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FACTORS AFFECTING THE WILLING TO JOIN IN COFFEE CROP INSURANCE IN DAK LAK PROVINCE, VIETNAM: A NOVEL APPLICATION OF BAYESIAN MODEL AVERAGING APPROACH

Le Dinh Thang[1*], Nguyen Van Si[2]
[1*,2]Economic mathematics, and statistics, University of Economics Ho Chi Minh City (UEH), HCMC, Vietnam.
Email: [1*]thangle29.n15@st.ueh.edu.vn, [2]nvs@ueh.edu.vn

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Abstract

Purpose of the study: this paper aims to determine factors affecting the willingness to join crop insurance. Besides, this paper is the purpose of developing a coffee tree insurance program.

Methodology: The authors used a systematic random sampling technique. The authors used the Bayesian Model Average (BMA) that calculated the probability of all independent variables affecting the dependent variable with significance level 0.05. Besides, the data based on 480 coffee farmers in Dak Lak province, Vietnam.

Main Findings: Authors calculated the probability of all independent variables affecting the dependent variable with significance level 0.05. Independent variables, including loans, drought risks, educational level, experiences, and productivity.

Applications of this study: This result is a vital science document for insurance companies and managers to apply and suggest recommendations for developing coffee tree insurance in the future.

Novelty/Originality of this study: Vietnam is an agricultural country, 60-70% of the population lives in rural areas, and agricultural insurance should have a considerable market. Farmers' agrarian insurance cultivated the coffee trees that are currently underdeveloped and challenging.

Keywords: *Coffee, Insurance, Program, Farmer, BMA, UEH.*

INTRODUCTION

In Vietnam, coffee is one of the critical export agricultural products and a critical socio-economic position, contributing about 2% of Vietnam's GDP and about 30% GDP of the Central Highlands provinces. Besides, coffee trees are directly creating jobs for over 2 million workers and farmers. This result makes an essential contribution to political - social - security stability in Vietnam and the Central Highlands in particular. In recent years, the coffee industry has made rapid and robust development, making Vietnam the second-largest coffee export in the world and the first in Asia with its coffee export turnover of approximately 3.35 billion USD during 2016-2017. Dak Lak province is considered the coffee center of Vietnam because it is the province with the highest coffee growing area in Vietnam over the past decade from 2009-2017 with about 200,000 ha per year and accounting for 31% of the coffee-growing region.

Moreover, according to the General Statistics Office of Vietnam, the coffee had the contribution of GDP, job creation, and high export turnover for many years as above mentioned things. In the coming years, coffee trees still play a significant role in the economy in Dak Lak province and Vietnam. However, in the process of development, production, and trading of coffee, many risks need to be supported to overcome such as the impact of heavy rain in the harvest season during the 2016-2017 crop so that the productivity average reduced to compare to the crop year 2015-2016. In August 2018, farmers suggested the Government to have the policy to support crop insurance for coffee. This insurance helped farmers cope with climate change and minimize losses in agricultural production (Ray P. K., 2001; Elvis Dartey Okoffo, Elisha Kwaku Denkyirah, Derick Taylor Adu & Benedicta Yayra Fosu-Mensah, 2016).

Facing this problem is to develop a coffee tree insurance program, the authors needed information on the willingness of farmers to buy coffee insurance, which does not study in Vietnam. Therefore, the authors examined the factors affecting the willingness to join crop insurance of coffee trees in Dak Lak province, Vietnam. This study is vital to improve the crop insurance program of coffee trees in Dak Lak province in the next years.

LITERATURE REVIEW

In this literature review, the authors provided an overview of previous studies on agricultural insurance readiness determinants. These studies include: a study by (Sherrick, B. J., Barry, P. J., Ellinger, P. N. and Schnitkey, G. D, 2004) from the United States, considered the country with the most modern agriculture in the world; Other studies come from Africa and Vietnam, which are considered a developing country and live mainly on agriculture. These studies used the logit regression method (Abraham Falola, Opeyemi Eyitayo Ayinde, and Babatola Olasunkanmi Agboola, 2018). Probit is to identify factors affecting the willingness to participate in agricultural insurance. The authors found two types of agricultural insurance: productivity insurance and weather insurance (Raftery, A, 1995).

According to (Barnett, B. J., C. B. Barrett, and J. R. Skees, 2006), this study showed that the determinants of willingness to participate in agricultural insurance on coffee were the other reviews cocoa, tobacco, cashew, and maize (Zhang Yan-yuan, JU Guang-wei, and Zhan Jin-tao, 2019). Factors included educational attainment, household size and production area, income, age, land ownership, and borrowing are statistically significant factors in many previous studies (Girma Gezimu Gebre, Hiroshi Isoda, Dil Bahadur Rahut Yuichiro Amekawa, Hisako Nomura, 2019). That studies followed by factors such as marital status, experience, productivity, age of farm, access to extension services, total losses incurred in the recent catastrophic event in terms of currency, actual production history, and property ownership raising, the source of income do not depend on nature (Barrett, C. B., and J. G. McPeak, 2005). Besides, the results reported in the literature showed heterogeneity of factors such as area, age, household size, and income groups from other sources such as pet ownership, income does not depend on nature (Carter, M. R., and C. B. Barrett, 2006) and (Adam Was and Paweł Kobus, 2018).

According to (Koloma, Y, 2015), (Okoffo, E.D., Denkyirah, E.K., Adu, D.T. et al., 2016), the area factor negatively affected the willingness to participate in agricultural insurance. Meanwhile, according to (Danso-Abbeam G, Setsoafia ED, Gershon I, Ansah K, 2014), the area factor positively affected the willingness to participate in agricultural insurance. (Abraham Falola, Opeyemi Eyitayo Ayinde, and Babatola Olasunkanmi Agboola, 2018) the age factor negatively affected the willingness to participate in agrarian insurance; According to (Aidoo R, Mensah Osei J, Wie P, Awunyo-Vitor D, 2014) and (Okoffo, E.D., Denkyirah, E.K., Adu, D.T. et al., 2016), the age factor positively affected the willingness to participate in agricultural insurance. Household size factor (Okoffo, E.D., Denkyirah, E.K., Adu, D.T. et al., 2016) negatively affected the willingness to participate in agricultural insurance; in contrast to the household size factor (Koloma, Y, 2015) adversely affects the willingness to participate in agricultural insurance. Similarly, for income groups from other sources, the animal ownership factor (Koloma, Y, 2015) positively affected the willingness to participate in agricultural insurance. Research by (BalmaIssaka, Yakubu, Buadu Latif Wumbei, Joy Buckner, and Richard Yeboah Nartey, 2016) suggested that non-dependent income harmed the willingness to participate in agricultural insurance.

There is little consistency in the results among researchers regarding the farmer's willingness to participate in agricultural insurance (Sarah Lyon, Tad Mutersbaugh, and Holly Worthen, 2018). To study this issue, authors tried to minimize the possibility of missing the independent factor that strongly affected the dependent element in the model, which can lead to inaccurate inferences and decisions (Jennifer A. Hoeting, David Madigan, Adrian E. Raftery, and Chris T. Volinsky, 1999). This study is considered one of the factors that previous studies have not considered (Khalil Ur Rahman; Songhai Shang; Muhammad Shahid; Yeqiang Wen; Zeeshan Khan, 2020). Therefore, the authors suggested using the Bayesian model averaging (BMA) to overcome the problem, as mentioned above.

Table 1: Summary of some articles related to the study

No	Authors	Samples	Research Model	Independent variables with significance
1	(Sherrick, B. J., Barry, P. J., Ellinger, P. N. and Schnitkey, G. D, 2004)	They surveyed 3000 farmers cultivated corn in Illinois, Iowa, and Indiana, USA.	Regression: Logit	1. Productivity 2. Area (-) 3. Land rented (-) 4. Income 5. Risk aversion 6. Actual production history
2	(Carter, M. R., P.D. Little, T. Mogues, and W. Negatu, 2007)	Surveyed 957 farmers cultivated coffee in Kilimanjaro, and 892 farmers grew coffee, cigarettes, and cashews in Ruvuma, Tanzania.	Regression: Logit	1. Household size 2. Income per person 3. Using savings or loans
3	(Falola A, Ayinde OE, Agboola B. O, 2013)	Surveyed 120 farmers cultivated cocoa in Nigeria.	Regression: Probit	1. Age (-) 2. Educational level 3. Access to extension services 4. Income
4	(Aidoo R, Mensah Osei J, Wie P, Awunyo-Vitor D,	Surveyed 120 farmers cultivated corn and cassava in Sunyani, Ghana	Regression: Logit	1. Age 2. Landowner (1/0) 3. Educational level

	2014)			
5	(Danso-Abbeam G, Setsoafia ED, Gershon I, Ansah K, 2014)	Surveyed 201 farmers cultivated cocoa in Bibiani-Anhiawso-Bekwai, Ghana.	Regression: Probit	1. Marital status 2. Educational level 3. Household size (-) 4. Experience 5. Farm size 6. Landowner 7. Farm age 8. Income 9. Control risk
6	(Koloma, Y, 2015)	Surveyed 39 farmers cultivated corn in Burkina Faso	Regression: Probit	1. Educational level 2. Number of family workforce 3. Area (-) 4. Pet owner
7	(BalmaIssaka, Yakubu, Buadu Latif Wumbei, Joy Buckner, and Richard Yeboah Nartey, 2016)	They surveyed 100 farmers cultivated corn in Nanumba province, Ghana.	Regression: Logit	1. Access to credit 2. Educational level 3. Join other forms of insurance 4. Number of sources of income not dependent on nature (-) 5. The total damage incurred in the recent disaster event in terms of currency
8	(Okoffo, E.D., Denkyirah, E.K., Adu, D. T. et al., 2016)	Surveyed 240 farmers cultivated cocoa at four villages in Dormaa, Brong-Ahafo, Ghana.	Regression: Probit	1. Age 2. Marital status 3. Educational level 4. Area (-) 5. Household size (-)
9	(Rafia Afroz, Rulia Akhtar, Puteri Farhana, 2017)	Surveyed 350 farmers cultivated rice in Kedah, Malaysia.	Regression: logistic	1. Age (-) 2. Area 3. Attend training courses 4. Income (-) 5. Experience
10	(Fonta, W.M., Sanfo, S., Kedir, A.M. et al., 2018)	Surveyed 267 farmers cultivated cotton, millet, and peanuts in Southwestern Burkina Faso	Regression: probit	1. Age (-) 2. Use additional watering (-) 3. Insurance fee (-) 4. Loans 5. Experience 6. Households knowledgeable about insurance 7. Income 8. Intercropping

Source: Authors collected

METHODS OF RESEARCH

The study was conducted in Dak Lak province, Vietnam. Dak Lak province is located in the center of the Central Highlands region, the average height of 400 meters - 800 meters above sea level. The province's climate is divided into two sub-regions. The Northwest has a hot, dry climate in the dry season; the East and South have a cold, moderate humidity. The weather is divided into two distinct seasons: rainy and dry seasons. The rainy season usually starts from May to October with

Southwest wind; the months with the most significant rainfall are some months, moisture accounts for 80-90% of the annual rainfall. Particularly in the eastern region, due to the influence of east Truong Son, the rainy season lasts longer until November. The dry season is from November to April of the following year; during this season, the humidity decreases, the northeast wind blows, evaporates, causing severe drought (Chao Feng, Lu-Xuan Sun, Yin-Shuang Xia, 2020).

Besides, Dak Lak province deliberately selected for its predominance of regional coffee production. In early 2018, the Statistical Office of Dak Lak Province surveyed 480 coffee farmers on the crop year 2016-2017 and using multi-stage sampling techniques. Cu Kuin District, Buon Ma Thuot City, Buon Ho Town, Krong Pac District, Krong Búk District, Krong Nang District, Ea H'Leo District, Cu M'Gak District in Dak Lak province known as one of the districts has the most significant area for growing coffee. Each community has two communes with the most significant coffee area selected, and then 30 coffee farmer households selected at a distance k from each municipality.

Summary of Bayesian Model Averaging (BMA) following:

The researchers study Factors affecting the willingness to join crop insurance of coffee trees in Dak Lak province, Vietnam. The authors applied a logistic regression model (Wang, D., Zhang, W., Bakhai, A., 2004). The logistic model described as follows:

$$Log(odds) = log\left(\frac{P(Y=1)}{P(Y=0)}\right) = \beta_0 + \beta_1.X_1 + \beta_2.X_2 + \dots + \beta_p.X_p \quad (1)$$

Note: Y is a binary outcome variable (dependent variable) with Y = 1 being a farmer willing to participate in insurance, Y = 0 otherwise, P (Y = 1) is the probability that Y receives value 1.

X_1, X_2... X_p is explanatory variables (independent variables) and β_1, β_2... β_p are the regression coefficients in the model.

According to (Wang, D., Zhang, W., Bakhai, A, 2004), a Bayesian solution to the model's uncertainty has been proposed and applied recently (A. Lawrence Gould, 2018). This method selects a subset of all possible models (max $K = 2^p$, ignoring interactions between explanatory variables) (Krzysztof Drachal, 2018) and uses the post-probability of the models to perform. All inferences and predictions (Notaro, Vincenza & Liuzzo, Lorena & Freni, Gabriele, 2016).

The following equations relate to the problem of optimal model selection proposed by (Raftery, A.E, 1996). The symbol Δ is a quantity of interest, such as the willingness to participate in agricultural insurance in logistic regression (1), M = {M_1, M_2... M_k} is defined as a collection of all models having considered, D is data (Zhang, Wei & Yang, Jun. 2015; Axel Theorell, Katharina Nöh, 2018).

Then, the posterior distribution of Δ, according to D is:

$$\Pr(\Delta|D) = \sum_{k=1}^{K} \Pr(\Delta|M_k, D).\Pr(M_k|D) \quad (2)$$

$\Pr(\Delta|M_k, D)$ is the average of the posterior distributions for each model; $M_{(k)}$ and the weight calculated by the probability of the corresponding posterior model (Xiao Huang, Guorui Huang, Chaoqing Yu, ShaoQiang Ni, Le Yu, 2017; Mark F.J. Steel, 2019; Yanlai Zhou, Fi-John Chang, Hua Chen, Hong Li, 2020). $\big(\Pr(M_k|D)\big)(k = 1,2,\dots,K)$. (2) A separate Mk model gives the prognostic distribution is:

$$\Pr(\Delta|M_k, D) = \int \Pr(\Delta|\beta^k M_k, D)\Pr(\beta^k|M_k, D)\, d\beta^k$$

With $\beta^k = (\beta_0, \beta_1, \dots, \beta_p)'$ is the vector of parameters in the model M_k.

Probability of the model $M_k \in$ M is given by (Lele Lu, Hanchen Wang, Sophan Chhin, Aiguo Duan, Jianguo Zhang, Xiongqing Zhang, 2019).

$$\Pr(M_k|D) = \frac{\Pr(D|M_k)\Pr(M_k)}{\sum_{j=1}^{K}\Pr(D|M_j)\mathrm{P}(M_j)} \quad (3)$$

With

$$\Pr(D|M_k) = \int \Pr(D|\beta^k, M_k)\Pr(\beta^k|M_k)\, d\beta^k \quad (4)$$

It is an integrated likelihood of the model M_k, $\Pr(\beta^k|M_k)$ is the predetermined density of β^k in M_k, $\Pr(\mathrm{D}|\beta^k, M_k)$ is the logical data, $\Pr(M_k)$ is the predetermined probability of M_k.

Note:

$$\hat{\Delta}_k = E[D|\Delta, M_k]$$

The posterior average and the variance of Δ:

$$E[\Delta|D] = \int \Delta \sum_{k=1}^{K} \Pr(\ \Delta|M_k, D) \Pr(\ M_k|D)\, d\Delta = \sum_{k=1}^{K} \left(\int \Delta \Pr(\ \Delta|M_k, D) d\Delta \right) \Pr(\ M_k|D) \ = \sum_{k=1}^{K} \hat{\Delta}_k \Pr(\ M_k|D)$$

$$Var[\Delta|D] = \sum_{k=1}^{K} \left(\mathrm{Var}[\Delta|D, M_k] + \hat{\Delta}_k^2\right) \Pr(\ M_k|D) - \ E[\Delta|D]^2$$

The process of implementing calculations by BMA technique has two difficulties as follows:

First, the integral evaluation in equation (4), can be approximated to solve $\Pr(\ D|M_k)$ based on the Laplace approximation method (Raftery, A.E, 1996)

$$log\ \ Pr(\ D|M_k) \approx log - log\ Pr\left(D|M_k, \hat{\beta}_k\right)\ -\ d_k\ log\ log\ n \quad (5)$$

With $\hat{\beta}_k$ is the posterior mean of β^k, d_k is the number of parameters in the M_k model, and n is the number of observations in the data. This form is called the Schwarz Bayesian information criterion (BIC). As (Taplin, 1993) suggested:

$$Pr(\ \Delta|M_k, D) \approx Pr\left(\ \Delta|M_k, \hat{\beta}_k, D\ \right)$$

$\hat{\beta}_k$ is the maximum likelihood estimate (MLE) of the parameter vector β^k.

Second: The total function in equation (2) will be reduced based on the Occam's window method (Madigan, D., Raftery, A.E, 1994). First, models with a very low probability to be compared to a model with a maximum probability removed, leaving the models in the following set:

$$\acute{A} = \left[M_k : \frac{max_l\ Pr(\ M_l|D)}{Pr(\ M_k|D)} \leq C\right] \quad (6)$$

Note: C is the constant selected according to the analytical data.

Next, remove the models with many variables, but the probability of post-production is smaller than the model with fewer variables :

$$B = \left[M_k : \exists\ M_l \in \acute{A},\ M_l \subset M_k, \frac{Pr(\ M_l|D)}{Pr(\ M_k|D)} > 1\right]$$

Note: $A =\ A/B$ then equation (2) is replaced by

$$\Pr(\ \Delta|D) = \sum_{M_k \in A} \Pr(\ \Delta|M_k, D) \Pr(\ M_k|D)$$

Define the variable

Table 2 explained the variables included in the analysis of farm households' willingness to participate in crop insurance. Authors have inherited the statistically significant variables of the previous studies, authors have been able to collect, including education, age, area, income, experience, labor, employment, and skill, Interest, collaterals, loans. Besides, the specific social characteristics in Dak Lak province, such as ethnic diversity (47 ethnic groups) and ethnic minorities have matriarchy, so authors add the ethnic factor of the household head, and the gender of the household head to examine its impact on the farmer's willingness to insurance. The implementation of BMA for logistic regression in this study done with software R version 3.6.2 follows:

Table 2: Defining of the variables in the research model

No.	Variables	Code	Description of variables	Measured
	Insurance	BAOHIEM	Coffee farmers' the willing to join crop insurance	Binary variable (1: Willing to join crop insurance, 0: others)
H1	Gender	GIOITINH	Gender of the head of household (Robert Ochago, 2017)	Binary variable (1: Male, 0: female)

H2	Educational level	TDHV	The number of years of studying classifies the educational attainment of the household head. (Roland Azibo Balgah, 2019)	Continuous variable (Year)
H3	Peoples	DANTOC	Head of the household is Kinh or another ethnicity	Binary variable (1: Kinh, 0: others)
H4	Age	TUOI	Age of household head. (Bruce J. Sherrick, Peter J. Barry, Paul N. Ellinger, Gary D. Schnitkey, 2004)	Continuous variable (Year)
H5	Area	DIENTICH	Coffee area of the household. (John Mano Raj, 2014)	Continuous variable (Hectare)
H6	Income	THUNHAP	The income of coffee farmers. (Kenneth W. Sibiko, Prakashan C. Veettil, and Matin Qaim, 2018)	Continuous variable (Mil/ha)
H7	Experience	KINHNGHIEM	Years of coffee production by the head of household	Continuous variable (Year)
H8	Labors	LAODONG	The number of employees in the household engaged in coffee production. (Filippa Pyk and Assem Abu Hatab, 2018)	Continuous variable (Person)
H9	Farmer Association	HOINONGDAN	Households are participating in farmer associations. (Guoqiang Tang, Yingzhao Ma, DiLong, LingzhiZhong, Yang Hong, 2016)	Binary variable (1: Join, 0: others)
H10	Productivity	NANGSUAT	Coffee production of households produced in the year. (Khanal Arjun Prasad, Khanal Suman, Dutta Jay Prakash, Dhakal Shiva Chandra and Kattel Rishi Ram, 2019)	Continuous variable (Quintal / ha)
H11	Landowner	SOHUUDAT	The head of the household owns coffee production land. (Tapiador, F. J., and Coauthos , 2017)	Binary variable (1: Household, 0: others)
H12	Loans	VAYVON	Homes get loans from banks or credit institutions. (Hasen, M., & Mekonnen, H., 2017)	Binary variable (1: Have a loan, 0: others)
H13	Drought risk	RRHH	The area for growing coffee is drought. (Man, Georg, 2015)	Binary variable (1: Drought, 0: others)
H14	Risk of erratic rain	RRMTT	The coffee plantation area suffered from unpredictable rain. (Sein Mar, Hisako Nomura, Yoshifumi Takahashi, Kazuo Oga,ta and Mitsuyasu Yabe, 2018)	Binary variable (1: Erratic rain, 0: others)

Source: Authors collected

Based on table 2, the authors had 14 hypotheses related to the coffee farmers' the willing to join crop insurance an above-mentioned hypotheses following: gender, educational level, peoples, age, area, income, experience, labors, farmer Association, productivity, landowner, loans, drought risk, and Risk of erratic rain.

RESEARCH RESULTS AND DISCUSSION

Table 3 shows that coffee farmers willing to pay agricultural insurance for their coffee farms are 256 households (53.4%), indicating that coffee farmers are very interested in agricultural insurance. The author also noticed a difference between a group of farmers willing to participate in coffee crop insurance and other groups. Besides, factors have relative differences between the two groups, such as gender, have the proportion of men and women of 98% and 96%. The average age of the two groups is 42.81 years and 43.72 years. The average number of employees of the two groups is nearly three people per household; The average number of years of experience of the two groups is about 17 years; area factor is almost equal with 1.29 ha and 1.27 ha; both groups have the same percentage of households participating in farmer associations or extension is 97%; The rate of land ownership between the two groups is 86% and 81%.

Table 3: Descriptive statistics of the coffee group's willingness to join coffee crop insurance for coffee producing farmers and other cases

Descriptive statistics by group								
Group: 0								
Code	**Vars**	**N**	**Mean**	**SD**	**Min**	**Max**	**Range**	**SE**
BAOHIEM	1	224	0.00	0.00	0.00	0.00	0.00	0.00
GIOITINH	2	224	0.96	0.19	0.00	1.00	1.00	0.01
TUOI	3	224	43.72	8.09	25.00	62.00	37.00	0.54
DANTOC	4	224	0.47	0.50	0.00	1.00	1.00	0.03
TDHV	5	224	6.93	2.62	1.00	12.0	11.0	0.07
LAODONG	6	224	2.67	0.98	1.00	6.00	5.00	0.07
KINHNGHIEM	7	224	17.05	6.35	3.00	40.00	37.00	0.42
DIENTICH	8	224	1.27	1.18	0.10	14.00	13.90	0.08
NANGSUAT	9	224	26.77	5.96	16.0	45.00	29.00	0.40
HOINONGDAN	10	224	0.97	0.17	0.00	1.00	1.00	0.01
THUNHAP	11	224	42.62	8.92	16.80	58.71	41.91	0.60
VAYVON	12	224	0.04	0.19	0.00	1.00	1.00	0.01
SOHUUDAT	13	224	0.81	0.39	0.00	1.00	1.00	0.03
RRHH	14	224	0.92	0.27	0.00	1.00	1.00	0.02
RRMTT	15	224	0.84	0.36	0.00	1.00	1.00	0.02
Group: 1								
Code	Vars	N	Mean	SD	Min	Max	Range	Se
BAOHIEM	1	256	1.00	0.00	1.00	1.00	0.00	0.00
GIOITINH	2	256	0.98	0.15	0.00	1.00	1.00	0.01
TUOI	3	256	42.81	7.77	26.00	68.00	42.00	0.49
DANTOC	4	256	0.72	0.45	0.00	1.00	1.00	0.03
TDHV	5	256	9.68	3.16	1.00	16.0	15.0	0.07
LAODONG	6	256	2.67	0.98	1.00	6.00	5.00	0.07
KINHNGHIEM	7	256	16.75	6.70	5.00	40.00	35.00	0.42
DIENTICH	8	256	1.29	1.43	0.20	16.00	15.80	0.09
NANGSUAT	9	256	29.97	7.16	15.0	46.00	31.00	0.45
HOINONGDAN	10	256	0.98	0.14	0.00	1.00	1.00	0.01
THUNHAP	11	256	44.81	8.20	17.52	57.14	39.62	0.51
VAYVON	12	256	0.22	0.42	0.00	1.00	1.00	0.03
SOHUUDAT	13	256	0.86	0.34	0.00	1.00	1.00	0.02
RRHH	14	256	0.97	0.16	0.00	1.00	1.00	0.01
RRMTT	15	256	0.88	0.32	0.00	1.00	1.00	0.02

Source: Dak Lak Statistical Office

Table 3 showed that there are apparent differences between the two groups with the following factors: the percentage of Kinh people with other ethnic groups is 72% and 47%; The average educational level between the two groups is grade 10 and grade 7; average yield difference of 3.2 quintals/ha; income of households willing to participate in insurance is 44.81 million/ha than the remaining group 2.19 million/ha and especially the bank loan rate is 29% compared to 10%. In particular, the group of farmer households willing to participate in coffee crop insurance has more risks of drought and erratic rain risk than other groups.

Table 4: Models proposed by BMA

21 models were selected								
Best 5 models (cumulative posterior probability = 0.659):								
	p!=0	**EV**	**SD**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
(Intercept)	100	-6.6734	1.2996	-7.212e+00	-5.810e+00	-8.374e+00	-8.085e+00	-7.124e+00
GIOITINH	3.0	0.0144	0.1532	.	.	.	.	.
TUOI	16.9	0.0058	0.0148	.	.	2.697e-02	4.231e-02	.
DANTOC	2.1	0.0053	0.0529	.	.	.	.	.
TDHV	100.0	0.3839	0.0447	3.839e-01	3.825e-01	4.021e-01	3.754e-01	3.897e-01
LAODONG	3.6	0.0035	0.0275	.	.	.	.	.
KINHNGHIEM	89.8	0.0531	0.0250	6.017e-02	6.057e-02	4.814e-02	.	6.070e-02
DIENTICH	1.4	-0.0005	0.0102					
NANGSUAT	95.4	0.0541	0.0216	5.601e-02	5.213e-02	5.644e-02	5.899e-02	6.399e-02
HOINONGDAN	0.0	0.0000	0.0000	.	.	.	.	.
THUNHAP	7.2	-0.0018	0.0081	.	.	.	.	.
VAYVON	100.0	2.3941	0.4653	2.376e+00	2.418e+00	2.360e+00	2.222e+00	2.445e+00
SOHUUDAT	6.7	-0.0293	0.1358	.	.	.	.	-4.436e-01
RRHH	58.1	0.7882	0.7933	1.353e+00	.	1.392e+00	1.436e+00	1.345e+00
RRMTT	1.5	0.0026	0.0479	.	.	.	.	.
NVAR				5	4	6	5	6
BIC				-2.431e+03	-2.430e+03	-2.427e+03	-2.427e+03	-2.426e+03
POST PROB				0.286	0.241	0.050	0.045	0.036

Source: Data processed by authors

Table 4 showed that 14 independent factors, the number of possible models not taking into account the models having interaction between elements is 2^{14} = 16384 models. Following the application of BMA, there are 21 models with the highest post-probability and the probabilities that affect the farmer's willingness to participate in agricultural insurance including gender (3%), age (16.9%), peoples (2.1%), educational level (100%), labor (3.6%), experience (89.8%), area (1.4%), productivity (95.4%), Farmer association (0%), income (7.2%), loan (100%), the landowner (6.7%), drought risk (58.1%), risk of erratic rain (1.5%).

Besides, 21 models that BMA considers the "most optimal" model 1 in table 5 have the highest post-probability (28.6%) and the lowest BIC (-2430.56). Therefore, the author chooses a model that he considers "optimal" as a model of 5 independent variables: educational level, experience, productivity, borrowing, and drought. Therefore, the author chooses model 1 to analyze the regression results and discuss them. The model of factors affecting the willingness to join crop insurance is such as table 4.

$$Log\big(odds(BAOHIEM)\big) = \alpha + \beta_1 * TDHV + \beta_2 * KINHNGHIEM + \beta_3 * NANGSUAT + \beta_4 * VAYVON + \beta_5 * RRHH + u$$

Estimated results of Logistic regression:

The authors examined the multi-collinear phenomena in the model by the correlation matrix. According to table 5 and figure 1, the model does not have a multi-collinearity phenomenon because the correlation coefficients of all pairs of variables with absolute value less than or equal to 0.44 (obviously less than 0.775) satisfy the conditions of (Jennifer A. Hoeting, David Madigan, Adrian E. Raftery, and Chris T. Volinsky, 1999).

Table 5: The results of the Logistic Regression Model

Logistic Regression Model					
Deviance Residuals:					
Min	1Q	Median	3Q	Max	
-2.3228	-0.8199	0.2178	0.8362	2.3953	
Coefficients:					
	Estimate	Std. Error	Wald Z	Pr(>|Z|)	
(Intercept)	-7.21178	0.96437	-7.478	7.53e-14	***
TDHV	0.38393	0.04359	8.808	< 2e-16	***
KINHNGHIEM	0.06017	0.01792	3.357	0.000787	***
NANGSUAT	0.05601	0.01668	3.357	0.000787	***
VAYVON	2.37571	0.45985	5.166	2.39e-07	***
RRHH	1.35314	0.55698	2.429	0.015123	*
Sign if. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
(Dispersion parameter for binomial family taken to be 1)					
Null deviance: 663.29 on 479 degrees of freedom					
Residual deviance: 495.82 on 474 degrees of freedom					
AIC: 507.82					
Number of Fisher Scoring iterations: 5					

Source: Data processed by authors

Besides, figure 1 showed that the correlation matrix in the model of factors affecting the willingness to join crop insurance.

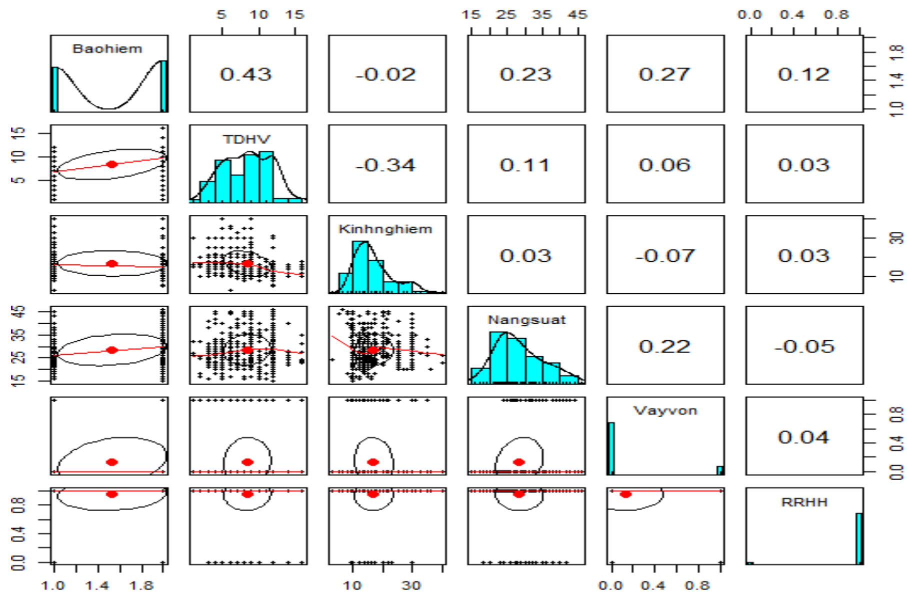

Figure 1: The correlation matrix in the model factors influences the willingness to join crop insurance

Source: Data processed by authors

Research results showed that the authors test all coefficients that are simultaneously zero with the statistic of the statistic likelihood ratio (LR). To ensure that these five factors are meaningful, according to (Barrett, C. B., and B. M. Swallow, 2006; Sein Mar, Hisako Nomura, Yoshifumi Takahashi, Kazuo Oga, ta and Mitsuyasu Yabe, 2018; Khanal Arjun Prasad, Khanal Suman, Dutta Jay Prakash, Dhakal Shiva Chandra, and Kattel Rishi Ram, 2019; A. Lawrence Gould, 2018), the LR statistical test, according to the Chi-square distribution, is 167.47 and the probability value Pr (> Chi2) <0.0001 so the Ho hypothesis is rejected. The five factors included in the Logistic model are important for insurance. Besides, the Pseudo R^2 coefficient = 0.393 means that the independent variables in the model explained 39.3 % the of dependent variable. AUC = 0.821 (95% CI: 0.784, 0.858) is greater than 0.8, so the model is considered a good model.

Therefore, the model of factors affecting coffee farmers' willingness to join coffee crop insurance in the Dak Lak province proposed below is considered an "optimal" model with whether survey authors:

$$Log(odds(Baohiem)) = -7.212 + 0.394 * TDHV + 0.06 * Kinhnghiem$$
$$+0.056 * Nangsuat + 2.376 * Vayvon + 1.353 * RRHH$$

When the educational level increases by one year of studying, the odds of being willing to join crop insurance increase by 47% $(OR = e^{0.394} = 1.47\ (95\%\ CI: 1.35, 1.6))$. The estimation results showed reliable statistical evidence of the relationship between the educational attainment of the household head and the willingness to participate in coffee crop insurance for coffee-producing farmers in Dak Lak province. Because the estimated coefficients are statistically significant level 0.01.

Households with more than one year of coffee production experience have an increase of 6% in their willingness to join crop insurance $\left(OR = e^{0.06} = 1.06\ (95\%\ CI: 1.03, 1.1)\right)$. The estimated results showed reliable statistical evidence of the relationship between the household's experience variable and the willingness to join coffee crop insurance in Dak Lak province due to the estimates are statistically significant level 0.01.

If the household's productivity increases by one quintal/ha, the odds of being willing to join crop insurance increase 8% $OR = e^{0.056} = 1.06\ (95\%\ CI: 1.02, 1.09))$. The estimation results showed reliable statistical evidence of the relationship between the yield variable of coffee trees and the willingness to join coffee crop insurance in Dak Lak province due to the estimate that s are statistically significant level 0.01.

Odds are 10.76 times more likely to be insured by farm households with bank loans than farmers without bank loans $(OR = e^{2.376} = 10.76\ (95\%\ CI: 4.37, 26.5))$. The estimation results showed reliable statistical evidence for the relationship between the variable of the effects of bank loans and the willingness to join coffee crop insurance of coffee-producing households in Dak Lak province due to the estimation coefficient as statistically significant level 0.01.

Odds willing to insure for farmers' households at risk of drought are 3.87 times higher than farmers without risk of drought $\left(OR = e^{1.353} = 3.87\ (95\%\ CI: 1.3, 11.53)\right)$. The estimation results showed reliable statistical evidence of the relationship between the drought risk variable and the willingness to join coffee crop insurance of coffee-producing households in Dak Lak province due to the coefficient of the estimates are statistically significant level 0.05. This result is new in the authors' research.

MANAGERIAL IMPLICATIONS

The managerial implications for loans (β = 2.3757): The State Bank should continue to improve and supplement many mechanisms and policies related to production and business. Sales and consumption in the agricultural and rural areas. Besides, the State Bank should continue directing credit institutions to develop and deploy credit products suitable to farmers and the characteristics of agricultural production; promptly implement solutions to remove difficulties for customers who borrow capital in the field of agriculture and rural areas; improve processes, procedures, shorten loan approval time for farmers to access loans most effectively. Besides, the banking industry continues to coordinate well with associations and unions to intensify the propagation and dissemination of agricultural and rural credit policies because this is a trusted channel.

The managerial implications for the drought risks (β = 1.3531): Dak Lak province should repair and damage irrigation works, dredging, and upgrading incident irrigation channels after the flood season in 2017 to ensure water storage for production in the summer crop production collection. Dak Lak province develops plans to prevent drought from coping with drought in time, in which priority is given to water to balance water sources for daily-life activities and domestic animals and then supply water for production. At the same time, it is also necessary to develop regulating schemes from large irrigation systems to supplement irrigated areas with independent or water-deficit constructions. It said that the excellent management of irrigation water sources of localities and units would be a critical factor in proactively preventing droughts, contributing to ensuring victory in agricultural production.

The managerial implications for educational level (β = 0.3839): Dak Lak province should continue researching and widely applying advanced processes and techniques, promoting mechanization in agricultural, coffee production. Application of synchronous mechanization process from soil preparation, planting, tending, harvesting, processing. Dak Lak province should continue to support the operation of intensive cultivation of coffee, maize, groundnut from seeds, intensive investment, apply high technology to develop production areas focusing on profitable products of the province. Dak Lak province should promote advanced and modern science and technology to improve the coffee's capacity and quality. Innovate the content and methods of learning survey, organizing ten cross-tours in the ecological region, combining field workshops to replicate the typical coffee model.

The managerial implications for experiences (β = 0.0602). Dak Lak province should organize the training course aims to equip knowledge about innovating training activities to transfer technical advances in agriculture such as coffee and guide implementation to improve the quality and effectiveness of agricultural extension training. One of the innovations targeted by the practice was on-site consultation. Accordingly, experts and trainees have shared, exchanged, and solved problems encountered in production at the scene. Besides, Dak Lak province should have the organization of a study tour to learn the experience of coffee tree models in localities to create appropriate mechanisms and policies and encourage cooperatives and households to produce and export coffee. This activity has more knowledge, apply it in practice, contribute to raising values, and develop sustainably in the future.

The managerial implications for productivity (β = 0.0560). Famers should cultivate rational intercropping of fruit trees such as pepper, durian, avocado... to improve the land use coefficient in the coffee garden; improve the ecological environment, reduce watering pressure in the dry season; minimize risks due to weather fluctuations, pests, prices, increase income for producers. At the same time, farmers should apply careful watering combined with reasonable fertilization to help coffee plants bloom in a concentrated manner, improve fertilizer efficiency, reduce labor, reduce costs, increase competitiveness for products.

CONCLUSIONS

Research results showed that the Bayesian Model Averaging (BMA) calculated the probability of all independent factors affecting dependencies and overcame the significant independent factor omission when selecting a model in previous studies. Besides, BMA calculated the post-probability of each model and, based on the post-probability magnitude, proposed the most "optimal" models. Factors included educational level, experience, productivity, loans, and drought risk significantly and positively affect coffee farmers' willingness to join crop insurance.

In particular, our results clearly showed the strong impact of the loan factor on coffee farmers' willingness to join crop insurance. Therefore, we recommend that farmers be assisted with production loans if they agree to participate in coffee tree insurance. Besides, we recommend that coffee farmers educated on agricultural insurance, and the need for agrarian protection for their coffee farms, as most farmers do not, such as knowledge about agricultural insurance, which is not common in Vietnam. Above mentioned things, authors have managerial implications for improving coffee farmers' willingness to join crop insurance.

LIMITATION AND STUDY FORWARD

The research limitations only surveyed 480 farmers who cultivated coffee trees in Dak Lak province. This sample is very little significant and exactly. Therefore, the next resarch-tested another example in other regions and cities. The future study needs to improve the variables for the model.

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A group of authors had contributed to this work. However, the first author collects the documents and investigates the data. The second author instructs how to run the data and analyze the research results. Finally, two authors have recommendations for improving the willingness to join in coffee crop insurance in Dak Lak province, Vietnam.

REFERENCES

1. Abraham Falola, Opeyemi Eyitayo Ayin, and Babatola Olasunkanmi Agboola (2018). Willingness to take agricultural insurance by cocoa farmers in Nigeria. *International Journal of Food and Agricultural Economics, 1(1), 97-107.* https://www.foodandagriculturejournal.com/97.pdf
2. Adam Was and Paweł Kobus (2018). Factors determining the crop insurance level in Pola,nd taking into account the level of farm subsidizing. *The Common Agricultural Policy of the European Union*, 3(1), 125-146. https://doi.org/10.30858/pw/9788376587431.11
3. Aidoo R, Mensah Osei J, Wie P, Awunyo-Vitor D. (2014). Prospects of crop insurance as a risk management tool among arable crop farmers in Ghana. *Asian Economic Financial Review*, *4*(3), 341-354.
4. A. Lawrence Gould (2018). BMA-Mod: A Bayesian model averaging strategy for determining dose-response relationships in the presence of model uncertainty. *Biometrical Journal*, 61(5), 1-13. https://doi.org/10.1002/bimj.201700211
5. Axel Theorell, Katharina Nöh (2018). Model Uncertainty Analysis for Metabolic Network Inference: A Case Study in Bayesian Model Averaging. *IFAC-PapersOnLine*, 51(19), 124-135, ISSN 2405-8963. https://doi.org/10.1016/j.ifacol.2018.09.010
6. BalmaIssaka, Yakubu, Buadu Latif Wumbei, Joy Buckner, and Richard Yeboah Nartey (2016). willingness to participate in the market for crop drought index insurance among farmers in Ghana. *African Journal of Agricultural Research, 11*(4), 1257-1265. https://doi.org/10.5897/AJAR2015.10326

7. Barnett, B. J., C. B. Barrett, and J. R. Skees (2006). *Poverty Traps and Index-Based Risk Transfer Products.* Department of Agricultural and Applied Economics: University of Georgia. https://doi.org/10.2139/ssrn.999399
8. Barrett, C. B., and B. M. Swallow (2006). Fractal Poverty Traps. *World Development, 34*(1), 1-15. https://doi.org/10.1016/j.worlddev.2005.06.008
9. Barrett, C. B., and J. G. McPeak (2005). *Poverty Traps and Safety Nets." Poverty, Inequality, and Development: Essays in Honor of Erik Thorbecke. A. de Janvry, and R. Kanbur, eds.* Norwell, MA: Kluwer Academic Publishers. https://doi.org/10.1007/0-387-29748-0_8
10. Bruce J. Sherrick, Peter J. Barry, Paul N. Ellinger, Gary D. Schnitkey (2004). Factors Influencing Farmers' Crop Insurance Decisions. *American Journal of Agricultural Economics*, 86(1), 103-114 https://doi.org/10.1111/j.0092-5853.2004.00565.x
11. Carter, M. R., and C. B. Barrett (2006). The Economics of Poverty Traps and Persistent Poverty: An Asset-Based Approach. *Journal of Development Studies*, *42*(1), 178-199. https://doi.org/10.1080/00220380500405261
12. Carter, M. R., P.D. Little, T. Mogues, and W. Negatu (2007). Poverty Traps and Natural Disasters in Ethiopia and Honduras. *World Development*, *35*(1), 835-856. https://doi.org/10.1016/j.worlddev.2006.09.010
13. Chao Feng, Lu-Xuan Sun, Yin-Shuang Xia (2020). Clarifying the "gains" and "losses" of transport climate mitigation in China from technology and efficiency perspectives. *Journal of Cleaner Production*, 263(1), 14-23. https://doi.org/10.1016/j.jclepro.2020.121545
14. Danso-Abbeam G, Setsoafia ED, Gershon I, Ansah K. (2014). Modeling farmer's investment in agrochemicals: the experience of smallholder cocoa farmers in Ghana. *Res Appl Econ, 6*(4), 1-15. https://doi.org/10.5296/rae.v6i4.5977
15. Elvis Dartey Okoffo, Elisha Kwaku Denkyirah, Derick Taylor Adu & Benedicta Yayra Fosu-Mensah (2016). Double-e-hurdle model estimation of cocoa farmers' willingness to pay for crop insurance in Ghana. *Okoffo et al. SpringerPlus*, 4(2), 1-19. https://springerplus.springeropen.com/track/pdf/10.1186/s40064-016-2561-2
16. Filippa Pyk and Assem Abu Hatab (2018). Fairtrade and Sustainability: Motivations for Fairtrade Certification among Smallholder Coffee Growers in Tanzania. *Sustainability*, 10(5), 1-18. https://doi.org/10.3390/su10051551
17. Fonta, W.M., Sanfo, S., Kedir, A.M. et al. (2018). Estimating farmers' willingness to pay for weather index-based crop insurance uptake in West Africa: Insight from a pilot initiative in Southwestern Burkina Faso. *Agric Econ, 6*(1), 1-10. https://doi.org/10.1186/s40100-018-0104-6
18. Girma Gezimu Gebre, Hiroshi Isoda, Dil Bahadur Rahut Yuichiro Amekawa, Hisako Nomura (2019). Gender differences in agricultural productivity: evidence from maize farm households in southern Ethiopia. *GeoJournal*, 3(1), 21-34. https://link.springer.com/article/10.1007%2Fs10708-019-10098-y
19. Guoqiang Tang, Yingzhao Ma, DiLong, LingzhiZhong, Yang Hong (2016). Evaluation of GPM Day-1 IMERG and TMPA Version-7 legacy products over Mainland China at multiple spatiotemporal scales. *Journal of Hydrology*, 533(1), 152-167. https://doi.org/10.1016/j.jhydrol.2015.12.008
20. Hasen, M., & Mekonnen, H. (2017). The impact of agricultural cooperatives membership on the wellbeing of smallholder farmers: Empirical evidence from Eastern Ethiopia. *Agricultural and Food Economics*, 5(6), 1-20. https://doi.org/10.1186/s40100-017-0075-z
21. Jennifer A. Hoeting, David Madigan, Adrian E. Raftery, and Chris T. Volinsky (1999). Bayesian Model Averaging: A Tutorial. *Statistical Science, 14*(4), 382-401. https://doi.org/10.1214/ss/1009212519
22. John Mano Raj (2014). Marketing of rain fall insurance in coffee: a concept failure or promotion failure? *A Journal of Radix International Educational and Research Consortium, 3(3),1-12.*
23. Khanal Arjun Prasad, Khanal Suman, Dutta Jay Prakash, Dhakal Shiva Chand,ra and Kattel Rishi Ram (2019). An assessment of factors determining the productivity of coffee the western hills of Nepal. International Journal of Agricultural Sciences and Veterinary Medicine, 7(2),11-17. https://www.researchgate.net/publication/333479102
24. Khalil Ur Rahman; Songhao Shang; Muhammad Shahid; Yeqiang Wen; Zeeshan Khan (2020). Application of a Dynamic Clustered Bayesian Model Averaging (DCBA) Algorithm for Merging Mul tisatellite Precipitation Products over Pakistan. *J. Hydrometeor*, 21(1), 17-37. https://doi.org/10.1175/JHM-D-19-0087.1
25. Koloma, Y. (2015). Crop Microinsurance for Maize Farmers in Burkina Faso: Access and Agriculture Performance in the Dandé Village. *Strategic Change, 24*(1), 115-129. https://doi.org/10.1002/jsc.2001
26. Kenneth W. Sibiko, Prakashan C. Veettil, and Matin Qaim (2018). Small farmers' preferences for weather index insurance: insights from Kenya. Sibiko et al. Agric & Food Secityur, 1(1), 1-14. https://doi.org/10.1186/s40066-018-0200-6
27. Krzysztof Drachal (2018). Some Novel Bayesian Model Combination Schemes: An Application to Commodities Prices. *Sustainability*, 10(8), 1-27. https://doi.org/10.3390/su10082801
28. Lele Lu, Hanchen Wang, Sophan Chhin, Aiguo Duan, Jianguo Zhang, Xiongqing Zhang (2019). A Bayesian Model AveraginA approach for moelling tree mortality in relation tthe o site, competiti,on and climatic factors for Chinese fir plantations. *Forest Ecology and Management*, 40(1), 169-177. https://doi.org/10.1016/j.foreco.2019.03.003

29. Madigan, D., Raftery, A.., (1994). Model selection and accounting for model uncertainty in graphical models using Occam's window. *J. Am. Stat. Assoc*, *89*(428), 1535-1546. https://doi.org/10.1080/01621459.1994.10476894
30. Man, Georg (2015). Competition and the growth of nations: International evidence from Bayesian model averaging. *Economic Modelling*, 51(1), 491-501. https://doi.org/10.1016/j.econmod.2015.08.012
31. Mark F.J. Steel (2019). Model Averaging and its Use in Economics. *Department of Statistics, University of Warwick*, 3(1), 1-106. https://arxiv.org/pdf/1709.08221.pdf
32. Notaro, Vincenza & Liuzzo, Lorena & Freni, Gabriele (2016). A BMA Analysis to Assess the Urbanization and Climate Change Impact on Urban Watershed Runoff. *Procedia Engineering*. 154(1), 868-876. https://doi.org/10.1016/j.proeng.2016.07.461
33. Okoffo, E.D., Denkyirah, E.K., Adu, D.T. et al. (2016). Double-hurdle model estimation of cocoa farmers' willingness to pay for crop insurance in Ghana. *SpringerPlus*, *5*(1), 873-879. https://doi.org/10.1186/s40064-016-2561-2
34. Rafia Afroz, Rulia Akhtar, Puteri Farhana (2017). Willingness to pay for crop insurance to adopt flood risk by Malaysian farmers: an empirical investigation of Kedah. *International Journal of Economics and Financial Issues*, *7*(1), 1-9.
35. Raftery, A. (1995). *Bayesian model selection in social research. In: Marsden, R.V.(Ed.), Sociological Methodology*. Blackwell: Cambridge, Mass. https://doi.org/10.2307/271063
36. Raftery, A.., (1996). Approximate Bayes factors and accounting for model uncertainty in generalized linear models. *Biometrika*, *83*(2), 251-266. https://doi.org/10.1093/biomet/83.2.251
37. Ray P. K. (2001). *Agricultural Insurance: Theory and practice and application to developing countries. 2nd edition*. Oxford: Pergamon Press.
38. Robert Ochago (2017). Barriers to women's participation in coffee pest management learning groups ithe n Mt Elgor Region. *Uganda Ochago, Cogent Food & Agriculture*, 3(1), 1-19. https://doi.org/10.1080/23311932.2017.1358338
39. Sarah Lyon, Tad Mutersbau,h and Holly Worthen (2018). Constructing the female coffee farmer: Do corporate smart-economic initiatives promote gender equity within agricultural value chains?. *The American Anthropological Association*, 2(1), 1-9. https://anthrosource.onlinelibrary.wiley.com/doi/epdf/10.1002/sea2.12129
40. Sein Mar, Hisako Nomura, Yoshifumi Takahashi, Kazuo Oga,ta and Mitsuyasu Yabe (2018). Impact of Erratic Rainfalonom Climate Change on Pulse Production Efficiency in Lower Myanmar. *Sustainability*, 10(1), 1-16. https://doi.org/10.3390/su10020402
41. Roland Azibo Balgah (2019). Factors Influencing Coffee Farmers' Decisions to Join Cooperatives. *Sustainable Agriculture Research*, 8(1), 42-58. https://doi.org/10.5539/sar.v8n1p42
42. Sherrick, B. J., Barry, P. J., Ellinger, P. N., and Schnitkey, G. D. (2004). Factors influencing farmers' crop insurance decisions. *American Journal of Agricultural Economics*, *86*(1), 103-114. https://doi.org/10.1111/j.0092-5853.2004.00565.x
43. Tiago M. Fragoso, Wesley Berto,li and Francisco Louzada (2017). Bayesian Model Averaging: A Systematic Review and Conceptual Classification. *International Statistical Review*, 86(1), 12-24. https://doi.org/10.1111/insr.12243
44. Taplin, R. H. (1993). "*Robust likelihood calculation for time series*". J Roy. Statist. Soc. Ser. B 55 829-836
45. Tapiador, F. J., and Coauthors (2017). Global precipitation measurements for validating climate models. Atmospheric Research, 197(1), 1-20. https://doi.org/10.1016/j.atmosres.2017.06.021
46. Wang, D., Zhang, W., Bakhai, A. (2004). Comparison of Bayesian model averaging and stepwise methods for model selection in logistic regression. *Stat. Med*, *23*(22), 3451-3467. https://doi.org/10.1002/sim.1930
47. Xiao Huang, Guorui Huang, Chaoqing Yu, ShaoQiang Ni, Le Yu (2017). A multiple crop model ensemble for improving broad-scale yield prediction using Bayesian model averaging. *An International Journal*, 211(1), 114-124. https://doi.org/10.1111/insr.12243
48. Yanlai Zhou, Fi-John Chang, Hua Chen, Hong Li (2020). Exploring Copula-based Bayesian Model Averaging with multiple ANNs for PM2.5 ensemble forecasts. *Journal of Cleaner Production*, 263(1), 121-132. https://doi.org/10.1016/j.jclepro.2020.121528
49. Zhang Yan-yuan, JU Guang-w,ei and Zhan Jin-tao (2019). Farmers using insurance and cooperatives to manage agricultural risks: A case study of the swine industry in China. *Journal of Integrative Agriculture*, 18(12). https://doi.org/10.1016/S2095-3119(19)62823-6
50. Zhang, Wei & Yang, Jun. (2015). Forecasting natural gas consumption in China by Bayesian Model Averaging. *Energy Reports*, 1(1), 216-220. https://doi.org/10.1016/j.egyr.2015.11.001

