Profit Gap Analysis on the Small Scale Production of Shallot: A Case Study in a Small Village in East Java Province of Indonesia

Sujarwo
A Graduate Student at Department of Agricultural Economics,
University of Kentucky
Email: sujarwo.ub@uky.edu

Sayed Saghaian
An Associate Professor at Department of Agricultural economics,
University of Kentucky
Email: ssaghaian@uky.edu

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Sujarwo and Sayed Saghaian

Department of Agricultural Economics

University of Kentucky

This study attempts to contribute to poverty alleviation through increasing efficiency of input allocation which can raise profit of the small scale farmers without changing the technology they use. Accordingly, this study addresses the problem of allocative inefficiency and profit gap of the farmer's shallot production. Double-log production function and polynomial cost function are applied to measure the profit gap analysis. The empirical results from double-log production function confirm that land, labor, fertilizer, and pesticide are allocated by farmers inefficiently. Furthermore, three simulations for efficient inputs allocation and profit gap analysis are taken into account based on the costs level spent by the farmers. The result shows that profit gaps are 4.72 percent, 13.96 percent and 17.92 percent for low, middle, and high input costs level, respectively.

Keywords**:** shallot production, double-log production, polynomial cost function, efficient input allocation, profit gap

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[1] Sujarwo is a graduate student and Sayed Saghaian is an Associate Professor, Department of Agricultural economics, University of Kentucky

Production efficiency, especially for small scale farming in East Java is an imperative issue since many farmers run their farms just based on experience, no farming records, and no evaluation. Furthermore, there are no local experiment stations conducted either by government or groups of farmers; even though, those are crucial in order to increase the factors productivity of shallot production. Regarding this problem, getting applicable results for the small scale farming will give significant contribution to poverty alleviation in the rural areas.

According to Schultz, 1964, small farmers in traditional agricultural settings are reasonably efficient in allocating their resources and responding positively to price incentives. This hypothesis relies on the assumption that traditional agriculture depends largely on their own resources and has enough period of time to make adjustment for the environment and price changes. Then, they will be able to apply resource management in the most efficient way.

The environment and market of shallot change significantly in the recent years. Consequently, it is more difficult for traditional and small scale farmers to adjust such conditions in order to find the most efficient way on shallot production. Undesirable yield of shallot production usually comes from weather changes. With the changing of weather such as increasing precipitation and reducing daylight, the shallot farmers commonly reduce the amount of fertilizers and increasing the amount of pesticides. Additionally, depletion of agricultural resources is another issue in the shallot production. In almost all seasons (wet and dry), farmers in the study area cultivate shallot in the same land for many years. Hence, soil's fertility issue has needed attention as well. Furthermore, prices of input and output in the market are given for the shallot farmers. They face asymmetric information of input and output prices that cause high risks in agricultural production. One way in the short run to increase farmer's income is coming from the efficient input allocation which will result in optimum output and input for maximizing profit.

Production and Efficient Allocation of Inputs

Efficiency in this study is measured as a level of inputs allocated in such away which can generate profit maximization based on a certain production technology used and on a certain level of costs spent by farmers. The technology is expressed through double-log production function.

Profit can be formulated as follow.

$$\pi = P_y . \prod_{j=1}^{8} e^{A_0} . X_j{}^{bj} - (\sum_{j=1}^{8} P_{Xj} . X_j + FC)$$

$$X_i^* = b_i \left[\frac{P_y}{P_{Xi}}\right] . Y$$

X_i^* is the optimum allocation of input-i used regarding prices of input and output given at the market.

Previous researches related to production efficiency for small scale farming were resulted various results. M.O. Oniah, O.O. Kuye, I.C. Idiong, *2008,* conducted a study about allocative efficiency in Obubra Local Government Area of Cross River State, Nigeria. This research estimates the production function and considers five inputs accordingly. The research finds that farm size (X_1), labor (X_2), seed (X_3), fertilizer (X_4), and capital (X_5) have the expected positive signs. The elasticities are 0.164, 0.620, 0.394, 0.056, and 0.004 for farm size, labor, seed, fertilizer, and capital, respectively. The sum of partial elasticity is 1.236 which shows that the farmers are operating at increasing return to scale. Moreover, the ratio of allocative efficiency for swamp rice inputs are greater than one which means that all inputs are under-utilized.

Amaza and Maurice, 2005, conducted research in rice-based production in Nigeria using stochastic frontier production function found that technical efficiency among 122 samples of farmers during 2002/2003 cropping season was varied widely between 0.26 and

0.97. Furthermore, the inefficiency equation revealed that farming experience and education significantly affected farmers efficiency levels.

Huyn Viet Khai and Mitsuyasu Yabe conducted research in Vietnam using data collected in 2006 and econometric model specified in stochastic frontier Cobb-Douglass production function. This study shows that technical efficiency of the farmers is around 81.6 percent. Among the inputs considered, rice land area has highest coefficient (0.765), fertilizer and pesticide coefficients are 0.093 and 0.034, respectively. The coefficients of hired labor and family labor are 0.005 and 0.023, respectively. Additionally, the most important factors which have positive influence on the efficiency are labor in rice cultivation, irrigation, and education.

Production Function using PCR

There were two estimations done in this paper, i.e. double-log production function and polynomial cost function. Based on double-log production function, return to scale (RTS) can be measured through sum of the coefficients and can be tested statistically through F-test for restricted and unrestricted models. Then, deciding fit cost function is examined through Ramsey's RESET test.

Double-log production function is specified as follow:

$$Ln\, y = \sum_{i=1}^{8}(\beta_0 + \beta_i LnX_i + \varepsilon)$$

Where y is the shallot production (ton), X_1 is the land used for shallot production (m^2), X_2 is the seed of shallot (kg). X_3 is the number of labor used (equal to man days). The fertilizer component indicated by 3 variables which are X_4 as phosphate (P) fertilizer (kg), X_5 as nitrogen (N) fertilizer (kg), and X_6 as potassium (K) fertilizer (kg). Then, X_7 as insecticide (gram) and X_8 as fungicide (gram) become pesticide elements. The last variable ε represents disturbance term.

Multicollinearity commonly exists on production function analysis especially due to small sample size and small range of data. VIF is applied to identify multicollinearity in the model specified. If there is higher multicollinearity, Principal Component Regression (PCR) will be applied to overcome this case.

PCR is applied as appropriate approach to transform the original independent variables data which are highly correlated into principal components without much loss information from the original data. The principal component matrix (P) contains exactly the same information as the original standardized data (Z), but they are arranged into a set of new variables which are completely uncorrelated one into the others and which are also ranked regarding the magnitude of the eigenvalues (Draper and Smith 1981, Myers 1986).

B. D. Fekedulegn, J.J. Colbert R.R. Hicks, Jr. Michael E. Schuckers (2002) analyzed data on their study using PCR and got back to the original standardized variable through this formula.

$$lny = \beta_o + \sum_{i=1}^{p} \sum_{j=1}^{z} \beta_i a_{ij} Z_j + \varepsilon \quad \ldots\ldots \sum_{i=1}^{p} a_i Z_i = P_i$$

Where a_{ij} is an element of the eigenvector associated with eigenvalue, β_i is coefficient of PCR, and c_j $(c_j = a_{ij} * \beta_i)$ is coefficient of standardized variables-j. The least square procedure is applied to obtain *lny* as a function of selected principal component, P_i. Once the fitted equation is obtained in terms of selected P's, it can be transformed back into a function on the original standardized variable as noted above.

The variance of the coefficients in vector c_j can be computed through the variance and standard error of the estimated coefficients of vector β_i. To calculate the variance of each element of the vector c_j, we can apply this formula (B. D. Fekedulegn, J.J. Colbert R.R. Hicks, Jr. Michael E. Schuckers, 2002).

$$var(c_j) = \sum_{i=1}^{p}\sum_{j=1}^{z} a_{ij}^2 var(\beta_i)$$

Transformation from principal component regression to original variable considering eigenvector, coefficient regressions, and standardized variables can be expressed below.

$$\widehat{lny} = \hat{\beta}_o + \sum_{i=1}^{p}\sum_{j=1}^{z} a_{ij}\hat{\beta}_i Z_j$$

Which,

$$\widehat{lny} = \hat{\beta}_o + \sum_{i=1}^{p}\sum_{j=1}^{z} a_{ij}\hat{\beta}_i \left[\frac{LnX_j - \overline{lnX_J}}{S(LnX_j)}\right]$$

When we state that

$$A_0 = \hat{\beta}_o - \sum_{i=1}^{p}\sum_{j=1}^{z} a_{ij}\hat{\beta}_i \left[\frac{\overline{lnX_J}}{S(LnX_j)}\right]$$

Then,

$$y = \prod_{j=1}^{z} e^{A_0}. X_j^{[b_j]}$$

Double-log production function estimated from PCR which can be transformed into original independent variables has standard error as follow.

$$se\,(b_j) = \sqrt{var\left(\frac{c_j}{s(LnX_j)}\right)} = \frac{se(c_j)}{s(lnX_j)}$$

Cost Function

The costs measured in this study consist of costs of 8 inputs considered in double-log production function and other costs which are harvest transportation, irrigation, and depreciation of tools used. The proportion of other costs is about 4 percent. Furthermore, the eight inputs are called input costs (IC) and the other costs are identified such as transportation costs, irrigation cost, and depreciation of tools used on shallot farming.

To choose the fit cost function, we specify the function in three econometric models as follows:

Linear $TC(y) = \beta_0 + \beta_1 y + \varepsilon$

Quadratic $TC(y) = \alpha_0 + \alpha_1 y + \alpha_2 y^2 + \mu$

Cubic $TC(y) = \phi_0 + \phi_1 y + \phi_2 y^2 + \phi_3 y^3 + \nu$

Linear, quadratic, and cubic models are considered to represent cost function of shallot production in the study area. Ramsey's RESET test for specification bias will be applied on examining the fit one.

Profit Gap Measurement

A profit gap is a different between the optimum and the actual inputs allocated by farmers at a certain amount of costs production. Optimum inputs allocation are measured based on factors elasticity from double-log production function at the particular costs production. Furthermore, optimum inputs allocation will be obtained when marginal value product of input is equal to input price. They also can be measured through output maximization subject to certain level of costs. Several simulations are taken into account in this study to evaluate efficient input allocation of small scale shallot farming. The simulations are based on input costs, IC. Afterward, we classify the simulation into low group of IC, middle group of IC, and high group of IC at the range of data.

Suppose π_{Gap} is profit gap (local currency, Rp), P_y is output price (Rp), C(y) is cost function, and b_0, b_j is inputs coefficient at double-log production function. Mathematically, the profit gap can be expressed bellow:

$$\pi_{\mathrm{Gap}} = \left\{ P_y . \prod_{j=1}^{8} b_0 . X_{j\,\mathrm{optimal}}^{bj} - C(y_{\mathrm{optimal}}) \right\} - \{ P_y . y_{\mathrm{actual}} - C(y_{\mathrm{actual}}) \}$$

Data

This research uses primary data obtained from a survey in a village of East Java, Indonesia. This village is one of the shallot production centers in Nganjuk Regency, East Java. The sample size is determined by a random sampling technique and chosen about 43 farmers but the data used are 36 observations since there are 7 outlier observations. The data was collected in the period of shallot production on April up to July 2005. Input and output price were also taken based on the market price in the study area during that period of time.

Regression Result:

Double-log production function and cost function

The first test conducted in the production function is to test whether multicollinearity exists in the production function or not. One common measurement of multicollinearity and applied in this study is variance inflation factors (VIF). If the VIF value is greater than 10, it will indicate for high multicolinearity in the model specified. Table 1 shows high multicollinearity since VIF is equal to 38.347 (>10) for land and labor variables respectively. One more indicator of multicollinearity is that the higher value of R^2 but most of coefficients are insignificant statistically. Double-log production function estimated through OLS has high R^2 (> 0.90) but there are only 3 variables significant at 5% significance level over 8 variables selected in the model.

The existing of muticollinearity also tends to lead to the result that the sign and value of linear regression coefficient are also not consistent with the expected ones (R.X. Liu, J. Kuang, Q. Gong, X.L. Hou, 2002). Accordingly, the result shows that labor coefficient has a negative value which is not consistent with what we expect theoretically. Therefore, PCR is definitely needed to be applied in this case to estimate double-log production function.

Table 1 also displays the result of Double-log production function using principal component analysis. Then, we find that there are two inputs from 8 inputs selected that do not have significant influence to the shallot production at 5% significance level. They are potassium fertilizer and insecticide. Additionally, all inputs coefficients have positive values and less than 1 which refers to diminishing marginal return of inputs.

Table 1. Regression of double-log production function (OLS and PCR)

Variable [1]	OLS estimates			PCR [2]	
	Coefficient	s.e	VIF	Coefficient	s.e.
Intercept	-0.152	0.950	.000	1.694**	0.0046
Land (m2)	0.921**	0.304	38.347	0.282**	0.0166
Seed (kg)	0.349**	0.120	9.063	0.214**	0.0122
Labor (man days)	-0.370	0.272	30.811	0.271**	0.0132
Phosphate (kg)	0.010	0.052	2.997	0.212**	0.0258
Nitrogen (kg)	0.128*	0.048	2.381	0.103**	0.0049
Potassium (kg)	0.034	0.052	3.041	0.017	0.0227
Insecticide (gram)	0.038	0.040	2.080	0.019	0.0259
Fungicide (gram)	0.038	0.024	1.603	0.052*	0.0208
	R^2 = 0.939	R^2_{adj} = 0.923		R^2 = 0.951	R^2_{adj} = 0.947
	F-test = 59.54			F-test = 208.53	

[1] Natural logarithmic form
[2] Using 3 principle component explain 84.4% of total variance the original data
** Significant at the 0.01 level
*   Significant at the 0.05 level

Among the coefficients, land and labor have the highest factors elasticity which are 0.282 and 0.271, respectively. This finding support the previous study conducted by Oniah, *et al*, (2008) which also found that labor had the highest factor elasticity. Additionally, Huyn Viet Khai and Mitsuyasu Yabe in Vietnam (2006) also found that land area had the highest factor elasticity. Among fertilizer used by farmers, phosphate has the highest elasticity which is 0.212. Moreover, coefficient of fungicide is 0.052 which is significant at 5% significant level. The important role of fungicide at that time was to control diseases which were intensively attack shallot crop, such as *Peronospora destructor* and *Alternaria porri*.

Besides factor elasticity, double-log production function also provides information about return to scale (RTS). RTS can be classified into constant return to scale, increasing return to scale, and decreasing return to scale. Total factors elasticity which is 1.168 can be tested through F-test to conclude whether there is increasing or constant RTS in shallot production.

Test for RTS to conclude whether 1.168 is constant RTS or not can be tested by imposing restriction in the model that total factors elasticity is equal to 1. Then, we analyze the restricted model. F-test can be used to determine whether RTS is constant or not.

This restricted regression analysis is conducted using PCR with 3 principal components which explain 88.8% total variation of restricted variables. Finally, test of return to scale can be done as follow:

$$F_{Value} = \frac{(\sum e^2_{rest.} - \sum e^2_{unrest.})/j}{\sum e^2_{unrest.}/(n-k)}$$

$$F_{Value} = \frac{(24.73641 - 0.491)/1}{0.491/(36-9)} = 1334.58$$

The critical value of F with 5% significance level and the degree of freedom, df=1 and 29, is 4.21. The result of F-test is equal to 1334.58 which is much higher than critical value of F-test. Therefore, we reject hypothesis that total factor coefficients is equal to one. In other words, we have enough evidence to conclude that there is increasing RTS in the production function.

This finding is the same with what has been found by O. Oniah, O.O. Kuye, I.C. Idiong, 2008 which found increasing RTS, 1.236, on rice production in Obubra Local Government Area of Cross River State, Nigeria. Moreover, Huyn Viet Khai and Mitsuyasu Yabe also found that the sum of factors elasticity on rice production was 1.035 showing the possibility of Vietnamese farmers increasing RTS.

Cost of shallot production

The cost functions of small scale shallot production are specified as a linear model, a quadratic model, and a cubic model. The cost models use predicted production function (y_hat) as the regressor variable(s) because this function will be used to get the predicted total cost of shallot production in profit gap analysis. The models statistically will be tested to choose a fit cost function using Ramsey's RESET test (Marno Verbeek, 2004).

Ramsey's RESET test is used to identify whether there is specification bias or not. Ramsey (1969) showed that any or all of these specification errors produce a non-zero mean vector for ε. Null hypothesis and alternative hypothesis are displayed below.

$$H_0: \varepsilon \sim N(0, \sigma^2 I)$$

$$H_1: \varepsilon \sim N(\mu, \sigma^2 I) \qquad \mu \neq 0$$

Table 3 shows that cubic cost function has significant value of RESET test at 5% significance level. Therefore, we reject null hypothesis and have an evidence to say that there is either functional specification bias or missing important variable(s) in this model. Quadratic cost function and linear cost function specified does not have significant value of RESET test at 5% significance level. So, we cannot reject null hypothesis and conclude that specification bias or omitting important variable(s) do not exist in the model.

Table 2. Linear, quadratic, and cubic cost functions

Variable	Linear		Quadratic		Cubic	
	Coeff.	t-Value	Coeff.	t-Value	Coeff.	t-Value
Intercept	814,401	5.08	276,985	0.92	53,962	0.09
y_hat	1,472	24.02	1,921.26	8.52	2,222.878	3.03
y_hat^2			-0.07284	-2.065	-0.18453	-0.71
y_hat^3					0.0000116	0.43
R^2	0.944		0.951		0.951	
R^2 adj	0.943		0.948		0.946	
F-test	576.80		318.21		206.97	

To decide the best fit model between the linear model and quadratic model, we can consider the coefficient of y_hat^2 and Ramsey's RESET test at quadratic form (power=2) which has F-value 4.263. That is exactly the same with the square of t-value at quadratic model which is -2.065 in Table 2. This information shows that at 5% significance level, the linear model cannot encompass quadratic model since the coefficient of y_hat^2 is significant at 5% significance level. As a result, quadratic cost model is the preferred one to represent the variation of total cost on small scale shallot production.

Table 3. Ramsey's RESET test

Power		2	3	4
Linear	RESET	4.263	2.172	2.100
	Pr > F	0.047	0.130	0.120
Quadratic	RESET	0.153	0.719	2.717
	Pr > F	0.698	0.495	0.062
Cubic	RESET	1.438	4.163	3.601
	Pr > F	0.239	0.025	0.025

Efficient allocation and profit gap

Double-log production function and cost function is used to estimate profit gaps which are the differences between the actual and the optimum level of cost and production. Before measuring profit gap, we can evaluate the validity of those functions using mean absolute percentage error (MAPE) (Tom Fomby, 2008) which is formulated below.

$$MAPE = \left(\sum_{i=1}^{n} \left| \frac{\hat{Y}_i - Y_i}{Y_i} \right| * 100 \right) / n$$

Where $\hat{Y}_i$ the predicted yield of observation-i is resulted from double-log production function and cost function as well, Y_i is the actual yield of observation-i, and n is the number of observations or the number of respondent in this study.

The calculation shows that the values of actual and predicted for average and standard deviation are relatively close. The actual value of average production is 2,302 kg (2,3 tons) and the predicted value of average production is 2,282 kg (2.28 tons). Moreover, the predicted and actual values of total cost are Rp. 4,170,366 and Rp. 4,661,515, respectively.

Table 4. Double-log production and cost functions: actual, predicted, MAPE

Econometric Model		Production (Kg)	Cost (Rp)
Predicted	Average	2282	4661515
	Standard deviation	1262	2423824
Actual	Average	2302	4170366
	Standard deviation	1329	1915335
MAPE		9.6	12.67

To get more precise picture of cost and production in actual and predicted value from 36 observations (farmers), Figure 1 and Figure 2 present in detail of each observations for costs and production level of the shallot farmers. As the nature of OLS estimation, there are higher gap between actual and predicted value for the lower-tail and upper-tail of estimation. And, the best estimation is around the mean..

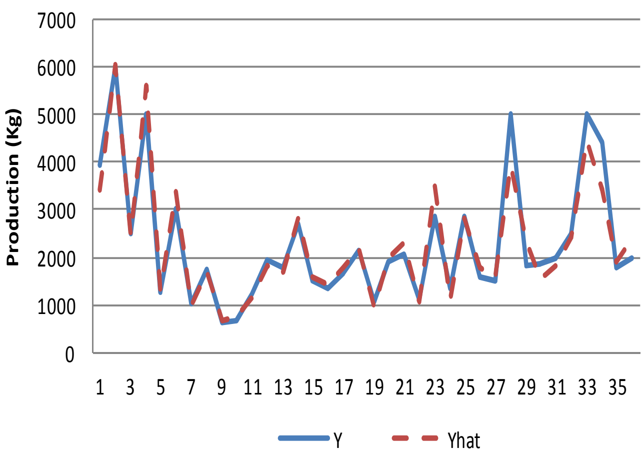

Figure 1. Production: Actual and Predicted

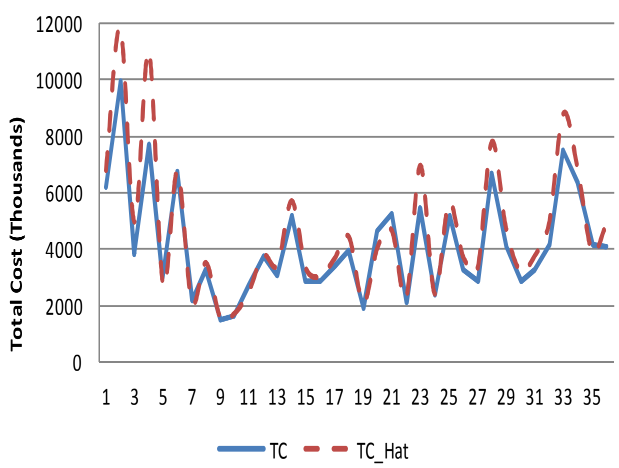

Figure 2. Costs: Actual and Predicted

In this study, there are simulations to evaluate allocative efficiency at 3 level of costs for the shallot production. The three simulations are:

1. Simulation-1: The low level of input costs used (IC) in shallot production. The cost is about Rp. 1,600,000. The respondents available at this cost level to be compared to optimum level at the same input cost level are 3 farmers.
2. Simulation-2: The middle level of input costs used (IC) in shallot production. The cost is about Rp. 4,000,000. The respondents selected at this cost level are 5 farmers.
3. Simulation-3: The high level of input costs used (IC) in shallot production. The cost is about Rp. 6,200,000. The respondents selected at this cost level are 4 farmers.

The question trying to answer in this analysis is that how allocation of inputs can be chosen by farmers at a certain level of costs in order to generate maximum profit with respect to double-log production function and cost function specified. Once certain level of input costs chosen in this analysis, we can examine and compare the actual profit and maximum profit which is called profit gap in this study.

Table 5. Allocative efficiency of shallot production at certain levels of input costs

	Land (m2)	Seed (kg)	Labor (man days)	Phos-phate (kg)	Nitro-gen (kg)	Potas-sium (kg)	Insec-ticide (gram)	Fungi-cide (gram)	Y_hat
Coefficient	0.282	0.214	0.271	0.212	0.103	0.017	0.019	0.052	-
Input price	350	5000	10000	7806	6800	8200	384	774	-
Simulation-1: allocative efficiency at IC ≈ Rp. 1,600,000,-									
Xi optimum	1088.01	57.74	36.55	36.72	20.38	2.78	65.17	89.91	997.51
Xi actual	830.66	59.13	58.90	11.79	7.30	4.85	99.56	231.17	798.64
Ratio	1.31	0.98	0.62	3.11	2.79	0.57	0.65	0.39	-
Simulation-2: allocative efficiency at IC ≈ Rp. 4,000,000,-									
Xi optimum	2813.69	149.31	94.52	94.97	52.70	7.20	168.53	232.50	3025.47
Xi actual	1630.46	137.57	128.05	26.16	26.83	19.10	394.86	467.38	2102.79
Ratio	1.73	1.09	0.74	3.63	1.96	0.38	0.43	0.50	-
Simulation-3: allocative efficiency at IC ≈ Rp. 6,200,000,-									
Xi optimum	4184.65	222.06	140.57	141.24	78.37	10.70	250.64	345.79	4809.44
Xi actual	2640.29	245.93	186.22	35.07	33.96	30.76	981.59	1142.88	3532.40
Ratio	1.58	0.90	0.75	4.03	2.31	0.35	0.26	0.30	-

The ratio represents the optimum input allocation divided by the actual input allocation. Then, the ratio which has a value <1 shows that the actual input is allocated more than should be. On the contrary, the ratio >1 shows that input is under-utilized. Finally, the ratio equal to 1 represents efficient input allocation.

Based on Table 5, the actual inputs which are used over the optimum level are labor, potassium, insecticide, and fungicide. On the other hand, land, phosphate, and nitrogen, are used less than the optimum level. But, farmers in the study area almost achieve optimum level of seed (ratio ≈ 1) in 3 types of simulation conducted.

This allocative efficiency of inputs in East Java, Indonesia is a little bit different from what was found by M.O. Oniah, O.O. Kuye, I.C. Idiong in Nigeria, 2008. The study for rice production provided information that the ratio of all inputs, i.e. farm size, labor, seed, and fertilizer were >1 or under-utilized.

Further analysis in this shallot farming is to find out how much profit gap occurs as a result of inefficient inputs allocation applied by farmers. Information of this analysis can be seen more detail at Table 6.

Table 6. Profit gap due to inefficient inputs allocation of small scale shallot production

		Sim-1	Sim-2	Sim-3
Optimum Allocation of Input	Costs of 8 inputs - IC (Rp)	1577621	4079879	6067771
	Output (Kg)	998	3026	4810
	Total revenue (Rp)	2159701	6550445	10412967
	Gross Profit Efficient (Rp)	582080	2470566	4345196
	Total Cost – Linear Function (Rp)	2121061	5423175	7832638
	Net Profit Efficient	38640	1127270	2580329
Actual average Allocation of Input	Costs of 8 inputs - IC (Rp)	1599641	3731264	6278716
	Output (Kg)	799	2103	3533
	Total revenue (Rp)	1729126	4552776	7648110
	Gross Profit Efficient (Rp)	129485	821511	1369394
	Total Cost – Linear Function (Rp)	1764982	3995093	6155067
	Net Profit Efficient	-35855	557682	1493043
Gross Profit Gap (Rp)		452595	1649054	2975801
Net Profit Gap (Rp)		74495	569588	1087286

Based on Table 6, increasing farm size or farm costs (IC) tends to increase net and gross profit gap. When at the low level of IC, there are Rp 452,595 for gross profit gap and Rp 74,495 for net gross profit gap. Then at the middle level of farm costs, there are Rp 1,649,054 and Rp 569,588 for gross profit gap and net gross profit gap, respectively. Finally, at the high level of IC, there is Rp 2,975,801 for gross profit gap and Rp 1,087,286 for net gross profit gap.

The three levels of IC simulated tend to have more gap of production between the actual and the optimum allocation of inputs. When Sim-1 has 199 kg more of output generated from optimum input allocation, Sim-2 and Sim-3 have 923 kg and 1,277 kg of production gaps, respectively. Figure 2 represents the decreasing at increasing return regarding the incremental output generated as the differences between the optimum and the actual inputs allocation (Figure 3).

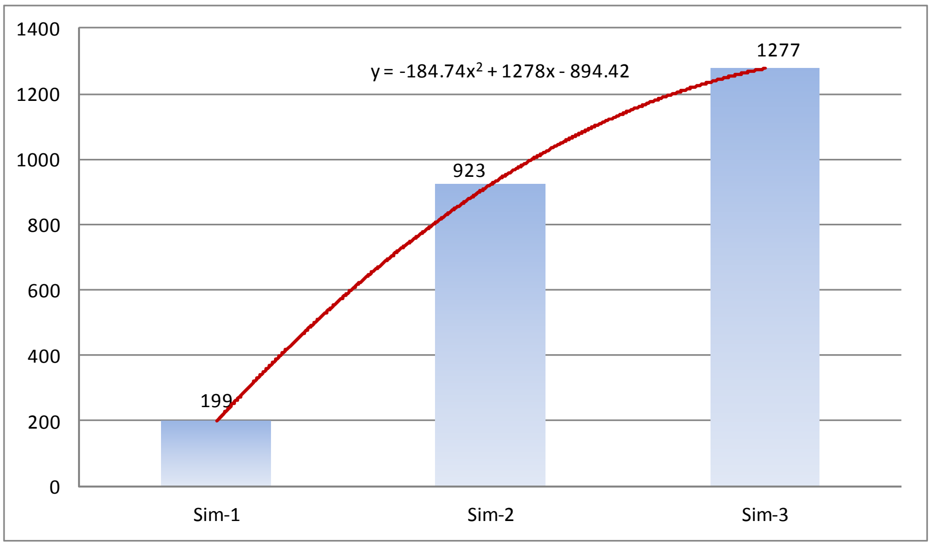

Figure 3. Production gaps in the inputs allocation

Conclusion and Implication

Based on double-log production function, land, labor and seed are the most important group of inputs which have highest factors elasticity. Among fertilizers used, phosphate has the highest contribution to production. Additionally, insecticide has higher factor elasticity than fungicide.

Total factor elasticity which represents return to scale is 1.168, and we have enough evidence statistically to conclude that the production function has increasing returns to scale. The cost function is further analyzed in this study and we find out that the quadratic cost function is the fit function to depict costs characteristic of the shallot farming in the study area.

Related to efficient allocation of inputs, farmers fail to allocate inputs efficiently. Labor, pesticide, potassium are used more than optimum allocation. On the contrary, others inputs such as land, phosphate and nitrogen are applied less than the optimum allocation of inputs. Only has the ratio of seed allocated around 1 which is very much close to efficient allocation of input.

The profit gap between the actual profit and the optimum profit is quite significant. Assuming that inputs and output prices are clearly identified, the farmers clearly know the production function and cost function, and they easily reallocate their resources into optimum inputs allocation level, shallot farmers can improve their profit and tend to increase profit along with increasing farm size and farm costs (IC) accordingly. Furthermore, farmers in their shallot production have to improve their input allocation to be more efficient, especially for farmer with land less than 0.1 ha.

The facts of the shallot farming based on direct observation at the study area which contribute negative impacts on farmers and efficiency in their shallot production are:

1. Farmers are price taker at input prices and output price along with asymmetric information and bargaining position problems. These problems generate more difficulty of the farmers to allocate their resources efficiently
2. The shallot farming depends greatly on weather. The weather happened at the cropping period influences the way how inputs, such as fertilizer, insecticide, and fungicide applied.

It means that productivity or elasticity of inputs will also be changed due to environment. Therefore, these results are not intended to generalize efficiency of shallot production on the other season. In contrast, when the environment for the next period of shallot production and the prices are the same, these simulations are valuable in order to guide farmers in their inputs allocation and generate maximum profit based on the optimum one.

3. There are no support in shallot farming in terms of technology, finance, and institution. As a result, there is almost no improvement in production technology and in understanding the relationship between input and output for both technically and economically.

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