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Mehraj Ahmad Teeli
Research Scholar, Asian International University, Manipur, India

Abid Hussain Rather
Lecture, Government Degree College, Kulgam, Jammu and Kashmir, India

Corresponding Author:
Mehraj Ahmad Teeli
Research Scholar, Asian International University, Manipur, India

Prognostication of mustard production founded on energy inputs by using artificial neural networks (ANN)

Mehraj Ahmad Teeli and Abid Hussain Rather

Abstract
The objective of the present study was to apply an artificial neural network (ANN) to investigate the relationship between energy inputs and mustard production in the South Kashmir region of Western Himalayas, India. The energy consumption pattern was determined for this purpose by collecting data from 132 farmers using face-to-face questionnaires. Human work, chemical fertilizer, farmyard manure (FYM), seeds, machinery, and diesel fuel all contribute to the total energy input. The total input and production energy for mustard output were found to be 3101.04 and 8552.49 MJ acre^{-1}, respectively. The energy indices for energy use efficiency, energy productivity, specific energy, and net energy were estimated to be 2.7, 0.11 kg MJ^{-1}, 9.06 MJ kg^{-1}, and 5451.44 MJ acre^{-1}, respectively. The findings found that the total consumed energy input may be classified as direct energy (29%) and indirect energy (71%) or renewable energy (33%) and non-renewable energy (71%). The lowest RMSE and MAPE of 0.0704 and 0.57 were obtained at 10 neurons, according to the modeling implementations. The best forecasting model was found at the equal amount of neurons. For mustard yield, the best topology's coefficients of determination (R^2) were 0.90. The generated ANN's promising potential reveals that it is a powerful and stout instrument that can be used an efficient and dynamic field of research in the arena of energy usage prediction.

Keywords: Artificial neural network, prognostication, mustard production, energy productivity, energy use pattern

Introduction
Mustard was one of the first domesticated crops and is one of the oldest known spices, according to Sanskrit writings dating back to around 3000 BC (Mehra, 1968) [14]. The crop belongs to the cruciferaceae or brassicaceae family. There are 150 species of biennial herbs in the genus Brassica, many of which are grown as oilseed crops, vegetables, or fodder (Thomas *et al*., 2004) [22]. The toria (Barassica Rapa), raya (*Brassica juncea*), and gobhi sarson (*Brassica napus*) varieties of rapeseed mustard have traditionally been farmed all over the world due to their excellent tolerance to conventional farming practices. However, in the Kashmir valley, *Brassica Rapa* (*Brown sarson* L.) is the only rapeseed - mustard crop that fits well in the oilseed - paddy rotation. To fully maximize the genetic potentiality of the crop, the best sowing timing is crucial (Akhter *et al*., 2015) [1]. Mustard is farmed only throughout the rabi season, with sowing beginning in the month of October and harvesting beginning in mid-May. It is mainly a temperate crop that thrives in a brief growing period. Mustard is produced in drier fields as the seed quality is superior (Rosangarten, 1969) [18]. It requires well- aerated soils that do not become waterlogged and are drought tolerant. Mustard performs best in soil with a near neural pH. Although it may also thrive in alkaline or slightly saline conditions. Despite its crucial importance for humans and animals, the rapeseed mustard production situation in South Kashmir is not encouraging. Oilseed acreage has declined dramatically from 32000 hectares in 1980-81 to 18359 ha in 2019-20. However, it is regarded as one of South Kashmir's most significant Rabi crops.
Agriculture has used energy as a significant input since the beginning of traditional farming. It is a well-known fact that agricultural output is directly proportional to energy inputs. In the form of bio-energy, agricultural sector is considered as a supplier and consumer of energy (Alam *et al*., 2005) [3]. It consumes large quantities of both commercial and non-commercials energies in the form of seed, farmyard manure, diesel fuel, machinery, chemical

fertilizers etc. Increased productivity and production are the results of efficient utilization of these energies which contributes to the profitability and competitiveness of agricultural sustainability in rural living (Singh *et al*., 2002) [20]. Agriculture's energy consumption has increased as a result of increasing population, limited arable land supply, unlimited human wants, and the desire for a higher standard of life. Increased energy use, on the other hand, has resulted in some serious human health and environmental issues. As a result, effective energy usage is a critical step in lowering environmental risks, mitigating natural resource damage, and sustaining agricultural production in the economy (Khoshroo *et al*., 2013) [13]. For researchers working on energy production and consumption analyses, as well as related environmental implications, energy modeling has been a significant concern (Al-Ghandoor *et al*., 2009) [2]. Among a wide range of modeling approaches, the artificial neural network (ANN) is a useful tool for predicting non-linear correlations in a variety of scientific research. ANNs were used in a study in Fereydonshahr, Iran, to forecast the production energy and greenhouse gas emissions (GHG) of wheat production in terms of input energies (Khoshnevisan,*et al*; 2013) [10]. (Khoshnevisan *et al*., 2014) [12] used multiple ANN models in terms of a few value parameters to model potato production and GHG emissions founded on energy inputs. ANN, a back-propagation (BP) learning algorithm, was used to predict environmental indices of apple production in the west Azerbaijan province of Iran using various input parameters, with the performance criteria being coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) (Taghavifar & Mardani, 2015) [21].

ANN is a massive parallel and distributed data processing system with performance characteristics similar to biological neural networks in the human brain (Nabavi-pelesaraei, 2016) [15]. ANN has been a burgeoning research field with ever-increasing modeling applications in a variety of scientific fields. The methodology of ANN is analogous to statistical modeling. AANs could also be used as a complementary effort to fitting non-linear data (Taghavifar & Mardani, 2015) [21]. The relative performance of artificial neural networks compared to standard statistical approaches is reported by (Khoshnevisan, *et al*; 2013) [10]. ANN has been extensively used to describe intricate non-linear correlations across a variety of scientific areas because it analyses input- output relationships without providing explicit information on the processes.

As for as the authors knowledge is concerned, there is no such study devoted to the energy input output estimation of mustard production in South Kashmir, Western Himalayas, and the use of ANN for the modeling of mustard energetic indices in South Kashmir region. As a result, mustard yield will be evaluated based on input energies, various ANN models will be constructed, and the prediction accuracies of the produced models will be covered.

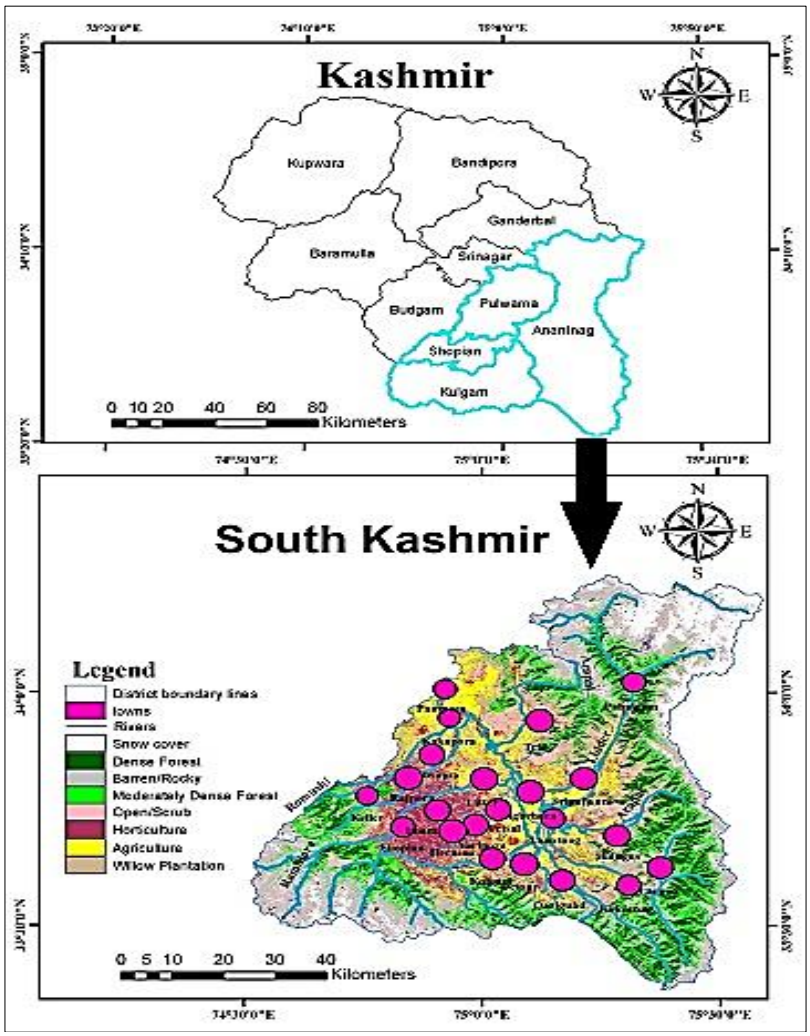

Fig 1: Location map of South Kashmir (study area)

Materials and Methods

Data for this study was collected from mustard farmers in the South Kashmir region of the Western Himalayas, India, and using face to face questionnaire. The mustard farms were chosen at random from the investigation zone's four administrative units. The sample size for each stratum was estimated using the Nyman approach derivation as shown in eq. (1) (Mohammadi, *et al*., 2010) [17].

$$n = \frac{(\sum N_h S_h)}{N^2 D^2 + \sum N_h S_h^2} \quad (1)$$

Where n represents the sample size; N denotes the number of mustard farmers in the target population; N_h represents the number of mustard farmers in the h stratification;S^2_h is the variance of h stratification; d permitted error ratio derived from population mean x-X, z is the reliability coefficient (1.96 which represents 95% confidence); $D^2 = d^2/z^2$; the permissible error in the sample population was defined to be 5% within 95% confidence interval (Mahammadi 2009). Accordingly, it was obtained to be 132 farms using face to face questionnaire method.

Field preparation, manuring, sowing, fertilizing, and harvesting were among the agricultural activities used on the research plot. Plowing with tractors and oxen is part of the field preparation, and manures are applied thereafter. Snowfall and rainfall, which fall in the winter and spring seasons, respectively, satisfy the water requirements.

Energy Analysis

Direct, indirect, renewable, and non-renewable energy sources are used in agricultural systems. Labor and diesel fuel are examples of direct energy, while fertilizers, manures, seeds, and machines are examples of indirect energy. Furthermore, renewable energy sources incorporate human labor, seeds, and FYM, but a non-renewable energy source comprises of diesel fuel, chemical fertilizers, and machinery. Human labor, seed, machinery, diesel, farmyard manure (FYM), and chemical fertilizers were all used as inputs, with mustard yield serving as output energy metric. The prior investigations were utilized to estimate the energy equivalent coefficients in order to transform inputs and outputs into energy equivalents. The table 1 lists these sources. The energy equivalents were calculated by multiplying the amount of inputs and outputs per acre by their conversion factors.

Table 1: Energy equivalents of input and output variables in mustard production

A. Inputs	Unit	Energy equivalent MJ acre^{-1}	References
Human labor	H	1.96	(Ilahi *et al*., 2019) [9]
Machinery	H	62.7	(Canakci *et al*., 2005) [4]
Chemical fertilizers			
Nitrogen(N)	Kg	66.14	(Yilmaz *et al*., 2005) [23]
Phosphate(P_2O_2)	Kg	12.44	(Royan *et al*., 2012) [19]
Farmyard manure	Kg	0.3	(Elsoragab *et al*., 2020) [6]
Diesel fuel	L	56.31	(Ghosh *et al*., 2019) [8]
Seed	Kg	25	(Singh *et al*., 2002) [20]
B.Output			
Mustard seed	Kg	25	(Singh *et al*., 2002) [20]

It is important to evaluate the agricultural system's energetic efficiencies using the energy ratio between inputs and outputs. The specific energy, energy use efficiency, energy productivity, energy intensiveness, and net energy gain were calculated using the energy equivalents (Table 1) as follows.

$$\text{Specific energy} = \frac{Energy\ input\ (MJ\ acre^{-1})}{Mustard\ output\ (kg\ acre^{-1})} \quad (2)$$

$$\text{Energy use efficiency} = \frac{Energy\ output\ (MJ\ acre^{-1})}{Energy\ input\ (MJ\ acre^{-1})} \quad (3)$$

$$\text{Energy productivity} = \frac{Mustard\ output\ (kg\ acre^{-1})}{Energy\ input\ (MJ\ acre^{-1})} \quad (4)$$

$$\text{Net energy} = \text{Energy output (MJ acre-1)} - \text{Energy input (MJ acre-1)} \quad (5)$$

Development of artificial neural network model

For validation, testing, and training, data was split and restructured into three sections of 10, 20, and 70%. The algorithm used in the present study was a feed-forward ANN with back propagation (BP). The optimization of neurons which are present in the hidden layers is a crucial stage in the creation of MLP neural networks. It's worth noting that while increasing the number of hidden layers reduces modeling inaccuracy, it also introduces the risk of over fitting, which lowers prognostic ability. As a result, the implementations utilized a neural network with two hidden layers. Neurons were raised to analyze model performance variation in order to find the number of ideal neurons in the hidden layer. ANN biases and weights are determined at random at first. To address this flaw, the network was trained 100 times for every number of hidden neurons (per network structure). Figure 2 shows the general setup of the multilayer artificial neural network employed in this study. The ANN is trained using the Levenberg-Marquardt (LM) method, which is often considered the quickest BP

algorithm and is a well recommended as a first preference supervised approach (Demuth *et al*., 2004) [5].

In order to improve the accuracy, convergence speed, and performance of artificial neural networks, the inputs and outputs were normalized or scaled linearly between zero and one before being used for model performance. The following formula is used to normalize the data.

$$X_n = \frac{X_v - X_{v,\min}}{X_{v,\max} - X_{v,\min}} \quad (6)$$

Where X_n is a normalized input variable, X_v represents the raw input variable and $X_{v,min}$ and $X_{v,max}$ denote minimum and maximum of input variable respectively. For the purpose of modeling, it is noteworthy to evaluate the performance of developed representation by different statistical criterion. For model performance and quality analysis, the coefficient of determination (R2), the root mean square error (RMSE), the mean absolute percentage error (MAPE), and the mean square error (MSE) are used as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(z_i - t_i)^2} \quad (7)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(z_i - t_i)^2 \quad (8)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2}\right) \quad (9)$$

$$MAPE(\%) = \frac{100}{n}\sum\left|\frac{t_i - z_i}{t_i}\right| \quad (10)$$

Where z_i and t_i are the predicted and actual outputs for the ith training vector, and n, is the total number of training vectors.

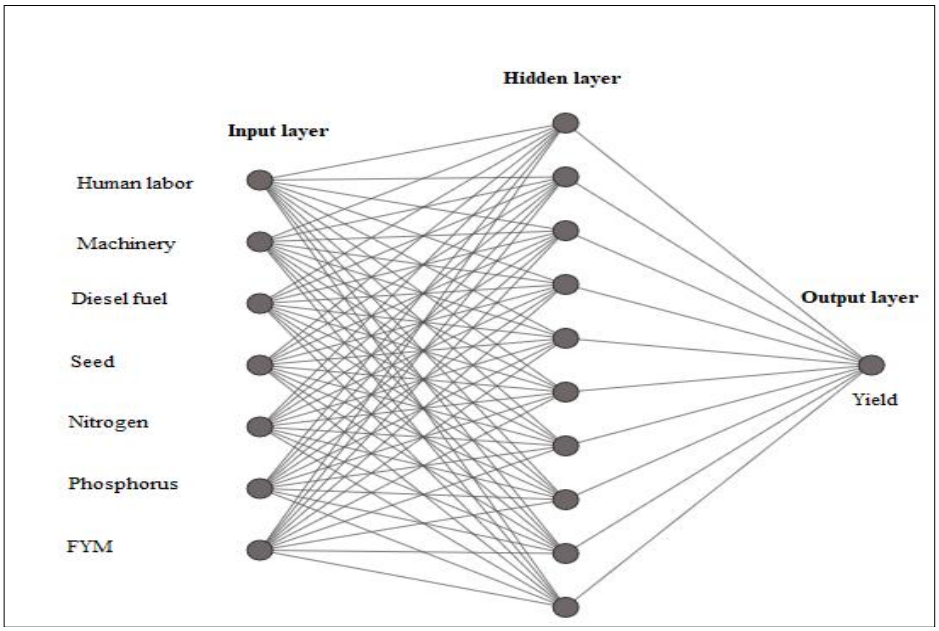

Fig 2: The general multi-layer perception feed- forward ANN configuration with one hidden layer

Results and Discussion

Energy consumption pattern

The energy equivalents for mustard production are summarized in Table 2. As can be observed, mustard production contributed a sum energy input of 3101.04MJ acre-1. Nitrogen fertilizer is the largest energy consumer among the input parameters, accounting for 34%, followed by diesel fuel (22.15%), and farmyard waste (21.5%). Farmers in the investigated region misunderstand nitrogen fertilizer consumption, resulting in inconsistent nitrogen fertilizer consumption in mustard production. The low cost of chemical fertilizers, as well as the lack of expert monitoring, may have a role in the high rate of fertilizer usage in research region. Figure 3 shows the additional energy input allocations. Mustard production in the studied area was found to be 342.10 kg acre^{-1}. In South Kashmir region, the input and output energy values were estimated to be 3101.04MJ acre^{-1} and 8552.48 MJacre^{-1}, respectively.

Table 2: Amount and energy equivalent of input and output variables in mustard production

Input (unit)	Quantity per unit area (acre)	Total energy equivalent (MJ acre^{-1})	%age
A. Inputs			
Human labor (h)	113.79	216.21	6.97
Machinery (h)	1.48	92.82	2.99
Chemical fertilizers			
Nitrogen(N) (kg)	16.03	1060.85	34.20
Phosphate(P_2O_2) (kg)	20.53	225.44	8.23
Farmyard manure (kg)	2229.87	668.96	21.5

Diesel fuel (L)	12.10	681.86	22.15
Seed (kg)	4.99	124.86	4.02
Total energy		3101.04	
B.Output			
Mustard seed (Kg)	342.10	8552.48	

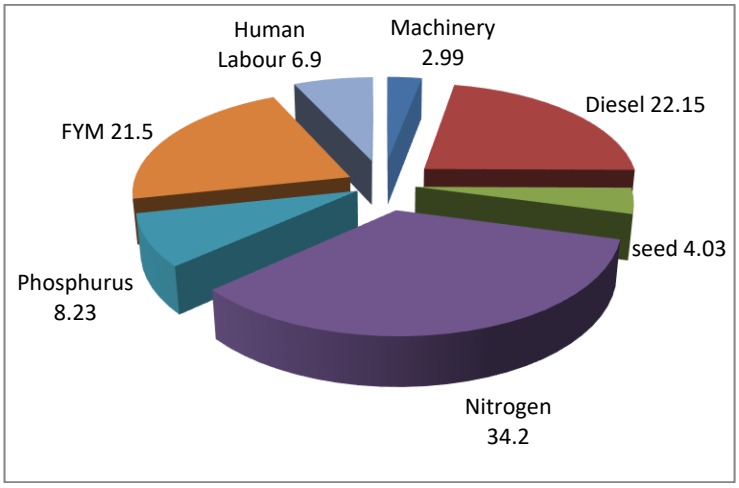

Fig 3: The distribution of total input energy in mustard production.

In the study region, the proportion of energy consumed from direct, indirect, renewable, and non-renewable energy sources was also examined. Figure 4 depicts the overall energy input distribution as direct, indirect, renewable, and non-renewable. Percentages of various energy forms describe each group's contribution and provide necessary instructions for agricultural landowners and policymakers to follow in order to ensure the cultivation sector's long-term sustainability The energy use efficiency, specific energy, energy productivity and net energy gain of mustard production in the South Kashmir region of western Himalayas were calculated using the Eqs. 2-5 and the results are tabulated in table 3.

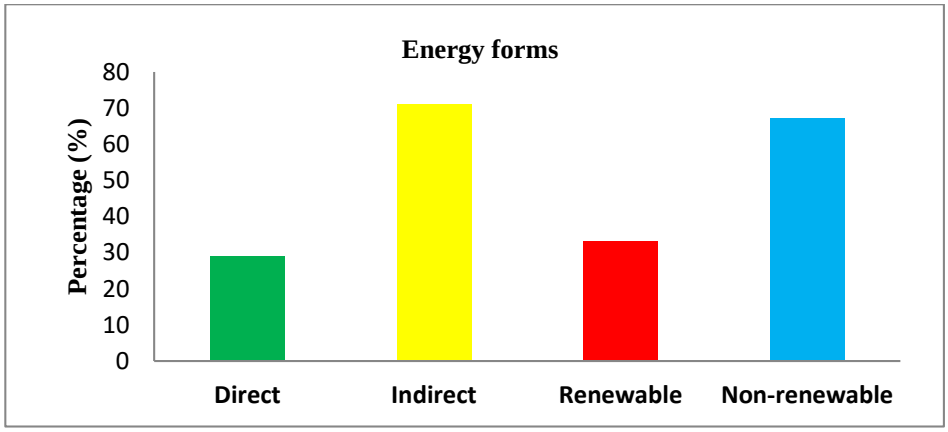

Fig 4: The %age share of energy forms of each input in mustard production

The energy indices of mustard production in the South Kashmir western Himalayas, India are listed in table 3.

Table 3: Quantity of energy indices of mustard production

Items	Unit	Value
Energy use efficiency	-	2.7
Energy productivity	Kg MJ^{-1}	0.11
Specific energy	MJ kg^{-1}	9.06
Net energy	MJ $acre^{-1}$	5451.44
Direct energy	MJ $acre^{-1}$	898
Indirect energy	MJ $acre^{-1}$	2202.95
Renewable energy	MJ $acre^{-1}$	1010
Non-renewable energy	MJ $acre^{-1}$	2091
Total energy input	MJ $acre^{-1}$	3101

Artificial Neural Network Performance

The Levenberg-Marquardt back propagation algorithm was used to create the adopted trainlm, which took into account the normalization range, activation function, and variable amount of neurons within the hidden layer. In the modeling process, the fluctuation of RMSE with increased amount of neurons within the hidden layer is seen. As can be observed, increasing the number of neurons reduces the RMSE significantly. At 10 neurons, the lowest RMSE of 0.07 was found. MAPE of 0.57 was attained with the same amount of neurons. As a result, the outperforming modeling representation was chosen as ANN with 7-10-1 topology. For predicting mustard yield in the study area, an R2 value of 0.90 was obtained. Table 4 summarizes the findings of the ANN model. In addition, Figure 5 shows a scatter plot of expected production energy against actual values.

Table 4: The optimum outcome of different model arrangements

Item	R^2	RMSE	MAPE
Mustard yield	0.90	0.07	0.57

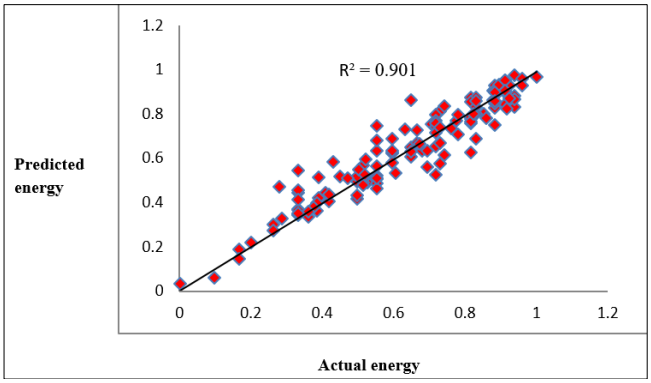

Fig 5: The scattering of data around unity line

Economic model assessment of mustard production

The Cobb-Douglas production function was used to estimate the energy inputs and mustard yield relationship on different types of farms. As a result, mustard yield also refer to as an endogenous variable was considered to be a function of an exogenous variables such as machinery, diesel fuel, human labor, nitrogen and phosphate fertilizers, seed, and farmyard manure. The relationship between the endogenous and exogenous variables are shown in table 5. The existence of autocorrelation in the residuals from the regression analysis was assessed using the Durbin-Watson test for the data utilized in this analysis. The result revealed that the Durbin-Watson value was found to be 2.0, indicating that there is no auto-correlation within the estimated model at the 1% significance level. The R^2 (coefficient of determination) for this linear regression model with constant parameters was 0.87. (Table 5). The MPP approach and partial regression coefficients on the output level were used to examine the sensitivity of energy inputs.

Table 5: The MPP approach and partial regression coefficients on the output level were used to examine the sensitivity of energy inputs

Endogenous variable yield	Coefficient	t- ratio	MPP
Exogenous variables			
Model : $In\, y_i = a_0 + \alpha_1 In\, X_1 + \alpha_2 In\, X_2 + \alpha_3 In\, X_3 + \alpha_4 In\, X_4 + \alpha_5 In\, X_5 + \alpha_6 In\, X_6 + \alpha_7 In\, X_7$			
Constant	0.6	2.4*	
Human labor	0.47	3.5	0.87
Nitrogen	-0.11	-0.6	-0.14
Phosphate	0.31	2.4*	0.58
Machinery	0.02	0.1	0.44
Diesel fuel	0.43	3.0*	0.61
Seed	0.22	1.5	0.46
FYM	0.07	1.6	0.27
Durbin-Watson	2.0		
R^2	87		
Returns to scale $(\sum_{i=1}^{7} \alpha_i)$	1.41		

*, ** indicates significance at 1% and 5% level, respectively.

Table 5 shows that phosphate and diesel fuel energies make a considerable contribution at the 1% level. The effect of nitrogen fertilizer on mustard output was determined to be statistically negligible, indicating a negative sign. A negative MPP of inputs indicates that adding more units of inputs has a negative impact on production, implying that more inputs result in lower yield

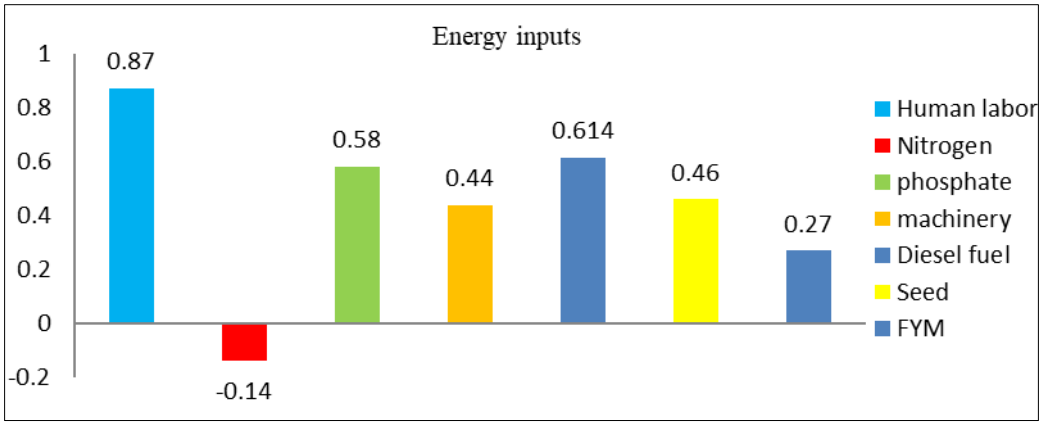

Fig 6: Sensitivity analysis of energy inputs of mustard production in South Kashmir.

Figure 6 depicts the outcomes. Human labor (0.87) had the maximum value, followed by diesel fuel (0.61) and phosphate fertilizer (0.61). (0.58). According to the findings, a 1MJ increase in human labor, diesel, and phosphate fertilizer inputs resulted in increases in mustard yield of 0.87 kg acre-1, 0.61 kg acre-1, and 0.58 kg acre-1, respectively.

Conclusion

The total sum of energy utilization and yield of mustard production were estimated to be 3101.04 MJ acre^{-1} and 8552.48 MJ acre^{-1} respectively. Nitrogen was the most energy-intensive of all inputs, accounting for 34.20 percent, followed by diesel fuel at 22.5 percent. The energy consumption efficiency, productivity, specific and net energy gain had average rates of 2.7, 0.11 kg MJ^{-1}, 9.06 MJ kg^{-1}, and 5456.44 MJ acre^{-1}, respectively. The results of the energy modes research revealed that indirect and non-renewable energy had a much higher share than direct and renewable energy. An ANN model with a 7-10-1 structure performed best in forecasting mustard yield. R^2, RMSE, and MAPE for the optimal topology were found to be 0.90, 0.07, and 0.57, respectively.

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