Mechanization Index and Machinery Energy Ratio Assessment by means of an Artificial Neural Network: a Mexican Case Study

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ABSTRACT

A single hidden layer artificial neural network (ANN) model was developed to estimate simultaneously two mechanization indicators, Mechanization Index (MI) and Machinery Energy Ratio (MER), used to characterize a group of farms in a target farming region. Values of the two mechanization indicators could be obtained without direct calculation of their equations by using the ANN model. To develop the model, data representative of a developing farming system in Mexico were obtained from farmers, local makers of agricultural machinery, researchers and government officials, as well as from relevant databases. A wide range of variables of farming activities were examined, and from these, 11 were used as input variables for the model. The values of the model's outputs correlated well (Pearson's= 0.963 and 0.947 for MI and MER respectively) with actual, calculated values, indicating that the model is valid. Sensitivity analyses were also conducted to investigate the effects of each input item on the output values.
Since the ANN model can predict two mechanization indicators for a target farming system, it could be a good tool for appraising mechanization of regional farms. Also it overcomes some of the limitations of using as inputs simple data available from local databases that may contain errors.

Keywords: Mechanization indicators, artificial neural network, Mexico

1. INTRODUCTION

In order to maximize the efficacy of introducing agricultural technology to farms in a target region, the farming system of the region should be first characterized, especially to identify possible resource constraints and to capture the diversity of farming systems (Sims, 1987; Collado and Calderón, 2000; Oida, 2000). Monitoring the mechanization status in the target region, in combination with other agronomic indicators such as productivity potential (García *et al.*, 2005), would afford a better assessment of the sustainability of the farming system.

Therefore, the purpose of this study was to develop an artificial neural network (ANN) model to predict mechanization indicators based on energy consumption, using as inputs to the model simple data available from local databases.

The sample farming area selected for the study was 1306 ha representing the target farming system in central Mexico. The mechanization indicators, Mechanization Index (MI) and Machinery Energy Ratio (MER), were chosen because they would allow us to identify which farming systems in the region would benefit from mechanization and to estimate the intensity of mechanization as part of an agricultural modernization program. The ANN model gives estimates of the mechanization indicators using limited data available from the target region, without the need to calculate them directly, which would require more data. The model is based on statistical analyses of actual data, and enables us to distinguish between necessary and unnecessary items of raw data. A fundamental hypothesis of this study is that it is feasible to train an ANN model to establish a non-explicit function, which corresponds to the ANN network itself, between a selected set of simple inputs, such as farm size, and number of tractors owned, and two mechanization indicators as the outputs.

The potential practical application of this work consists on mapping the proposed mechanization indicators for a much wider area without direct calculations. Further analysis based on the interrelation between the produced data with complementary parameters already available in local databases, would contribute to assess the mechanization status in the region.

2. DATA SOURCE AND PROCESSING

A target farming area was selected by taking into account previous research experience and advice from experts in the region (CIMMYT INIFAP 2000 database; Collado and Calderón, 2000; and INIFAP Bajio Research Station, personal communication, Celaya Guanajuato México, August 2004). The selected region is located in the Mexican central state of Guanajuato, between 19° 55' 05" and 21° 51' 49" North latitude, and between 99° 41' 04" and 102° 05' 11" West longitude, in the Rural Development Districts V and III. Its total cropping area is 295326 ha. (available at URL: http://www.oeidrus.guanajuato.gob.mx/ubis. In Spanish).

The prevailing farming system in the region of study is characterized by the use of tractors as main power source, as encouraged by the government in response to the restriction of timeliness of seasonal farm works and labor shortage trends. Land tenure varies from 1 to 30 ha per farmer. The main crops are: Maize, Beans, Wheat, Sorghum and Barley; it is a common practice the rotation of crops from season to season exchanging sites. This system is applied mainly under reliable rain-fed conditions in places with even topography and free of stones.

The data used in this study were compiled for 102 farms representative of the entire 48284 farm households (or production units, as defined by The National Institute of Statistics, Geography, and Computation. URL: http://www.inegi.gob.mx/est/default.aspx?c=4346) practicing the target farming system in the region.

The data consist of 250 items for each farm, in the following 6 categories:
Social issues: farmer age, school years, migrating family members (if any).
Asset: farm size (three ownership types, established with different crops), machinery commonly used (units, type, model), tractors (model, ownership type).

Farming strategies: land source (leased, owned), straw management, crops (type, cropping area), farming method (type of tillage operation, sequence, time).

Production factors: working hours, inputs for crop production (seeds, agrochemicals, fertilizers, etc.), animal traction (type, time).

Finance: unitary costs for crop production, source of finance.

Policy support: subsidizing source, technical assistance if any.

To simplify the modeling process, we made the following assumptions:
a) Crops of the same type were managed in the same way.

b) Technical machinery parameters, such as power rate, were constant among similar types of machine.
c) Each individual farmer makes his or her own decisions about the distribution of resources and capital for crop production.
d) A two wheel drive tractor with 50 kW rated power and weight of 2550 kg consuming 16 litres of diesel fuel per hour as found by the National Standardization Centre of Agricultural Machinery (CENEMA, 2004) was set as a standard as suggested by expert researchers in the region and subsequently confirmed in-situ (Collado M.; Arévalo A. INIFAP's researcher, interviewed by author, Celaya Guanajuato México, August 2004).

To assess the technological status and the agricultural production strategies, the farming system was analyzed according to its energy input-output flow using the methods as in Rydberg and Jansen (2002); Collado and Calderón (2000); and Chandra (1998). This approach distinguished the energy source type: renewable versus non-renewable.

The values of input energy from the amounts of seeds, fertilizers, agrochemicals, animal traction and hand-labor were computed using unitary literature values as in Collado *et al*.(2000), Rydberg and Jansen (2002) and Chandra (1998). The chosen values for the present analysis are shown in Table 1.

Table 1. Unitary values selected for input-output energy flow calculations

Inputs (MJ/kg)			Outputs (MJ/kg)	
Nitrogen fertilizer	65		Maize	16
Phosphate fertilizer	15		Wheat	14
Potassium fertilizers	10		Barley	15
Agrochemicals	135		Beans	14
Cereal seeds	25		Sorghum	14
Seeds from local source	3		Cereals	15
Labor	2	MJ/hr	Vegetables	1
Animal traction (Mules)	4	MJ/hr	Husk	14
Fuel (Diesel) and Oils	56	MJ/litre	Straw	12
Farm implements	80			
Machinery fabrication	160			

Similarly, overall output energy was the summation of crop yield produced and straw energy values. In the case of machinery input energy for crop production; fixed components such as machine mass and storage facility, as well as variable components such as fuel and energy due to tractor traction invested during the working hours, were computed separately.

Technical information on the type of machinery found in this region, such as fuel consumption and power rate, was obtained from the National Standardization Centre of Agricultural Machinery (CENEMA, 2004).

3. INPUT AND OUTPUT PARAMETERS

Based on their availability and how representative they were of all the data, 42 continuous and categorical input items were chosen as the first candidate set of the input items. Underlying distributions were uniform, representativeness was checked and data sets with 5% or more of data points missing were rejected. The mean, variance, Pearson's correlation coefficient, and other statistics of the items are shown in Table 2 (Columns market "a subscript" refers to the range of data that enhances the network forecasting capability as discussed in section 6.1).

Because the items have different scales, the data were normalized into the range of 0.1 to 0.9 to maintain the neural network sensitivity as per Drummond *et al*., 2003; Abdullakasim *et al*., 2005; Zhang *et al*., 1998; Prosperi M., personal communication, Kyoto Japan, October 2004. Outliers and collinear values in the scatter plots of the 42 candidate variables were rejected, and the scatter plots redrawn and reexamined to identify superfluous items. Finally, based on the responses of the ANN model, 11 input parameters that produced outputs which correlated well with the calculated outputs and a wide range of response values of the model's outputs were selected.

Table 3 shows the selected parameters fed into the ANN model during the training process. These items represent key factors (finances, assets and farming strategies) of the farming system and were identified as factors in the mechanization status. They produced superior performance during the teaching process. Another advantage is that data on these items are generally available in local databases.

Based on the general concept of mechanization (Sims, 1987) and the structure of ANN models, two mechanization indicators, which are functions of finance, asset, farming strategies and production factors, were chosen. The indicators are included in Tables 2 and 3, and are defined mathematically as equations 1 and 2 in the following section. The ANN model was trained to output these indicators from the data of the 11 input parameters. The validity of the model was checked by comparing its output values with those calculated using equations 1 and 2.

Table 2. Descriptive statistics of selected items in the faming system

Item		1	1a	2	2a	3	4	4a	5	5a	6	6a	7	7a	8	9	10	10a	11	11a	12	12a
		Total land with crops (ha)		Total farmland ownership (ha)		Number of crops	Tractor units ownership		Tractor use intensity (hr/yr)		Labor intensity (hr/yr)		Animal traction intensity (hr/yr)		Number of tillage operations	Straw use (%)	Benefit/Cost ratio		Mechanization Index		Machinery Energy Ratio	
Maximum		92.0	50.0	50.0	34.0	6.0	4.0	3.0	791.2	430.0	6204.5	2530.0	240.0	67.5	9.0	100.0	1.485	1.485	11.563	3.873	0.757	0.726
Minimum		2.6	2.6	1.3	1.3	2.0	0.0	0.0	23.7	23.7	89.6	89.6	0.0	0.0	0.0	0.0	0.394	0.557	0.078	0.078	0.483	0.483
Median		47.3	26.3	25.7	17.7	4.0	2.0	1.5	407.5	226.9	3147.0	1309.8	120.0	33.8	4.5	50.0	0.939	1.021	5.821	1.975	0.620	0.604
Range		89.4	47.4	48.7	32.7	4.0	4.0	3.0	767.5	406.3	6114.9	2440.4	240.0	67.5	9.0	100.0	1.091	0.928	11.485	3.795	0.274	0.244
Average		25.6	12.0	13.6	7.2	2.9	1.3	1.0	221.0	105.1	1295.1	608.7	18.3	14.7	5.6	39.1	0.970	1.010	2.083	0.756	0.627	0.609
Standard deviation		24.2	7.5	12.7	5.4	0.9	1.1	0.9	205.5	64.4	1315.1	455.2	33.3	18.6	1.9	47.6	0.223	0.240	2.476	0.514	0.059	0.059
Variance		587.5	56.6	160.4	28.7	0.8	1.2	0.9	4.2E+4	4.1E+3	1.7E+6	2.1E+5	1.1E+3	3.4E+2	3.612	2.3E+3	0.050	0.058	6.130	0.264	0.003	0.003
Coefficient of variation		94.7	62.5	93.1	74.6	32.0	82.6	94.3	93.0	61.2	101.5	74.8	182.4	126.3	34.0	121.8	23.0	23.8	118.9	68.0	9.4	9.6
Correlation coefficient	1		1.0	0.94	0.89	0.12	0.53	0.16	1.00	1.00	0.96	0.87	0.14	0.16	0.25	0.00	-0.24	-0.08	0.91	0.89	0.46	0.03
	1a			0.89	0.89	-0.01	0.15	0.16	1.00	1.00	0.87	0.87	0.16	0.16	0.02	-0.21	-0.08	-0.08	0.89	0.89	0.03	0.03
	2				1.00	0.19	0.46	0.15	0.94	0.88	0.92	0.84	0.26	0.24	0.22	-0.03	-0.23	-0.19	0.73	0.61	0.40	0.03
	2a					0.12	0.14	0.15	0.88	0.88	0.84	0.84	0.25	0.24	0.04	-0.21	-0.18	-0.19	0.61	0.61	0.02	0.03
	3						0.00	0.02	0.11	-0.02	0.15	0.07	0.38	0.09	0.13	-0.08	-0.15	-0.24	0.05	-0.09	0.05	0.10
	4							0.99	0.52	0.14	0.51	0.22	-0.07	0.01	0.27	0.02	-0.21	-0.09	0.53	0.29	0.61	0.55
	4a								0.15	0.15	0.26	0.26	-0.07	-0.07	0.28	-0.20	-0.21	-0.21	0.30	0.30	0.61	0.61
	5									1.00	0.95	0.85	0.14	0.20	0.25	-0.01	-0.23	-0.05	0.91	0.89	0.46	0.00
	5a										0.85	0.85	0.20	0.20	0.02	-0.23	-0.05	-0.05	0.89	0.89	0.00	0.00
	6											1.00	0.25	0.18	0.25	0.03	-0.27	-0.28	0.86	0.74	0.45	0.15
	6a												0.18	0.18	0.00	-0.14	-0.28	-0.28	0.74	0.74	0.15	0.15
	7													1.00	0.01	-0.25	0.36	0.55	0.01	0.03	-0.38	-0.62
	7a														-0.20	-0.22	0.55	0.55	0.03	0.03	-0.62	-0.62
	8															-0.09	-0.18	-0.17	0.23	0.07	0.29	0.31
	9																-0.19	-0.18	0.05	-0.21	0.12	0.07
	10																	1.00	-0.22	0.00	-0.79	-0.78
	10a																		0.00	0.00	-0.78	-0.78
	11																			1.00	0.47	0.15
	11a																				0.15	0.15
	12																					1.0

Note: “a subscript” denotes the range of data that enhances the network forecasting capability as discussed in section 6.1.

Table 3. Input and output parameters to train the ANN model

Item	Variable name	Source	Variable type and units
INPUTS			
1	Total farm land ownership	Data-set entry	Continuous (ha)
2	Number of crops	Data-set entry	Discrete (natural number)
3	Tractor units ownership	Data-set entry	Discrete (natural number)
4	Labor intensity	Computed from data-set	Continuous (base on working hours per cropping season)
5	Animal traction intensity	Computed from data-set	
6	Number of tillage operations	Data-set entry	Discrete (natural number)
7	Straw management	Data-set entry	Continuous (base on percentage burned)
8	Benefit / Cost ratio	Computed from data-set	Continuous (unit-less)
9	Technical assistance	Data-set entry	Dichotomy

10	Land tenure	Data-set entry	Ejidos (ownership by government type), Hired, Private
11	Support from migration	Data-set entry	Dichotomy
OUTPUTS			
A	Mechanization Index	Computed from data-set	Continuous (unit-less)
B	Machinery Energy Ratio	Computed from data-set	Continuous (unit-less)

4. DEFINITIONS OF MECHANIZATION INDEX AND MACHINERY ENERGY RATIO

4.1 Mechanization Index

$$MI = \sum_{i=1}^{n} ((M_{e(a,i)} / M_{av})(L_{(a,i)} / TL_{(a)})) \tag{1}$$

where:

MI = Mechanization Index for the production unit ‘a’

Me(a,i) = Overall input energy due to machinery for crop ‘i’ in the production unit ‘a’

Mav = Regional-average energy due to machinery

L(a,i) = Land area cultivated with crop ‘i’ in the production unit ‘a’

TL(a) = Total farm land ownership of the production unit ‘a’

This index proposed by Andrade and Jenkins (2003) is an indication of the amount of machinery a given farmer uses for farm work compared with the average in the region.

The second term includes a ratio between the land area cultivated with different crops and the total land ownership. This term was introduced because it reflects the importance of land demand for cultivation.

4.2 Machinery Energy Ratio

$$MER = \sum_{i=1}^{n} (M_{e(a,i)} / T_{e(a,i)}) \tag{2}$$

where:

MER = Ratio between machinery energy and total input energy

Te(a,i) = Total input energy (from: labor, machine, seed, fertilizers, agrochemicals, animals) for the production of the crop ‘i’ in the production unit ‘a’.

This ratio, as described by Collado and Calderón (2000), indicates the investment in machinery energy in comparison with the other input energy sources required for crop production. The ratio is useful for comparing the contributions of mechanization among the individual farms.

5. ARTIFICIAL NEURAL NETWORK MODEL

The ANN model was calibrated using the Stuttgart Neural Network Simulator (SNNS) software package (SNNS Group, 1997). During the calibration process, 30 architecture combinations were trained. Variations of the backpropagation learning algorithm were applied. As presented by Zhang et al. (1998), the square error of the estimates between the observed and actual output is fed-back through the network causing changes of the weights, with the purpose of preventing that the same error will happen again. Batch-backpropagation provided smooth curves, with results generally better than those of the other training backpropagation methods. At this stage, results from cross-validation analysis in relation to network size and number of training cycles were analyzed to select the best combination to keep the model simple, as described in the following sections.

5.1 Split-Sample Validation Technique

At this stage, data sets of 96 farm patterns or production units samples, each containing the 11 inputs and the two outputs, were collated as described in Section 3 above. The reference values of the two outputs were calculated from equations 1 and 2, and are compared below with the outputs of the model. The ANN model was trained, tested and validated using the split-sample validation technique described by Zhang *et al*. (1998) and the SNNS Group (1997). The data sets of the 96 farm patterns were divided randomly into three subsets, containing 54 patterns for training, 20 patterns for testing and 22 patterns for the validation phase. The number of the patterns in the training subset was set to about 60% of the total data, as per Zhang *et al*. (1998). Extraction of the training subset was repeated several times at random to check the quality of the trained networks generated, as indicated by high R^2 values and a wide range of outputs.

5.2 Number Of Hidden Units

To determine the optimal architecture of the ANN, the architectures of networks with hidden units ranging from one to 30 were trained, tested and validated. This process was conducted by the split-sample validation technique. The validation subset contained 22 patterns, selected as described above, that were not used in the training and testing phases. This subset was used to test the correlation between the values of the outputs given by the ANN model and those calculated from equations 1 and 2.

Network architectures with hidden units ranging from one to 30 were simultaneously trained and tested with the respective subsets. The learning (training) process was "early-halted" at the 80000^{th} interaction when the squared summed error for the testing subset reached its minimum value (Zhang *et al*., 1998; SNNS Group, 1997).

The accuracy of the ANN model was validated using the validation data set. Figure 1 shows the correlation between the model's outputs and calculated outputs. Networks containing 2 to 8 hidden units showed better performance. A single hidden layer with two neuron units was selected for our model because the number of hidden units should be as few as possible (Zhang *et al*., 1998; SNNS Group, 1997). An ANN architecture with fewer hidden layers can avoid over-fitting problems observed during the trial-and-error procedure. Consequently, our model's structure was determined as 11:2:2, inputs/hidden units/outputs respectively. The generalization error of this architecture, in other words, the recorded values of the squared summed error calculated on the training and the verification sets during the learning monitoring was equal to 0.55. The best correlation coefficient between the output of the ANN model and actual value of the indicators was 0.9 for the Machinery Energy Ratio and 0.93 for the Mechanization Index as shown in Figure 1.

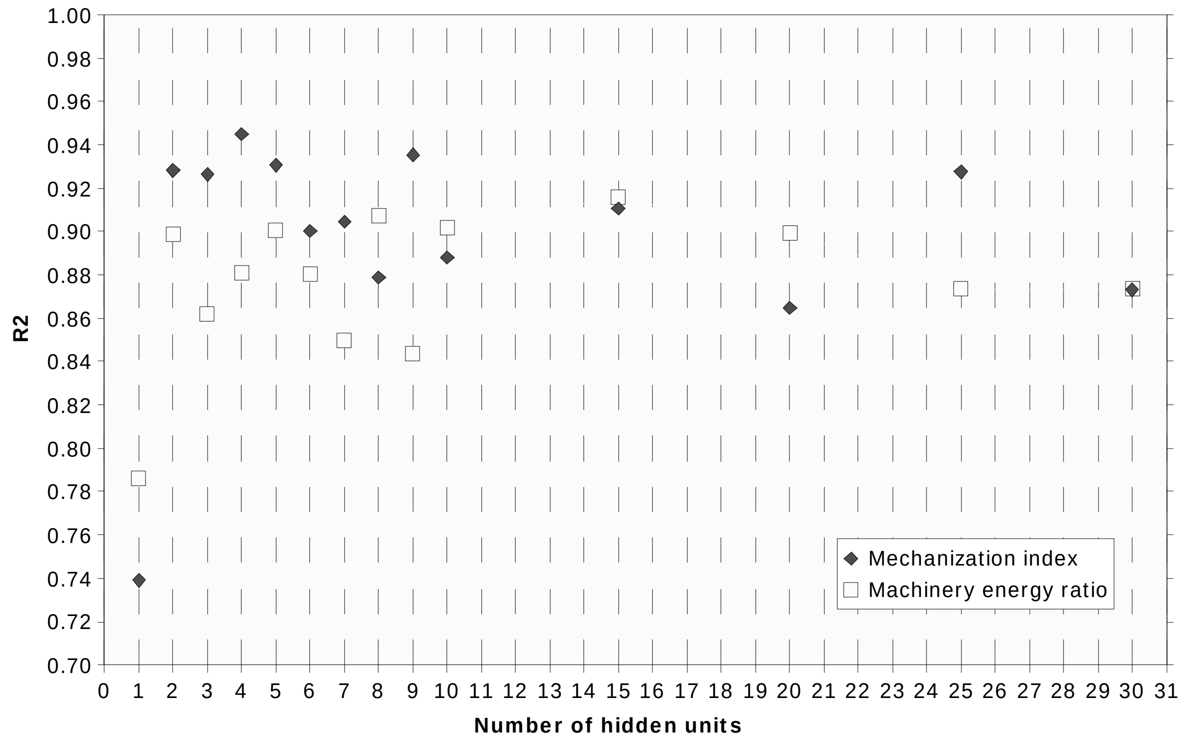

Figure 1. Correlations between the ANN model's outputs and calculated outputs for each number of hidden units

Note: columns with no sign were not validated.

6. RESULTS AND DISCUSSION

6.1 Residuals Validation And Reconsideration Of The Target Farming System

Figure 2 shows the residuals and relative errors of the two output indicators for each validation pattern, obtained by comparing the outputs of the model and the outputs calculated using equations 1 and 2.

The full data set (96 patterns) was also tested for the residuals and relative errors. Data patterns that generated residuals greater than ±0.025 and relative errors greater than ±0.15 for both the MI and MER were rejected from the original data set in order to determine a boundary which represents the applicable range of the ANN model. Rejecting such data patterns enhances the network forecasting capability.

The remaining, representative values of the items that redefine our target farming system are given in Table 2 (see columns 1a, 2a, 4a to 7a, 10a, 11a, and 12a). The rejected data sets were regarded as those that could be analyzed under different farming systems.

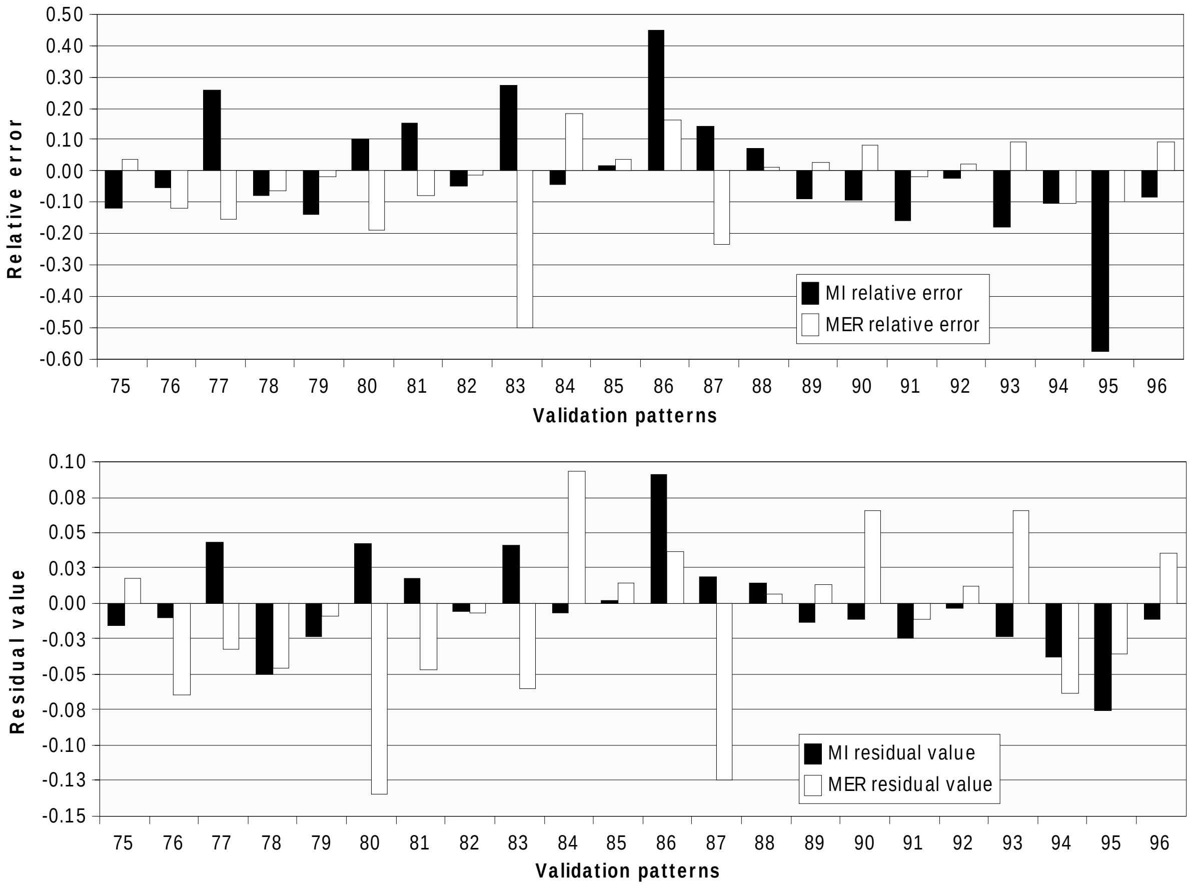

Figure 2. Residuals and relative errors of the validation set.

6.2 Sensitivity Analysis

In order to assess the predictive ability and validity of the developed ANN model, two sensitivity analyses were examined. In each case, the robustness and sensitivity of the model were determined by examining and comparing the outputs produced during the validation stage with the calculated values.

In the first approach, the ANN model was trained by withdrawing each input item one at a time while not changing any of the other items for every pattern. The resulted normalized output values, presented in Figure 3, followed a linear trend on small scatter of points close to the diagonal line, indicating that the ANN model is a good predictor of the output when the number of items is restricted and outliers are rejected from the data set of each item.

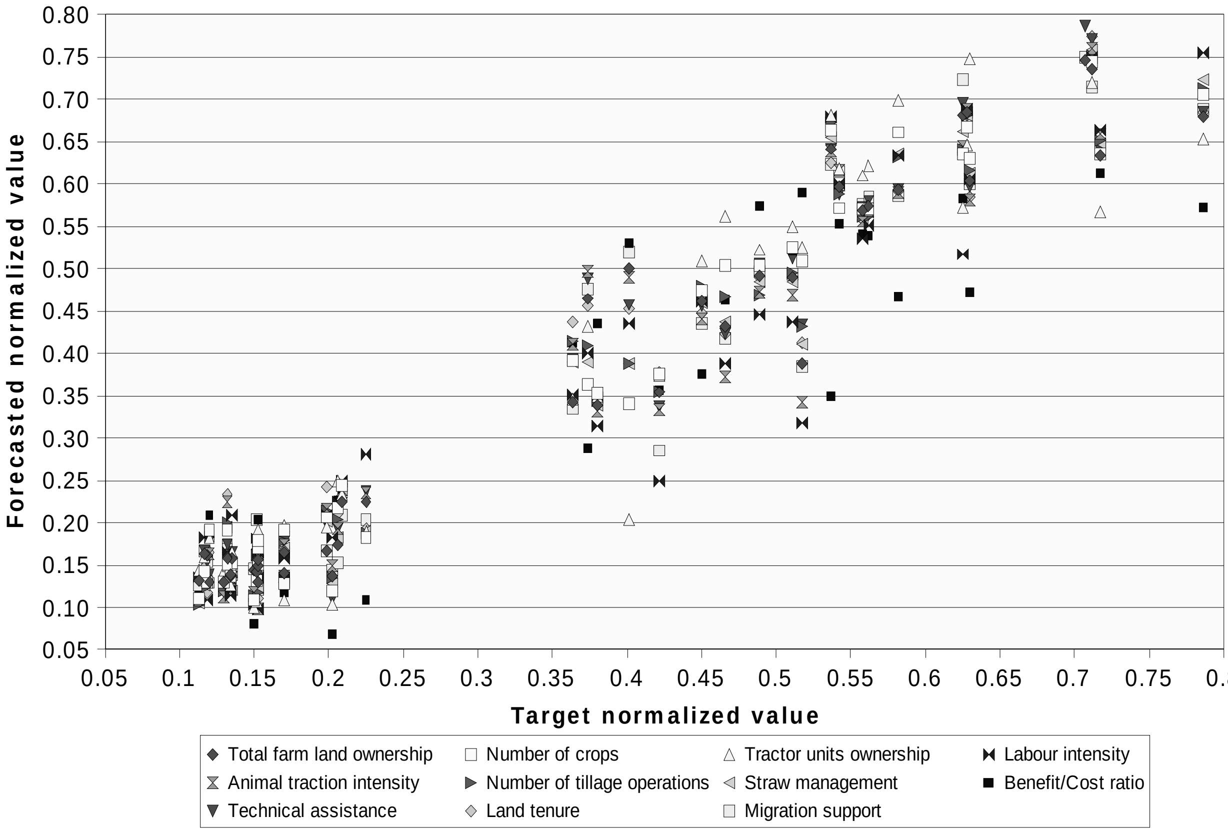

Figure 3. Predicted outputs trend while withdrawing each selected input.

In the second approach, the validity of the developed ANN model was assessed by observing how the model’s outputs changed with a change in a selected input item. Pattern No. 42 (in Figure 4) was chosen as a standard because it produced a range of output values that, from the residuals validation method described above, were representative of all the data patterns. Figure 4 shows these patterns sorted for clarity.

In the case of pattern No. 42, all but one of the input variables that were continuous were fixed to their original values as used for training, while a set of artificial normalized data between 0 and 1 in 5% increments was generated for the selected input that was not fixed. For each selected input item, these generated artificial patterns were validated by the previously trained ANN with two hidden units in a single layer.

For the categorical inputs, the analysis was conducted as follows: For each of the 22 units of the validation set, one of the categorical input items was selected. The values of the selected categorical inputs were artificially generated (items 9, 10 and 11 in Table 3). The effect of changing one value of the selected categorical input on the output value was examined.
This process was repeated until the model response was tested for all the input variables. The subsequent discussion on the effect and degree of contribution introduced by the artificial variations of the inputs to the ANN model was based on the observed forecasted trend of the output as well as observed general farming system performance.

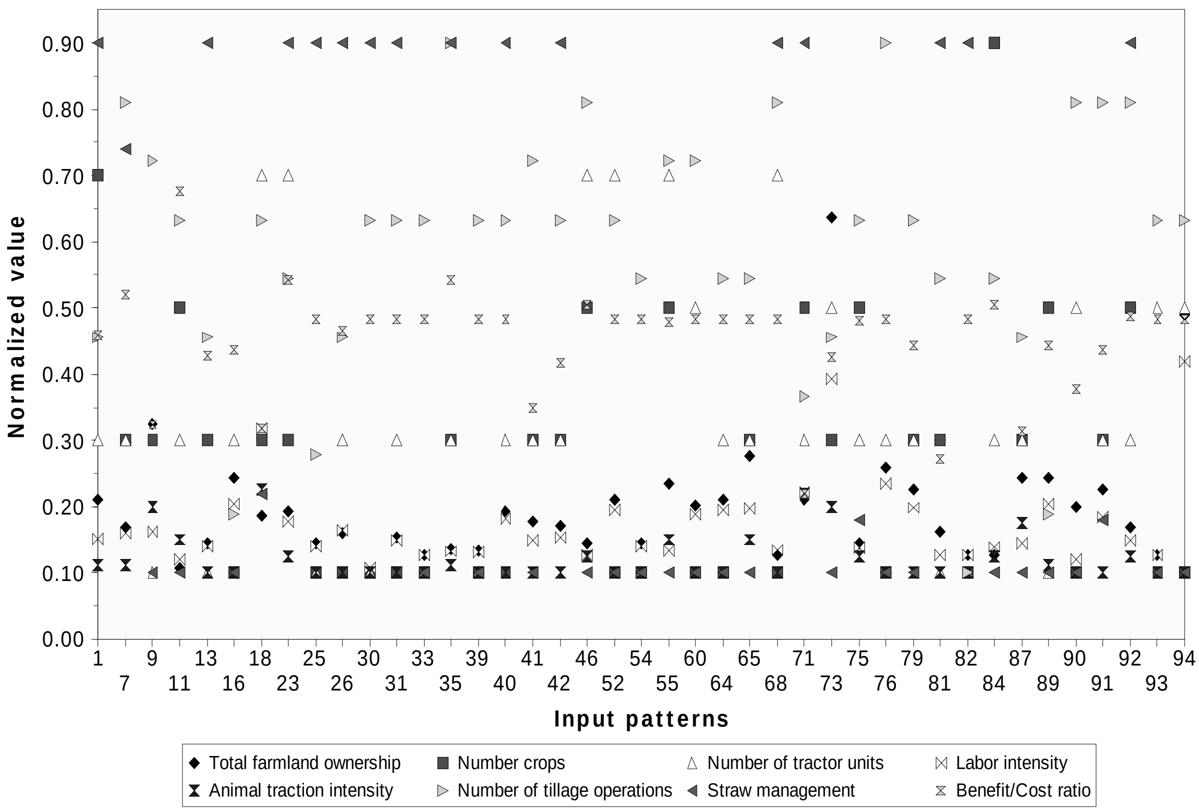

Figure 4.Candidates for standard pattern selection.

6.3 Continuous Inputs

Figures 5 and 6 show the relationship between the predicted mechanization indicators and the fluctuation of the continuous inputs. The amount that each input item contributes to the ANN model can be obtained from these figures. The effects of each input item on the output trend and observed facts in an actual situation in the target region are discussed in this section.

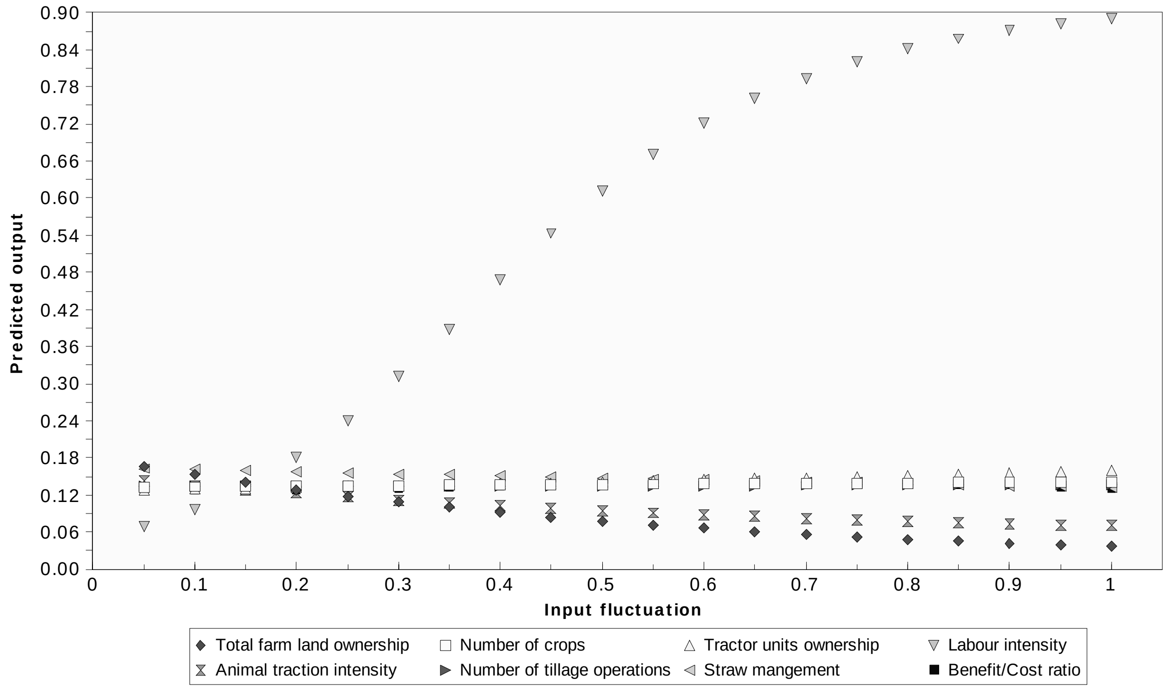

Figure 5. Effect of incremental increases in continuous inputs on the Mechanization Index.

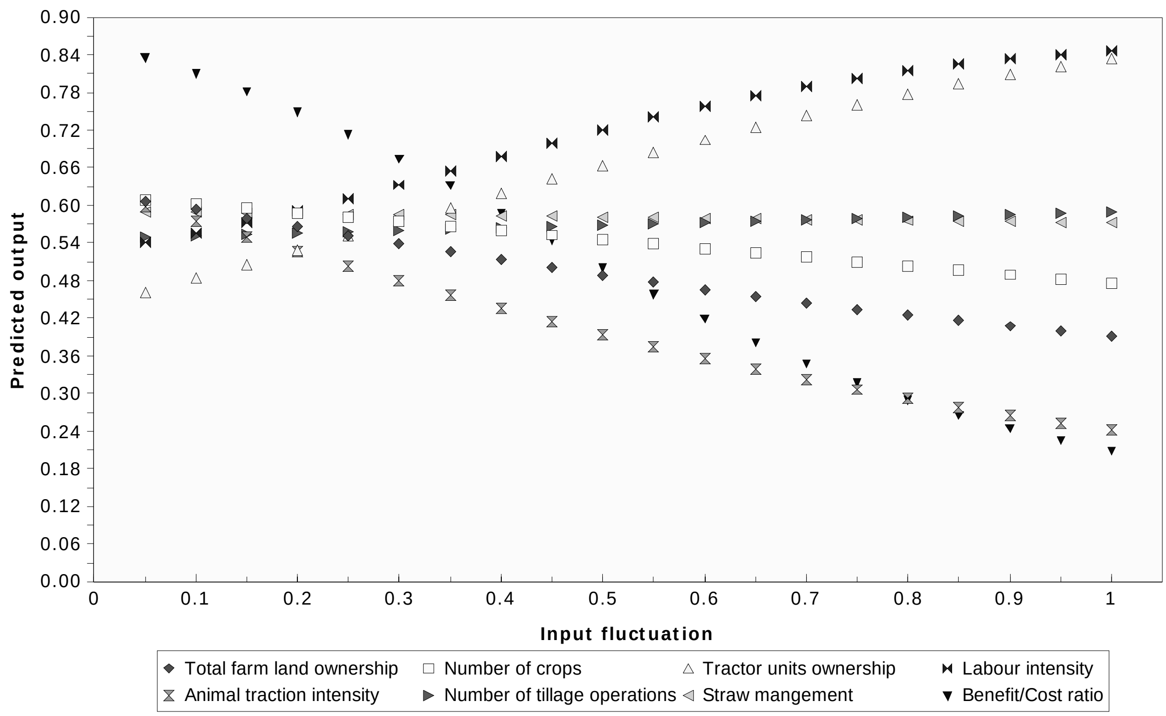

Figure 6. Effect of incremental increases in continuous inputs on the Machinery Energy Ratio.

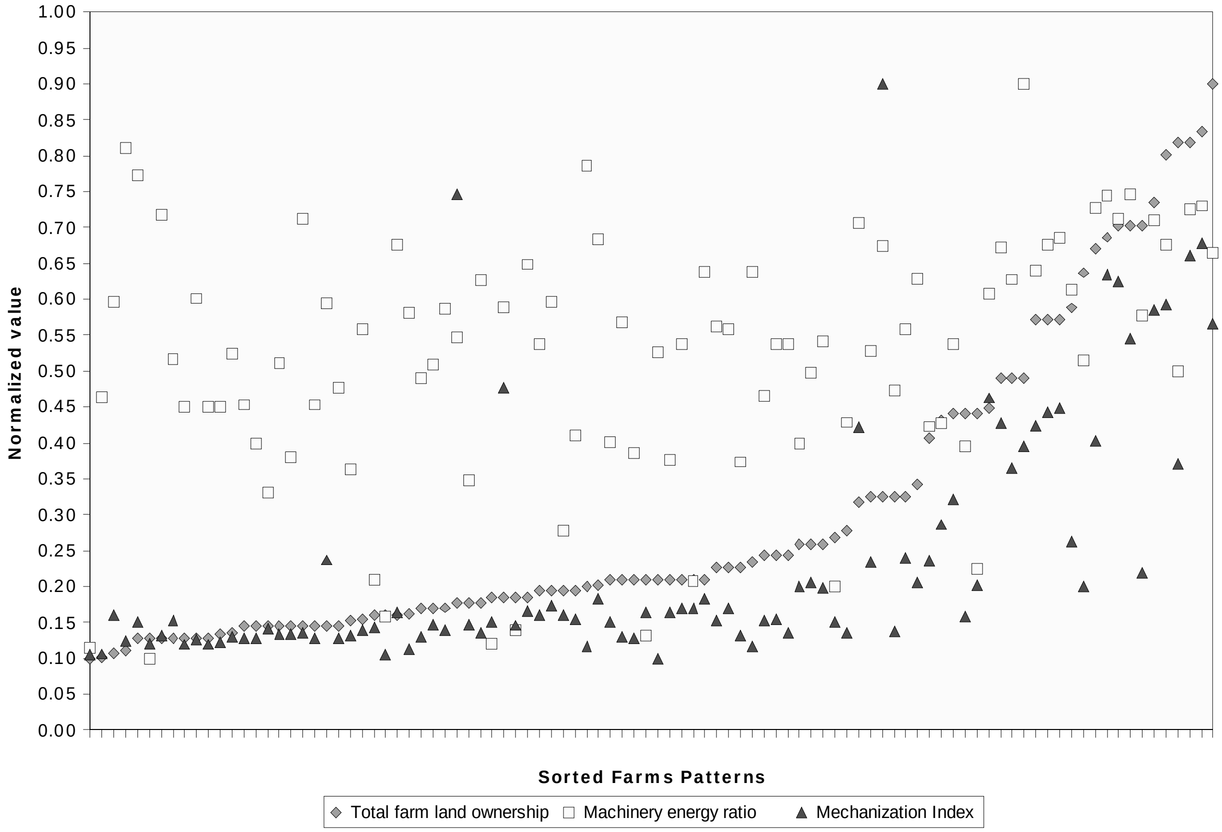

Figure 7. Actual total farm land ownership and mechanization indicators.

Artificial increments in the input Total Farm Land Ownership produced a reverse trend effect in both mechanization indicators. To clarify this point Figure 7 is presented to show the actual farm data patterns and corresponding Mechanization Indicators. However, no clear relationship was found in this graph.

The input Number of Crops affects mainly the MER (compare Figures 5 and 6). In reality, the production of the most common crops (wheat and sorghum) was more mechanized than the production of maize, beans and vegetables which are optional crops in this region. This means that introducing additional optional crops would require greater amount of seeds, agrochemicals and fertilizers but not much additional machinery use. The output of the model reflects this situation.

As shown in Figure 5 and 6, the input Tractor Units Ownership contributes more to the MER than it does to the MI. Since tractors are the main power source in this farming system, Tractor

Units Ownership directly increases mechanization intensity in comparison to farms where tractors are hired.

In Figure 5, the input Labor Intensity has the most significant effect on the outputs of this model, especially for the MI. Hand-labor is applied basically in two fashions in the target region. Firstly, it performs simple tasks such as weed control which introduces a peak on the labor demand trend often not available. Therefore, this situation is observed as the first stage for improving mechanization status by means of introducing appropriate machinery. The second case is that the hand-labor is also applied intensively for calibration, operation and assistance during the mechanized farming tasks. Consequently, from this point of view, we recommend better practical technical training for mechanized farm work in order to improve efficiency of machinery use.
Animal Traction Intensity makes a significant contribution, as it reduces both indicators. This is simply because farms not applying tractor energy much depend on animal traction. As animal traction requires less energy than does a mechanized farming using the tractor, it will be advantageous in certain situations, and some farms should consider animal traction for tasks such as weeding which require little power, which are also the most time demanding tasks.
The Number of Tillage Operations bears little sensitivity to the ANN model. However, considering that the most repetitive and highly power consuming farming tasks in order of importance were harrowing, disc ploughing and surface leveling, introducing a new factor on tillage effectiveness or “quality” would improve the capability of the analysis while applying the ANN model.

Straw Management represents a similar marginal decreasing effect on both mechanization indicators. However, at the farm level it implies (besides feeding for livestock) incorporation into the field for soil improvement as well as to protect the soil surface against wind and water erosion. Introducing this input into the ANN model leads a reduction in tillage techniques which in turn diminish the MI (see Figure 5).

Benefit-Cost Ratio presents high reverse trend effect on significance for the MER. This result is related to the analysis of the input Number of Crops mentioned above, that the most popular crops in the region such as wheat and sorghum require more hours of machine work than do the less common crops such as maize. In contrast, the Benefit-Cost ratio on producing maize was the highest in the farming system under study.

6.4 Categorical Inputs

Figure 8 shows how modifying the categorical inputs affect the ANN model's outputs. The graph was created by changing the value of one of the selected categorical inputs (items 9, 10 and 11 in Table 3) in the 22 units in the validation set, while keeping the values of the other input items unchanged.

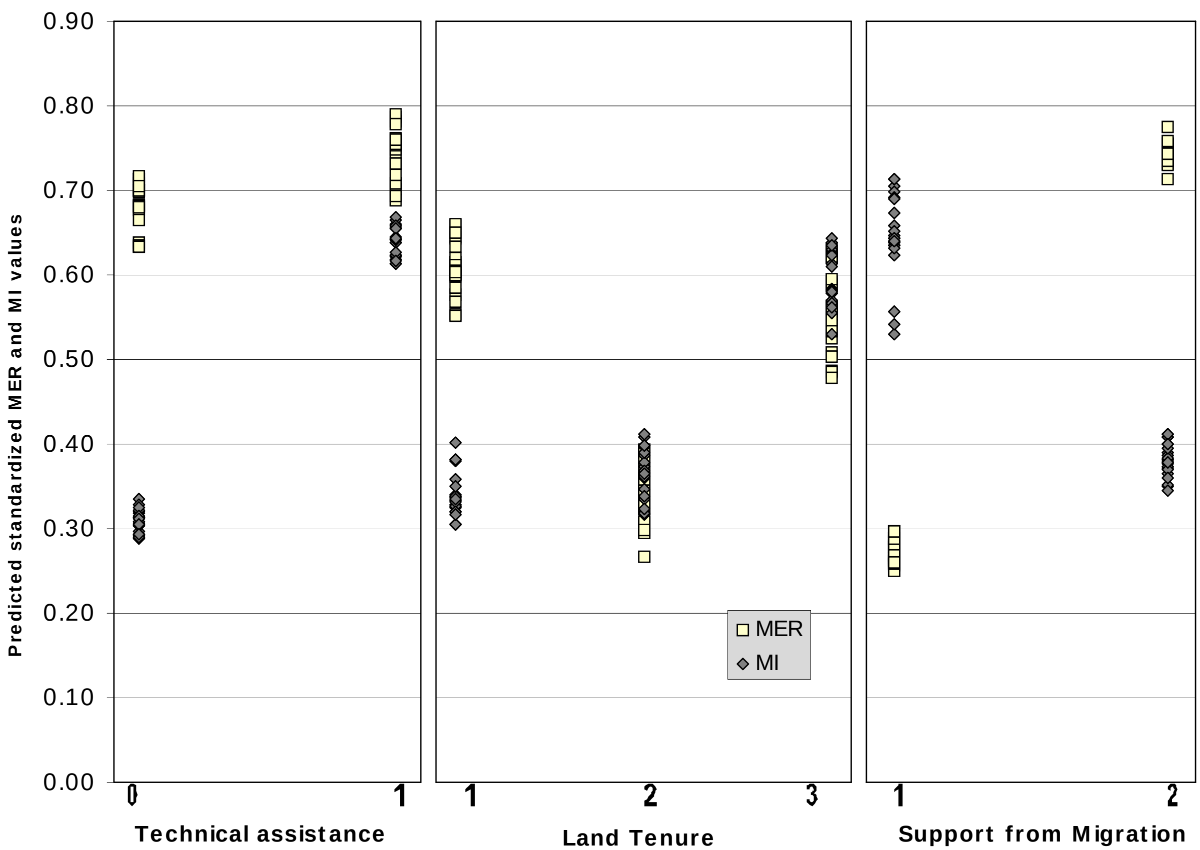

Figure 8. Effect of change in categorical inputs on the mechanization indicators.

Technical Assistance Availability increases the MI, and to a lesser degree, the MER, as shown in Figure 8.

Land Tenure, in the case of Ejidos (ownership by government type, scored 1), had a negative impact on the MI, but a positive impact on the MER, compared to Private Ownership type (scored 3). This suggests that Ejido ownership discourages machinery enhancement. Similarly, Hiring Farm (scored 2) introduces a negative impact for both indicators. Consequently this confirms that the privately owned farms favor tractors use.

Support from Migration (scored 1) means direct external financial support from family members who have migrated. This input was included to the ANN model because it was common in the region. As shown in Figure 8, it increases the MER. However, an opposite non rational effect is observed for the MI. This result implies that, with the support from migrating family members, the farmers could hire machinery more and that this type of farm was not mechanized by the tractor much.

7. CONCLUSION

The developed ANN model predicted well the two mechanization indicators, Mechanization Index and Machinery Energy Ratio, for the farms in the study area in Mexico, since the correlation between the model's outputs, i.e. predicted values, and the calculated values of the indicators was quite strong according to the results after the validation phase (22 cases), as described in section 5.2 above (Pearson's=0.963 and 0.947; R^2=0.93 and 0.90 for MI and MER respectively). Furthermore, the developed Mechanization Indicators would provide sufficient information to identify the target farming system as well as to assess their mechanization status.

The model is based on a single hidden layer artificial neural network. It has 11 input items, 2 hidden units, and the 2 output units. During the simulation process, the model was sensitive enough while predicting information which agrees well with the observed performance of the target farming system. Therefore, each of the 11 selected input variables contributed the improvement in the performance of the ANN.

The wide range of the actual output values for the Mechanization Index and Machinery Energy Ratio (0.078 to 3.83, 0.483 to 0.726 respectively) in the studied farming system suggests that this ANN model may be applied to other regions in the country with conditions similar to those in this study.

We recommend that the ANN model is tested using specific inputs from different farming systems in other regions of the country, especially where the tractor type described in this study is not the main power source. We also recommend analyzing the impact of Tillage Operations on the model by introducing a factor that appraises efficiency on the use of energy and appropriate land cultivation.

Further practical application of this work consists on generating a map of mechanization(In Spanish) indicators for a much wider area. Analyzing the interrelation between this baseline data, in conjunction with available farm monitor reports could allow between others: resolving indications of average effectiveness of energy conversion, to identify priority areas to replace obsolete agricultural machinery, as well as, to asses the suitability of introducing new tractor units in the region.

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