minimum cost, or use inputs in optimal proportions for given input prices and technology. Figure 2 below illustrates technical and allocative efficiency. Refer also to (Khan and Saeed, 2011).

A firm is using two inputs X_1 and X_2 to produce a type of product. II' is the isoquant curve, representing all points with the same amount of output obtained by using minimum inputs. For different points on the curve we same output but different combination of inputs X_1 and X_2. So if firm is on II' it is efficient. If it uses inputs in amounts as determined by point A it will be inefficient. Graphically inefficiency is the segment AB. In relative terms, inefficiency is the ratio AB/OA. This ratio is less than one. Inefficiency is the proportion by which inputs could be reduced without loss in output. Technical efficiency is the ratio OB/OA. Allocative efficiency is achieved at point E, because it is the touch point of isoquant and the budget line L. At this point the proportion of inputs is optimal and the same amount of output is produced at minimum cost. AE is the ratio OC/OB. Economic efficiency would be the production of TE and AE. At point E TE, AE and economic efficiency equal to one.

Figure 2: Technical and allocative efficiency



LITERATURE REVIEW

In (Jondrow, et al., 1982), are laid foundations of Stochastic Frontier Analysis. In the classical production econometric model the error term was considered as monolithic, as far as all individuals were considered equally efficient. They argued that individuals or firms cannot have the same efficiency, so part of the error term reflects the individual or firm inefficiency. He also showed how to calculate the inefficiency part of the error term. Later (Aigner et.al., 1977) assumed that the error term was a sum of a symmetric normal and negative half-normal components, and also showed how to estimate the model coefficients by using Maximum Likelihood estimation procedure. Many other authors have contributed to the theory of SF analysis so far.

There exists also a vast empirical literature worldwide discussing efficiency in agriculture. (Coelli and Battese, 1996) studied inefficiency factors for Indian farms and found that age, education and farm size were important factors for technical efficiency of Indian farms. They used one-stage SFA, that is they put in one model the production inputs and inefficiency determinants or factors. (Darlington and Shumwa, 2015) argue that efficiency change is driven by education, extension, the ratio of family-to-total labor, farm size, as well as weather variables, and agro-temperature. (Khan and Saeed, 2011) in a study on Pakistan found that public education and again extension services are determinants of efficiency, of tomatoes growers. At the same result arrived other researchers, like (Adem and Gebregziabher, 2014) in the case of Ethiopia by the use of SFA technique. (Elibariki, et al., 2008) used SFA to analyze efficiency for a particular crop, small farmers growing maize in Tanzania, based on a sample of farmers. They confirm the role of extension services, but also high input prices, low education, land fragmentation, limited capital having a negative effect on farmers' technical efficiency. (Hazneci et al., 2015) calculated production efficiency scores using Stochastic Frontier Analysis. They also used Tobit model to identify the inefficiency determinants; education of farmers and feeding frequency had significant effect on technical inefficiency of dairy farms in Turkey. The literature suggests however alternative techniques for assessment of efficiency; (Anang et al., 2016), used propensity score matching to study inefficiency sources in rice growing farms in Gana and found that among major determinants of inefficiency included the respondent's age, sex, educational status, distance to the nearest market, herd ownership, access to irrigation and specialization in rice production. (Kizito et al.2015), used SFA based on a sample of Tanzania urban agriculture farmers; according to them land size, total variable costs, and extension service had a negative effect on technical efficiency. (Dinar et al., 2007) used a non-neutral Stochastic Frontier Approach to analyze effects of both public and private extension on farm performance in the Cretan case. They found that combining both types of extension service is more efficient as compared to no extension or only one type (public or private) extension service. In a study for Italian organic and conventional farm (Madau, 2005) used SFA technique and found that conventional farms producing cereals were more efficient than organic ones. He also found that land was the input with the highest elasticity. (Bozoglu et al., 2007) used SFA based on information gathered for a sample of farm managers and found that education, experience, credit use, participation by women and information negatively affected technical inefficiency; age, family size, off-farm income and farm size had a positive relationship with inefficiency. (Kiprop e al., 2015) used SFA to identify significant factors having an effect on small farmers' poverty in Kenya. Factors having an effect on poverty were land fragmentation, age of the household head, education level of the household head, number of males and females, amount of output (maize), tillage method, land size, household income, and membership to a group and access to extension services. (Abate et al., 2014) studied effect of cooperation on farmers' efficiency and argue that agricultural cooperatives are effective in providing support services and this contributes to members' technical efficiency. (Theriault et al., 2013) use SFA technique and factors such as farm size, access to inputs credits were found to have an effect on technical inefficiency of cotton farmers. (Addai et al., 2014) studied effects of farmer–based organization on the technical efficiency of maize farmers across various agro-ecological zones of Ghana and they didn't find any relevant effect. In a very interesting study, (Saldias et.al, 2012) studied the influence on technical efficiency of access to credit and public support policies for specialized small farmers in Chile. They used a translog stochastic frontier production functions for 109 livestock and 342 crop producers and found high efficiency scores of 89% for farmers specialized in crop production in Chile. They also found that technical efficiency increases with decreasing use of inputs, dependence on on-farm income, farmer education, family size and the age of the family head. Extension services do not appear to help farms become more efficient, and even reduce efficiency among specialized crop producers. The volume of credit increases efficiency in crop production and reduces it in live-stock production. Simwaka, et al., (2013), in a study for farmers in South Africa, use time-varying and time-invariant inefficiency models of production. The results show that fertilizer, labor, seeds, and age contribute significantly to technical efficiency.

METHODOLOGY

To evaluate efficiency of vegetable production, we can use farm-level data for each of 12 regions of Albania and later by pooling regional results we can have an assessment for the country as a whole. We don't have such data, so we use an opposite or aggregate approach; to evaluate efficiency of vegetable production we use aggregate (regional level) data. Each region is considered a cross-section and for each of them we collected the necessary data for 9 out of 10 years of the period 2006-2015. From the methodological point of view, there are a number of approaches and methods that can be used to evaluate efficiency. DEA (Data Envelopment Analysis), which is a non-parametric method, quantile regression, propensity score matching, and SFA (Stochastic Frontier Analysis), which is a parametric and econometric method. In our research we use SFA. The key point in SFA is that the residual term in a production econometric model is composed of two components, inefficiency component, and the error component. So its basic assumption is that all firms are not equally efficient. Based on this, the econometric model according to SFA would be:

$$\mathbf{Y = f(X, B) + v - u}$$

Where; X is a vector of independent variables, factors or inputs. B is a set of parameters to be estimated. Unlike the standard regression model SFA assumes that here the error term ***e*** is composed of two parts, of an error part (**v**) and inefficiency part (**u)**:

v-u=e

Where the component **u** is **≥0**). f***(X, B)+e*** is called ***Stochastic Frontier, (SF)***. Using simple algebra we get **u=Y-SF**, thus inefficiency means less production for given inputs, so production for each individual (region, year) is under the frontier. To calculate efficiency or inefficiency score for each cross-section, here regions, first we have to calculate inefficiency term **u**. This could be indirectly calculated supposing different shapes of distributions for **u**. One of usually used forms is that of half-normal distribution (exponential shape is another). Under this assumption that $\mathbf{v \sim N(0, \sigma_v^2)}$, $\mathbf{u \sim N(0, \sigma_u^2)}$. The conditional distribution of u given e is $\mathbf{u \sim N(\mu_*, \sigma_*^2)}$ truncated at zero.

Inefficiency term ***u*,** (in fact its expected value), could be calculated using the so-called Jondrow formula:

$$\hat{u}_i = \frac{S\delta}{1+\delta^2}\left[\frac{\varphi(w_i)}{1-\phi(w_i)} - w_i\right]$$

Where;

$$w_i = e_i\delta / S \qquad \delta = \frac{S_u}{S_v}$$

And **φ** is density and **ϕ** is the cumulative distribution function for standard normal distribution. Then technical efficiency TE would be:

TE_i=exp(-u_i)

Technical efficiency **TE** for the i-th cross-section could be calculated alternatively directly by the formula:

$$TE_i = \left[\Phi\left(\frac{w_i}{S_*} - S_*\right) / \Phi\left(\frac{w_i}{S_*}\right)\right] * \exp\left(\frac{S_*^2}{2} - w_i\right)$$

Where:

$$S^2 = S_u^2 + S_v^2 \qquad w = -e\frac{S_u^2}{S^2} \qquad S_*^2 = \frac{S_u^2 S_v^2}{S^2}$$

Technical efficiency for the industry:

$$TE = 2\Phi(-S_u) * \exp\left(\frac{S_u^2}{2}\right)$$

Where; Φ is the cumulative standard normal distribution function. More technical information about estimating TE reader can find in Jondrow et al. (19), Aigner et al.(4) and Coelli and Battese (8), Coelli (9).To perform a SFA one could use various forms of production econometric models. Most commonly used models are **Cobb-Douglas** in log form**, Trans logarithmic** and **Quadratic form** models. In our research we used Cobb-Douglas model in log form. This model has the form:

$$\ln Y = a_0 + \sum_{i-1}^{k} a_i \ln X_i + v - u$$

Where; Y is the production of vegetables and X_i are inputs used. Estimation of the model together with the other parameters (S_u, S_v) needed for the calculation of TE is carried out using a Maximum Likelihood Estimator (MLE) procedure. For the estimation of these models literature recommends various software, such as GRETL, STATA, LIMDEP , etc. In our research we used GRETL. Since in our research we have panel data, then we can use three kinds of panel data models: *pool model*, *fixed effects* model and *random effects* models. For **n** individuals or cross-sections and **T** periods of time we have ***nT*** observations for each variable. The pool model assumes no differences between individuals and time periods (years in our case) and it is:

$$Y_{it} = a + bX_{it} + e_{it}$$

The fixed effects (FE) model is: $Y_{it} = (a + a_i) + bX_{it} + e_{it}$

In FE models the coefficient **b** is fixed, whereas coefficients $\mathbf{a_i}$ reflect, if any, individual differences. No time-invariant independent variables can be included in this model.

The random effects (RE) model is: $Y_{it} = a + bX_{it} + (u_i + e_{it})$

In RE models individual differences, if any, are reflected by $\mathbf{u_i}$. No correlation between X-is and $\mathbf{u_i}$ is assumed for this model. For more information about panel data models we recommend (Gujarati, 2003), (Wooldridge, 2009), (GRETL User's Guide, 2012) and (FRONTIER 4.1 by Coelli, 1995). Variables used, their scale of measurement and mode of their operationalization are presented in the following table:

Table 1: Variables and their description and operationalization

Variable	Description	Scale of measurement	Operationalization
Technical efficiency	Level of efficiency	Ratio	A coefficient from 0 to 1
Vegetable production (LQ)	Amount vegetables output	Ratio	Quintals
Land with vegetables (LS)	Amount of land used for vegetable production	Ratio	Hectares
Number of tractors (LT)	Number of tractors in use	Ratio	Pieces
Irrigation (Irrig)	Percent of land potential for irrigation	Ratio	Percent of arable land
Climate (Clima)	Climatic conditions in terms of temperatures	Ordinal, multinomial	0=Under 50 ha of greenhouses, 1=51-150 ha, 2=Above 150 ha
Working days (Wd)	Number of working days spent on farm	Ordinal, dummy	0=Under average, 1=Above average
Farm size (Size)	Amount of land used for crops in hectares	Ordinal, dummy	0=Under average, 1=Above average
Terrain (Terr)	Amount of agriculture land as percent to total land in a given region	Ordinal, dummy	0=Under average % of agriculture land to total land, 1=Above average
Fertilizer use (Fert)	Amount of fertilizer used in thousand ALL	Ordinal, dummy	0=Under average, 1=Above average

We would like to use other variables as factors of efficiency, as literature suggests, like farmers' education, technical assistance offered to farmers over years, cooperation, access to credits, etc., but these data either don't exist or they are incomplete in terms of years or regions. For some other variables we would like more accurate and reliable data, like farm capital, use of fertilizers, farm labor, etc. These data are also are published in a non-systematic or inconsistent form, some are incomplete, and we have been constringed to use proxy variables or dummies instead of ratio scale variables. So the number of tractors (LT) is used as a proxy for farm capital and the Working days (Wd) is used a proxy for labor. For all variables we gathered regional-level secondary data for a 9-year period (2006-2009, 2011-2015) for each of 12 regions of Albania. Thus, our data is a panel format of 9 periods and 12 cross-sections, with 108 observation altogether. Unfortunately, we didn't have access to data for most variables for year 2010, so our panel is incomplete. However, since our aim is to obtain average efficiency estimates for the time horizon 2006-2015, a sample of 9 out of 10 years is sufficiently representative.

RESULTS

According to our approach, land used for vegetables is the key and the only real factor of production. The other factors or inputs, such as fertilizers, water for irrigation, etc. can only upgrade land capacity to produce more, so they only can improve land efficiency.

As we discussed above, SFA uses ML estimator to obtain estimates of the model parameters and variances of ***u*** and *v* components of the error term ***e***. For this we need to know which factors to include in the Cobb-Douglas production function and initial estimates for factor regression coefficients. Since we have panel data, as a first step we discussed panel data models. We have three major categories of panel data models: fixed effects (FE), random effects (RE) and pool models. Since we have time-invariant variables such as Climate, Terrain, etc., the fixed effect model might be excluded because it is inappropriate for that case, or we can estimate the FE model excluding time-invariant variables. Then we estimated a RE model including all input factors. The RE resulted:

Table 2: Random-effects (Generalized Least Squares), using 108 observations
Included 12 cross-sectional units, Time-series length = 9, Dependent variable: LQ

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
Const	4.48514	0.528014	8.4943	<0.00001
LS	1.03867	0.0815821	12.7316	<0.00001
LT	0.0909095	0.0891018	1.0203	0.31005
Irrig	-0.00191047	0.00396546	-0.4818	0.63102
Terr	0.116539	0.197652	0.5896	0.55678
Clima	0.0557291	0.180158	0.3093	0.75771
Wd	0.0146833	0.149144	0.0985	0.92177
Fert	0.0982861	0.195466	0.5028	0.61619

'Within' variance = 0.0124775; 'Between' variance = 0.0398248

Theta used for quasi-demeaning = 0.81342

Breusch-Pagan test

Null hypothesis: Variance of the unit-specific error = 0

Asymptotic test statistic: Chi-square (1) = 72.7918

with p-value = 1.44073e-017

Hausman test

Null hypothesis: GLS estimates are consistent

Asymptotic test statistic: Chi-square (3) = 10.4329

with p-value = 0.0152233

Breusch-Pagan test rejects the null hypothesis of zero variance of the unit-specific error, so RE is preferable to FE model. Hausman test rejects the null hypothesis of consistent GLS estimates, so FE model is preferred to RE model. The FE model using only time-varying variables results like this:

Table 3: Fixed-effects, using 108 observations

Included 12 cross-sectional units, Time-series length = 9, Dependent variable: LQ

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
Const	4.08968	0.652901	6.2639	<0.00001
LS	1.12854	0.0859189	13.1350	<0.00001
LT	0.0768708	0.106241	0.7236	0.47116
Irrig	-0.00414483	0.00409752	-1.0115	0.31438

Mean dependent variable	13.14257	S.D. dependent variable	0.780168
Sum squared residuals	1.160404	S.E. of regression	0.111703
R-squared	0.982182	Adjusted R-squared	0.979500
F(14, 93)	366.1828	P-value(F)	8.99e-75
Log-likelihood	91.55623	Akaike criterion	-153.1125
Schwarz criterion	-112.8805	Hannan-Quinn	-136.7999
Rho	0.468170	Durbin-Watson	0.879597

Test for differing group intercepts -

Null hypothesis: The groups have a common intercept

Test statistic: F (11, 93) = 14.9972

with p-value = P (F (11, 93) > 14.9972) = 2.7711e-016

The Fisher test rejects the null hypothesis that groups (regions in our case) have common intercept, so the pool model is inappropriate. Both FE and RE model identify only land as a significant factor to vegetables production. So we may choose between either FE or RE model regression coefficients estimates.

If we exclude all insignificant factors and re-estimate the RE and FE models with only land as independent variable the results would be:

Table 4: Re-estimated one-factor RE and FE models, dependent variable: LQ

RE model	*Coefficient*	*Std. Error*	*t-ratio*	*p-value*
Const	4.32548	0.486725	8.8869	<0.00001
LS	1.14554	0.0624768	18.3355	<0.00001
FE model	R^2=0.98			
Const	4.28255	0.566887	7.5545	<0.00001
LS	1.15112	0.0736385	15.6321	<0.00001

For both models parameters are very close to each other. Both models are highly significant. Relationship between land and vegetable production is elastic; one percent increase in land is accompanied with 1.15% increase in production. Variability of land between regions is the source of almost 98% of variability of production and all other remaining potential factors contribute in total 2% of production variability among regions. How could be explained this result of only land being so influential? One plausible explanation might be that their effect on production is embedded in the effect of land and goes to production amount through land.

Then we used estimated parameters as initial estimates for a MLE estimation procedure, to obtain new estimates of the parameters as well as estimation of standard deviations for **u** and **v** terms. The results of estimations are:

Table 5: MLE, using observations 1-108

logl = ln(cnorm(e*lambda/ss)) - (ln(ss) + 0.5*(e/ss)^2)

Standard errors based on Outer Products matrix

Parameter	Estimate	Std. error	p-value
b0	4.2347	0.390507	1.97e-027 ***
b1	1.12807	0.0442247	1.62e-143 ***
Su	0.278068	0.0641697	4.75e-05 ***
Sv	0.200520	0.0572199	0.0005 ***

Log-likelihood 16.61045 Akaike criterion -25.22090

Schwarz criterion -14.49237 Hannan-Quinn -20.87087

Now we calculate:

$S^2 = 0.117484$ S=0.34276, $S_*^2 = 0.026445$, $S_* = 0.162618$ $\gamma = \frac{S_u^2}{S^2} = 0.66$

γ=66% is telling that 66% of the error term variance is dedicated to variance in inefficiency. The inefficiency variance is significant, meaning that inefficiency is statistically influencing regions' vegetables output along the study period.

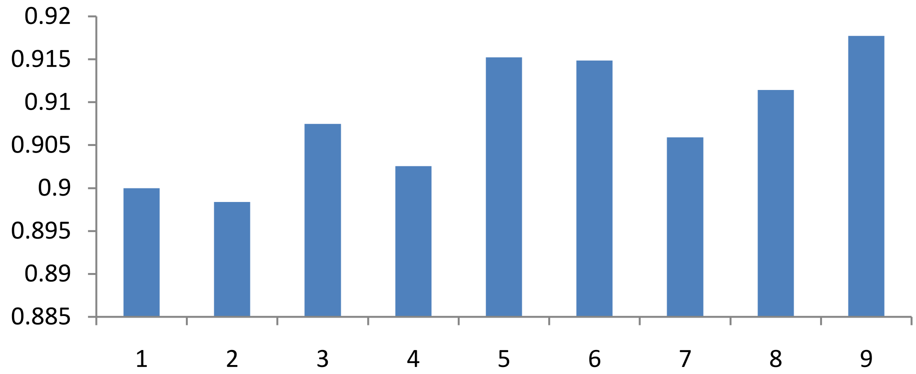
Next we calculate **w** (not shown here). The following table shows results on technical efficiency by year and region.

Table 6: Efficiency scores for land used for vegetable production by year and region

Region	2006	2007	2008	2009	2011	2012	2013	2014	2015	**Mean**
Berat	0.954	0.948	0.957	0.957	0.956	0.955	0.953	0.951	0.958	**0.954**
Dibër	0.941	0.927	0.917	0.946	0.949	0.950	0.947	0.943	0.947	0.941
Durrës	0.898	0.920	0.926	0.910	0.935	0.930	0.912	0.925	0.927	0.920
Elbasan	0.881	0.882	0.899	0.899	0.936	0.942	0.930	0.932	0.935	0.915
Fier	0.917	0.924	0.932	0.935	0.948	0.948	0.935	0.944	0.947	0.937
Gjirokastër	0.808	0.770	0.816	0.785	0.881	0.872	0.874	0.865	0.866	**0.837**
Korçë	0.932	0.943	0.935	0.929	0.917	0.913	0.924	0.929	0.932	0.928
Kukës	0.917	0.911	0.916	0.903	0.911	0.919	0.917	0.911	0.918	0.913
Lezhë	0.907	0.916	0.913	0.917	0.893	0.912	0.912	0.922	0.920	0.912
Shkodër	0.892	0.886	0.886	0.887	0.890	0.876	0.871	0.877	0.888	0.884
Tiranë	0.829	0.830	0.879	0.862	0.871	0.871	0.846	0.861	0.878	0.859
Vlorë	0.923	0.924	0.915	0.901	0.896	0.892	0.850	0.878	0.896	0.897
Mean	0.900	0.898	0.907	0.903	0.915	0.915	0.906	0.911	0.918	**0.908**

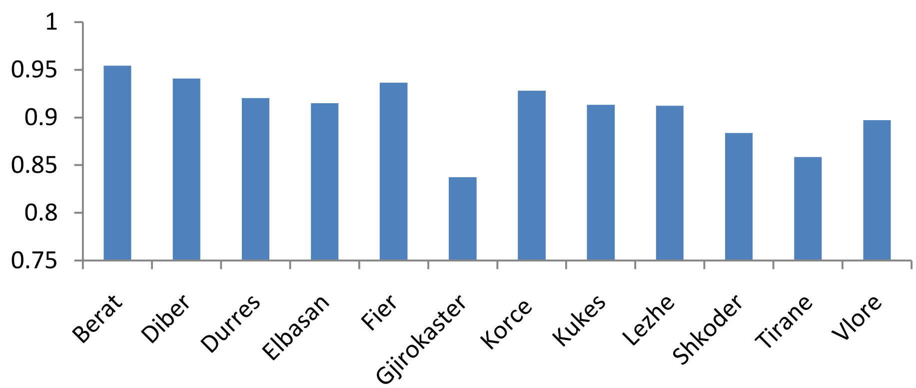
On a national scale, efficiency is about 91%, and inefficiency about 9%. This result reflects prevailing conditions in the study period. This means that under the given amount of inputs and existing technology, farmers' knowledge and skills, business environment etc., there is little to be done to further improve technical efficiency, because at maximum it can be improved by only 9%. In other words, to achieve the same amount of product, nationally could be saved at maximum 9% of the current input base. Some regions can do more, but others much less.

Figure 3: Technical efficiency by years



Nationally, technical efficiency shows a positive trend, though not a strong one.

Figure 4: Technical efficiency by regions



Berat, Diber, Fier and Korca are consistently the most efficient regions, and Gjirokastra, Tirana and Vlora are consistently the least efficient.

The last model we estimated is the model of efficiency to identify which are factors that affect the level of efficiency (Tables 7 and 8):

Table 7: Heteroskedasticity-corrected TE model using observations 1-108

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
Const	0.664056	0.0351044	18.9166	<0.00001
LT	0.0359194	0.00595533	6.0315	<0.00001
Irrig	0.00108535	0.000312159	3.4769	0.00075
Terr	0.00638209	0.00737326	0.8656	0.38880
Clima	0.0287008	0.00636861	4.5066	0.00002
Size	-0.0836689	0.00894942	-9.3491	<0.00001
Wd	0.0488113	0.00841832	5.7982	<0.00001
Fert	-0.0207248	0.00688663	-3.0094	0.00331

TE=0.664+9.0359*LT+0.00108*Irrig+0.00638*Terr+0.0287*Clima=0.0488*Size+0.0488*Wd-0.02072*Fert+ε

Table 8: Statistics based on the weighted data:

Sum squared residuals	352.3981	S.E. of regression	1.877227
R-squared	0.572852	Adjusted R-squared	0.542951
F(7, 100)	19.15867	P-value(F)	5.05e-16
Log-likelihood	-217.1074	Akaike criterion	450.2148
Schwarz criterion	471.6718	Hannan-Quinn	458.9148

All factors included in the model result statistically significant, except for Terrain, so Terrain doesn't affect significantly amount of vegetable production. Size of farm and use of fertilizers are negatively associated with vegetables output; smaller farms and those using less fertilizers seem more efficient. Capital, Labor, and irrigation are positively associated with amount of vegetable production. Climatic conditions, which may coincide with more intensive production systems, also affect production positively.

CONCLUSIONS AND DISCUSSION

Doing this research we assume that all variables are measured without errors; otherwise, results would reflect also such errors. Data come from the Ministry of Agriculture and/or the Institute of Statistics, which are the official producers and distributors of the data.

Variables included are all aggregates representing regional levels. This means that areas planted with specific vegetables and therefore their production for different vegetables and different farms are hidden. Thus, it would be interesting and at the same time very useful to further investigate the efficiency measure for specific vegetables on farm level data as well.

A key finding of our study is that efficiency scores seem for almost every region very similar. This means that regions in Albania on the average do not differ substantially in terms of the efficiency of use of available resources; in other words, under the existing economic, technical, technology, social and environment conditions there is no room for much higher technical efficiency. Or, said differently, if another country has lower efficiency score this doesn't mean that in absolute terms its productivity is lower than that of Albania. Similar regional efficiency score might be because of similarity of factors that affect efficiency, or because the combined effect of these factors is similar for a large part of farms. Furthermore, despite this, within regions there might be farms with large differences in their technical efficiency.

Another explanation of this finding could be the low input base for majority of Albanian farms. If we refer to (World Development Indicators, 2017), Albania is using about 90 kg of fertilizers per hectare of arable land, while Greece is using 160 kg, UK and Netherlands are using about 240 kg. At low input use production per unit of inputs, or average production per unit of input use could be higher. If farm resources are scarce farmers try to do use them with utmost care. But this reveals a critical need for the Albanian farmers, the need to increase use of inputs for more production and associated perhaps with high efficiency. More theoretically, as the law of diminishing returns states, as the use of an input increases, for a given technology and other inputs fixed, a point is reached after which other additions of input result in output decrease; in other words, marginal product is decreasing. If technology improves, though law of diminishing returns holds, production per unit of input or productivity increases and so it is expected to happen with the technical efficiency scores. For large amounts of inputs, part of them might be superfluous, or be inefficient, because of management difficulties, more complex operations, resulting so in decreasing marginal product and also in the total product and productivity. This may also lead to lower efficiency scores for the input used. For a more in depth discussion see (Pindyck and Rubinfed, 1989), (Carrol, 1983), Debertin, 2012a, 2012b).

To conclude, efficiency of vegetable production in Albania results on the average high, with remarkable fluctuations from region to region. Nationally the efficiency score is roughly 0.9, with the highest peak region of Berat with the score of 0.954 and the lowest value that of Gjirokastra with the score of 0.837. Its trend is positive with moderate increases and fluctuations over years. One possible explanation of this result is that the input base of most Albanian farmers is low and they do operate in the irrational range of input use, where the production elasticity is greater than one.

As expected, land used for vegetable results a very powerful and significant factor for their production. Almost 98% of production variation among regions is related with variation of land area. Practically this means that it suffices to add the amount of land and this is translated into more production. This may mean also that inputs' and technology base in different regions base is similar, otherwise land increase in different regions would produce different output volume.

Efficiency of vegetable production in Albania results significantly and positively dependent on farm capital used, irrigation, amount of labor used and climatic conditions, or intensity of production systems. Size of farms affects negatively the efficiency, meaning that smaller farms are more efficient; this may be due to the better use and higher care for the use of inputs by smaller farms because they are also poorer. Fertilizer use also affects negatively the efficiency. This may be due to the fact that larger amounts of fertilizers need higher management and technical skills and more knowledge to scale it up during the production process and effectively combine them with other inputs such water, insecticides, manure, etc.

This reveals an important problem, the need for better and systematic technical assistance to farmers for the use of inputs, fertilizers included, and production techniques what would possibly lead to higher technical efficiency.

Our findings confirm findings of other empirical research about a number of factors of technical efficiency. This is about capital, irrigation, farm size, labor and climatic conditions such as temperatures. But we couldn't assess the effect a number of other factors, such as availability and quality of extension service, access to farm credit, education and age of farmers, etc. This result underlines the need for a more comprehensive study on technical efficiency, in terms of number and type of factors, but also type of products to be taken into consideration.

SCOPE FOR FURTHER RESEARCH

An assessment of technical efficiency based on farm level data is more than necessary in Albania. This could provide more information about more factors affecting technical efficiency as literature suggests and in many instances also confirms empirically. But this needs information on the relevant variables. In Albania there is an alarming deficit of data about these variables; so we urge government to thoroughly evaluate the agriculture information system and make possible collection and publication of systematic country-level and regional disaggregated data about use and prices of fertilizers, pesticides and insecticides, water for irrigation, technical assistance to farmers, use of good agricultural practices, human capital, on-farm capital, access to agriculture credits, etc. In a more comprehensive study, we suggest SFA methodology to assess inefficiency in other crops, fruit-tree and animal husbandry. This could provide a more general and detailed framework of efficiency level in the agriculture sector of Albania.

REFERENCES

Abate, G.T., Francesconi, G.N., Getnet, K. (2014). Impact of agricultural cooperation on smallholders/ technical efficiency; empirical evidence from Ethiopia, Annals of Public and Cooperative Economics 85:2 2014 pp. 1–30

Addai, K. N., Owusu,V., Danso-Abbeam A. G. ((2014). Effects of Farmer – Based- Organization on the Technical efficiency of Maize Farmers across Various Agro - Ecological Zones of Ghana, Journal of Economics and Development Studies March 2014, Vol. 2, No. 1, pp. 141–161, USA

Adem, M., Gebregziabher, K. (2014). The effect of agricultural extension program on technical efficiency of rural farm households –evidence from northern Ethiopia: Stochastic Frontier Approach, International Researchers Volume No.3 Issue No.3 September, 2014

Aigner, D., Lovell, C.A., and Schimidt, (1977). Formulation and Estimation of stochastic frontier production models. Journal of Econometrics 6:21-32 (1992).

Anang, B.T., Bäckman, S., Sipiläinen, T. (2016). Agricultural microcredit and technical efficiency: The case of smallholder rice farmers in Northern Ghana, Journal of Agriculture and Rural Development in the Tropics and SubtropicsVol. 117 No. 2 (2016) 189–202, ISSN: 2363-6033 (online); 1612-9830 (print)

Bozogˇlu, M., Ceyhan, M. (2007). Measuring the technical efficiency and exploring the inefficiency determinants of vegetable farms in Samsun province, Turkey, Elsevier, Agricultural Systems 94 (2007) 649–656.

Carrol, Th.M. (1983). Microeconomic theory, concepts and applications, St. Martin Press, Inc., USA, pp 181-244

Coelli, T., Battese, G.(1996). Identification of factors which influence the technical efficiency of Indian farmers. Australian Journal of Agricultural Economics, 40 (August): 103-128.

Coelli, T.J,(1995). "A Guide to Frontier version 4.1c: A Computer program for Stochastic Frontier production and Cost Function Estimation": Working paper 96/07, Centre for Efficiency and Productivity Analysis Dept. of Econometrics, University of New England

Darlington, S., Shumway, R.C., (2015). Analysis of Technical Change, Efficiency Change, and Total Factor Productivity Change , in U.S. Agriculture, School of Economic Sciences, Working Paper Series WP 2015-4

Debertin, D.L., (2012a). Agricultural Production Economics, Second edition, Amazon Createspace 2012, pp 431.

Debertin, D.L., (2012b). Applied Microeconomics Consumption, Production and Markets, pp 254.

Dinar, A., Karagiannis, G., Tzouvelekas, V.(2007). Evaluating the Impact of Public and Private Agricultural Extension on Farms Performance: A Non-neutral Stochastic Frontier Approach (Rural Development Dept, World Bank, USA), retrieved on date 12.04.2017 from: http://economics.soc.uoc.gr/wpa/docs/Extension.pdf

Elibariki E. M., Shuji, H. Tatsuhiko, N. (2008). An Analysis of Technical Efficiency of Smallholder Maize Farmers in Tanzania in the Globalization Era". The XII World Congress of Rural Sociology of the International Rural Sociology Association, Goyang, Korea, 2008

Farrell, M.J. (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, Series A, 120, 253-281. retrieved on date 10.06.2017 from: http://dx.doi.org/10.2307/2343100

Gretl User's Guide (2012), pp 133-139.

Gujarati, D. (2003). Basic Econometrics, 4-th edition, McGraw-Hill, Inc. pp 636-652 (ARDL)

Hazneci, E., Ceyhan, V. (2015). Measuring the Productive Efficiency and Identifying the Inefficiency Determinants of Dairy Farms in Amasya Province, Turkey. Journal of Agriculture and Environmental Sciences June 2015, Vol. 4, No. 1, pp. 100-107

Jondrow, J, C., Lovell, C.A, Materov, I.S.,Schmidt, P. (1982). "On the Estimation of Technical Efficiency in the stochastic Frontier Production Function Model". Journal of Econometrics 19 no.2/3:233-38.

Khan, H.,Saeed, H. (2011). Measurement of Technical, Allocative and Economic Efficiency of Tomato Farms in Northern Pakistan, International Conference on Management, Economics and Social Sciences (ICMESS'2011) Bangkok December 2011

Kiprop, N.I.S., Bett K., Hillary, B.K., Mshenga, P., Nyairo, N. (2015). Analysis of Technical Efficiency among Smallholder Farmers in Kisii County, Kenya. IOSR Journal of Agriculture and Veterinary Science (IOSR-JAVS) e-ISSN: 2319-2380, p-ISSN: 2319-2372. Volume 8, Issue 3 Ver. I (Mar. 2015), PP 50-56

Kizito K. M., Malongo, R., Mlozi, S. (2015). Measuring Farm-level Technical Efficiency of Urban Agriculture inTanzanian Towns: The Policy Implications. World Journal of Social Science, Vol. 2, No. 1; 2015, E-ISSN 2329-9355 , retrieved on date 5.05.2017 from: URL: http://dx.doi.org/10.5430/wjss.v2n1p62

Madau, F.A. (2005). Technical Efficiency in Organic Farming: an Application on Italian Cereal Farms using a Parametric Approach, National Institute of Agricultural Economics (INEA) 07100 – Sassari (ITALY), presentation at the XIth Congress of the EAAE (European Association of Agricultural Economists), 'The future of rural Europe in the global agri-food system', Copenhagen, Denmark, August 24-27, 2005

Pindyck, R.S., Rubinfeld, D.L. (1989). Microeconomics, Macmillan Publishing Company Inc, New York, pp 162-199

Saldias, R., von Cramon-Taubadel, S. (2012). Access to Credit and the Determinants of Technical Inefficiency among Specialized Small Farmers in Chile, retrieved on date 3.05.2017 from: https://ideas.repec.org/p/zbw/daredp/1211.html

Simwaka, K., Ferrer, S., Harris G. (2013). Analysis of factors affecting technical efficiency of smallholder farmers: Comparing time-varying and time-invariant inefficiency models, African Journal of Agricultural Research, Vol. 8(29), pp. 3983-3993, 1 August, 2013

Theriault, V., Serra, R.(2013). Institutional Environment and Technical Efficiency: A Stochastic Frontier Analysis of Cotton Producers in West Africa, Journal of Agricultural Economics doi: 10.1111/1477-9552.12049

Wooldridge, G. (2009). Introductory Econometrics, 4-edition, South-Western Cengage Learning, pp 445-471

World Development Indicators (2017), retrieved on date 4.07.2017 from: http://data.worldbank.org/data-catalog/world-development-indicators