Input shadow prices and overall efficiency of vegetable farms in Uzbekistan

Aziz A. Karimov

International Livestock Research Institute,
Regional Office for East and Southeast Asia,
17A Nguyen Khang Street, Trung Hoa ward,
Cau Giay district, Hanoi, Vietnam
E-mail: az.karimov@cgiar.org

Abstract: This paper attempts to estimate overall inefficiency of the sample of vegetable farms in Uzbekistan. Using the duality between the directional input distance function and the cost function, the study reports allocative inefficiency scores in addition to technical inefficiency in the vegetable farming system. Model results suggest for substantial reduction of input costs while maintaining the current level of production technology. Findings imply for better organisation of farming, improving access to market information, and developing extension services. The derived shadow prices of land and labour in the existence of production inefficiency could be of great interest to policy makers and researchers. Insofar as market-based reforms could take place and better incentives are provided, inefficient farmers could learn from farming best practices and adopt innovative and cost-effective ways of farming.

Keywords: vegetable production; directional input distance function; Uzbekistan; shadow prices; overall efficiency; computational economics.

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Biographical notes: Aziz A. Karimov is a Scientist at the International Livestock Research Institute based in Hanoi, Vietnam. Previously, he was a Research Fellow at the World Institute for Development Economics Research of the United Nations University (UNU-WIDER). Aziz has a PhD in Agricultural Economics from the Center for Development Research of the University of Bonn and MA in Economics from Northeastern University. His particular interests include applying productivity and efficiency methodologies to the fields of agricultural and resource economics as well as environmental economics.

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1 Introduction

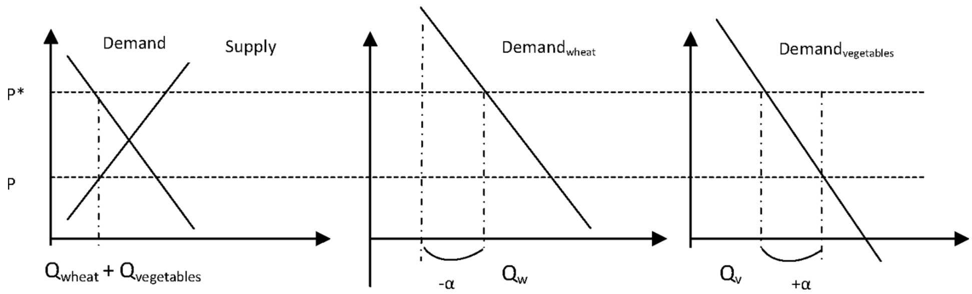
Uzbekistan has a favourable agro-climatic condition suitable for the production of a variety of vegetables and fruits, famous in Central Asia (CA). While cotton has been the main agricultural commodity since the last century, fruit and vegetable production also remained significant to the country (Azimov, 2006; Djalalov, 2006). Following independence in 1991, Uzbekistan's external market affairs with other countries of former Soviet Union (FSU) collapsed. This, and other factors, such as environmental degradation, water scarcity, increased soil salinity, and the state-led cotton and grain policy (Karimov, 2014a), greatly influenced the cropping pattern. Vegetable production volumes and yields went down, illustrating a similar trend in other FSU countries in the initial years of independence. Abbasov (2005) stressed that insufficient supply of organic fertilisers, fuels, and obsolete plant protection technologies further worsened the productivity. Buriev et al. (2005) listed other relevant factors that adversely affected vegetable yields, including limited access to irrigation water, the use of outdated irrigation technologies, and inadequate mechanisation. Olimjanov and Mamarasulov (2006) linked low vegetable productivity with the poor functioning institutions, emphasising that the fall in vegetable production led to the decrease in consumption of vegetables and caused nutritional deficiencies among rural and urban population. The decline also overlapped with policies related to agriculture such as price control, subsidised credit, and low-priced irrigation provision. Besides, land- and farm-related reforms were directly related to strengthening the cotton and grain production sector. Wall (2008) also argued that land reforms were implemented towards increasing the efficiency of the state quota system, rather than promoting individual farming.

Because of food security reasons at the national level and government's attention to attract foreign investment in the vegetable value chain and food processing industry (Vakhabov et al., 2006), the attention moved to increasing volumes of vegetable production. In this regard, improving efficiency of vegetable producers in resource utilisation became a key factor. As literature show improvements in resource utilisation can lead to significant productivity increases (Swinnen and Vranken, 2010) and close the gap between efficient and inefficient farmers. As these differences exist, it is vital to know the extent of technical efficiency (TE) and allocative efficiency (AE). This will give the complete representation of the overall/economic efficiency (EE) of farmers implied by the economic theory of production. Results from empirical estimation of farm efficiency could be a useful regulatory document when formulating targeted policies at municipal level. As appropriately specified by Kumbhakar and Heshmati (1995), efficiency analysis is a constructive guide that reveals which farms are efficiently operating and, so, which ones will keep going in the long-run. It makes it possible to assess farmers' relative performance with the purpose of minimising costs through optimal input mixture and to provide base for improved policy making.

2 Background

In the last two decades, the prices of vegetables increased (Karimov, 2012), but more notably, the prices of resource endowments increased more relative to the prices of vegetables. Because of existing state quotas for cotton and partly for wheat, input prices were only partially liberalised (Karimov and Nino-Zarazua, 2014b). It is apparent from the example of other transition countries that partial liberalisation leads to increases in allocative inefficiency (AI), because of resource diversions (Murphy et al., 1992). The study used the term 'inefficiency' rather than 'efficiency' because of duality applied in the empirical part. AI scores are measures of the extent to which the representative farm's incentives differ from the market prices used in the estimation. To the extent that market prices are measured accurately, the AI score is, in fact, a measure of the distortions in agricultural input markets. The individual distortion scores still represent the degree to which a farm's costs could be reduced if the distortions were removed. For instance, in the case of Uzbekistan, inputs for strategic crops are delivered by state semi-owned organisations and are charged fixed prices, while farmers who grow other crops have to purchase the same inputs in market prices. This leads to AI which can be explained by Figure 1 that illustrates the effect of price liberalisation that is partially implemented. The assumption here is that there is one resource endowment, diesel, used in the production of wheat and vegetables. *P** is the willingness-to-pay by both types of farmers under efficient rationing. Under the partial reform, diesel is sold freely, but wheat producers are forced to buy it at price P, whereas the vegetable producers purchase it at any market price above the *P*. Thus, their total demand is equal to $Q_{vegetables} + \alpha$. Since total supply is equal to $Q_{wheat} + Q_{vegetables}$, wheat producers only receive $Q_{wheat} - \alpha$. This will result in an increase in the shortage of wheat production under the state quota, because inputs will be diverted from wheat production to production of vegetables because of higher prices.

Figure 1 Input diversion



Source: Adapted and modified from Roland (2000), with kind permission from MIT Press

The goal of this work is to measure the extent of economic inefficiency (EI) which requires estimation of not only AI but also technical inefficiency (TI). Because of the interest of the study, inefficiency scores are calculated at the vegetable farming level (VFL) not at crop-specific plot level. Thus, the homogenous output level is constructed for each vegetable farm (VF) by valuing vegetable production in monetary terms. The methodology allows for the derivation of the shadow prices of inputs, such as land, labour, and others. The important thing is these shadow prices are obtained under the existence of production inefficiencies.

The analytical model introduced here was developed by Chambers et al. (1996) also known as the benefit or shortage function established by Luenberger (1992) in consumer theory. The study applies the duality theorem to build a relationship between the cost function and directional input distance function (DIDF) for the estimation of components of EI. This approach also allows us to calculate the EI of each input (EII) for which it is possible to attach a monetary value. Shadow prices are derived from the observed input mixes under the assumption that they are implicitly used by farms to allocate their inputs. For this purpose we develop a parametric model which is explained in the empirical part. The observed input mix is inefficient when some inputs are perceived as more expensive, or cheaper, than their market valuation.

Estimation of cost function could be problematic because observed market prices may not capture a reality. Thus, the prices may not clearly reflect the opportunity cost of producers. Lau and Yotopoulos (1971) stressed that farms may evaluate the opportunity costs of inputs incorrectly and adopt satisfying rather than maximising behaviour. Furthermore, Quiggin and Bui-Lan (2012) emphasised that the divergence between market and shadow prices may be due to the difference in the quality of inputs. If the circumstance is such that producers are operating under the cost minimising bundle, AI measures the scope of divergence between the observed market prices and the opportunity costs of farmers (Osborne and Trueblood, 2006). In such cases, farmers that minimise costs will always be inefficient in their use of resources because they will always over or underutilise resources and this will reflect on AI when it is measured.

This is especially the case in Uzbek agriculture, where the economy is regulated by the state to some extent. Thus, VFs are assumed to be cost minimisers who face some price distortions in the input market. In this case, AI is defined as an indicator that measures the level of distortion occurring in the input market faced by cost minimising farmers, rather than the farmers' capability to minimise costs. This definition matches the one utilised in environmental economics (Bhattacharyya et al., 1994) and could be interpreted as shadow prices reflect market distortions (Osborne and Trueblood, 2006).

3 Methodology

3.1 Economic inefficiency model

The primal representations of the technology are provided by the radial and directional distance functions, which have $L(y), y \in \Re_{+}^{q}$ input requirement sets. By the cost minimisation problem, it is known that $C(y,\psi) \leq \psi x$ for all $x \in L(y)$. Consequently, the study employs the cost function and obtains the dual version of the technology as follows:

$$C(y,\psi) = \inf_{x} \left\{ \psi x : \vec{D}_i(y,x;g) \geq 1 \right\} \tag{1}$$

Here, $\psi \in R_{+}^{S}$ is an input prices' vector. As long as $x \in L(y)$, this is valid:

$$(x - \vec{D}_i(y,x;g_x) * g_x) \in L(y) \tag{2}$$

As proven by Shephard (1953), input distance and cost functions are dual with each other. Chambers et al. (1996) applied the duality theorem and established a connection between the directional input distance and the cost functions, replicating a similar framework offered by Luenberger (1992, 1995) in consumer theory:

$$C(y,\psi) = \inf_{x} \left\{ \psi x - \vec{D}_i(y,x;g_x) * \psi g_x \right\} \tag{3}$$

$$\vec{D}_i(y,x;g_x) = \inf_{w} \left\{ \psi x - C(y,w) : \psi g_x = 1 \right\} \tag{4}$$

This shows that the production factors, symbolised by *x*, and their deflated prices, symbolised by ψ are dual. Based on this, optimisation problem can be written as follows:

$$C(y,\psi) = \inf_{x} \left\{ \psi x - \vec{D}_i(y,x;g_x) * \psi g_x \right\} \tag{5}$$

$$\vec{D}_i(y,x;g_x) = \inf_{\psi} \left\{ \frac{\psi x - C(y,\psi)}{\psi g_x} \right\} \tag{6}$$

Chambers et al. (1996) illustrated that these equations allow an additive (not multiplicative, as is the case in radial functions) decomposition of EI:

$$\mathrm{EI}_i = \frac{\psi x - C(y,\psi)}{\psi g_x} = \vec{D}_i(y,x,g_x) + \mathrm{AI}_i \tag{7}$$

Here, $\vec{D}_i(y,x,g_x)$ is the TI measure of inputs and $\mathrm{AI}_i \geq 0$ is the AI of inputs. As can be seen, EI is the normalised difference between the actual and minimum costs. A directional vector g_x is used for normalisation. Finally, EII can be obtained following by Silva and Lansink (2013) and specified as follows:

$$\mathrm{EII} = \frac{\psi x - \psi x'}{\psi' g_x} = \frac{\sum_{n=1}^{N} \psi_n (x_n - x'_n)}{\psi g_x} \tag{8}$$

This formulation not only allows calculating EII but also assessing whether these inputs are overused (EII > 0) or underused (EII < 0).

The study employs the DIDF model to estimate EI, because of its flexibility in the calculation. An approach used is non-parametric which utilises the data envelopment analysis (DEA) technique. It fulfils all assumptions related to *L*(*y*) and measures the directional distance between each observation and the relevant frontier. AI is calculated by solving the mathematical programming problems that estimate TI and EI. With this in mind, the study runs the following linear programming model:

$$\begin{aligned}
&C(y,\psi) = \min\left\{ \psi x : x \in L(y) \right\} \\
&\text{s.t.} \\
&\sum_{k=1}^{K} \gamma_k y_{kq} \geq y_q, \ q = 1,\ldots,Q, \\
&\sum_{k=1}^{K} \gamma_k x_{ks} \leq x_k, \ \mathrm{s} = 1,\ldots,S, \\
&\gamma_k \geq 0, \ \mathrm{k=1,\ldots,K}, \\
&\sum_{k=1}^{K} \gamma_k = 1.
\end{aligned} \tag{9}$$

K is a sample of VFs and y and x are the observed output and input vectors for each VF, respectively. Input prices are denoted with the symbol ψ. The symbol γ_k is the intensity variable. Since AI is derived as a leftover, after subtracting TI from the calculated EI, TI is obtained by running the following linear mathematical programming problem, such as:

$$
\begin{aligned}
&\vec{D}_i(y, x; g_x) = \max\left\{\beta : (x - \beta g_x) \in L(y)\right\} \\
&\text{s.t.} \\
&\sum_{k=1}^{K} \xi_k y_{kq} \geq y_{k'}, \; q = 1, \ldots Q, \\
&\sum_{k=1}^{K} \xi_k x_{ks} \leq x_{k's} - \theta g_{xs}, \\
&\xi_k \geq 0, \; k = 1, \ldots, K, \\
&\sum_{k=1}^{K} \xi_k = 1.
\end{aligned}
\tag{10}
$$

Here, the intensity variable is denoted with the symbol ξ_k. This mathematical setting assumes variable returns to scale (VRS) production technology. Since SI also needs to be calculated, equation (10) must be computed under the constant returns to scale (CRS) production technology. The CRS is imposed easily by removing the $\sum_{k=1}^{K} \xi_k = 1$ constraint. After obtaining results of fewer than two production technologies, SI can be calculated using the mathematical formula specified in equation (11).

3.2 Scale inefficiency

SI is calculated utilising the following expression:

$$
\overrightarrow{\mathrm{SI}}(y, x, g_x) = \vec{D}_{\mathrm{CRS}}(y, x, g_x) - \vec{D}_{\mathrm{VRS}}(y, x, g_x) \tag{11}
$$

where $\overrightarrow{\mathrm{SI}}(y, x, g_x) \geq 0$. Here, $\vec{D}_{\mathrm{CRS}}(y, x, g_x)$ is TI under CRS, while $\vec{D}_{\mathrm{VRS}}(y, x, g_x)$ is TI under VRS. Färe and Grosskopf (2004) stated that $L_{\mathrm{VRS}}(y) \subseteq L_{\mathrm{CRS}}(y)$ if $\overrightarrow{\mathrm{SI}}(y, x, g_x) = 0$, as such, the VF is considered scale efficient. If $\mathrm{SI}(y, x, g_x) \succ 0$, the VF is scale inefficient.

3.3 Duality theorem and shadow prices

The study employs a parametric method to build a differentiable frontier (via duality) to derive the input shadow prices specified below:

$$
\frac{\psi_j}{\psi_l} = \frac{\partial \vec{D}_i(y, x_j; g_x) \times \partial x_l}{\partial x_j \times \partial \vec{D}_i(y, x_l; g_x)} \tag{12}
$$

Here, ψ_j is the observed input price of the j input and ψ_l is the unknown shadow price of input l. The shadow price ratio reveals each input's relative value that is equal to the matching marginal performance ratio. If the price of one of the inputs in $L(y)$ is known, then it is also possible to recover the price of the other unknown inputs

(Färe et al., 2001, 2009). If the *j*th input price is known, with the assumption that the shadow price *j* input is equal to its observed price, the *l*th input price can be derived from the following mathematical formulation:

$$\psi_l = \psi_j \frac{\partial \vec{D}_i(y, x_l; g_x) / \partial x_l}{\partial \vec{D}_i(y, x_j; g_x) / \partial x_j} \tag{13}$$

To make things easier a Bennet–Bowley indicator could be calculated, which does not require an optimisation model and a parametric specification. However, it requires input and output prices.

Parameterisation requires a functional form specification for the underlying technology. Aigner and Chu (1968) recommended the quadratic form (e.g., Cross et al., 2013; Serra et al., 2011), while Färe and Lundberg (2005) had proven that it is the one that satisfies the translation property. The study takes the directional vector that is equal to one, which leads to a unit reduction in inputs. This makes the maintenance of the same output level possible. The generalised quadratic DIDF can be written as:

$$\begin{aligned}\vec{\Delta}(y, x; 1) = \alpha_0 + \sum_{s=1}^{S} \alpha_s x_s + \frac{1}{2}\sum_{s=1}^{S}\sum_{s'=1}^{S} \alpha_{ss'} x_s x_{s'} + \sum_{q=1}^{Q} \beta_q y_q \\ + \frac{1}{2}\sum_{q=1}^{Q}\sum_{q'=1}^{Q} \beta_{qq'} y_q y_{q'} + \sum_{s=1}^{S}\sum_{q=1}^{Q} \delta_{sq} x_s y_q\end{aligned} \tag{14}$$

An approach by Aigner and Chu (1968) permits the imposition of the parametric restrictions on the chosen functional form. This can be estimated as a restricted linear programming model. The optimal values for $\alpha_0, \alpha_{ss'}, \beta_q, \beta_{qq'}$, and δ_{sq} are obtained by minimising equation (15) subject to certain constraints and properties listed in equations (16)–(21) which are specified in the appendix.

$$\min \sum_{k=1}^{K} \left\{ \vec{D}_i(y^k, x^k; 1) \right\} \tag{15}$$

4 Data and empirical results

4.1 Data description

The study used data obtained from the survey which was conducted in Khorezm and Fergana provinces of Uzbekistan in 2007–2008 agricultural year (for detailed information see Karimov, 2012). The questionnaire consisted of input–output data related to quantities and prices. Socio-economic and demographics of households were also collected during the survey. Overall 243 vegetable farms were used in the efficiency analysis.

A model comprises of one output and six input variables. The aggregate farm output value is utilised as the ‘output’ measure. The VFs price their output quantities at market prices. Consequently, the valued output variable provides efficiency scores which take into account the quality of the output and market imperfections (Karimov, 2012). This also helps to avoid missing information for some farms. Since certain farms were only able to provide output value, aggregation helps to avoid any missing observation that will be dropped from the analysis. The input variables which had information on the physical quantities were land and diesel. A labour quantity is calculated based on survey information obtained from the VFs during the interview. Labour is expressed in person-days of work per ha. One person-day equals to 8 hours per day. Land is measured in ha of cultivated land. Diesel is used as a proxy for fuel input resource and expressed in kg. Out of these three input variables, farmers were only able to report their diesel prices. For other inputs, such as fertiliser and seeds, farmers reported unit costs. Thus, they are measured in value terms. 'Other expenses' is an aggregated variable that consisted of the sum of expenses on Water User Associations (WUAs, Renamed Water Consumers Association in 2009), chemicals (other than chemical fertilisers), organic manure, and machinery services, and measured in monetary values.

Because the study used the input cost, rather than input price, prices are assumed to be unity in the model specification (see also, Singbo and Lansink, 2010). A linear aggregator was used to combine all inputs and outputs. Since output and some of the inputs, such as fertiliser, seeds, and other expenses are measured in monetary values, the quality differences between outputs and inputs are taken into account.

Table 1 presents the descriptive statistics of the output and input variables used in the model estimation. The average vegetable grown area (VGA) is 1.15 ha and ranges between 0.10 ha and 4.6 ha in the sample. Vegetable output value per ha is 7770 thousand Uzbek Soum (UZS) and ranges between 1280 thousand UZS and 8030 thousand UZS. There is only one input variable (diesel) which has the observed price information. It is used to derive the shadow prices of other agricultural inputs, such as land and labour. Although the range of diesel prices is between 500 UZS and 592 UZS, the standard deviation is low. The average reported diesel price for the Khorezm province sample is 541 UZS, while it is equal to 533 UZS in the province of the Fergana. According to calculations obtained from survey, seeds have the largest cost share (69%) followed by costs for fuels (15%), fertiliser (6%), labour (5%), other expenses (4%). According to the budget prepared for vegetable production which was obtained from the provincial department of agriculture and water resources, the cost structure follows the succeeding order: seed cost share (54%), followed by labour (15%), fertiliser (14%), fuel (11%), and other expenses (6%).

Table 1 Descriptive statistics of variables (per hectare)

		Mean	*Standard deviation*	*Minimum*	*Maximum*
Output (1000 UZS)		7946	6441	128	36936
Land area (ha)	X1	1.15	1	0.1	4.6
Seed cost (1000 UZS)	X2	1053	2089	0.5	12484
Diesel (kg)	X3	224	209	4	1047
Fertiliser cost (1000 UZS)	X4	178	136	3	731
Labour (kg)	X5	178	146	5	703
Other expenses (1000 UZS)	X6	62	62	0.9	356
Diesel observed price (UZS)		539	20	500	592

4.2 Results from the economic inefficiency model

It is worth being reminded that the values of inefficiency indicators that are equal to zero describe fully efficient VFs. The value above zero signifies the existence of some degree of inefficiency in the VFL. In other words, VFs with zero inefficiency scores are located on the frontier line and serve as a reference group for other VFs that are not located in this frontier line. The representative farm model here can be viewed as the one that minimises costs, according to the incentives it faces.

The results described in Table 2 illustrate that the mean of the EI and the normalised difference between the maximum and actual costs is equal to 0.61. This illustrates high levels of EI at VFL. For instance, only 7 out of 243 VFs were fully economically efficient (EI = 0) in the given sample. These efficient VFs spent 32% less on inputs than the ones which had some degree of EI. The range of EI levels was between 0.01 and 0.98. Hence, it can be observed that TI and AI played an important role in determining EI at VFL. The AI indicator formed 27% of the EI. This result signals that input resource allocation decisions lacked the cost minimising behaviour in a large number of VFs in the given sample. The arithmetic mean of TI at VFL is equal to 0.34. The results indicate huge gains from efficiency improvements among VFs. For example, average VFs could reduce input resources by 34% and still be able to reach the current output levels under the VRS. On average, VFs were found to be scale efficient in 63 out of 243 cases. The arithmetic mean of the SI was 0.07, which indicates that the scale effect on the EI was at a lesser extent compared to TI and AI.

Table 2 Summary of the results from the economic inefficiency model

	Mean	*Standard deviation*	*Minimum*	*Maximum*
Economic inefficiency	0.61	0.26	0	0.98
Technical inefficiency	0.34	0.22	0	0.78
Allocative inefficiency	0.27	0.21	0	0.97
Scale inefficiency	0.07	0.1	0	0.62

Source: Adapted from Karimov (2013a)

Where there was SI, in 49% of cases, it was due to decreasing returns to scale (49%) followed by increasing returns to scale (IRS) and CRS, 26% and 25 respectively. Since the overall SI is very low, it is difficult to formulate policy implications just by looking at increasing or decreasing returns to scale indicators. The study also reports the Spearman rank correlations among the inefficiency measures in Table 3. As seen there is no positive link between TI and AI indicators. This backs up the hypothesis that the allocatively inefficient VFs are not necessarily technically inefficient in their farm operations.

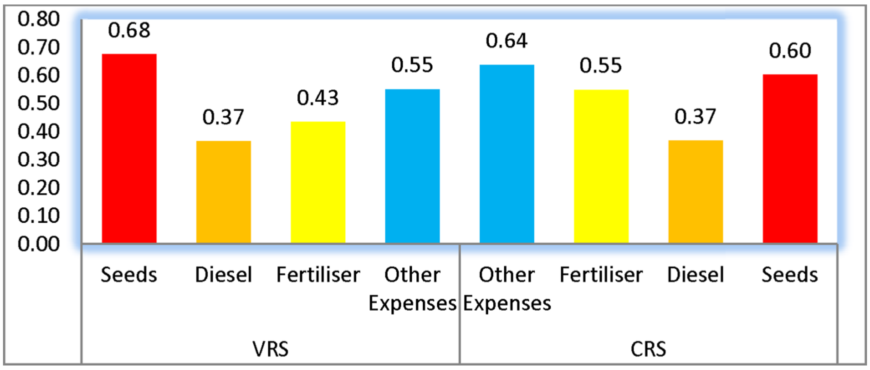
Table 3 Spearman's rank correlation

	Economic inefficiency	*Technical inefficiency*	*Allocative inefficiency*
Economic inefficiency	1		
Technical inefficiency	0.6057	1	
Allocative inefficiency	0.6155	–0.178	1

Figure 2 illustrates the EI of the input resource under variable and CRS technologies. Under the VRS technology, the largest contributor to EI is seeds, while it is the 'other expenses' variable in the case of the CRS. This suggests that the 'seeds' variable is largely influenced by the problems related to the farmer and poor access to high yielding variety.

These problems could be related to the application of poor quality seeds, usage of obsolete technologies, incorrect seeding norms, and mismanagement of seedling process. All these lead to an over or under utilisation of seeds. Since CRS technology also includes scale effects, farmers are less economically inefficient on larger land areas. This result suggests there is a significant amount of input cost savings, which can be used to promote policies which attract investments in new technology and purchase quality and new variety of seeds (Awotide et al., 2013).

Figure 2 Economic inefficiency of each input (VRS and CRS technologies) (see online version for colours)



Source: Adapted from Karimov (2013a)

4.3 Results from the shadow price model

The study had difficulty in obtaining labour prices during the survey. Moreover, since there is no rural land market in the country, it was also impossible to obtain land prices. Thus, one of the objectives of this study was to derive the shadow prices for the resource endowments (land and labour) used in vegetable production, taking into account the possible inefficiencies at the VFL. It is probable to derive the price that would induce a cost-minimising farmer to choose the amount of land and labour actually used. Since farmers are assumed to be cost-minimisers, the only disadvantage is the disparity between market prices and farmers' true opportunity costs. This work notes that utilised approach used to derive shadow prices is still better than assuming an arbitrary price for land and labour.

The study imposed several constraints, including monotonicity, homogeneity, and symmetry, on empirical model and estimated the quadratic DIDF, of which the results are illustrated in Table 4. The results presented allow for the deriving of shadow price of land (SPLAN) and the shadow price of labour (SPLAB) for each VF. The SPLAN can be described as the empirically estimated shadow value for per ha of agricultural land in which the farmer cultivates vegetable crops over a given agricultural year or season. Here, 'shadow' refers to the input resource price that is not directly observed in the local or provincial market, and also reflects the relative scarcity, given the resource constraints. The agricultural land used by the farmer belongs to the state. A farming entity leases it from the state and obtains the user rights. Farmer pays land tax, depending on the type of crop grown and the attributes of the land. Since there does not exist a land market for farming entities in the country, the model results could serve as a benchmark for valuing agricultural land for policy-making and project appraisal. As seen from the model results, on average, SPLAN under the current economic situation equals to 6,470,000 UZS ha^{-1} for average VF, that is approximately equal to 5135 USD (One US Dollar is equal to 1260 UZS, 2007 year). There are only a few studies that calculated shadow prices in the context of Uzbek farmers. One of them is conducted by Djanibekov (2008) who reported differing SPLAN ha^{-1}, depending on the cropping calendar and three types of farming units in the Khorezm province. In the case of individual farms in the months between January and June, Djanibekov reported that SPLAN equal to 92 USD ha^{-1}. In the months between July and September, there was a much larger SPLAN, equal to 367 USD ha^{-1}. To be able to compare SPLAN per ha from this study with the one obtained in the study by Djanibekov, the total SPLAN per ha acquired from model was divided by the number of months in a year. This gives the monthly SPLAN ha^{-1} which is equal to 540,000 UZS (428 USD) ha^{-1}.

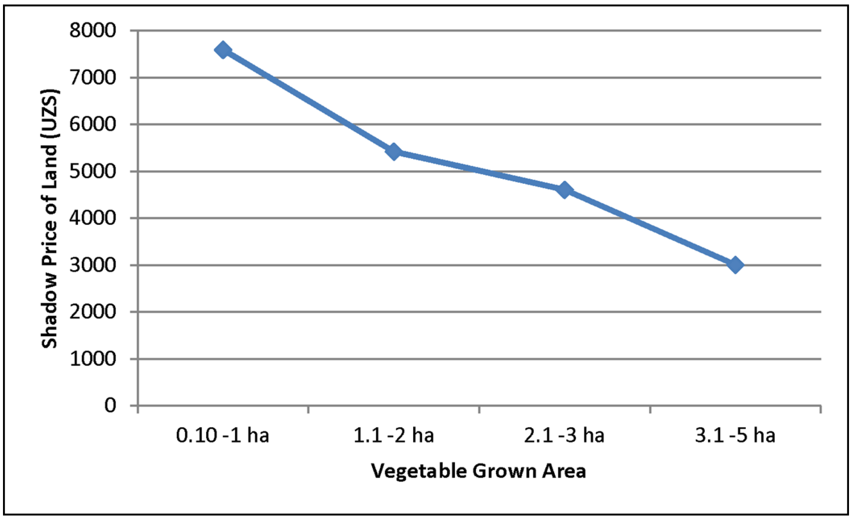
It is interesting to see the relationship between the VGA and the SPLAN obtained from the model estimation. As seen from Figure 3, SPLAN is inversely related to the VGA. The SPLAN is high when land is scarce. However, it starts going down with the increase of VGA.

Table 4 Model parameter estimates

Coefficient	*Variable*	*Estimate*	*Cost share* (%)	*Coefficient*	*Variable*	*Estimate*
α_0	Constant	0.1488		α_{33}	X_3X_3	–0.0025
α_1	X_1	0.5439	0.4	α_{34}	X_3X_4	0.0908
α_2	X_2	0.0387	69.3	α_{35}	X_3X_5	–0.0025
α_3	X_3	0.1290	14.7	α_{36}	X_3X_6	–0.1429
α_4	X_4	0.1767	6.3	α_{44}	X_4X_4	0.0347
α_5	X_5	0.0566	5.2	α_{45}	X_4X_5	0.0139
α_6	X_6	0.0551	4.1	α_{46}	X_4X_6	0.0060
α_{11}	X_1X_1	–0.2575		α_{55}	X_5X_5	–0.0427
α_{12}	X_1X_2	0.0056		α_{56}	X_6X_6	0.0060
α_{13}	X_1X_3	0.0908		α_{66}	Y_1	0.0347
α_{14}	X_1X_4	–0.0427		β_1	Y_1Y_1	–0.8091
α_{15}	X_1X_5	0.1524		β_{11}	X_1Y_1	0.1267
α_{16}	X_1X_6	0.0515		δ_{11}	X_2Y_1	–0.1411
α_{22}	X_2X_2	0.0056		δ_{12}	X_3Y_1	–0.0074
α_{23}	X_2X_3	–0.0026		δ_{13}	X_4Y_1	0.0694
α_{24}	X_2X_4	–0.0025		δ_{14}	X_5Y_1	–0.0233
α_{25}	X_2X_5	0.0060		δ_{15}	X_6Y_1	0.1096
α_{26}	X_2X_6	–0.0039		δ_{16}		–0.0073

Source: Adapted from Karimov (2013a)

Figure 3 Vegetable gown area and the shadow price of land (see online version for colours)



Although there is a market wage for labour, it was impossible to obtain the price information related to labour at the farm level. Since it is an important input variable in the production process, the study is interested in calculating its shadow price. Results illustrate that it is equal to 54,670 UZS (43 USD) ha^{-1} and ranges between as low as 3200 UZS (2.5 USD) ha^{-1} and as high as 300,000 UZS (238 USD) ha^{-1}.

The SPLAB per person-day equals to 395 UZS, or approximately 0.31 USD, on average. The SPLAB in the study by Djanibekov ranged between 47.9 USD and 51.4 USD per 1000 working hours in the baseline scenario. This study quantified the labour in person-days, which has to be converted into person-hours, so that it is possible to compare it with the shadow prices reported in Djanibekov (2008). As already described, one person-day was specified as equal to 8 person-hours. Since the calculated SPLAB is equal to 0.31 USD per person-day, it can be easily converted for per man-hours. This would be equal to 0.039 USD per person-hours. It will give 39 USD per 1000 person-hours, on average. The research finds a bit larger SPLAB for efficient farms, equal to 49.3 USD per 1000 person-hours. Additionally, the results of this study show that the shadow prices differ among the sampled farms. The developing country literature also provides evidence of the differing shadow prices of input resources (e.g., Picazo-Tadeo and Reig-Martinez, 2005). Moreover, the SPLAB obtained from the model are much lower than the market wage observed in the local market. It signals the fact of existing market imperfections in the observed system. Thus, the new intensification strategy should be directed towards non-traditional means of production, such as investing in new technologies and increasing the access to market information.

The relationship between SPLAB and VGA can be pictured by drawing a figure similar to the previous one. As seen from Figure 4, there is a downward U-shaped relationship between these two variables. The positive relationship reaches its maximum at some point, after which it starts decreasing with the increase in the VGA. This simply means that the larger the VGA, the less labour is used per ha of VGA. The smaller farms primarily rely on the labour force, due to the high cost of mechanisation and fuels. Moreover, in small areas, mechanisation may not be possible. Farms with 3 ha and above invest in land and use mechanisation services. This, in turn, decreases the scarcity value of labour.

The study attempted to see if there are any significant differences among the shadow prices obtained from the efficient and inefficient farms. Table 5 illustrates the computations for the shadow prices of land per ha and labour per person-day, distinguished by the fully efficient and inefficient farms. As a result, the inefficient farms have a slightly larger shadow price of land and labour ha^{-1}, in comparison to efficient farms. Because technically inefficient farms are not necessarily allocatively inefficient, it is not possible to argue that TI farms face larger shadow prices, because of allocative inefficiencies.

Figure 4 Vegetable grown area and the shadow price of labour (see online version for colours)

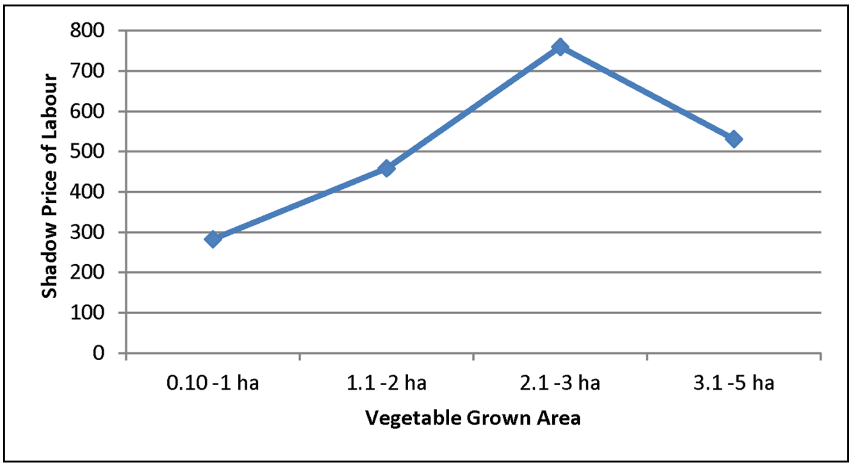


Table 5 SPLAN and SPLAB distinguished by fully efficient and inefficient VFs

	Mean	*Standard deviation*	*Minimum*	*Maximum*
All farms (*N = 243*)				
SPLAN per ha (1000 UZS)	6470	2976	0	21,893
SPLAB per ha (UZS)	54,672	33,917	3232	300,598
SPLAB per man-day (UZS)	395	316	44	2907
Efficient farms (*N = 34*)				
SPLAN per ha (1000 UZS)	6129	3827	0	11563
SPLAB per ha (UZS)	49,443	47,628	3232	204,845
SPLAB per man-day (UZS)	497	565	168	2907
Inefficient farms (*N = 209*)				
SPLAN per ha (1000 UZS)	6525	2820	0	21,893
SPLAB per ha (UZS)	55,522	31,199	10555	300,598
SPLAB per man-day (UZS)	378	252	44	2657

Since the diesel input price is used to derive the shadow price of land and labour, the study checked if the different diesel prices are the source for the varying of the shadow prices between efficient and inefficient farms. It is found that inefficient VFs did encounter a marginally lower price, 538 UZS for per kg of diesel, vs. 542 UZS for per kg of diesel for efficient VFs. *T*-test statistics, however, found that differences between these prices was insignificant. Thus, varying diesel prices are the likely reason for the shadow price differences between efficient and inefficient farms is not a solid argument. Färe et al. (2009) argued, in the example of salmon farmers, that the reason could be more technical and more related to the pre-assigned directional vector, rather than the logical and related AI.

It is found that all utilised resource endowments contribute to AI by signalling the poor functioning input markets (Karimov, 2013b). This study illustrates that most of the allocatively inefficient farms (who had AI scores of 0.41 and above) had their largest cost shares among seed inputs as presented in Table 6. These cost shares were less than those observed and the optimal cost shares, as well as the larger than cost shares, of allocatively efficient farms (who have AI scores up to 0.40). This infers that farmers acquired more than the efficient amounts of seeds compared to other factors of production. Diesel also has a relatively high cost share among the inputs after the seeds. What is interesting in this context is that allocatively more efficient farms had larger cost shares than most inefficient farms. However, the high cost share of diesel indicated by the low AI score did not signal the increase in productivity with an increase in fuel consumption. Since AI is more about the cost-minimising mix of inputs, here, it is suggesting possible savings by a reduction in other inputs more than diesel. By comparing observed and optimal cost shares, It can be concluded that farmers' expenses related to fertiliser, labour, and other expenses are closer to the optimal cost shares, while differences between them in land, seeds, and diesel inputs suggest some distortions.

Table 6 Comparison of observed cost shares with optimal cost shares and between the allocatively most and least efficient farms

	Land	*Seeds*	*Diesel*	*Fertiliser*	*Labour*	*Other expenses*
Observed cost share	0.004	0.69	0.15	0.06	0.05	0.04
Optimal cost share	0.01	0.55	0.23	0.09	0.08	0.04
AI (0.00–0.40)	0.01	0.56	0.21	0.09	0.07	0.05
AI (0.41–above)	0.002	0.82	0.09	0.04	0.03	0.03

Source: Adapted from Karimov (2013a)

The study also categorised efficiency scores by VGAs, as illustrated in Table 7. From the analysis, it can be seen that the TI plays a major role in the overall inefficiency, especially for farms with large land areas. The TI is lowest in the farms with a VGA of less than one ha. This suggests that, as the land consolidation process occurs, attention should be given to increasing farmers' skills and effectively managing larger crop-grown areas. The results of the AI, across land categories, suggest that small, medium, and large farms are equally influenced by market distortions. The average EI of land was found to be decreasing from 0.29 to 0.01 across different land categories. Here, a negative sign signals the underutilisation of resources, while a positive sign implies overutilisation. There is a decrease in the EI of seeds from 0.70 to 0.40. It appears that farms with larger VGAs are more allocatively and technically efficient in the utilisation of seeds. This shows that seeds have highest EE in the largest land category. The same can be said with regards to other expenses. Results related to diesel is mixed; however, the lowest EI is achieved in the highest land category. The same conclusion is also relevant to fertiliser and, to a lesser extent, labour and land.

Table 7 Comparison of efficiency scores by VGAs

			Economic Inefficiency of each Input					
VGA (ha)	*TI*	*AI*	*Land*	*Seeds*	*Diesel*	*Fertiliser*	*Labour*	*Other expenses*
0.10–0.99	0.31	0.25	0.29	0.70	0.37	0.45	0.30	0.57
1.00–1.99	0.36	0.28	–0.08	0.75	0.44	0.41	0.39	0.56
2.00–2.99	0.36	0.22	0.21	0.50	0.30	0.48	0.25	0.45
3.00–5.00	0.38	0.26	–0.01	0.40	–0.10	0.30	0.28	0.51

5 Conclusions

The study examined vegetable growers' economic efficiency in the context of sampled farmers from two regions of Uzbekistan. Findings show that there is a room for efficiency improvements among VFs in the use of input resources. As the model estimates show, VFs were not able to allot their resources optimally in the cost-minimising sense. This implies that all producers struggled to attain optimum input–output mixes. While seeds turned out to be the most inefficiently used input, all other inputs also had some degree of inefficiency.

Because of the unavailability and difficulty of getting market prices of labour and land for the estimation of AI, the study empirically derived shadow prices of these inputs taking into account existing resource use inefficiencies. While estimations delivered different levels of shadow prices among efficient and inefficient producers, they were not statistically different. This suggests that AI is not a major contributor for overall EI which is also apparent from model results. While reducing AI requires better operating markets, improving TE of farmers should be the immediate goal for policy makers and those who are involved in decision-making process. These results can be also helpful to the continuing discussion on land and labour reforms in the country.

The new intensification strategy should be directed toward the non-traditional means of production and easy access to market information. It is also important that more attention should be also towards improving the efficiency and technical skills of the agricultural service organisations and the development of extension services (Bekchanov et al., 2010). It is believed that these organisations will help farmers to adopt technical and research innovations with a likely impact on labour and land productivity. The strategy of the externalisation of many growing tasks will further improve the effectiveness of farming systems. This is especially strategically important because of government's policy to consolidate farming lands. Finally, the results of this study are in accordance with the OECD's (2008) policy recommendations for developing countries, which states that agricultural production can be further improved through suitable technology and management techniques applied to farms, resources, and agricultural land. In this regard, improving water productivity (Bekchanov et al., 2012) will also be a vital issue in bettering TE of producers. Future research should attempt to include water as an input in efficiency analysis because of its key role in vegetable production.

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Abbreviations

AE	Allocative efficiency
AI	Allocative inefficiency
CA	Central Asia
CRS	Constant returns to scale
DEA	Data envelopment analysis
DIDF	Directional input distance function
EE	Economic efficiency
EI	Economic inefficiency
EII	Economic inefficiency of input
FSU	Former Soviet Union
IRS	Increasing returns to scale
OECD	Organization for Economic Cooperation and Development
SI	Scale inefficiency
SPLAN	Shadow price of land
SPLAB	Shadow price of labour
TE	Technical efficiency
TI	Technical inefficiency
UZS	Uzbek Soum
USD	United States Dollar
VF	Vegetable farms
VFL	Vegetable farming level
VRS	Variable returns to scale
VGA	Vegetable grown area

Appendix

Feasibility constraint:

$$\vec{D}_i(y^k, x^k; 1) \geq 0, \quad k = 1, ..., K; \tag{16}$$

Monotonicity constraint:

$$\frac{\partial \vec{D}_i(y^k, x^k; 1)}{\partial x_s} \geq 0, \quad s = 1,...,S, \quad k = 1,...,K$$
$$\alpha_s + \sum_{s'=1}^{S} \alpha_{ss'} x_{s'} + \sum_{q=1}^{Q} \delta_{sq} y_q \geq 0, \quad s = 1,...,S \tag{17}$$

Quasiconcavity constraint:

$$\frac{\partial \vec{D}_i(y^k, x^k; 1)}{\partial y_q} \leq 0, \quad q = 1,...,Q, \quad k = 1,...,K$$
$$\beta_q + \sum_{q'=1}^{Q} \beta_{qq'} y_{q'} + \sum_{s=1}^{S} \delta_{sq} x_s \leq 0, \quad q = 1,...,Q \tag{18}$$

Symmetry:

$$\alpha_{ss'} = \alpha_{s's}, \quad s \neq s', \quad \beta_{qq'} = \beta_{q'q}, \quad q \neq q' \tag{19}$$

Translation property:

$$\sum_{s=1}^{S} \alpha_s = 1, \quad \sum_{s'=1}^{S} \alpha_{ss'} = 0, \quad s = 1,\ldots,S, \quad \sum_{q=1}^{Q} \delta_{sq} = 0, \quad q = 1,...,Q \tag{20}$$

Non-negative input utilisation on the frontier:

$$x_s^k - \vec{D}_i(y^k, x^k; 1) \geq 0, \quad s = 1,\ldots,S, \quad k = 1,\ldots,K \tag{21}$$

The shadow prices of inputs can be derived using the envelope theorem (Färe et al., 2009). Given the DIDF's parameter estimates and the observed input price of *j*, *l* input's shadow price is found using the following formula:

$$\psi_l = \psi_j \left(\frac{\alpha_l + \sum_{s'=1}^{S} \alpha_{ls'} x_{s'} + \sum_{k=1}^{K} \delta_{lq} y_q}{\alpha_j + \sum_{s'=1}^{S} \alpha_{js'} x_{s'} + \sum_{k=1}^{K} \delta_{jq} y_q} \right). \tag{22}$$