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Adoption Study of Cropping Calendar Information System (CCIS) at the Sub-District Level in Indonesia

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ABSTRACT

Many efforts have been released to face the impacts of climate change. The Indonesian Ministry of Agriculture has launched cropping calendar information system (CCIS), one of the efforts to enhance adaption on climate change. The study was conducted using samples from 34 provinces to assess the implementation and adoption of CCIS. The adoption was measured by four response variables as endogenous variables, which were the number of technologies applied (Y_1), the number of adopters (Y_2), the land area of technologies implementation (Y_3), and the land area of implementation based on cropping calendar recommendation (Y_4) whereas as exogenous variables were 10 variables. The data were analysed using Structural Equation Modelling. The amount of technologies applied (Y_1) was significantly influenced by the number of participants (X_2), the synergy (X_3) and the agro-ecosystem (X_6) though the influences of X_2 and X_6 were in a negative direction. The second response variable (Y_2) was significantly affected by the synergy (X_3), the sources of information (X_5), the agro-ecosystem (X_6), and the rice cropping index (X_7), thus only the synergy that have a significant and negative influence on the number of participants. Meanwhile, the planting season (X_1), the agro-ecosystem (X_6), and the disaster were found significantly influencing the land area of implementation (Y_3). Yet, only the disaster provided a positive direction whilst the other variables gave negative influence. The last, Y_4 was significantly and negatively induced by the synergy (X_3) and the feedback methods (X_9), whilst it was positively influenced by the rice cropping index (X_7).

Keywords*: cropping calendar information system, adoption, influencing factors, rice farmers*

1. INTRODUCTION

Climate change (CC) has impacts for global and local scales especially on food insecurity. To address the impact of CC, mitigation is not adequate to assure a sustainable improvement. At the international and national levels, some programs are developed to address impacts on CC. The next step relies on the role of local communities in the implementation of both for mitigation and adaptation actions. However, the obstacles in particular related to the communication and integration of climate change into spatial planning are still occurred. The potential impacts and response options of CC are needed to be understood and handled within local planning processes and policy development. Moreover, the community vulnerabilities and possible climate change impacts need to be relevant to local decision makers, stakeholders and citizens [12]. In the developing countries, mostly, the high numbers of poor people in these countries are generally more vulnerable. More than that, the economic and technological capacity to adapt CC usually is very narrow in the developing countries [17].

The adverse effects of climate change are already occurred in Indonesia, characterized by the frequent occurrence of droughts, heat waves and floods. World Bank has ranked Indonesia 12th among 35 countries that deal with high mortality risks due to multiple hazards, including tsunamis, floods, landslides, droughts, and earthquakes whereas 40% of Indonesia's population are at risk of such hazards. World Bank gives prediction that by 2100, the CC impacts will cost 2.5-7% of GDP of Indonesia [2].

Some technologies to face climate change impacts are relatively similar consisting of seed variety, mixed farming [16][10][15], System Rice Intensification (SRI), cropping pattern [10], site specific nutrient management [16], as well as water [10][15][16], as well as soil management [15]. However, the efforts to mitigate and adapt CC still meet several obstacles, mainly related to the communication and integration of CC into spatial planning. The community vulnerabilities and possible climate change impacts need to be relevant to local decision makers, stakeholders and citizens [12]. In the developing countries, the high numbers of poor people in these countries are generally more vulnerable. Moreover, the economic and technological capacity to adapt CC usually is very narrow in the developing countries [17].

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As a response to adapt CC, the Indonesian government through the Ministry of Agriculture (MoA) has promoted a package of technologies to adapt climate change impacts including cropping calendar, seed varieties, types and doses fertilizers, machineries, as well as other information such as prediction of flood, droughts, pest and diseases. The package of technologies has been disseminated using institutions, media, methods, channels and extension workers. According to [11] the dissemination of the information and technologies related to adapt CC takes an imperative part to face the CC in Indonesia. In 2012, as efforts to adapt the CC, MoA has developed an integrated Cropping Calendar Information System (CCIS) as a reference for stakeholders in planning and managing food crop. The information system contains the next planting season estimation at sub-district level, which includes the initial time of planting, disaster-prone areas (flood, drought, and pests/diseases) as well as recommendation technologies (varieties, seed, and fertilizer). The technical guidelines for socialization and implementation of the information and technology have been disseminated in local levels [3]. The CCIS is designed in a simple format to be easily understood by users such as extension workers and farmers in setting the calendar and rice-crop pattern (irrigated, rain fed and swamps) in accordance with the climatic conditions. However, the uses as consideration for farming in sub-districts remain low. Therefore, efforts are needed to accelerate the dissemination of CCIS. Thus, the awareness and implementation of recommended technologies of CC adaptation can be increased [1]. Based on [6], the most important technology to adapt CC for farmers is cropping calendar. The implementation, sometimes, pushes the farmers to change their existing custom in farming. Terminology used for the CCIS is planting calendar or cropping calendar. The cropping calendar is defined as a schedule of rice or other crops growing season from the fallow period and land preparation; crop establishment and maintenance; harvest and storage. In general, using cropping calendar or planting calendar has a purpose for better planning of all farm activities and the cost of production.

In order to increase and improve the implementation and adoption of CCIS at the users' level, an evaluation research is required at once to obtain a feedback from the stakeholders by measuring the adoption level. The feedback from the end-users (farmers) in the dissemination system is needed to bring improvement to the whole sustainable system of CC adaptation. This research then only emphases on rice farmers as the most vulnerable communities affected by CC. Due to Indonesia has wet land, rain fed, swamp and tidal land which are potentially cultivated by rice, this research will underline the different adoption of CCIS in four types of agro-ecosystem. As a part of an adoption study, this paper also analyses the influencing factors that contributes to increase the adoption of CCIS.

2. METHODOLOGY

Research Setting

This research was limited on studying of Cropping Calendar Information System (CCIS) produced by the Indonesian Ministry of Agriculture as one of adaptation strategy tools. A research was conducted after the launching of CCIS in 34 provinces in Indonesia, which was from 2015 – 2016. The unit of analysis used in this research was at the sub district level as the lowest target unit of CCIS socialization with total samples were 235 units.

Data Collection

Collection data in this research used a survey using structural questionnaires whereas the questions were developed from the variables. The variables were also used for evaluating the implementation of CCIS. The variables, definition and data types were shown in Table 1. The primary data were collected from database of CCIS implementation in 2016. The data were obtained from survey using structural questionnaire conducted by AIATs (Assessment Institute for Agricultural Technology) from 34 provinces. Source for the primary data was extension units at the sub districts level.

Data Analysis

The adoption was measured from the implementation of Y_1, Y_2, Y_3, and Y_4 as response or endogenous variables, which reflected the number of technologies applied (Y_1), the number of adopters (Y_2), the land area of technologies implementation (Y_3), and the land area of implementation based on cropping calendar recommendation (Y_4). The data analysis using Structural Equation Modelling (SEM) was applied on explanatory variables on four response variables (Y_1, Y_2, Y_3, and Y_4). This model was developed in order to study relationships among and between explanatory variables (constructs) and response variables [14]. The data analysis was processed by using Smart-PLS software. In order to generate the accuracy of model, validity and reliability were applied to evaluate model.

Table 1. The variables used in the research

No.	Variables		Data Type	Annotation
Explanatory Variables				
1.	X_1 (planting season)	X1a (dry season)	Nominal	1= yes; 0=no
		X1b (wet season)		
2.	X_2 (participants of CCIS socialization)	X2a (extension workers)	Ratio	persons
		X2b (local government staffs)		
		X2c (farmers)		
		X2d (others)		
3.	X_3 (collaboration)		Interval	1= very poor – 5= very good
4.	X_4 (feedback)		Nominal	1= yes; 0=no
5.	X_5 (information resource)		Interval	1= very poor – 5= very good
6.	X_6 (agro-ecosystem)	X6a (irrigated land)	Nominal	1=yes; 0=no
		X6b (rain fed)		
		X6c (swampy land)		
		X6d (tidal land)		
		X6e (dry land)		
7.	X_7 (planting index of rice)		Ratio	times/year
8.	X_8 (constraints)	X8a (existing planting time)	Nominal	1= yes; 0=no
		X8b (scarcity of fertilizers)		
		X8c (scarcity of mechanization)		
		X8d (scarcity of seeds of recommended variety)		
		X8e (scarcity of water resource)		
		X8f (scarcity of labours)		
		X8g (pests and diseases)		
		X8h (lack of information)		
		X8i (capital)		
		X8j (internet connection)		
		X8k (irrigation)		
9.	X_9 (feedback methods)	X9a (interview)	Nominal	1= yes; 0=no
		X9b (field observation)		
		X9c (field day meetings)		
		X9d (plot demonstration)		
		X9e (farm demonstration)		
		X9f (on farm research)		
		X9g (display)		
10.	X_{10} (natural disasters)	X10a (floods/landslide)	Nominal	1= yes; 0=no
		X10b (drought)		
		X10c (extra-ordinary pests and diseases)		
Response Variables				
11.	Y_1 (the amount of technologies applied)		Ratio	numbers of technologies of CCIS
12.	Y_2 (the number of adopters)		Ratio	persons
13.	Y_3 (the land area of technologies implementation)		Ratio	hectares
14.	Y_4 (the land area implementation based on cropping calendar recommendation)		Ratio	hectares

3. RESULTS AND DISCUSSION

Model Test Analysis

Reliability Test

Reliability test in *Structural Equation Modelling* (SEM) used method of measuring composite reliability and size of extract variants. The analysis of the results of the study was carried out using measurement model analysis, structural model analysis and suitability analysis of all models [13]. Covariance errors are arranged so there will be a correlation among the variables to obtain a lower Chi-Square value. Since the latent variable does not have a definite scale, in order to define the model, the zero point and the measurement unit for each latent variable are defined by specifying one factor charge of each latent variable in the model with a value of 1 [9].

The calculation results of construct reliability for latent variables can be seen in the table below, where the results of calculations for the value of construct reliability produced a very good reliability value because it the value was > 0.7 (Table 2). According to [8], good reliability was reflected by construct reliability values (CR) > 0.7 whereas [4] stated that reliability requirements can be seen from the value of construct reliability as well as the Cronbach's alpha value >0.7.

Validity Test

Validity test was conducted after constructing the variability test until the results are optimal. Optimal results are obtained after analyzing the model by examining the program output against the possibility of offending estimates. According to the recommendations from [8], the observation variables can be used as an indicator of the construct or its latent variable if t-value of the factorare greater than the critical value (> 1.96).

Table 2. The result of construct reliability value

No.	Variables	Cronbach's Alpha	Annotation
1.	x1	1,000	Reliable
2.	x2	1,000	Reliable
3.	x3	1,000	Reliable
4.	x5	1,000	Reliable
5.	x6	1,000	Reliable
6.	x7	1,000	Reliable
7.	x9	1,000	Reliable
8.	x10	1,000	Reliable
9.	y1	1,000	Reliable
10.	y2	1,000	Reliable
11.	y3	1,000	Reliable
12.	y4	1,000	Reliable

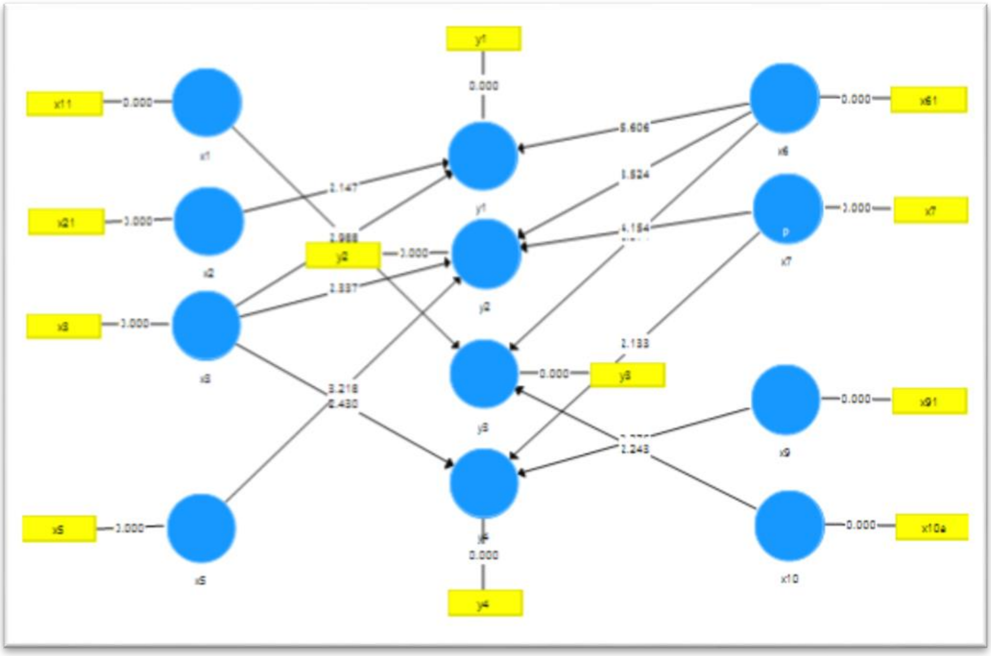

Figure 1. Output results of t-values test as seen at Smart-PLS interface

As can be seen from Figure 1, t-value of all indicators are greater than 1.96, so that from x1 to X10 are valid as mentioned in Table 3.

Table 3. The result of validity test

Indicator	Latent	Standard Deviation	T Statistics	Valid (if T stat > 1.96)
X_1	Y3	0.049	2.988	Valid
X_2	Y1	0.073	2.147	Valid
X_3	Y1	0.076	3.188	Valid
X_3	Y2	0.049	2.337	Valid
X_3	Y4	0.072	2.430	Valid
X_5	Y2	0.118	3.218	Valid
X_6	Y1	0.081	5.606	Valid
X_6	Y2	0.187	3.524	Valid
X_6	Y3	0.074	2.574	Valid
X_7	Y2	0.157	4.154	Valid
X_7	Y4	0.096	2.133	Valid
X_9	Y4	0.104	3.275	Valid
X_{10}	Y3	0.053	2.243	Valid

Annotation:
Y_1 = the amount of technology applied
Y_2 = the number of adopter
Y_3 = land area of technology implementation from CCIS
Y_4 = land area based on recommendation schedule from CCIS

Measurement Model Analysis (Outer Model)

This research used validity and reliability test for all latent variables, which are $X_1 – X_{10}$ and $Y_1 – Y_4$ using *SmartPLS* software. The measurement of individual of reflective is valid when loading value (λ) of latent variable is ≥ 0.5. If one of the indicators has loading value less than 0.5, this indicator should be removed/detached because it indicates inadequacy of the indicator in measuring the latent variables properly. The analysis result of structural equation path diagram of PLS using *SmartPLS* software is presented in Figure 2.

Evaluation of the outer model is divided into two stages, namely convergence validity (indicators of validity, construct reliability, and AVE value) and discriminant validity (cross loading and root AVE). According to [5] an indicator has a good reliability if the value of the loading factor is greater than 0.5. The next evaluation is discriminant validity conducted in two stages, viz. looking at the cross loading value and comparing the correlation between constructs with AVE roots. The first stage is cross loading criteria. This step ensuring each indicator that measures the latent construct/variable itself must correlate higher than the other latent constructs/variables, or it can also be directly seen from the value of AVE, if the value of AVE> 0.5 then the model is a good one.

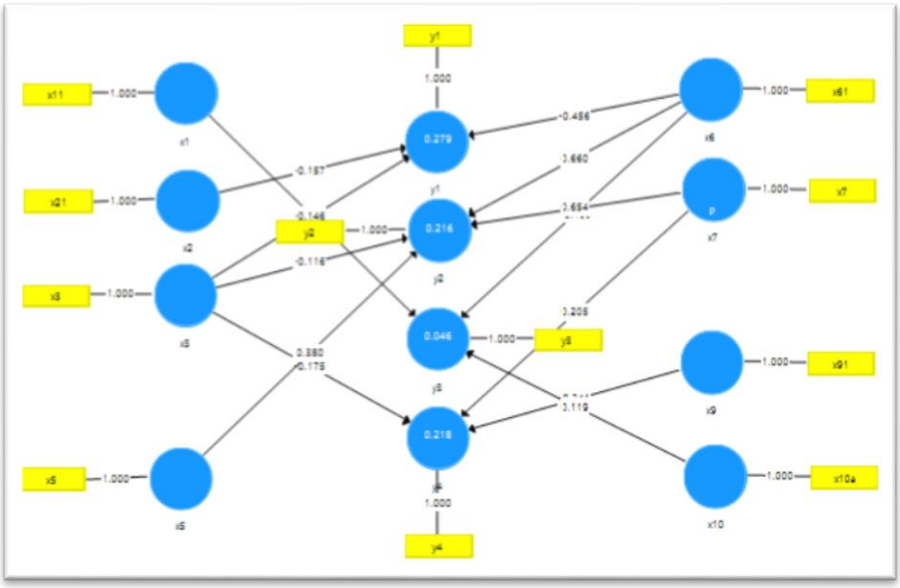

Figure 2. Model fix of output result of diagram path as seen at Smart-PLS interface

The output results can be seen in the table below, that shows the correlation of each indicator to its latency has a higher value than the other latent correlations. So it can be concluded that the indicators on the three latent variables have good levels of discriminant validity.

Table 4. Correlation results of latent variables

Cross Loading	x1	x10	x2	x3	x5	x6	x7	x9	y1	y2	y3_	y4
x11	1,000	-0,066	-0,122	0,008	0,211	-0,195	0,177	0,064	0,094	-0,015	-0,117	-0,075
x21	-0,122	-0,003	1,000	0,013	-0,087	0,011	0,023	0,126	-0,159	0,123	-0,006	0,033
x3	0,008	-0,042	0,013	1,000	-0,073	0,058	-0,040	-0,170	0,214	-0,131	0,107	-0,125
x5	0,211	-0,287	-0,087	-0,073	1,000	-0,848	0,709	-0,485	0,422	0,291	0,077	0,263
x61	-0,195	0,368	0,011	0,058	-0,848	1,000	-0,851	0,486	-0,444	-0,225	-0,118	-0,328
x7	0,177	-0,166	0,023	-0,040	0,709	-0,851	1,000	-0,328	0,309	0,365	0,012	0,324
x91	0,064	0,349	0,126	-0,170	-0,485	0,486	-0,328	1,000	-0,401	0,024	-0,205	-0,379
x10a	-0,066	1,000	-0,003	-0,042	-0,287	0,368	-0,166	0,349	-0,217	0,100	0,059	-0,063
y1	0,094	-0,217	-0,159	0,214	0,422	-0,444	0,309	-0,401	1,000	-0,178	-0,120	-0,024
y2	-0,015	0,100	0,123	-0,131	0,291	-0,225	0,365	0,024	-0,178	1,000	0,026	0,239
y3	-0,117	0,059	-0,006	0,107	0,077	-0,118	0,012	-0,205	-0,120	0,026	1,000	0,032
y4	-0,075	-0,063	0,033	-0,125	0,263	-0,328	0,324	-0,379	-0,024	0,239	0,032	1,000

The second stage aims to define the average variance extracted (AVE) value. In order to fulfill the requirement, the AVE value must be greater than 0.5, or r it can be said that all latent variables have met convergent validity and have high discriminant validity if they have a value of AVE> 0.5. From the analysis, the AVE value for all latent variables are >0.5 (Table 5). Thus, all latent variables used in this research have met convergent validity and have high discriminant validity, so that it can be continued for the next analysis, which is an inner model analysis.

Table 5. Average variance extracted (AVE) results of latent variables

Variabel Laten	Average Variance Extracted (AVE)
x1	1,000
x10	1,000
x2	1,000
x3	1,000
x5	1,000
x6	1,000
x7	1,000
x9	1,000
y1	1,000
y2	1,000
y3_	1,000
y4	1,000

Structural Model Analysis (Inner Model)

Structural model analysis explains describes the relationship between exogenous latent variables and endogenous latent variables as well as illustrates a positive or negative direct influence, which is denoted by the output of SmartPLS path coefficient including mean, STDev, and T-value. This analysis also resulted Rsquared that representing how far the endogenous variables ($Y_1 - Y_4$) can be explained by the exogenous variables or [7] mentioned that R^2 in PLS-SEM approach elucidates the level and the significance of the path coefficients used in the model. From the analysis, R squared for Y_1, Y_2, Y_3, and Y_4 are 0.279, 0.216, 0.046, and 0.218 respectively. 0.279 coefficient means that the variance of Y1 can be explained by X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, and X_{10} as much as 27.9% whereas 72.1% of the endogenous variable is explained by other variables that are excluded from the model. This result also applies form Y_2 with R^2 by 0.216. In this case, all exogenous variables jointly can explain the variance of Y_2 by 21.6%, and the rest is explained by others exogenous variables. According to [7] these results still can be categorized as a high significance due to the topic of the research that is related to behaviour, though in other study, for instance marketing topic, the level of R_2 less than 0.5 can be categorized as a moderate significance.

The next step of the structural model analysis (inner model) is to identify the estimated value of the path coefficient, which includes the direct positive and real effect of a latent variables with others. This analysis can be conducted using testing the hypothesis and proposed from the the value of T-values. The limit for rejecting and accepting the hypothesis proposed is T-table 1,960 (two tailed). The hypotheses were accepted when the T-stats were less than 1.96 whereas they were rejected if the results of T-stats were more than 1.96. In general, there were 10 hypotheses rejected because T-statistics (T-stat) of each variable was greater than T-table. This means that each variable used significantly influenced the endogenous variable (Table 6).

From the table 6, the number of participants (X_2) significantly influences on the amount of technologies applied (Y_1), which was represented by T-stats of 2.147 or greater than T-table yet in the negative direction by 0.157, or each increasing the number of participants by 10%, the amount of technology applied will decrease by 15.7%. The second hypothesis mentioned that the synergy (X_3) has a direct significant and positive influence on the amount of technologies applied with coefficient by 0.242. This implies for 10% of increasing synergy, the amount of technologies applied will also increase by 24.2%. The agro-ecosystem (X_6) influences significantly on the amount of technologies applied, yet in the negative direction with T-values of 5.606 and coefficient of (–) 0.456, which means for every changing of agro-ecosystem by 10%, the amount of technologies applied decreases by 45.6%.

The second hypothesis assessed the relation between the synergy and the number of adopters (Y_2). Based on the research and analysis results, the synergy (X_3) negatively significant effects the number of adopters by 0.116 and T-values of 2.337. Hence, the increasing of synergy by 10% will decrease the number of adopters by 23.37%. The next analysis mentioning the relation between the source of information (X_5) and the number of adopters. The source of information significantly and positively affected the number of adopters with coefficient of 0.380, or each improving of the source of information by 1%, the number of adopters will rise by 3.8% and T-values of 3.218. The agro-ecosystem (X_6) and the rice cropping index (X_7) also significantly influenced the number of adopters and both were in positive trend, which were 0.660 and 0.654.

The third response variable was the land area of implementation (Y_3). The analysis data resulted three exogenous variables that significantly induced Y_3. These variables were the planting season (X_1), the agro-ecosystem (X_6), and the disaster (X_{10}), but only the disaster showed a positive influence (0.119) while the rest influenced negatively. The coefficients of planting season and agro-ecosystem were (-) 0.146 and (-) 0.190 individually. Therefore, every changing of planting season by 10%, it will reduce the land area of implementation by 14.6%, and so for the agro-ecosystem. The shifting of agro-ecosystem by 10% will lower the Y_3 by 19% where the increasing number of disaster, in turn, drove the increasing the land area of implementation by 11.9%.

Table 6. Result analysis of T-stat in the inner model

No	Hypotheses	Path	Original Sample	Mean	StDev	T Statistics
1.	The number of participants influences the amount of technologies applied	X_2 -> Y_1	-0.157	-0.154	0.073	2.147
2.	The synergy affects the amount of technologies applied	X_3 -> Y_1	0.242	0.240	0.076	3.188
3.	The agro-ecosystem affects the amount of technologies applied	X_6 -> Y_1	-0.456	-0.461	0.081	5.606
4.	The synergy affects the number of adopters	X_3 -> Y_2	-0.116	-0.106	0.049	2.337
5.	The sources of information influence the number of adopters	X_5 -> Y_2	0.380	0.412	0.118	3.218
6.	The agro-ecosystem affects the number of adopters	X_6 -> Y_2	0.660	0.709	0.187	3.524
7.	The rice cropping index affects the number of adopters	X_7 -> Y_2	0.654	0.692	0.157	4.154
8.	The planting season affects the land area of implementation	X_1 -> Y_3	-0.146	-0.176	0.049	2.988
9.	The agro-ecosystem influences the land area of implementation	X_6 -> Y_3	-0.190	-0.249	0.074	2.574
10.	The disasters affect the land area of implementation	X_{10} -> Y_3	0.119	0.156	0.053	2.243
11.	The synergy affects the land area based on cropping calendar recommendations	X_3 -> Y_4	-0.175	-0.167	0.072	2.430
12.	The rice cropping index influences the land area based on cropping calendar recommendations	X_7 -> Y_4	0.205	0.230	0.096	2.133
13.	The feedback method influences the land area based on cropping calendar recommendations	X_9 -> Y_4	-0.341	-0.349	0.104	3.275

Annotation: α = 5%

As can be seen from Table 6, the last endogenous variable (Y_4) or the land area based on cropping calendar recommendation (ha) was significantly influenced by the synergy (X_3), the rice cropping index (X_7), and the feedback methods (X_9). The synergy and the feedback methods brought a negative influence with coefficient of (-) 0.175 and (-) 0.341, or any improving of synergy surprisingly will decrease the land area by 17.5% and any changing of the feedback methods by 10% will reduce the land area by 34.1%; however, the increasing of cropping index will enlarge of the land area by 20.5%.

4. CONCLUSIONS

The adoption of CCIS at the district level in 34 provinces in Indonesia was described from four response variables, which were the number of technologies applied, the number of adopters, the land area of technologies implementation, and the land area of implementation based on cropping calendar recommendation. Each response variable was influenced by different factors both in positive and negative direction. The result analysis underlined that the number of technologies applied was influenced by the number of participants, the synergy, and the agro-ecosystem. There were four exogenous variables which significantly affected the number of adopters namely the synergy, the sources of information, the agro-ecosystem as well as the rice cropping index. Meanwhile, the third response variable, the land area of technologies implementation was significantly induced by the planting season, the agro-ecosystem, and the disasters whereas the synergy, the rice cropping index, and the feedback methods were found as the significant factors influencing the land area of implementation based on cropping calendar recommendation.

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