Quantification of mechanization index and its impact on crop productivity and socio-economic factors

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Abstract: In this study mechanization index (MI) was assessed, its influence on corn productivity in correspondence with socioeconomic factors of Pakistani farmers were further analyzed through inter correlation and linear regression analysis. An overall MI ensued 0.60 per hectare with an average corn yield 142.7 mon/ha. Furthermore, results revealed that large farmers had higher MI and corn yield as compared to the small and medium ones and it varied from 0.85 to 0.34 with negative fluctuation in farm size. Moreover, farmers specific and socioeconomic variables (such as farmers education, farming experience, dependency burden, ownership status of machines and external support towards agriculture machinery) were used to observe their influence on MI. Education level, owned and subsidized agriculture machinery have a significant effect while farming experience and dependency burden found an egative effect on MI. So, improving the farmers educational level through literacy campaign and long-term investment for creating support services infrastructure is require to increase the MI at corn farms of Pakistan.

Keywords: mechanization index, corn, productivity, socio-economic factors

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1 Introduction

Agriculture has always played an imperative role in the economy of Pakistan. Irrespective of hasty urbanization and economic discrepancy, it still provides 42% employment of the total labors and contributes 19.8% to gross domestic product (GDP) (GOP, 2016). Machinery, tools and their implements are crucial to agriculture. Moreover, an inclusive narration of the application of these inputs generally entitled as mechanization (Bagheri and Bordbar, 2014).

Mechanization is considered as a set of technological expertise to ensure enhancement of productivity by introducing timely field operations, and quality of grain (Kepner et al., 2003). As productivity is positively correlated with potential unit farm power (mechanization) (Singh, 2006), hence, increasing demand of productivity signpost the requirement of efficient mechanization in developing countries. More specifically, the efficient utilization of farm power with better management of agriculture machinery is assertive for sustainable production in Pakistan (Rehman et al., 2016, Iqbal et al., 2015). In order to maximize the efficiency of mechanization, the farming system should be first characterized, especially to identify possible resource constraints and to capture the diversity of farming systems (Zangeneh et al., 2015).

Numerous studies have been conducted in different

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regions of the world for mechanization assessment in reference with the intensity of power or energy availability (Zangenehet al., 2015; Ramirez et al., 2007; Hormozi et al., 2012; Singh, 2006). However, thequality of mechanization with the intensity of farm power is not suitable, as it doesn't have time dimensions (Sundaram et al., 2012). Moreover, as the majority of the farmers in developing country like Pakistan use tractors for agriculture as well as non-agriculture commodities, therefore, quantification of mechanization based on mechanical tractive farm power to total farm power, does not bring to light the actual use scenario.

The mechanization should incorporate the relevance and utility of using equipment for different field operations at the individual farm level (McNulty and Grace, 2009). So, mechanization index (MI) based on the ratio of energy used by machinery to the total energy used by human, animal, and machinery at corn farms, were suggested for estimation and future planning (Singh, 2006).

Furthermore, investigating the status of MI in selected area, along with potential agricultural productivity and other socioeconomic indicators, will lead to an improvement in the sustainability of the agricultural system (Zhangeneh et al., 2010). Industrialization of the country and economic development of farmer has a direct relation with mechanization (Singh, 2006), which implies that mechanization status is location-specific and dynamic. Hence, formulation of mechanization needs the quantification, its impact on productivity and economic factors (Hormozi et al., 2012).

More specifically, country's significant dependency on agriculture and indeed development in mechanization for macro level planning has lead this study to assess the MI at crop (corn) production level in Pakistan. The particular objectives are avaluation of MI (based on energy), influencing factors (socioeconomic) and effect of MI on crop yield, which is lacking in the proceeding studies.

2 Material and methods

2.1 Study area and data acquisition

Corn, being an important industrial commodity, accounts 2.2% to value addition and 0.4% to GDP of Pakistan (GOP, 2016). Due to conventional farming ways and less involvement of innovative technology, the country is facing productivity problems (Rehman et al., 2015). So, for assessment of mechanization index (MI), its impact on crop yield and to study the possible potential constraints that affects MI, this research was performed in three (main) corn producing districts (Figure 1) of Punjab (main corn producer province), Pakistan during Kharif production season of corn in 2015.

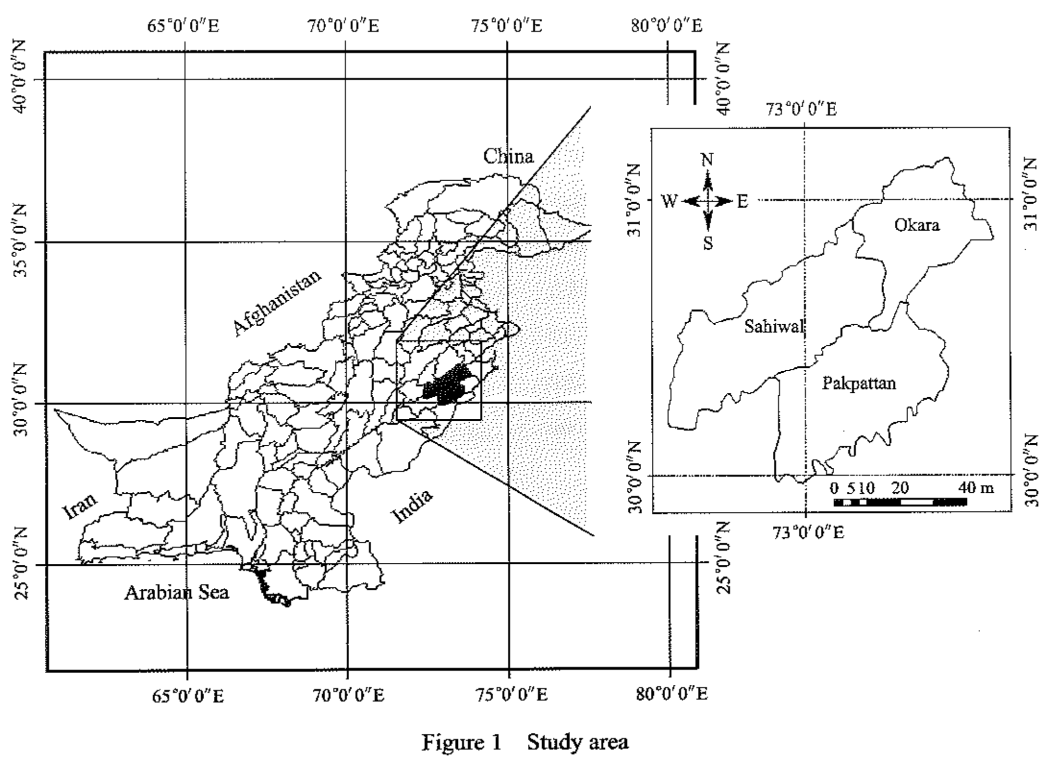

Figure 1 Study area

Face to face questionnaire method has been adopted to acquire the data, from a total of 160 farmers by direct communication with the respondents (corn farmers). Majority of the farmers in Pakistan are small farmers (81%) cultivating 39% of area, although large farmers are less in numbers (7%) while cultivating 40% of area (GOP, 2004). So, to gain more realistic results and a clear picture of MI, data were collected from different farm categories such as small (0-<5 ha), medium (5-<10 ha) and large farmers (10->10 ha). The questionnaire consisted of per acre (lately changed to per hectare) data in quest concerning working hours of inputs-output (human labor, animals, machinery, diesel fuel and crop yield) consumed in field practices such as field preparation, seeding, fertilization, irrigation, plant protection, harvesting (cobs picking), post harvesting (cutting of corn stalks and residue) and threshing. The main key factors that influence successful mechanization include socioeconomic, supporting infrastructure and technical skills (Olaoye and Rotimi, 2010). So, a questionnaire was also delved down into information on socio-economic characteristics of the farmers such as level of education, farming experience, dependency burden, ownership status and supporting infrastructure.

2.2 Technical details

MI is the ratio of machine energy (fuel energy and machinery energy) to the sum of machine energy, animal energy and human energy as suggested by Nowacki (1978). A higher value of MI is the affirmation that most of the work has been done by machine.

$$MI = \frac{Mech._E}{(Mech._E + An._E + Hu._E)} \tag{1}$$

where, MI is MI based on energy; $Mech._E$ is the machine energy (MJ/ha); $An._E$ animal energy (MJ/ha); $Hu._E$ human energy (MJ ha^{-1}).

The energy associated with fuel, human and animal working hours were estimated directly by multiplying their equivalences (Table 1), however, the machine energy was calculated using Equation (2).

$$Mech._E = \frac{(W_m \times E_{eq} \times t_m)}{T_{em}} \tag{2}$$

where, $Mech._E$ is the machine energy (MJ/ha); W_m is the mass of machine (kg); E_{eq} is the energy equivalent for machinery (Table 1); t_m is the time that machine used per unit area (h/ha); T_{em} is the economic life of machine (h).

Table 1 Energy equivalents used for MI in corn production

Inputs, unit		Energy equivalents, MJ per unit	References
1. Labor, h			
	Male	1.96	Nassiri and Singh, 2009
	Female	1.57	Nassiri and Singh, 2009
2. Animal	Bullock (medium)	10.1	Nassiri and Singh, 2009
3. Machinery, kg			
	Tractor	138	Elhami et al., 2016
	Plow + Disk	180	Elhami et al., 2016
	Boundaries (Ridger)	160	Elhami et al., 2016
	Leveler	149	Elhami et al., 2016
	Sprayer	129	Elhami et al., 2016
	Rotary Hoes	148	Elhami et al., 2016
	Thrashing (h)	62.7	Elhami et al., 2016
4. Diesel		47.8	Elhami et al., 2016

2.3 Analytical technique

Collected data were analyzed using descriptive statistics and quantitative classification. Lately, the influence of various socioeconomic factors on MI and MI on crop (corn) yield has been examined by employing multi-regressive technique and inter-correlation respectively. MI articulated as a function of socioeconomic attributes and subsidized supporting parameters as depicted in Equation (3).

$$MI = f(x_1, x_2, x_3, \ldots, x_n) \tag{3}$$

where, x_1, x_2, x_3, …, x_n are the selected attributes e.g., farmer's education level (completed years of schooling), farming experience (years), dependency burden (number of dependent family members), ownership status of agriculture machines (1=owner, 0= otherwise), and subsidy/external support on agriculture machinery (1=availed, 0= otherwise), hereafter, x_1, x_2, x_3, x_4 and x_5, respectively.

Generally, the relationship between attribute's matrix (hereafter X) and the dependent variable vector (Y) (here MI) is acute for significant model selection. To assess this relationship between Y and X, a multi-regressive approach (Equation (4)) is used.

$$Y = \beta_0 + X\beta + \varepsilon \tag{4}$$

where, $X = \begin{bmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{T1} & \cdots & x_{Tk} \end{bmatrix}$, $\beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_T \end{bmatrix}$, $\varepsilon = \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_T \end{bmatrix}$, β_0 is the intercept; β is the regression coefficient; ε is the remaining unexplained noise (error); k is the number of selected attributes, and T the number of respondents.

The primary purpose under consideration in this study was to find the set of variables (a subset of X) that resulted in the minimum residual errors. Primarily, the sum of the squared errors

($SSE = g(\beta_n) = \sum_{t=1}^{T}\left(y_t - \left(\beta_0 + \sum_{n=1}^{k}\beta_n x_{nt}\right)\right)^2$) is employed in the standard regression analysis as a measure of fitting. Moreover, several models resulted from the selected attributes X and MI were investigated using multi-regression method. They were developed using different combinations of the MI and attributes X under some constraints. The model having the minimum g (β_n), a variance inflation factor (VIF) less than 5 for the attributes, and a t-test of statistical significance was considered to be the optimum model among the different combinations that were considered.

3 Results and discussion

To deal with the specific objectives, the study involved descriptive and influential analysis. The descriptive statistics entailed mean and percentage (Table 2).

Table 2 Summary of descriptive statistics

Variables	Definition of variables	Average value
Education (Continues)	Number of schooling years	6.74
Farming experience (Continues)	Number of years	19.05
Dependency burden (Continues)	(Number of dependent persons in family)	6.74
Ownership of agricultural machinery (Dummy)	1= Owner; 0= Otherwise	0.34
Subsidy on agricultural implements (Dummy)	1= Availed; 0= Otherwise	0.13
Small farmers (Continues)	Percentage	43.75
Medium farmers (Continues)	Percentage	35.38
Large farmers (Continues)	Percentage	21.88
Corn yield (Continues)	Yield per hectare	142.7
MI (Continues)	MI per hectare	0.6

Note: SE refers to standard error and all parameters are significant at 1%.

Table 2 presented that the average level of education, agriculture farming experience and dependency burden of respondent were observed 6.74, 19.05 and 6.74 respectively. The average farmers having owned agricultural machinery were observed 0.34, while farmers availing subsidy were stated 0.13. Smaller farmers contributed higher in the sample, as 43.75%, followed by medium 35.38%, the large farmers were the least one (21.88%). An overall of MI (based on Equation (1)) was found 0.60 for corn production with an average yield 142.7 mon ha^{-1} in the target region.

3.1 Mechanization index and its impact on crop productivity

A notable relationship of MI and corn productivity per hectare was found as is shown in Figure 2. A significant variation is found between MI and productivity in the perspective of farm size. Comparative to medium and small farmers the MI of the large farmer is 1.4 and 2.5 times higher, respectively. Similarly, corn yield of the large farmer is respectively 17% and 48% higher than medium and small farmers. This implies that the MI and crop productivity dependent on the farm size. Perhaps, the large farmers may have more capital and resources to utilize at their farm which leads toward higher MI and production per hectare. Small farmers found constraints in the use of machinery due to the smaller size of fields and limited capital resources. Our result is in the same trend of recent studies, for instance, Singh and De (1999), and Alam and Singh (2003) also reported the large farmers used to advance technology for example tractors and had higher crop productivity comparative to other group of farmers.

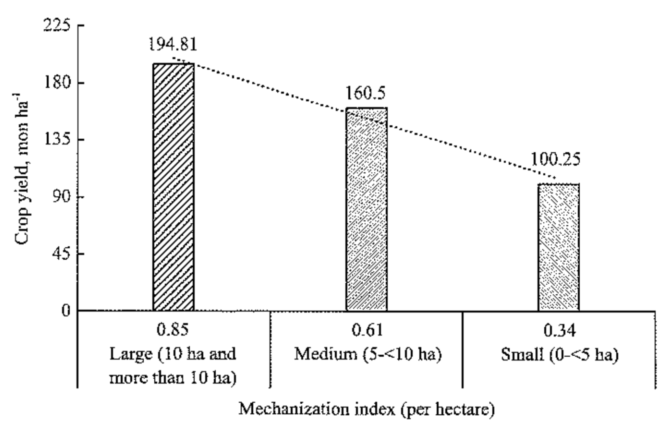

Figure 2 Effect of MI on crop yield

3.2 Effects of socioeconomic and external support on mechanization index

Equation (5) revealed the results of influential analysis of external support with socioeconomics and farmer's characteristics on MI. Outcomes depicted that education, ownership, and agriculture machinery subsidy have a significant effect on MI. While experience and dependency burden have a negative effect on MI.

$$MI = 0.015x_1 - 0.006x_2 + 0.192x_3 - 0.037x_4 + 0.046x_5 + 0.803 \quad (5)$$

Furthermore, we categorized farm MI on the base of farmer's characteristics such as, ownership of agricultural machinery, education, experience, dependency burden and supporting infrastructure (subsidized agriculture machine). We found astonishing results that, the MI of machinery owners is 0.3 times higher than their counter part. On another hand, the MI decreased with the increase of the experience in farming because the majority of farmers in this study are old farmers with more experience. Despite the old farmers are living with more experience, however, they are less likely to adopt or reluctant to use innovative or new technologies, particularly in the developing countries. Our results are in the same line with Owombo et al. (2012), where they also found a negative relationship between farm MI and experience. Moreover, we found that with increasing number of schooling years the farm MI significantly increases. Specifically, those farmers with more than 10 years of schooling have higher MI than farmers having schooling years less than 10 years. Naqvi and ashfaq (2014) also found the similar results, with a higher level of farmer's education, farmers are more prone to adopt advanced technology and consequently achieved the optimum level of crop productivity. Furthermore, our findings revealed a negative correlation between MI and dependency burden, varied from 0.67-0.33 with the increase in dependent persons from 3->6 respectively, because affordability towards agriculture machinery decreases with increasing financial burden. Results further depicted that MI of farmers availed subsidy is higher than that of non-availed ones, therefore a long-term investment for creating support services infrastructure is required and government must take sustainable measures to boost up mechanization.

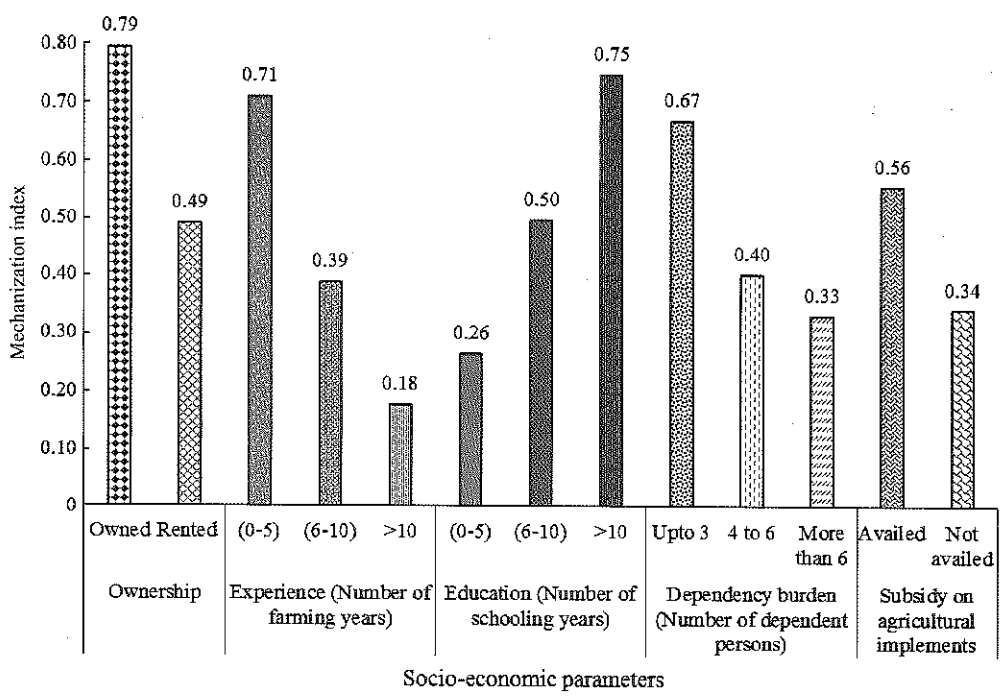

Figure 3 Effect of socioeconomic parameters on MI

4 Conclusions

In this study MI at corn production systems of Pakistan were assessed, hereupon, its impact on corn productivity was appraised through inter correlation analysis and furthermore, the correspondence of socioeconomic factors with MI was examined through linear regression. The intention was to provide an index that could facilitate mechanization planners and policy makers to assess and formulate future strategies. For this purpose, a cross sectional data of 160 corn growers were collected from three main corn producing districts (Sahiwal, Okara, Pakpattan) of Punjab, Pakistan. Assessment confided that average MI at crop (corn) level was 0.60 per hectare with an average corn yield 142.7 mon/ha and it varied from 0.85 to 0.34 with negative fluctuation in farm size. It is proclaimed that the farmers having higher crop yields (194.81 mon/ha) have adopted higher levels of mechanization (0.85 per ha) to ensure timeliness operations. The analysis has further revealed as a consequence of socioeconomic influence on MI, owned and subsidized agricultural machinery have a significant effect on MI. The literacy rate was also found significant, while farming experience and dependency burden has negative effect on MI. An insufficient level of MI has been perceived, therefore, long-term investment for creating support services infrastructure is required. The Government must take endurable measures to encourage mechanization.

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