Asian Journal of Applied Sciences (ISSN: 2321 – 0893)
Volume 10 – Issue 5, October 2022

Pattern and Determinants of Rice Combine Harvester Adoption in Isabela, Philippines

Hernaiz G. Malanon[1] and Isabelita M. Pabuayon[2]

[1]Philippine Center for Postharvest Development and Mechanization (PHilMech)
CLSU Compound, Science City of Munoz, Nueva Ecija, Philippines
Email Address: hgmbpre7@yahoo.com

[2]University of the Philippines Los Banos (UPLB)
Los Banos, Laguna, Philippines
Email Address: Impabuayon@uplb.edu.ph

ABSTRACT - With the need to promote wider adoption of rice combine harvesters (RCH) in the Philippines, this study analyzed the adoption process and investigated the factors that influenced complete adoption of the technology. Data was gathered through survey of 230 rice farmers and supplemented by key informant interviews in 24 rice-producing municipalities of the province. Results showed that RCH was adopted by farmers with higher level of education, higher income, larger farm holdings and with irrigated farms situated in the lowlands. About 90 percent of rice farmers in the area are already using RCH and adoption was considered permanent since all adopters did not revert to traditional practice after initially using the technology. The remaining non-mechanized farms are the rain-fed areas with poor road access, terraced small plots and waterlogged farms that deter the use of heavy machines. The respondents cited reduction of harvesting-threshing time which averts the exposure of farmers to climate risks brought by tropical cyclones and reduction of harvesting-threshing costs and postproduction losses as primary reasons for adoption of RCH. Empirical estimates using Logistic Regression revealed that RCH adoption increases with farm size and educational attainment. Topography is also an important determinant of adoption as farms situated in the lowland are more likely to adopt RCH than in the upland areas. With these findings, it is recommended that drivers and barriers of RCH adoption RCH be considered in the technology promotion.

Keywords: Adoption pattern, Determinants of adoption, Logistic regression, Rice combine harvester

---

1. INTRODUCTION

Rice remains the most important commodity in the Philippines. With its economic and political implications, the crop has been at the forefront of government development agenda. While the government is very active in providing support through subsidies in the form of seeds, fertilizers, farm chemicals, extension services, credit and mechanization technologies, the contribution of the private sector is also significant. In conjunction with the increasing cost of labor due to dwindling labor supply and the increasing climatic variability, the use of machines such as rice combine harvesters started to gain acceptance. It is important to note that harvesting and threshing operations accounts for 35-40% of total labor costs in rice farming and this has been continuously increasing due to these factors.

Adoption of RCH lags behind other Asian countries but the diffusion of the technology in the country is relatively fast in some regions and provinces. Initial adoption of RCH in the Philippines started in 2010 and this increased to 3% adoption in 2013 based on a study by PhilRice (Bordey *et al.*, 2016). This was substantiated by PHilMech report in 2015 when adoption of combine harvester in the country was updated at 4.16 percent in 2014 (Malanon *et al.,* 2015). Since that period, adoption rose steadily and even dramatically in some areas.

The different factors affecting technology adoption are generally categorized into technological, household specific, economic, and institutional factors. Technological factors refer to the attributes of the technology while household specific factors refer to the socio-demographic characteristics of adopters which include age, gender, education, and household size. Economic factors include farm size and income while institutional factors include the farmer's membership to a social group and access to information, extension services, market, and credit. Age is commonly included in studies determining factors affecting agricultural technology adoption. Most studies have shown that age negatively affects adoption (Ayodele, 2012; Howley, O. Donoghue and Heanue, 2012). Younger generations are more likely to adopt farm mechanization as older farmers are less likely to abandon their traditional practices learned through experience and observation (Ghosh, 2010). Education is another important factor that influences technology adoption. Studies show that education has a positive effect on adoption (Truong, 2008; Uaiene et al., 2009). Education affects the attitudes and perceptions of the respondents which make them more open and rational to technological innovations. Household size is an indicator of labor availability although this depends on the ages of family members. Families with large household size are less likely to adopt labor replacing technologies such as mechanization. This was demonstrated by studies of Mariano *at al.,* (2012) and Mlenga and Maseko (2015). Farm size also affects agricultural mechanization technology adoption as shown by Truong (2008), Ghosh (2010), Akudugu *et al.,* (2012) and Mariano *et al.,* (2012). Farmers who operate larger farms are more likely to adopt new technologies since they can afford to devote a part of their land to try and test its effectiveness (Uaiene *et al.,* 2009). This is in contrast to small holder farmers who are generally more risk averse. Moreover, agricultural mechanization technologies, particularly the large machines require economies of scale operation in order to be cost effective; hence, small fragmented farms are less likely to be mechanized. Extension has been found to have a positive effect on the adoption of agricultural technologies. This was illustrated by Uaiene *et al.*, 2009, Akudugu *et al.*, 2012 and Truong, 2008. Farmer's membership to social groups such as associations and cooperatives likewise affect adoption of technologies. With membership to social groups, farmers are able to share experiences and gain information about the technology (Uaiene *et al.*, 2009).

Previous studies on the determinants of rice combine adoption showed that variables such as education, farm size and household size affect adoption of rice combine harvesters in Northeast Thailand (Poungchompu and Chantanop, 2016). Higher education and farm size both positively affected adoption while an increase in household size negatively affected adoption. Hassena *et al.* (2000) showed through logit analysis that proximity to a hiring station, topography, education level, and area were factors that significantly affected farmer's decision to adopt combine harvester for wheat. The odds of using a combine harvester increased by a factor of 1.6 when wheat area increased by 1 hectare. Moreover, the likelihood of using a combine significantly increased by a factor of 3.8 for farmers who had better access to the technology due to favorable topography. Furthermore, educated farmers were more likely to use a combine harvester than non-educated farmer. The authors explained that educated farmers were better aware of the yield loss and consequent economic loss of using traditional harvesting and threshing methods.

Djokoto and Blackie (2014) found out that plot size, gender, household size and level of formal education influenced adoption of mechanized harvesting technology in Kpong Irrigation Project in Ghana. The authors explained that plot size was the most important determinant of adoption while other variables such as age, source of capital, marital status and experience in cultivating rice did not influence adoption of mechanized harvesting technology. The authors recommended that consideration should be given to larger plot sizes and farmers with higher level of education should be encouraged to go into farming at the irrigation facility. Moreover, government should improve rural infrastructure to encourage young people to remain in agriculture particularly in the Kpong Irrigation Project area.

Truong (2008) also established the important factors affecting the mechanization of rice harvesting and postharvest operations in Mekong Delta in South Vietnam and significant variables include farmers' education and perception on machines, capital, rice area, technical training, knowledge of extension workers, methods of extension organization, and information system. Attendance to training and farmers' knowledge were two important factors that positively and significantly affected the use of machines in rice harvesting and drying. In addition, higher level of education and female managed-farms also increased the use of harvesters. The information from the intermediate agents likewise contributed to the use of harvesters by rice farmers.

In the Philippines, adoption studies are already well documented in selected areas, but the adoption and diffusion of rice combine harvesters in Isabela, the second largest producer of rice and has been the earliest and most extensive adopter of rice mechanization technologies is still lacking. Understanding the adoption pattern and the factors affecting adoption provides inputs in devising mechanization strategies that could be replicated in other major rice producing areas of the country. This will ensure success of the mechanization intervention in improving productivity, income and rice competitiveness.

2. METHODOLOGY

2.1 Research and Sampling Design

The study employed both qualitative and quantitative methods of design and analysis. Quasi-experiment using Matched Comparison Group Design in which data from representative sample farmers adopting the mechanization technologies (treatment group) was compared with the data from a sample of non-adopting farmers (comparison group).

The number of sample respondents was determined by adapting Yamane (1967):

$$n = \frac{N}{1 + N * e^2} \qquad \text{(Equation 1)}$$

Where:

n = Sample size
N = Population size
e = Acceptable sampling error ranging from 1-10%

The respondents were composed of 230 rice farmers, randomly selected in major rice producing municipalities of Isabela. In addition, 30 facility (RCH and rice thresher) operators and 30 key informants were interviewed.

2.2 Data Collection and Research Instrument

Data were gathered through personal interview of rice farmers that adopted and not adopted rice combine harvester. Key informant interviews in 24 rice producing areas, actual field observations and secondary data collection were done to supplement the gathered information.

2.3 Analytical Procedure

1) Data were encoded, tabulated and analyzed using the Statistical Package for Social Sciences (SPSS). Descriptive statistics such as percentage, frequency distribution, cross tabulation and measures of central tendency were used in describing the socio-economic characteristics of the respondents, farm characteristics and rice postproduction practices or farmers in addressing climate-related risks.

2) Logit regression model was used to determine the factors affecting adoption of rice combine harvester. Defining adoption as a discrete phenomenon is generally done using binary logit or probit models. Logit and probit analysis are typically employed in studies determining the factors affecting technology adoption because they provide more detailed information on the characteristics of farmers who would adopt a specific technology (Mariano *et al.*, 2012). The specific variables included in the mechanization technology adoption model, data measurement and the hypothesized signs are described below. Mechanization technology adoption was hypothesized to be a result of the interaction of several variables sorted out into socio-economic characteristics of the farmer-users, production and post-production practices, technology attributes, biophysical characteristics of the area, management aspect of the facility where farmers avail custom service, existing grains marketing system, delivery mechanism including subsidies and other government support and climate variables.

   Most technological adoption studies have characterized adoption as a discrete phenomenon, i.e. adopters versus non-adopters, rather than a continuum that reflects the intensity of use of various technologies. This study did not depart from this view because of the distinct features of mechanization technology adoption process. Unlike the adoption of most agricultural technologies that started with farmers' acquisition or procurement of technology and ended with the permanent modification of practices, farmers do not purchase the machines and only used them on certain conditions. Most rice farmers use the technologies through custom service as the machines are capital intensive while the average farm size of rice farmers in the country is relatively small.

   Several studies found a significant association between human capital and technological adoption. Higher human capital accumulation as indicated by farmer's education measured by the number of years the respondent attended school, years of experience in farming, attendance to trainings/seminars and affiliation in farm organizations are hypothesized to increase the likelihood of mechanization technology adoption. These variables are expected to have positive signs. In addition, most adoption studies likewise include variables reflecting family income and farm size or volume of production. Larger farms can better spread the fixed costs of a given technology over a larger output compared to smaller farmers, thereby lowering average fixed costs. In this study, bigger farms are hypothesized to be more likely to adopt mechanization technologies because larger farms face higher risk in harvesting large volume of harvest. The farm size is expressed in hectares and is hypothesized to have a positive sign.

   For the dependent variable mechanization technology adoption, a value of one was assigned for farmers who adopted the mechanization technologies (whether partially, temporarily, fully or permanently) and zero for farmers who never used the technologies.

The mechanization technology adoption function is specified as:

$$Ln(P_i/1-P_i) = f(yr, ed, in, hh, te, ha, to, tr, kg, fa) \qquad \text{(Equation 2)}$$

Where:
yr = age of farmer
ed = educational attainment, in number of years attended school
in = annual family income, in Php
hh = number of household members
te = tenurial status dummy 1 = owner; 0 = tenant/shareholder
ha = farm size, in ha
to = topography dummy 1 = lowland; 0 = upland
tr = attendance to trainings or seminars related to postharvest and mechanization dummy 1 = yes; 0 = no
kg = yield per hectare, in kg
fa = availability of RCH facility dummy 1 = yes; 0 = no

Since the dependent variable is in binary form having only two values, the use of ordinary multiple regression technique is not applicable because a number of important assumptions of such model is not satisfied and the predicted values cannot be interpreted as probabilities. An alternative is to use logistic regression model, which required far fewer assumptions but directly estimate the probability of an event occurring or not occurring. In logistic regression, maximum-likelihood method was used to estimate the parameters. A logistic regression model is usually written in terms of the log of odds, which is called logit, as:

$$Log \left\{ \frac{Prob\ (event)}{Prob\ (noevent)} \right\} = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(Equation 3)}$$

Where β_{is} are estimated coefficients and X_{is} are the independent or explanatory variables. The logistic coefficient is interpreted as the change in the log-odds associated with one unit change in the independent variable. The coefficients do not measure marginal effects of independent variables but only show if any variable has significant influence on the dependent variable. The significance of the estimated coefficients may be shown in terms of Wald Statistic, *t*-ratios, correlation coefficients or $E(\beta_i)$, i.e. exponentiation value of β_i. Among these, $E(\beta_i)$ gives a more direct interpretation of β_{is} and it is derived by rewriting the equation in terms of odds rather than log odds as follows:

$$\frac{Prob\ (event)}{Prob\ (noevent)} = e^{\beta 0 + \beta 1X1 + \cdots + \beta nXn} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(Equation 4)}$$

Now, e raised to the power β_i is the factor by which the odds change when the i^{th} independent variable increases by one unit. If β_i is positive, $E(\beta_i)$ is more than 1 which means that the odds are increased. If β_i is negative, $E(\beta_i)$ is less than1 which means that the odds are decreased. If $\beta_i = 0$, $E(\beta_i) = 1$ which leaves the odds unchanged.

3. RESULT AND DISCUSSION

3.1 Socio-demographic profile of the farmer-respondents

The socio-demographic characteristics of the respondents categorized into adopters and non-adopters of rice combine harvesters are presented in Table 1. Adopter refers to a rice farmer who used rice combine harvester, whether temporarily or permanently. Farmer adopters mainly avail rice combine harvester custom rental from facility service operators although 13 percent of the farmer respondents own rice combine harvesters. On the average, the adopters of rice combine harvesters (RCH) were slightly older than the non-adopters although the difference was not significant based on *t*-test. The age distribution of technology adopters, however was more skewed as higher percentage of the farmers were within 50 and above age bracket compared to the non-adopters that show more even distribution. Although there was a high percentage of farmers who were older than 60 years, most of them were not already actively working in the farm. In terms of education, the RCH adopters attended school longer than the non-adopters, with an average of 10 years. This was more than two years higher than the average of non-adopters. Thirty six percent of the technology adopters reached college level or completed a degree compared to 17 percent of the non-adopters. The adopters were also more well-off declaring incomes more than three times higher than the earnings of non-adopters. The distribution of income revealed that there was lower incidence of poverty for adopters as only 14 percent of the respondents had incomes below the poverty threshold level of Php109,680.00 annual family income (composed of five members) as reported by the Philippine Statistics Authority (PSA) in 2015. For non-adopters, 25 percent of the respondents had incomes lower than the poverty threshold level. Meanwhile, the average year of experience in farming showed that RCH adopters were more experienced than their non-adopter counterparts.

The RCH adopters were also more active in joining farm organizations as 40 percent were members of associations compared to two percent of the non-adopters. Farm organizations were either irrigators' associations (IA) or farm cooperatives. The respondents have relatively low participation to seminars or trainings related to postharvest or mechanization. Less than 30 percent of technology adopters were able to attend seminars, trainings or product demonstrations on mechanization particularly on the use of RCH. On the other hand, only two percent of the non-adopters were able to participate in trainings or seminars related to postharvest or mechanization. Machinery demonstrations were mostly done by the Department of Agriculture (PHilMech, RFUs and LGUs) and private machinery distributors in the province like Agri-Component Corporation and ACT Machineries. The very low participation of non-adopters to seminars and product demonstrations indicate the lack of seminars conducted in their locality and the non-adopters, being small holder farmers have no means to attend to seminars or demonstrations usually conducted in major rice production municipalities or at the Agricultural Training Institute (ATI).

Table 1. Socio-demographic characteristic of rice farmers, by rice combine harvester adoption, 230 farmer respondents, Isabela, 2018

SOCIOECONOMIC CHARACTERISTIC	ADOPTER *(n=190)*	NON-ADOPTER *(n=40)*	MEAN DIFFIRENCE (*t*-test)	ALL *(n=230)*
Sex (%)				
Male	88	76		86
Female	12	24		14
Age (Mean)	*54.17*	*51.02*	*3.15*^{ns}	*53.62*
Below 40	11	22		13
40-49	25	27		25
50-59	30	24		29
60 and above	34	27		33
Education (Mean)	*10.03*	*7.59*	*2.45****	*9.61*
Primary	28	59		33
Secondary	36	24		34
Tertiary	36	17		33
Household size (Mean)	*4.05*	*3.89*	*0.16*^{ns}	*4.04*
1 to 3	39	41		39
4 to 6	50	41		50
7 to 9	10	12		10
10and above	1	6		1
Family income, Php	*324,264.00*	*104,089.00*	*220,174.00****	*291,312.00*
Above poverty (%)	86	75		84
Below poverty (%)	14	25		16
Farming experience (mean)	*29.21*	*28.79*	*0.42*^{ns}	*29.14*
Below 20	25	18		24
20-29	26	38		28
30-39	29	23		28
40 and above	20	21		20
Membership in farm organizations (%)				
Yes	40	2		32
No	60	98		68
Attendance to seminars/trainings/demos related to mechanization (%)				
Yes	27	2		22
No	73	98		78

^{ns} Not significant at 10% level (*P* >.100)
*** Significant at 1% level (*P*<.001)

3.2 Farm characteristics of farmer-respondents

The RCH adopters operated significantly larger farms with an average landholding of 4.02 hectares per farm compared to the non-adopters that reported an average of 1.55 hectares (Table 2). Majority (71%) of adopters have farms ranging from 1.0 hectare to 5.0 hectares and six percent declared to have more than 10 hectares. Conversely, 44 percent of the non-adopters were considered as smallholder farmers, with farms less than one hectare. Meanwhile, 89 percent of the RCH adopters have irrigated farms while most of non-adopters have non-irrigated or rainfed farms. Related to this, 96 percent of the RCH adopters have farms situated in low-lying or plain areas while 68 percent of the non-adopters have farms located in the upland. In terms of land tenure, more than half (54%) of the adopters were owners, 35 percent were tenants and 11 percent were leaseholders. On the other hand, 41 percent of the non-adopters were owners, 39 percent were share tenant and 20 percent were leaseholders. For cropping intensity, 91 percent of the adopters and all non-adopters planted rice two times a year. Other farmers in some parts of the province grow mungbean after harvesting rice during the dry season.

Table 2. Farm characteristic of rice farmers by rice combine harvester adoption, 230 farmer respondents, Isabela, 2018

FARM CHARACTERISTIC	ADOPTER *(n=190)*	NON-ADOPTER *(n=40)*	MEAN DIFFIRENCE (*t*-test)	ALL *(n=230)*
Farm area (Mean)	*4.02*	*1.55*	*2.46****	*3.55*
Less than 1.0 ha	14	44		20
1.0 to 5.0 ha	71	51		67
5.1 to 10 ha	9	5		8
Above 10 ha	6	-		5
Irrigated farm (%)				
Yes	89	24		77
No	11	76		23
Topography (%)				
Lowland	96	31		79
Upland	4	68		21
Land tenure (%)				
Owner	54	41		53
Tenant	35	39		35
Leaseholder	11	20		12
Cropping intensity (%)				
Twice/year	91	100		93
Once a year	9	-		7

*** Significant at 1% level ($P < .001$)

3.3 Rice harvesting-threshing methods employed by rice farmers

Key informant interview revealed that large majority (90%) of the rice farmers in Isabela were already using rice combine harvesters in harvesting and threshing their crops as of 2018 (Table 3). This was based on reports from 24 major rice producing municipalities in the province. Seven municipalities declared almost 100 percent adoption rate while four municipalities reported less than 80 percent adoption. Only 10 percent of the total rice area still employed the traditional method of harvesting and threshing. The remaining non-mechanized areas were rain-fed upland farms with poor road access and terraced small plots. There were also farms in irrigated lowland areas that have waterlogged/soft soil condition which impede the use of heavy machines such as rice combine harvesters. Aside from drudgery and more time needed to reach these areas, rice combine harvesters were not cost effective to use, both for the farmers and machinery service providers because of low productivity. Meanwhile, there were some farmers who were adopters of rice combine harvester but employed manual harvesting for heavily lodged crop caused by flooding and tropical cyclones.

Table 3. Rice harvesting-threshing method employed by rice farmers, Isabela, 2018

MUNICIPALITY/CITY	HARVESTING-THRESHING METHOD	
	Rice combine harvester	Manual harvesting/ Mechanical threshing
Alicia	99	1
Angadanan	78	22
Aurora	97	3
Burgos	90	10
Cabatuan	99	1

Cauayan City	98	2
Cordon	85	15
Delfin Albano	99	1
Echague	91	9
Gamu	98	2
Ilagan City	60	40
Luna	99	1
Mallig	98	2
Naguilian	80	20
Quezon	93	7
Quirino	90	10
Ramon	99	1
Reina Mercedes	95	5
Roxas	70	30
San Isidro	99	1
San Manuel	70	30
San Mateo	99	1
Santiago City	96	4
Tumauini	90	10
Average	*90.50*	*9.50*

3.4 Factors considered in adoption and non-adoption of RCH

The reasons cited for adoption and non-adoption of RCH are enumerated in Table 4. For adopters, the reduction in harvesting and threshing time was the primary reason declared by the respondents. On the average, it takes one day to harvest one hectare of rice farm using manual labor. After harvest, field drying is done to facilitate threshing and minimize threshing loss. Bundling and in-field hauling are done to assemble the harvested crop in a single area before threshing. Harvesting to threshing operation usually takes two days to complete while RCH can do the same activity in 2-3 hours. The reduced time minimizes the exposure of farmers to risks such as typhoons, prolonged rainfall and price fluctuations.

Meanwhile, reduction of harvesting and threshing costs was cited by 58 percent of the respondents as main reason in adopting RCH. This was especially observed in areas where labor is scarce as manifested by high labor cost. Related to reduction of harvesting time, 36 percent of technology adopters mentioned weather as principal reason in using RCH, 30 percent cited reduction of losses while four percent pointed out the inadequate and/or inefficient laborers.

For the non-adopters, nearly 50 percent asserted displacement of labor as main reason for not adopting RCH. Non-adopters were generally situated in upland non-irrigated areas where there was still surplus labor. One-third of the respondents stated that their farms are not accessible for large machines such as RCH, while 29 percent stressed that they have small farm and 14 percent disclosed that they have rice threshers they don’t want to be displaced.

Table 4. Reasons for adoption/non-adoption of RCH, Isabela, 2018

REASON	ADOPTER		NON-ADOPTER	
	Number Reporting	Percent Reporting@	Number Reporting	Percent Reporting@
Reduce time in harvesting and threshing	131	69	-	-
Reduce harvesting-threshing costs	110	58	-	-
Inclement weather	68	36	-	-
Reduction of losses	57	30	-	-
Inadequate labor/ Inefficient workers	8	4	-	-
Displacement of labor	-	-	19	48
Inaccessible farms	-	-	13	33
Small farm holding	-	-	12	29
Available thresher	-	-	6	14

@There are multiple responses

3.5 RCH adoption rate

The adoption profile of respondents showed that rice farmers in the province started to adopt rice combine harvesters as early as 2010 while majority (41%) adopted the technology in 2013 to 2014. The adoption timetable follows the phases of technology diffusion as categorized by Rogers (1962); innovators, early adopters, early majority, late majority and laggards. The technology adoption curve or life cycle forms a bell-shaped curve as depicted in Figure 1.

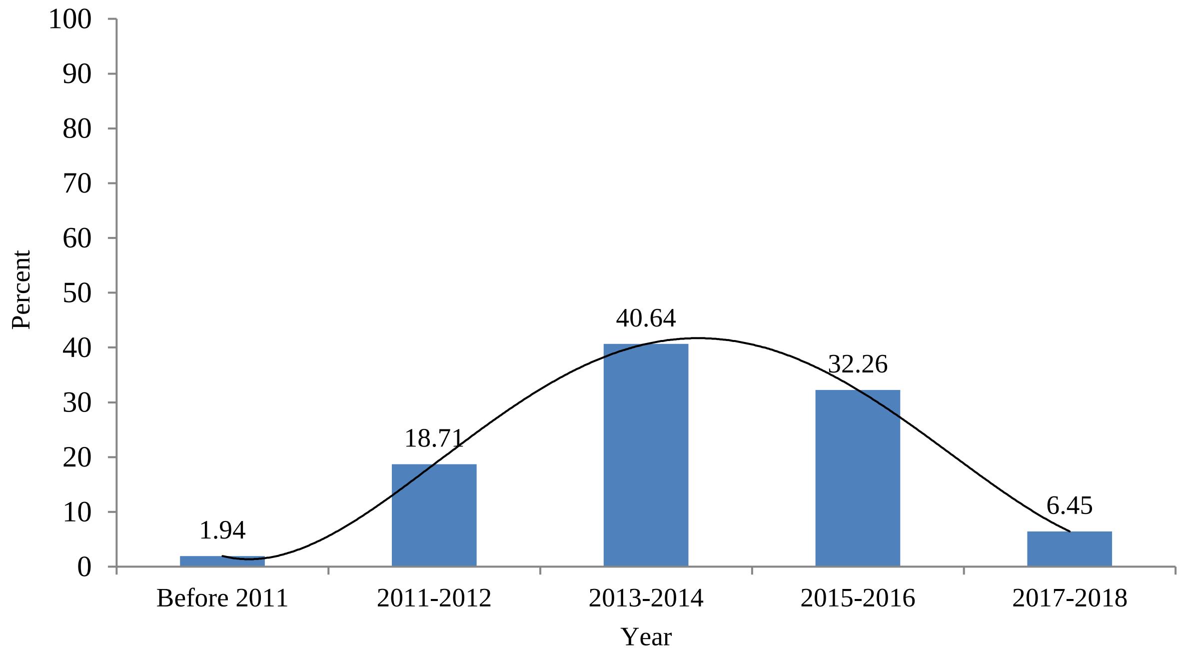

Figure 1. RCH adoption rate, Isabela

3.6 RCH adoption pattern

Figure 2 shows the RCH adoption pattern of rice farmers in Isabela. PHilMech study revealed that adoption of rice combine harvesters was already at 17% in 2013. This was based on the percentage of area harvested using RCH. Another PHilMech study in 2014 found out that technology adoption increased to 26.55%. In 2018, adoption reached 90.53% of the total area devoted for rice production. The mode of RCH adoption was considered as *in toto* or full/complete and permanent. All the interviewed adopters declared that they permanently use RCH since they started to adopt the technology. In addition, the technology adopters utilize RCH to their whole farms for both cropping seasons.

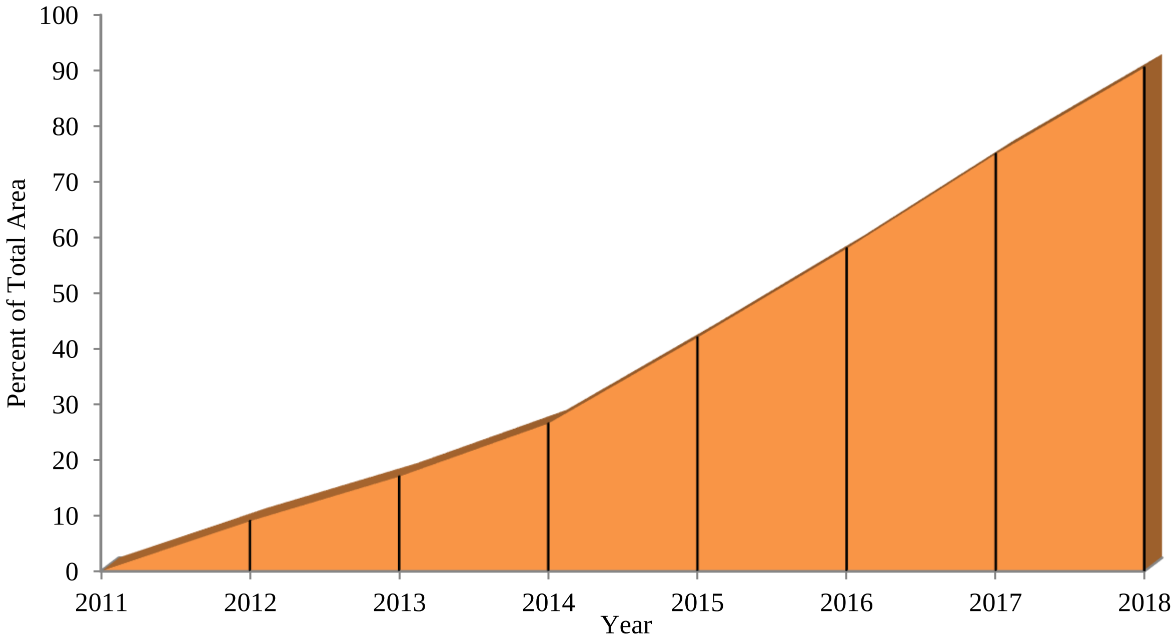

Figure 2.RCH adoption pattern of farmer respondents, Isabela, 2011-2018

3.7 Increase in the number of RCH as indicator of adoption

There was a dramatic increase in the number of rice combine harvesters in the province since the inception of the government program in 2011 when several units of machines were distributed to selected farm organizations. These demonstration units were provided to serve as pump priming strategy to stimulate adoption. Field demonstrations and seminars/trainings were conducted on the operation and maintenance of the facilities. The distribution of facilities and provision of trainings were spearheaded by PHilMech in collaboration with local government units. On the part of the private sector, the aggressive efforts of the machinery distributors by offering attractive financing schemes likewise enable private entrepreneurs to invest in these machines. Dealers offer very low down payments and interest charges payable every cropping period. Moreover, the social resistance in some areas was addressed by the government through provision of package of mechanization technologies to displaced farm workers. Some displaced laborers were absorbed by growing number of rice mill operators in the area. The intensification of government infrastructure projects and burgeoning economic activities in the province likewise opened up more employment opportunities for the displaced skilled farm labor. Most of them were able to find jobs in the construction services sector. For the non-skilled workers who were left at the farm, they demanded compensation in the form of higher wages for transplanting activities. This was done to defray part of their foregone income brought about by the proliferation of combine harvesters.

PHilMech study revealed that in 2014, the total number of RCH was 504 units and this rose to 678 units in 2016. As of 2018, the number of operational units was 1,274 units (Figure 3).

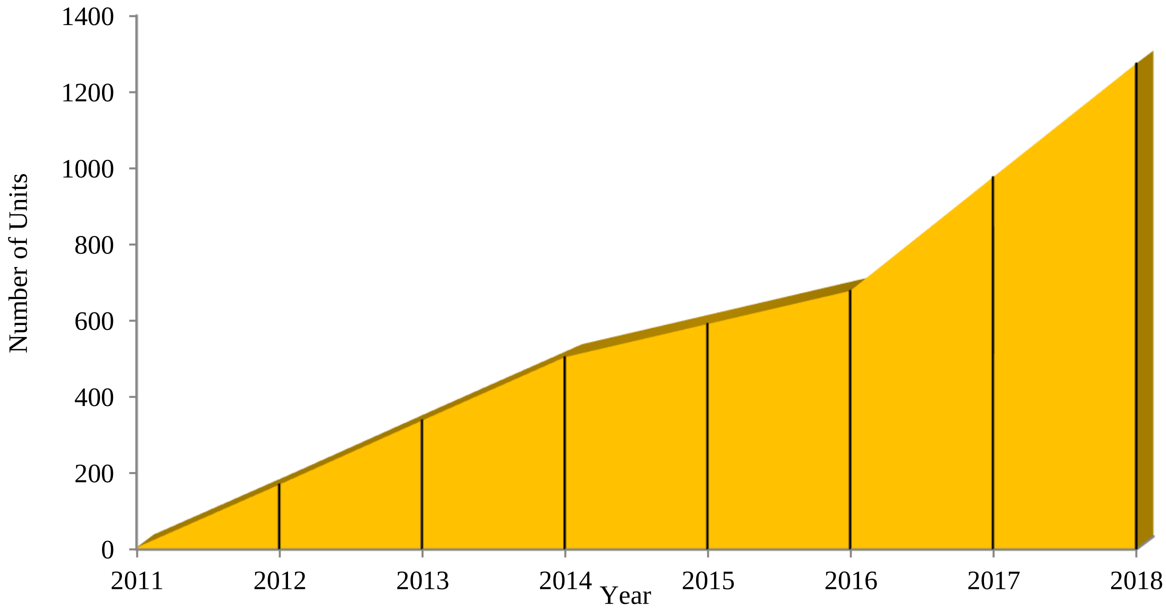

Figure 3. Number of RCH, Isabela, 2011-2018

3.8 Factors influencing adoption of rice combine harvester

The results of the logistic regression analysis showing the factors affecting RCH adoption are shown in Tables 5 and 6. Separate models were done for the dry and wet seasons to examine if there was seasonal variation in terms of RCH adoption. The significance of the logistic regression model was determined using the likelihood ratio Chi-square test. Based on the result, the values of the Chi-square test were 30.486 for the dry season model and 29.221 for the wet season model. The *p*-values or the probability of obtaining this statistic were both less than the critical value of 0.01. This means that for both seasons, all the explanatory variables included in the model have significant effect on the adoption decision of rice farmers at 1 percent level in comparison to a model without predictor variable.

The Goodness-of-fit-test was also determined to analyze how well the model fits the data. The study used the Hosmer and Lemeshow's statistic to test whether or not the observed event rates match expected event rates in subgroups of the model population. Having a large *P*-value indicates a good model fit. The Hosmer and Lemeshow Chi-square statistic for the two models were 9.384 and 7.070, with *P*-values of 0.311 and 0.529 for dry and wet season, respectively. Since the two models have large *P*-values, the two logistic regression models fit the data well.

Of the 10 hypothesized factors affecting RCH adoption, four variables were found significant at 10% level, for both models. The significant factors were topography, farm size, availability of RCH and education.

Topography was the most important variable affecting adoption of RCH at 1% level. As explained in the previous section, small, terraced farms situated in remote, inaccessible areas were less likely to be mechanized because of drudgery and more costly for machinery service providers. On the part of the farmers, they have no inclination to mechanize their farms because of added cost and available labor. Smallholder farmers mainly employ family labor or practice *bayanihan* (exchange labor) with their neighbors.

Farm size was also found to be a significant factor in RCH adoption. This substantiated numerous findings indicating that farmers with large farm holdings are more likely to adopt technologies than small farmers. It is important to note that the use of rice combine harvester involved no capital investment but farmers with larger farms face bigger risks associated with harvesting large area, managing more laborers and the timeliness of completing the harvesting-threshing operations to minimize risks. Because of these factors, farmers with larger farms recognized the need for mechanical harvesting technologies more than farmers with smaller landholdings.

The availability or sufficiency of facilities in the locality displayed significant although a negative coefficient. This implies that the concentration of RCH was not necessarily situated in major rice production areas where adoption is high. The mobility of the machines and the widespread use of cellular phones enable rice farmers to avail of custom service even if the providers are situated in other municipalities.

Other significant variable was education. This was another confirmation that adoption of technologies typically requires increased level of human capital. In the model, the average number of years that the farmer attended school reflects human capital. An increase in the level of human capital increased the likelihood of RCH adoption. Education is often considered influencing productivity by affecting farmer's ability to understand the complicated information related to the technology and to adjust quickly to new practices.

The rest of the variables (age, income, household size, tenure, attendance to trainings/seminars and yield) were found to be insignificant. This may be explained by the relatively homogenous characteristics of these variables between adopters and non-adopters. Although income differs significantly for the adopters and non-adopters, the variable did not exhibit a significant effect towards adoption. Payment for RCH service does not involve cash so farmers with meager incomes were not prevented from using RCH. The household size likewise did not manifest significant effect on adoption. Some family members were either engaged in other job, students or too young to be involved in farm activities. In addition, the increasing indifference of young generation towards farming had an influence on the effect of household size on adoption. Moreover, tenure did not have a significant effect towards adoption. This shows that share tenants may not have an influence on the decisions of their land owners whether to use or not use RCH, especially if the land owners have RCH. Furthermore, farmer's attendance to seminars/on-farm trials related to combine harvesters was found to be an insignificant factor in adoption.

To measure the magnitude of the effects of the significant predictors in the model, the odds ratio was determined. The odds ratio or the exponentiation of the coefficient shows the increase in the odds or likelihood of adopting combine harvesters for every unit increase in these variables. For categorical variable topography, the odds ratio was 1.070 and 1.067, during the dry season and wet season, respectively; meaning farms situated in lowland areas were more likely to adopt RCH by 1.070 and 1.067 times compared to farms in upland or non-irrigated areas. For continuous variable hectarage, the odds ratio or exponentiation of $E(\beta_{ha})$ suggests that a one hectare increase in farm area cultivated increases the likelihood of mechanical adoption by 1.231 times during the dry season and 1.227 times during the wet season. This is also interpreted as: a one hectare increase in farm area increases odds of RCH adoption by 23 percent. Similarly, the odds ratio for education indicates that a one year increase in the years of attending school increases the odds of mechanical dryer adoption by 18.7 percent during the dry season and 17.1 percent during the wet season. It is surprising to note that the availability or sufficiency of facilities exhibited a significant but less than one odds ratio. The odds ratio for availability of facilities decreases the odds of adoption by about one percent for both seasons. Table 5. Logistic regression analysis of the factors affecting the adoption of rice combine harvesters among rice

farmers in Isabela, dry season, 2018

VARIABLE	ODDS RATIO	STD ERROR	*P*-VALUE
Age	1.005	0.025	0.824
Education	1.187*	0.099	0.081
Income	1.000	0.000	0.159
Household Size	1.249	0.249	0.371
Land Ownership	1.108	0.605	0.865
Farm Size	1.231**	0.088	0.018
Topography	1.070***	0.017	0.000
Attendance to seminars/trainings/demos	0.721	0.665	0.809
Yield	0.975	0.018	0.153
Availability of facilities	0.989**	0.004	0.013
Chi-Square	30.486***	(*P*<.001)	
Hosmer and Lemeshow	9.384^ns	(*P* = 0.311)	
Cox & Snell Pseudo R^2	0.287		
-2 Log Likelihood	93.568		

*significant at 10%; **significant at 5%; ***significant at 1% level; ^ns not significant at 10% level

Table 6. Logistic regression analysis of the factors affecting the adoption of rice combine harvesters among rice farmers in Isabela, wet season, 2018

VARIABLE	ODDS RATIO	STD ERROR	*P*-VALUE
Age	1.004	0.024	0.880
Education	1.171*	0.098	0.100
Income	1.000	0.000	0.114
Household Size	1.210	0.245	0.437
Land Ownership	1.214	0.595	0.744
Farm Size	1.227**	0.091	0.025
Topography	1.067***	0.017	0.000
Attendance to seminars/trainings/demos	0.663	0.667	0.531
Yield	0.984	0.018	0.366
Availability of facilities	0.990**	0.004	0.018
Chi-Square	29.221***	(*P*<.001)	
Hosmer and Lemeshow	7.070ns	(*P* = .529)	
Cox & Snell Pseudo R^2	0.277		
-2 Log Likelihood	94.833		

*significant at 10%; **significant at 5%; ***significant at 1% level; ns not significant at 10% level

4. CONCLUSION AND RECOMMENDATION

This study provides empirical information on the pattern and determinants of RCH adoption in Isabela, the second largest producer of rice, the earliest to adopt and among the largest adopters of RCH in the country. Results show that RCH was adopted by farmers with higher level of education, higher income, larger farm holdings and with irrigated farms situated in the lowlands. The findings also indicate that RCH already reached near complete adoption as about 90 percent of the farmers in the study area are already using the technology and not reverted to traditional practice after initially using RCH. The remaining non-mechanized farms are the rain-fed areas with poor road access, terraced small plots and waterlogged farms that deter the use of heavy machines. The respondents cited reduction of harvesting-threshing time which averts the exposure of farmers to climate risks brought by tropical cyclones, reduction of harvesting-threshing costs and postproduction losses as primary reasons of RCH adoption.

The result of the logistic regression analysis revealed that the adoption of RCH is influenced by variables such as land topography, farm size, availability of RCH in the area and educational attainment. The findings could serve as guide in devising strategies to promote wider adoption of the technology considering the advantages of RCH in reducing the exposure of rice farmers to climate risks, reduction of costs and losses and contribution of mechanization in enhancing the competitiveness of the local rice industry.

5. ACKNOWLEDGEMENT

The authors gratefully acknowledge the support of the Philippine Center for Postharvest Development and Mechanization and the Department of Science and Technology – Accelerated Science and Technology Human Resource Development Program for the research funding.

6. REFERENCES

[1] AKUDUGU, M. A., GUO, E. and S.K. DADZIE. 2012. Adoption of Modern Agricultural Production Technologies by Farm Households in Ghana: What Factors Influence their Decisions. Journal of Biology, Agriculture and Healthcare, 2(3).

[2] AYODELE, O. 2012. Economic Impact of Agricultural Mechanization Adoption: Evidence from Maize Farmers in Ondo State, Nigeria. Research Gate, 1(2), 25–32.

[3] BORDEY, F., MOYA, P., BELTRAN, J., & DAWE, D. (Eds.). (2016). Competitiveness of Philippine Rice in Asia. Science City of Muñoz (Philippines),: Philippine Rice Research Institute, International Rice Research Institute.

[4] DJOKOTO, J.G. and S. BLACKIE. 2014. Harvesting Technology Adoption among Irrigated Rice Farmers on the Kpong Irrigation Project in Ghana. Journal of Agriculture and Environmental Sciences. March, 2014, Vol. 3, No. 1, pp. 23-37.

[5] HASSENA, M., ENSERMU, MWANGI, W., and V. HUGO. 2000. A Comparative Assessment of Combine Harvesting vis-a-vis Conventional Harvesting and Threshing in Arsi Region, Ethiopia. CIMMYT.

[6] HOWLEY, P., DONOGHUE, O. and K. HEANUE. 2012. Factors Affecting Farmers' Adoption of Agricultural Innovations: A Panel Data Analysis of the Use of Artificial Insemination among Dairy Farmers in Ireland. Journal of Agricultural Science, 4(6). https://doi.org/10.5539/jas.v4n6p171. Retrieved on March 15, 2019.

[7] GHOSH, B. K. 2010. Determinants of Farm Mechanisation in Modern Agriculture: A Case Study of Burdwan Districts of West Bengal. International Journal of Agricultural Research, 5, 1107--1115. https://doi.org/http://scialert.net/abstract/?doi=ijar.2010.1107.1115. Retrieved on January 25, 2019.

[8] MALANON, H.G., DELA CRUZ, R.S., BOBIER, S.B., DULAY, M.N., and Z.L. CABANAYAN. 2015. Evaluating the Effects of Mechanical Transplanter and Combine Harvester on Rice Production, Farm Income and Rural Employment. Unpublished Terminal Report. Philippine Center for Postharvest Development and Mechanization.

[9] MARIANO, M. J., VILLANO, R., and E. FLEMING. 2012. Factors Influencing Farmers' Adoption of Modern Rice Technologies and Good Management Practices in the Philippines. Agricultural Systems, 110, 41–53. https://doi.org/10.1016/j.agsy.2012.03.010

[10] MLENGA, D. H. and S. MASEKO. 2015. Factors Influencing Adoption of Conservation Agriculture: A Case for Increasing Resilience to Climate Change and Variability in Swaziland. ResearchGate, 5(22), 11–15.

[11] POUNGCHOMPU, S., and S. CHANTANOP. 2016. Economic Aspects of Rice Combine Harvesting Service for Farmer in Northeast Thailand. Asian Social Science, 12(8), 201.

[12] TRUONG, C. 2008. Factors Affecting Technology Adoption among Rice Farmers in the Mekong Delta through the Lens of the Local Authorial Managers: An Analysis of Qualitative Data. Omonrice, 16, 107-112.

[13] UAIENE, R. N., ARNDT, C. and W.A, MASTERS. 2009. Determinants of Agricultural Technology Adoption in Mozambique. Discussion Papers, (67E), 1–29.

[14] YAMANE, T. 1967. Elementary Sampling Theory. First Edition. Prentice Hall, Inc., 405 pp.