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Research

Economic analysis of potential of citrus and walnut fruits by artificial neural network

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Abstract
South Asian countries have a wealth of opportunities to use the rainfed lands to the farmers' advantage with the largest amount of rainfed land. The economic circumstances of the farmers operating in these areas are appalling due to the inefficient use of these lands. The work reported in this paper was carried out in the Jammu, Kathua, and Udhampur districts of the Jammu division. Two horticultural crops, viz., citrus and walnuts, were discovered to be cultivated in the chosen sample location. The influence of several elements to the financial potential of these horticultural crops was investigated using production functional analysis and marginal value productivity (MVP). The use of artificial neural networks (ANNs) further assisted this. According to a production functional analysis, the main variables in the districts of Udhampur and Kathua are machine labour and fertilisers, followed by human labour and fertilisers in the Jammu district. However, sensitivity analysis revealed the importance of manure, fertilisers, and manpower. In the rainfed portions of Jammu division, manpower combined with fertilisers is often thought of as the key determining factor for the profitability of horticulture crops like citrus and walnut. The absence of better varieties was identified via Garett ranking as the main restriction, followed by a lack of knowledge and expensive inputs, respectively.

Article Highlights

(1) Human labour, machine labour and fertilizers proved to be the important factors for farmers' income in the production function analysis.
(2) Human labour, manure and PPC turned out to be indispensable factors for farmers' income in the ANN model.
(3) Non-availability of the improved varieties found out to be the major constraint for the farmers in the rainfed regions.

Keywords Rainfed region · Production function analysis · Marginal value productivity · Artificial neural network · Sensitivity analysis

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1 Introduction

India is the nation with the possession of maximum rainfed area under its fold. These rainfed areas are not conducive for the growth and cultivation of crops, as these areas are inflicted with myriad of problems. The productivity and efficiency in these areas are abysmally low in comparison to irrigated areas. The situation becomes more evident and problematic when considering the fact that these regions are also not being adequately managed by government entities. Though, multiple projects like NWDPRA (National Watershed Development Project for Rainfed Areas), Watershed Development Fund and PM's Special Package, NMSA (National Mission for Sustainable Agriculture), etc. were initiated by the government, but still the development of these areas is a distant dream. Therefore, it is not uncommon to find the fact that, most of the poor farmers are found in the regions, where rainfed farming are generally been practiced.

At the same time, it would be an exaggeration in making the statement that these areas are redundant in nature. Many studies in the past have focussed upon the remunerative potential of these rainfed areas. Rainfed farming turns out to be more imperative for India as India has the largest possession of rainfed area in the world. In these regions, there are multitude of areas where the profitability of the farmers can be increased. One such area, where the remunerative potential of the farmers can be explored is horticulture.

With respect to Jammu region, horticulture is an attractive and viable option for the farmers. No doubt, there are some farmers, who are taking advantage from the growth of such crops, but in essence, their contribution is very much limited. One of the reasons is that not all the farmers in the region adopted the cultivation of horticultural crops. There exists a myriad of problems for the farmers for not adopting the cultivation of otherwise profitable horticultural crops. It becomes quite prerequisite at this point of time to make the cultivation of horticultural crops a profitable phenomenon in the rainfed regions. To make it a ubiquitous phenomenon, the extent of the cultivation of horticultural crops needs to be expanded, especially from the less productive rainfed regions. Therefore, this paper focuses upon increasing the income of the farmers, engaged in the cultivation of horticultural regions in the rainfed regions. The paper discusses about the parameters/variables that are important and of much wider significance in the cultivation of horticultural crops, and therefore, the farmers need to focus upon these important parameters, so as to enhance their profitability in the cultivation of horticultural crops. In addition, as the threat of climate change is becoming more and more pronounced, it is important to sustain the income of the farmers under the looming threat of climate change. In this context, keeping more and more area, as the source of additional production turns out to be the only option of meeting the threat of climate change.

Many studies have focussed on the different aspects of the cultivation, such as the climate change and conserve soil biodiversity [41], system of rice intensification [33], applicability of denitrification and decomposition model in legume-cereal rotation [32], method of forecasting [39] including others. But there is some need to focus upon enhancing the options of earning revenues for the farmers in these regions. Therefore, the present work focusses upon the estimation of important parameters like machine labour, human labour, farmyard manure (FYM), pruning, fertiliser, plant protection chemicals (PPC), picking and assembly cost, that affect the remunerative potential of horticultural crops like citrus and walnut in rainfed areas of Jammu division. Three regions of Jammu namely Jammu, Kathua and Udhampur were selected for study. The obtained data were subjected to the production functional analysis. Further, the data were subjected to marginal value productivity (MVP), for finding out the contribution of the different factors/inputs in the remunerative potential of the selected horticultural crops, and at the end, this was finally been supported by multi-layer perceptron neural network with back propagation method.

2 Method of analysis

2.1 Study area

The study was carried out in the Jammu regions of Jammu & Kashmir union territory. The period of study was 2020–2021. Jammu and Kashmir is a mountainous state with latitude of 32.17 and 37.06 and longitude of 73.2 and 80.36, respectively. Majority of area, i.e., about 69% of area in the UT is rainfed in nature (Digest of statistics, 2018–2019). On account of the geography of the state, economy of UT is dependent upon agriculture as well as allied activities which resulted into a wide variety of agricultural and horticultural products, respectively. Within Jammu division, three districts i.e., Jammu, Kathua and Udhampur were purposefully (on the basis of the possession maximum rainfed area) selected. These three districts were in possession of one-third of the total rainfed area of the division (Fig. 1). Within these districts, citrus horticultural crops were selected from Jammu and Kathua districts, respectively and walnut horticultural crop was selected from Udhampur region.

2.2 Sampling procedure and data collection

Primary data were used for the present study, based on the objective of the study schedules were prepared and data was collected accordingly. It becomes quite pertinent at this point of time that the data were actually recorded for 97 farmers that were engaged in the agricultural and non-agricultural enterprises in the respective districts of Jammu division. Out of those 97 farmers, 30 farmers were selected from the Jammu region, 25 farmers were from Kathua region and 42 farmers were selected from Udhampur district. Much of the study area in Udhampur district were hilly. Though, districts were selected purposively but the subsequent selection of blocks and villages were random in nature so as to make the sampling distribution purely scientific in nature.

2.3 Schedule preparation

Schedules were prepared scientifically as per the defined objectives. Different variables were noticed in the cultivation of citrus and walnut; therefore, different schedules were prepared for both the fruit crops. Variables like machine labour, human labour, FYM, pruning, fertiliser, plant protection chemicals (PPC), picking and assembly cost, were taken into consideration. Apportion cost was one of the important parameters that was included in the schedule so as to bring out the cost that is to be shared among multiple cost units (units is defined here as 'years'). Though, by-products like 'shell' and 'husk' could also make their contribution towards the income generation for the farmers, but, as the farmers were not much aware about the efficacy about these by-products, this was not taken into account while calculating the profitability of these horticultural crops for the farmers. Selling of the citrus crops and walnut crops were only being taken into consideration while calculating the returns and income for the farmers.

2.4 Data analysis

As the data were collected for the paper under some other major project, therefore, the analysis of data has been done both using the parametric and non-metric tools. After subjecting the data to the test of normality, the data were analysed first by using simple formulas of gross and net returns, respectively. Then, the parametric tools of production functional analysis, more specifically, stochastic frontier analysis with Cobb–Douglas form of production were employed. There were variety of reasons for the employment of this production function. Primarily, it is of simple functional form and therefore, easy for computation. In addition, it also gives significant estimates for most of the variables used in the data. Also, by using this production function, elasticities are directly measured.

The general form of production function used in the analysis is presented in Eq. (1).

$$\mathrm{Yt} = \beta_0 + \sum_{i=1}^{7} \beta_i x_i + U, \tag{1}$$

where 'Y_t'and X_i (i = 1,2, 3,…,7) represent the levels of output and levels of inputs, respectively. In addition, the respective constants βo and βi's (i = 1,2,3,…,7) reflect the efficiency parameters as well as the production elasticities of the particular input variables for the given population at a particular period 't'. The term 'U' represents the error term.

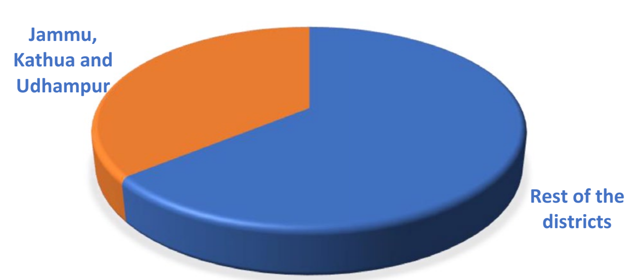


Fig. 1 Figure representing the proportionate share of Jammu, Kathua and Udhampur in comparison to rest of the districts. Source: Digest of statistics, 2016–17 (J&K)

The fitted Cobb–Douglas production function is represented in the mathematical form for the present case as shown in Eq. (2).:

$$Y = a_o X_1^{b1} X_2^{b2} X_3^{b3} \dots X_n^{bn} e^n. \tag{2}$$

In the above functional model, 'Y_t' denotes the dependent variable; 'X_i' depicts the regressors, 'a' is the constant representing the intercept or the production function and finally b_i's reflects the regression coefficients of the respective resource variables. Subsequently, the above function has been transformed into logarithmic transformation to suit the specific needs of the study as mentioned in Eq. (3).

$$\text{Log}\,Y = \text{Log}\,a + b_1 \text{Log}\,X_1 + b_2 \text{Log}\,X_2. + \dots + b_n \text{Log}\,X_n + u\,\text{Log}\,e. \tag{3}$$

The fitted Cobb–Douglas production function with seven variables has been represented as shown in Eq. (4).

$$Y = a_o X_1^{b1} X_2^{b2} X_3^{b3} X_4^{b4} X_5^{b5} X_6^{b6} X_7^{b7}. \tag{4}$$

where, Y is the gross returns of the crop enterprise in rupees as a dependent variable, X_1 is the total cost on human labour, $X_2$is the total cost on machine labour, X_3 represents total cost on manure, X_4 presents total cost on fertilisers, X_5 is the total cost on plant protection chemicals, X_6 is the total cost on picking/pruning, X_7 is the miscellaneous cost.

To bring out the uniformity in the different factor inputs, the monetary contribution of each input factor was taken into consideration. Further, monetary contribution of each input is very much dependent upon the productivity of the input; therefore, MVP was calculated by using Eq. (5).

$$\text{MVP} = b\frac{\overline{Y}}{\overline{X}} \mathrm{P_y}, \tag{5}$$

where, b = Regression coefficient of particular independent variable. $\overline{Y}$ = Geometric mean of dependent variable. $\overline{X}$ = Geometric mean of independent variable. P_y = Price of dependent variable.

Statistical significance was measured by t-statistic as shown in Eq. (6).

$$\text{t-statistic} = \frac{\textit{Regression coefficient}}{\textit{Standard error}}. \tag{6}$$

As said earlier, the data were not exclusively been prepared for the paper, therefore, there is possibility that assumptions of normality and linear assumption could have been violated. Thus, it becomes very important to use some other non-parametric tool. In this context, Artificial Neural Network (ANN) model was chosen as this method does not restrict itself to a well-defined set of rigid conditions and assumptions [46]. This method has already been applied in many of the economic applications in the past. For example, in case of forecasting GDP [24, 28] including others. Moreover, many studies have also been conducted earlier that has applied the process of linear regression vis-a-vis ANN [10, 18, 50].

The option that was selected was a multilayer perceptron (MLP) neural network with back propagation. The model considered seven input layers (excluding the bias input), which is equal to the number of variables. In determining the number of hidden layers, it is commonly recommended to follow the 'rule of thumb' principle, which suggests that the optimum number of hidden neurons usually lies between the number of input neurons and the number of output neurons [9]. Thus, in this context, the 'architecture' part of the model in SPSS considered 'two' as the minimum number of units in the hidden layer. Consequently, three hidden layers (without the bias) were employed for the analysis. The model utilised the hyperbolic tangent (tanh) as the activation function for the hidden layer. The network was trained to output values by using identity function (linear activation function). The stopping rule for the maximum number of steps without a decrease in error has been set to 1. Furthermore, 'automatic commands' have been chosen for both calculating the prediction error and determining the maximum number of training epochs. Ultimately, the upper limit for training time has been set at 15 min.

In this model, supervised learning techniques along with that of feed-forward–backward-propagation (FFBP) algorithm was employed. In the FFBP, inputs tend to move in a forward path and the resultant estimated errors tend to move in a backward direction. ANN model was implemented using the neural network module function in IBM's SPSS (Statistical Package for the Social Sciences). This was further been assisted by the sigmoid activation function. The given dataset was differentiated into two datasets, i.e., training set and testing set. Different proportions of data allocated to training and testing sets can be represented by various ratios, such as 50:50, 60:40, 70:30, 80:20, and 90:10. The rationale for separating the sample is based in the principle that the identical data should not be utilised for both model construction and validation purposes. The training set has been used to estimate the network parameters and, as a result, serves as the sample for analysis. On the contrary, testing is employed to mitigate overfitting and acts as the validation dataset. Past research have traditionally used a 90:10 data division. In addition, only a limited number of studies [11, 19, 35] have utilised an 80:20 division. The 60:40 partition has been utilised by Beale et al. [5] and Kumar and Rani [30] in their research studies. Previous study researchers have utilised a 50:50 ratio for dividing training and testing data equally [12, 23]. In this specific case, the ratio of data partitioning was determined to be 70:30 based on the size of the dataset and the desired evaluation precision. In order to reduce the effects of a single partition, the cross-validation technique was used, iteratively employing different portions of the data for testing and training [2, 7, 20, 36].

3 Results and discussion

3.1 Analysis of sample data

Data were collected through personal interview method by employing the usage of objectively prepared schedules. Data collected (Table 1) were not of similar size. 30 samples were collected from Jammu district, 25 samples were collected from that of Kathua district and finally, 42 samples were collected from that of Udhampur district. Data were resorted to different places, therefore, variability in terms of standard deviation was observed to be high in these three separate districts.

For analysis of any sample data, several statistical measures needs to be applied. These statistical tests are important so as to carve out the meaningful details from the data. For the appropriate statistical test, checking of normality of data is of paramount importance.Therefore, the collected primary data were subjected to the one-sample Kolmogorov–Smirnov test (Table 2) on IBM SPSS. The test of normality has shown varied results and therefore, the significance of the variables under study were further been subjected to subsequent tests.In the Jammu district, only machine labour and fertilisers have shown normal distribution behaviour, whereas the rest of the variables have shown non-normal distribution, respectively. On the contrary, in Kathua district, only machine labour has shown the non-normal distribution, the rest of the variables were showing the normal distribution. Finally, in case of Udhampur district, only 'fertilizers' showed the normal distribution. Now, as the sample size is also different in all the districts and, moreover, normality is not met, therefore, certain test was applied. In case of Kathua district, there was normality distribution, therefore, homogeneity of variances was estimated by Levene test (Table 3).

The variance was not homogeneous as the Levene statistic turned out to be significant, therefore, Welch test was applied in place for one-way ANOVA. The Welch test has also been significant showing the non-homogeneity of variances, therefore, post-hoc analysis test is applied using Games Howell method (Table 4), respectively. Post-hoc analysis revealed the relation to be significant among all the variables in the Kathua district. Table revealed the significant relationships among the different variables in the cost of cultivation of citrus in Kathua district.On the contrary, as for citrus (Jammu) and walnut (Udhampur), the population is non-normal in nature, therefore, a non-parametric Kruskal–Wallis H-test (Table 5) was performed for both.

The operation of these test on SPSS revealed that null hypothesis is rejected both for Jammu district (citrus) and Udhampur district (walnut) respectively, therefore, there is significant difference among the cost of different variables

Table 1 Descriptive statistics of sample data

	Citrus (Jammu)			Citrus (Kathua)			Walnut (Udhampur)		
	N	Mean	Std. deviation	N	Mean	Std. deviation	N	Mean	Std. deviation
Human labour	30	2022.16	187.68	25	1901	217.96	42	2604.38	504.08
Machine labour	30	1698.5	285.2	25	1233.72	214.62	42	1896.88	409.46
Manure	30	1093.56	1543.61	25	1266.32	269.1	42	1383.31	522.94
Fertilisers	30	703.6	128.47	25	793.88	119.97	42	841.10	124.77
PPC	30	298.86	48.16	25	167.64	22.66	42	256.40	62.44
Picking	30	5886.03	355.8	25	7016.08	374.01	42	7880.90	1058.97
Misc	30	1794.26	265.35	25	2012.28	174.37	42	2357.12	677.97
Valid N (listwise)	30			25			42		

Table 2 Test of normality of citrus crop and walnut crops

		Human labour	Machine labour	Manure	Fertilisers	PPC	Picking	Misc
Test of normality for citrus (Jammu)								
N		30	30	30	30	30	30	30
Normal parameters[a,b]	Mean	2022.17	1698.50	1093.57	703.60	298.87	5886.03	1794.27
	Std. deviation	187.68	285.21	1543.62	128.47	48.16	355.80	265.36
Most extreme differences	Absolute	0.18	0.12	0.48	0.13	0.16	0.17	0.18
	Positive	0.18	0.07	0.48	0.13	0.13	0.17	0.10
	Negative	− 0.12	− 0.12	− 0.36	− 0.08	− 0.16	− 0.14	− 0.18
Test Statistic		0.18	0.12	0.48	0.13	0.16	0.17	0.18
Asymp. Sig. (2-tailed)		0.016[c]	0.200[c,d]	0.000[c]	0.187[c]	0.045[c]	0.028[c]	0.013[c]
Test of normality for citrus (Kathua)								
N		25	25	25	25	25	25	25
Normal parameters[a,b]	Mean	1233.72	1266.32	793.88	167.64	7016.08	2012.28	1794.27
	Std. deviation	214.62	269.10	119.97	22.66	374.01	174.37	265.36
Most extreme differences	Absolute	0.18	0.14	0.13	0.12	0.09	0.13	0.18
	Positive	0.18	0.14	0.11	0.11	0.09	0.13	0.10
	Negative	− 0.11	− 0.09	− 0.13	− 0.12	− 0.09	− 0.13	-0.18
Test statistic		0.17	0.18	0.14	0.13	0.12	0.09	0.13
Asymp. Sig. (2-tailed)		0.072[c]	0.031[c]	0.200[c,d]	0.200[c,d]	0.200[c,d]	0.200[c,d]	0.200[c,d]
Test of normality for walnut (Udhampur)								
N		42	42	42	42	42	42	42
Normal parameters[a,b]	Mean	1896.88	1383.31	841.10	256.40	7880.90	2357.12	42
	Std. deviation	409.46	522.94	124.77	62.44	1058.97	677.97	2357.12
Most extreme differences	Absolute	0.20	0.21	0.09	0.18	0.10	0.21	677.97
	Positive	0.20	0.21	0.08	0.13	0.10	0.21	0.21
	Negative	− 0.11	− 0.13	− 0.09	− 0.18	− 0.08	− 0.11	0.21
Test statistic		0.21	0.20	0.21	0.09	0.18	0.10	0.21
Asymp. Sig. (2-tailed)		0.000[c]	0.000[c]	0.000[c]	0.200[c,d]	0.001[c]	0.200[c,d]	0.000[c]

[a]Test distribution is normal

[b]Calculated from data

[c]Lilliefors significance correction

[d]This is a lower bound of the true significance

Table 3 Test of homogeneity of variances and Welch test for Kathua district (citrus)

Cost	Levene statistic	df1	df2	Sig
Based on mean	13.36	6	168	0.000
Based on median	10.52	6	168	0.000
Based on median and with adjusted df	10.52	6	104.25	0.000
Based on trimmed mean	13.21	6	168	0.000
Cost	Statistica	df1	df2	Sig
Robust tests of equality of means				
Welch	2198.47	6	65.63	0.000

Table 4 Table showing post-hoc analysis for Kathua (citrus) district

Dependent variable	Cost				
Games-Howell					
(I) Variables		Std. error	Sig	95% confidence interval	
				Lower bound	Upper bound
Human labour	Machine labour	61.18	0.00	479.05	855.51
	Manure	69.26	0.00	421.20	848.16
	Fertilisers	49.76	0.00	952.14	1262.10
	PPC	43.83	0.00	1592.88	1873.84
	Picking	86.58	0.00	− 5384.24	− 4845.92
	Misc	55.83	0.43	− 283.39	60.83
Machine labour	Human labour	61.18	0.00	− 855.51	− 479.05
	Manure	68.84	1.00	− 244.85	179.65
	Fertilisers	49.18	0.00	286.76	592.92
	PPC	43.16	0.00	927.73	1204.43
	Picking	86.24	0.00	− 6050.61	− 5514.11
	Misc	55.31	0.00	− 949.03	− 608.09
Manure	Human labour	69.26	0.00	− 848.16	− 421.20
	Machine labour	68.84	1.00	− 179.65	244.85
	Fertilisers	58.93	0.00	287.64	657.24
	PPC	54.01	0.00	925.45	1271.91
	Picking	92.15	0.00	− 6034.51	− 5465.01
	Misc	64.13	0.00	− 944.69	− 547.23
Fertilisers	Human labour	49.76	0.00	− 1262.10	− 952.14
	Machine labour	49.18	0.00	− 592.92	− 286.76
	Manure	58.93	0.00	− 657.24	− 287.64
	PPC	24.42	0.00	548.27	704.21
	Picking	78.56	0.00	− 6470.83	− 5973.57
	Misc	42.33	0.00	− 1349.36	− 1087.44
PPC	Human labour	43.83	0.00	− 1873.84	− 1592.88
	Machine labour	43.16	0.00	− 1204.43	− 927.73
	Manure	54.01	0.00	− 1271.91	− 925.45
	Fertilisers	24.42	0.00	− 704.21	− 548.27
	Picking	74.94	0.00	− 7088.94	− 6607.94
	Misc	35.17	0.00	− 1957.26	− 1732.02
Picking	Human labour	86.58	0.00	4845.92	5384.24
	Machine labour	86.24	0.00	5514.11	6050.61
	Manure	92.15	0.00	5465.01	6034.51
	Fertilisers	78.56	0.00	5973.57	6470.83
	PPC	74.94	0.00	6607.94	7088.94
	Misc	82.53	0.00	4745.34	5262.26
Misc	Human labour	55.83	0.43	− 60.83	283.39
	Machine labour	55.31	0.00	608.09	949.03
	Manure	64.13	0.00	547.23	944.69
	Fertilisers	42.33	0.00	1087.44	1349.36
	PPC	35.17	0.00	1732.02	1957.26
	Picking	82.53	0.00	− 5262.26	− 4745.34

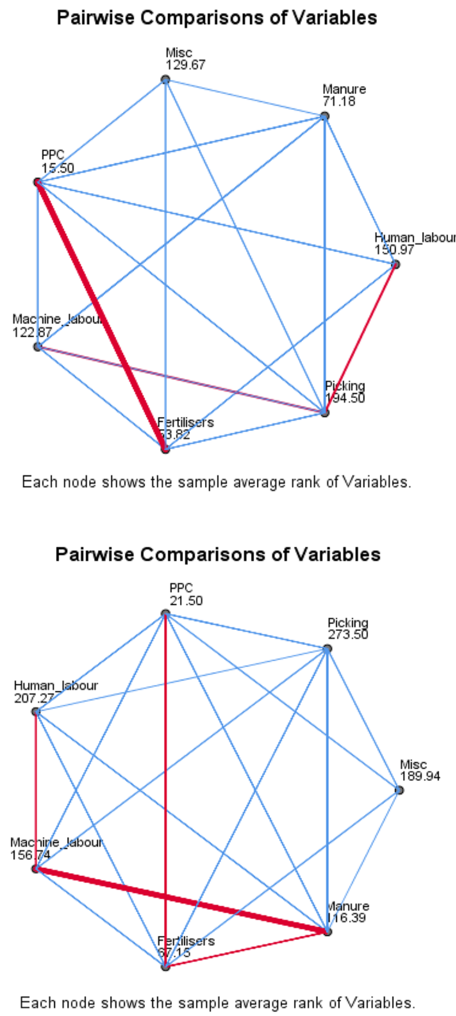
The mean difference is significant at the 0.05 level

Table 5 Table showing significance (Kruskal–Wallis) for Jammu (Citrus) and Udhampur district (Walnut)

Independent-samples Kruskal–Wallis test summary for Jammu district (citrus)	
Total N	210
Test statistic	185.44[a]
Degree of freedom	6
Asymptotic Sig. (2-sided test)	0.000
Independent-samples Kruskal–Wallis test summary for Udhampur district (walnut)	
Total N	294
Test statistic	259.39[a]
Degree of freedom	6
Asymptotic Sig. (2-sided test)	0.000

[a]The test statistic is adjusted for ties

Fig. 2 Figure showing pair-wise comparisons of variables in Jammu and Udhampur. Economics of citrus (Lemon) cultivation



in these two districts. Pairwise comparison (Fig. 2) among the different variables disclosed the fact that there is strong association between PPC (plant protection variables) & fertilisers on the one hand and also between human labour and picking on the other in Jammu district. In Udhampur district, machine labour has strong association between manure and human labour, on the one hand and between PPC and fertilisers on the other.

Simple calculations of gross and net returns were carried out to find out the profitability of different horticultural crops in different districts. Table 6 represents economics of citrus cultivation in Jammu and Kathua district. Total variable cost at

Table 6 Economics of citrus cultivation under rainfed conditions

S. No	Particulars	Jammu (Rs./acre/annum)	Kathua (Rs./acre/annum)
(A)	Variable cost		
(a)	Machine Labour	1672.78	1233.88
(b)	Human Labour	2100.43	1976.56
	Hired labour	1166.91	1411.83
	Family labour	933.52	564.73
(c)	FYM	1030.38	1215.85
(d)	Pruning	360.34	425.20
(e)	Fertiliser	665.86	785.72
(f)	Plant protection chemicals	306.20	161.32
(g)	Picking and assembly cost	5949.24	7020.11
(h)	Miscellaneous	1784.09	2105.23
(i)	Interest on working capital	970.85	1044.67
	Total variable cost	14,840.17	15,968.54
(B)	Fixed cost		
(a)	Apportion cost of establishment	2800	2687
(b)	Depreciation on equipment	621.39	579.10
(c)	Estimated rental value	2200.91	2167.47
(d)	Land revenue	0.00	0.00
	Interest on fixed capital	674.68	652.03
	Total fixed cost	6296.98	6085.60
	Total cost	21,137.15	22,054.14
	Returns		
	Citrus in kg	1870	1790
	Average price of citrus per kg	21.07	20.97
	Gross returns	39,400.90	37,536.30
	Net returns	17,051.57	15,482.16
	Family labour income	17,985.09	16,046.89
	Farm business income	18,659.77	16,698.92

Rs. 14,840.17 (in case of Jammu district) and Rs. 15,968.54 (in case of Kathua district) was found to be higher in comparison to their relative fixed cost. Net returns were found to be higher (Rs. 17,051.57 per acre per annum) in case of Jammu district in comparison to Kathua district (Rs. 22,054.14 per acre per annum). Subsequently, family labour income and farm business income were found out to be Rs. 17,985.09 per acre per annum and Rs. 18,659.77 per acre per annum, in case of Jammu district and Rs. 16,046.89 per acre per annum and Rs. 16,698.92 per acre, in case of Kathua district, respectively.

3.2 Economics of walnut cultivation

Cultivation of walnut was observed as one of the most profitable ventures. It was found in Udhampur district only. Total cost (Table 7) was worked out to be Rs. 22,659.60 per acre per annum, in which, the proportion of variable cost at Rs. 18,514.22 per acre per annum was found to be higher than that of fixed cost at Rs. 4145.38 per acre per annum. As far as the gross returns were concerned, it was worked out to be Rs. 85,555.75 per acre, which was found out to be highly remunerative. Net returns were found to be Rs. 62,896.15 per acre per annum and subsequently, family labour income and farm business income were calculated to be of Rs. 64,465.39 per acre per annum and Rs. 64,909.54 per acre per annum, respectively.

Table 7 Economics of walnut cultivation under rainfed conditions

S.No	Particulars	Udhampur (Rs./acre/annum)
(A)	Variable cost	
(a)	Machine Labour	1893.67
(b)	Human Labour	2690.12
	Hired labour	1120.88
	Family labour	1569.24
(c)	FYM	1360.10
(d)	Fertiliser	878.94
(e)	Plant protection chemicals	272.18
(f)	Picking and assembly cost	7853.00
(g)	Miscellaneous	2355.00
(h)	Interest on working capital	1211.21
	Total variable cost	18,514.22
(B)	Fixed cost	
(a)	Apportion cost of establishment	2200
(b)	Depreciation on equipment	128.50
(c)	Estimated rental value	1372.73
(d)	Land revenue	0.00
(e)	Interest on fixed capital	444.15
	Total fixed cost	4145.38
	Total Cost	22,659.60
	Returns	
	Walnut (kg)	488.89
	Average price of walnut per kg	175.00
	Gross returns	85,555.75
	Net returns	62,896.15
	Family labour income	64,465.39
	Farm business income	64,909.54

3.3 Factors affecting remunerative potential of citrus and walnut

As one of the main objectives of the paper is to find out the factors/variables that affect the remunerative potential of horticultural crops, therefore, it becomes pertinent to adopt a suitable input–output relationship among the different variables. Keeping this context in mind, the Cobb–Douglas production function had been applied (Table 8). This function has revealed the importance of certain variables in relation to other in affecting the remunerative potential for the farmers. The resource-use efficiency of citrus and walnut clearly delineates the fact that walnut proved to be more beneficial as far as the returns of the farmer were concerned. The returns to scale of walnut found out to be most beneficial for the farmers. The sum of elasticities of walnut in Udhampur worked out to be 1.48 (increasing returns to scale), that of lemon in Kathua came out to be 1.12 (increasing returns to scale) and that of lemon in Jammu, it came out to be 1.03 (constant returns to scale). The coefficient of determination (R^2) came out to be 97.94, 98.92 and 91.09 for lemon in Jammu &Kathua and walnut in Udhampur. Two variables (human labour and fertilisers), one variable (fertilisers) and two variables (machine labour and miscellaneous) came out to be positively significant, and all these variables were also found to be under-utilised. Thus, there was high scope of manipulating the cost in these inputs so as to increase the income/returns of the farmers in the proportion of the value of their respective regression coefficients. Further, so as to increase the resource-use efficiency, cost in the inputs like machine labour, manure, plant protection chemicals, picking/pruning and miscellaneous in case of Jammu district and in the inputs like machine labour and miscellaneous in case of Udhampur district needs to be reduced.

Table 8 Input-use efficiency of citrus and walnut by employing production function analysis

Variables	Citrus (Jammu)		Citrus (Kathua)		Walnut (Udhampur)	
	Coefficients	MVP	Coefficients	MVP	Coefficients	MVP
Constant or intercept	9.758 (0.460)		3.166 (1.867)		4.315 (2.047)	
X_1 Human labour	0.877* (0.055)	7.351	0.310 (1.219)	6.240	0.201 (0.278)	6.142
X_2 Machine labour	− 0.001 (0.001)	− 0.013	0.207 (3.503)	5.823	0.235* (0.035)	10.722
X_3 Manure	− 0.008 (0.017)	− 0.295	0.164 (6.301)	4.985	0.251 (0.489)	15.464
X_4 Fertilisers	0.177* (0.039)	10.380	0.046* (0.018)	2.224	0.417 (0.536)	41.809
X_5 Plant protection chemicals	− 0.004 (0.005)	− 0.633	0.008 (2.990)	1.377	0.138 (0.191)	41.477
X_6 Picking	− 0.003 (0.004)	− 0.018	0.124 (1.658)	0.656	− 0.029 (0.913)	− 0.309
X_7 Misc	− 0.010 (0.050)	− 0.230	0.266 (2.273)	4.768	0.271* (0.146)	9.925
R^2%	97.94		98.92		91.09	
∑bi	1.03		1.12		1.485	

*Significant at 5 per cent level of significance (figures in parentheses show standard error)

3.4 Artificial neural network

As the data used for the present paper were not exclusively been collected for the said purpose, but rather, it was a part of the other wider data collection exercise, therefore, the assumption of normality was violated in many of the instances. Keeping this context in mind, a robust test of ANN (Artificial Neural Network) model was applied on the primary data. Moreover, ANN model is considered as the add-on test to further the veracity of the findings. The findings of RMSE (Root mean square error) (Table 9) revealed the 'model-fit' of the parameter estimation. Average RMSE values for the training and testing procedures needs to be relatively small (around 0.10). The best RMSE configuration for training (mean values) has been found for Kathua, followed by Jammu and Udhampur.

It can be observed from the table that the RMSE values in all the districts (except RMSE testing value for the Jammu district) came around to be 0.10. Therefore, the said data can well be analysed for sensitivity analysis. Now, it is pertinent to mention here that, RMSE has been employed in comparison to that of other statistical metrices like MAE (Mean Absolute Error) or MAPE (Mean Absolute Percentage Error) on account of the fact that, the former serves as the aggregated mean and it involves the process of the square root (quadratic mean) of the error, thus, it gives more significance to the large error. Matrices like MAE gives emphasis to the arithmetic average (only) of absolute errors. In this regard, it stands in contrast to some of the earlier studies [24, 49]. In this way, RMSE is an add-on process over that of the R^2 that is used in case of regression.

Sensitivity analysis was calculated so as to present the normalized importance of the different variables under study. Moreover, it is important, so as to make a comparison between the importance of the different variables of that of production function analysis to that of the sensitivity analysis.

In Jammu district, human labour and fertilizers have found out to be significant parameters, when analysed through production functional analysis. But in the sensitivity analysis (Table 10), PPC came out to be most significant/important parameter that influences the economic potential in this district. This is followed by picking and pruning. In Kathua district, again fertilizers turned out to be significant variable in the production function analysis. In sensitivity analysis, human labour was found out to be most important variable and fertilizers, on the other hand, proved out to be least significant variable, respectively. Finally, in case of Udhampur district, machine labour proved to be the dominant factor that influenced the production potential of the walnut cultivation. But sensitivity analysis revealed 'manure' to be most important variable in the district followed by fertilizers. On the other hand, 'machine labour' proved to be least significant variable. Carefully analysing both the analysis revealed that fertilisers, PPC and manure proved to be most important variables in the sensitivity analysis, whereas, human labour and machine labour found out to be the significant variables in the production function analysis.

3.5 Constraints in horticulture

Second major objective of the paper was to find out the constraints that the farmers were experiencing in the rainfed regions. Garett score of the data revealed non-availability of improved verities as one of the major bottlenecks that the

Table 9 RMSE values for different districts of the Jammu division for citrus cultivation

Network	Sum of square error (training)	Sum of square error (testing)	RMSE (training)	RMSE (testing)
RMSE values for citrus (Jammu)				
1	0.867	0.50	0.35	0.86
2	3.51	0.45	0.56	3.51
3	2.17	0.57	0.49	2.17
4	0.94	0.37	0.43	0.94
5	5.26	0.48	0.66	5.26
6	4.53	0.31	0.75	4.53
7	4.05	0.49	0.58	4.05
8	1.72	0.47	0.46	1.72
9	1.19	0.61	0.36	1.19
10	0.85	0.30	0.32	0.85
Mean	2.50	0.46	0.49	2.51
Std Dev	1.68	0.10	0.14	1.68
RMSE values for citrus (Kathua)				
1	2.67	1.38	0.38	0.44
2	7.9	9.1	0.66	1.14
3	1.94	2.42	0.32	0.63
4	4.08	0.52	0.46	0.29
5	2.4	1.4	0.51	0.29
6	7.41	3.59	0.64	0.71
7	7.35	0.89	0.60	0.42
8	4.52	4.03	0.53	0.66
9	2.97	2.95	0.38	0.76
10	1.64	1.91	0.29	0.56
Mean	4.288	2.819	0.481	0.59
Std Dev	2.42	2.48	0.13	0.25
RMSE values for walnut (Udhampur)				
1	15.180	9.040	0.689	0.951
2	11.4	3.18	0.597	0.564
3	8.96	1.78	0.521	0.445
4	12.16	1.57	0.616	0.396
5	12.94	5.74	0.668	0.664
6	13.08	4.15	0.672	0.565
7	9.53	4.53	0.630	0.502
8	11.79	10.24	0.649	0.855
9	9.6	8.2	0.566	0.827
10	12.5	1.48	0.59	0.50
Mean	11.71	4.99	0.62	0.63
Std Dev	1.92	3.22	0.05	0.19

farmers were facing in the rainfed regions, respectively (Table 11). Though, there were lots of other problems that the farmers were experiencing there, but, three most important problems were taken into consideration i.e., non-availability of improved varieties, lack of information and costly inputs. It is worthwhile to mention here that, the constraints varied from district to district but, still the overall problems were taken into consideration for the meaningful analysis of the problems in existence, in all the three districts taken together.

Table 10 Sensitivity analysis for different districts of the Jammu division

Neural networks	Human labour	Machine labour	Manure	Fertilisers	PPC	Picking	Misc
Sensitivity analysis of Jammu							
NN (1)	0.68	0.31	0.09	0.08	1.00	0.69	0.16
NN (2)	0.28	0.25	0.36	0.09	1.00	0.88	0.61
NN (3)	0.51	0.75	0.43	0.37	0.96	1.00	0.22
NN (4)	0.32	0.42	0.02	0.15	1.00	0.65	0.23
NN (5)	0.80	0.56	0.70	0.55	1.00	0.57	0.50
NN (6)	0.85	0.25	0.50	0.62	1.00	0.15	0.38
NN (7)	0.70	0.36	0.19	0.14	1.00	0.87	0.24
NN (8)	0.43	0.56	0.31	0.18	1.00	0.97	0.51
NN (9)	0.98	0.72	0.23	0.13	1.00	1.00	0.03
NN (10)	0.59	0.37	0.42	0.25	0.99	1.00	0.30
Average importance	0.62	0.46	0.32	0.26	0.99	0.78	0.32
Normalized importance	62%	46%	33%	26%	100%	78%	32%
Sensitivity analysis of Kathua							
NN (1)	1.00	0.76	0.31	0.15	0.74	0.51	0.78
NN (2)	0.68	0.51	0.57	0.49	0.18	0.49	1.00
NN (3)	1.00	0.90	0.11	0.18	0.76	0.50	0.70
NN (4)	1.00	0.88	0.33	0.52	0.51	0.63	0.57
NN (5)	1.00	0.12	0.67	0.24	0.68	0.40	0.31
NN (6)	0.46	0.15	0.32	0.23	0.22	0.39	1.00
NN (7)	1.00	0.49	0.34	0.10	0.01	0.23	0.84
NN (8)	1.00	0.95	0.23	0.69	0.65	0.07	0.87
NN (9)	0.83	0.74	0.32	0.41	0.43	0.45	1.00
NN (10)	0.77	1.00	0.42	0.12	0.62	0.37	0.42
Average importance	0.87	0.65	0.36	0.31	0.48	0.40	0.75
Normalized importance	100%	74%	42%	36%	55%	46%	86%
Sensitivity analysis of Udhampur							
NN (1)	0.62	0.37	0.48	0.26	0.19	1.00	0.17
NN (2)	1.00	0.26	0.80	0.92	0.04	0.04	0.73
NN (3)	0.60	0.86	0.77	1.00	0.88	0.47	0.09
NN (4)	0.18	0.42	0.84	0.44	0.77	0.56	1.00
NN (5)	1.00	0.33	0.39	0.49	0.29	0.10	0.84
NN (6)	0.45	0.13	0.70	1.00	0.12	0.23	0.27
NN (7)	0.36	0.14	0.62	0.04	0.52	1.00	0.80
NN (8)	0.62	1.00	0.66	0.10	0.73	0.58	0.52
NN (9)	0.74	0.26	0.90	1.00	0.22	0.16	0.50
NN (10)	0.28	0.19	0.76	0.29	0.40	0.72	1.00
Average importance	0.58	0.40	0.69	0.55	0.42	0.49	0.59
Normalized importance	85%	57%	100%	80%	60%	70%	86%

Table 11 Garett score of constraints of different enterprise under the rainfed conditions in four districts

Factors	First	Second	Third	Fourth	Fifth	Sum	Average	Rank
Non-availability of improved varieties	197	48	0	–	–	245	61.25	I
Lack of information	55	51	53	–	–	159	39.75	II
Costly inputs	0	82	58	–	–	140	35	III

3.6 Discussion

The study was conducted in the Jammu division and three districts were purposively selected (Fig. 1) for working out the research objectives. Sample data for the study revealed the data to be wider as the standard deviations turned out to be high in all the three districts (Table 1). Further, the normality of the data was subjected to appropriate tests and the data were found suitable both for the application of the parametric and non-parametric tests (Table 2). For the proper and meaningful analysis of the data, both parametric and non- parametric statistical tools were considered. It was discovered while surveying that citrus cultivator in the Jammu district had more and wider access to the market area and moreover, it is now turning into a profitable venture [1, 42]. Some of the progressive farmers had shifted their occupation from the traditional rice–wheat cropping pattern exclusively to that of citrus cultivation. But their proportion was quite low. Even some of the cropping pattern has now been inclined towards the cropping pattern that includes the citrus cultivation [16] and the potential future of such crops proved to be significant [3, 29]. This all has to be seen in relation to that of the growth that the horticulture industry is experiencing over the recent decades [44].

Careful perusal of the data revealed that, citrus cultivation was more remunerative in the Jammu district in comparison to that of Kathua district (Table 6). As far as the variable cost is concerned, the proportion of the labour cost turned to be high as the labour cost has increased over the years in the region [8]. The labour cost rather turned out to be one of the major constraints [6]. Comparing analysis of the Jammu and Kathua district revealed the high profitable for the former in comparison to later. The main reason for the profitability is due to the proximity of the former to the urban areas, where the demand for fruit is high because of the changed consumption habits. This has to be seen in the context of rising urban area in the Jammu districts and the urbanized people are, in general, most cautious about the health standards [21].

Walnut occupies very prominent position in union territory of Jammu and Kashmir. In the present sample, farmers in *Battal* and *Bryalta* village of *Majalta* block were cultivating walnut. Walnut cultivation was not prevalent in Jammu district and the contribution of walnut cultivation to the total country's walnut production is very prominent [44, 44]. As far as the variable cost (Table 7) is concerned, human labour cost is one of the major components. Over the years, the employment of the machine labour had been increased [26]. Net returns from the walnut cultivation proved to very promising as had been suggested by many of the past studies [31]. Fertilizers turned out to be the most important variable that contributed to the profitability of citrus cultivation in both Jammu and Kathua districts, respectively. While surveying, it was observed that most of the farmers in the region were not even employing any type of fertilizers. One of the main reasons for this is that the farmers in these regions were very poor in nature and therefore, their affordable capacity is less. Machine labour turned out to be a significant contributor in the walnut cultivation [26]. As the data collected were part of another study, therefore, artificial neural network (Table 10) was applied. In addition, it has been proved as a robust method, when the data used to be a non-parametric in nature. PPC, human labour and manure turned out to be the major component in Jammu, Kathua and Udhampur regions, respectively. Thus, non-parametric model has revealed that PPC, human labour and manure were the most important variables and factors that influenced to a great extent the profitability of citrus and walnut in Jammu division.

Overall, the deficiency of the water was proved out to be the major constraint in the rainfed regions. Water mismanagement was one of the main reasons that the farmers in the rainfed regions were poor [17]. But, even within the rainfed regions, some factors acted a pioneered role in decreasing the yield of crops in the rainfed regions. During the survey, non-availability of improved varieties was discovered to be the main constraint that the farmers were experiencing in the region. These findings did not find consonance with many of the past findings, as many of the past studies revealed out the different constraints that the rainfed farmers were experiencing in rainfed areas like soil physical constraints [22], conservation agriculture [47], small size and fragmented landholdings [40], labour shortage [38]., agroclimatic constraints [14], socio-economic constraints [25] etc. Even in Jammu region, the present findings revealed distinctive results from the past studies. Lack of awareness, lack of structural market and lack of interactions with respective government and organizations [16], credit constraints [48], marketing constraints [34] and infestation including others. While surveying, it was discovered that many of the villages were not even well connected by roads. This made the interaction of the farmers with the institutions like KVKs very cumbersome in nature. Therefore, in absence of regular interactions with the agricultural specialists, there was less adoption of improved varieties by the farmers in these regions [37]. This has further led to the problem of 'lack of information' in these regions. Because of such kind of problems in existence, the poverty is inextricably linked to the farmers practicing rainfed farming. Consequently, this led to the third major problem i.e., costly inputs.

4 Conclusion

Jammu and Kashmir is one of the important union territories with a latitude of 32.17 and 37.06 and longitude of 73.2 and 80.36, respectively and it has more area under rainfed in comparison to that of irrigated. The sample analysis of three different districts in horticultural crops revealed the importance of citrus crops in terms of profitability and desirability. Even among these two crops, the profitability is high for walnut crops. Variables like fertilisers, human labour, machine labour, PPC and manure turned out to be significant in improving the income from these crops. Therefore, there is immense need to improve the applications of these important inputs. In other words, there is the need of amelioration in the pesticide application, mechanization and manure.

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Declarations

Ethics approval and consent to participate This article does not contain any studies with human participants or animals performed by any of the authors.

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