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Socio-economic Determinants of Agricultural Household Income in Thailand: A Comparative Study Using Multiple Linear Regression and Backpropagation Neural Networks

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Abstract

This paper considers the socio-economic factors that affect the income of agricultural households in Thailand using a comparative study based on multi-linear regression-OLS and stepwise-and backpropagation neural networks. The analysis relies on data from the 2021 Household Socioeconomic Survey of the National Statistical Office of Thailand and covers many socio-economic variables. The results show that household size, the type of agriculture practiced, education level, household head age, and the total agricultural area significantly affect agricultural household income. Specifically, household members, level of education, and the type of agriculture were determined to have the highest influence in agricultural household income. The study further compares the effectiveness of three statistical models-linear regression, stepwise linear regression, and backpropagation neural networks-in the forecast of agricultural family income. As a matter of fact, the results showed that the model of backpropagation neural networks is superior to the two linear regression models, underlining the potential of the model for accurate and reliable forecasting in this context. The best model from the backpropagation neural network achieved an adjusted R-squared of 0.415 and MSE of 56,492,699,868.34, while in OLS method, the best model achieved an adjusted R-squared of 0.373 and MSE of 74,424,842,411.89, and from stepwise, 0.372 with MSE of 74,480,254,991.51. The overall contribution of this research is the valuable insight into the complex interaction between the various factors that define agricultural household income, which provides a basis for informed decision-making for policy interventions targeted at rural livelihoods.

Keywords: Socio-Economic Determinants, Agricultural Household Income, Multiple Linear Regression, Backpropagation Neural Network

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Introduction and Background

Agriculture is a pivotal sector in Thailand's economy, playing a crucial role not only in ensuring domestic food security but also as a major contributor to the country's export economy. Thailand is globally recognized as a leader in the production and export of key agricultural commodities, including rice, rubber, cassava, sugarcane, and various tropical fruits such as durian and mango. This sector is fundamental to the livelihoods of rural communities, where the majority of the agricultural workforce is concentrated. In 2023, approximately 30% of the national workforce was employed in agriculture (Ministry of Labour, 2023), underscoring its importance as a source of employment, particularly in less industrialized regions of the country.

However, despite the large proportion of labor engaged in agriculture, its contribution to the nation's Gross Domestic Product (GDP) remains disproportionately small. In 2024, the agricultural sector accounted for only 8.81% of Thailand's total GDP (Office of the National Economics and Social Development Council, 2024). This disparity between labor participation and economic output highlights the sector's limited capacity to generate added value in terms of GDP from production. This situation prompts critical consideration of the factors that impact productivity and income in the agricultural sector, setting the stage for future exploration of how to increase its economic value and role in national development.

Thailand's agricultural landscape, however, has undergone significant transformations over recent decades, driven by a complex interplay of economic, social, and policy-related factors. The expansion of the capitalist economy, fueled by the Green Revolution and the introduction of new socioeconomic policies, has opened up new opportunities for rural households to participate in market-oriented production (Podhisita, 2017). Concurrently, changes in household dynamics, such as declining fertility rates and shrinking household sizes, have created labor and land constraints in many rural areas, necessitating adaptations in farming practices (Bisht et al., 2020). In this dynamic context, the socio-economic determinants of agricultural household income in Thailand are particularly critical, as they influence the livelihoods and resilience of a significant portion of the population. Additionally, the structure of the Thai economy has transitioned, with the industrial sector now contributing more to the country's gross domestic product (GDP) than agriculture (the United Nations Population Fund and the United Nations Office for Project Services, 2023). This shift has significant implications for the socio-economic conditions of agricultural households, which must adapt to changing market conditions and technological advancements (Zhang & Diao, 2020).

Furthermore, Thailand has undergone a broader socio-economic transition, characterized by increased life expectancy, declines in total fertility and infant mortality rates, and a shift from an agricultural to an industrial economy (Kosulwat, 2002). These changes have had profound impacts on the socio-economic determinants of agricultural household income (Gage & DeWitte, 2009). Over the past three decades, Thailand has shifted from being an agriculture-based economy to a more industrialized one, with the industrial sector's share of GDP surpassing that of agriculture (Kosulwat, 2002). This transformation has coincided with household demographic changes, including lower fertility rates and smaller average household sizes (Podhisita, 2017).

To investigate the socio-economic determinants of agricultural household income in Thailand, this study will employ three advanced statistical modeling techniques: linear regression, and backpropagation neural networks (BPNNs). A comparative

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analysis of these methods will provide valuable insights into the socio-economic factors influencing agricultural household income, contributing to more effective policy interventions aimed at supporting rural livelihoods. The analysis will begin with a review of relevant literature on the socio-economic factors affecting agricultural household income in Thailand, with a particular focus on household dynamics and the influence of the capitalist economy on agricultural transformations. The determinants of agricultural household income in Thailand are multifaceted, shaped by a broad range of socio-economic variables.

The Research objectives

1) Examine the socio-economic factors affecting agricultural household income in Thailand, including the impact of economic and social changes on agricultural practices.
2) Compare the effectiveness of two statistical analysis techniques—backpropagation artificial neural networks, linear regression, and backpropagation—in understanding the factors influencing agricultural household income.
3) Analyze the broader economic and social changes, such as demographic shifts and industrial economic changes, on agricultural household income in Thailand.

Literature Reviews

2.1 Artificial neural networks

Artificial neural networks are sophisticated computational models that mimic the structure and functioning of the human brain. (Pornpatcharapong et al., 2011) These models are composed of interconnected nodes, or "neurons," that can learn to perform complex tasks by processing and analyzing vast amounts of data. (Hua et al., 2023) Through a process of training, neural networks are able to identify patterns, make predictions, and solve problems in a wide range of applications, such as image recognition, natural language processing, and predictive analytics. By adjusting the strength of the connections between nodes, neural networks can adapt and improve their performance over time, making them a powerful tool for tackling complex, non-linear problems.

2.2 The Backpropagation Neural Network Model

The Backpropagation Neural Network Model is a widely used training algorithm in artificial neural networks. It plays a crucial role in supervised learning tasks, where the model learns by adjusting its parameters based on error signals. These error signals are generated by the difference between the predicted and actual outcomes. Backpropagation allows the model to fine-tune the weights of the connections between neurons, enabling it to minimize the overall error and improve its predictive accuracy.

The core idea behind backpropagation is to propagate the error from the network's output layer back through its hidden layers. This backward flow of error information allows the model to adjust the weights in each layer in a way that gradually reduces the error. This weight adjustment is done through an optimization process, typically gradient descent, which updates the weights in small steps to reach a configuration that minimizes the total error.

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In simple terms, backpropagation ensures that the neural network learns by constantly evaluating its mistakes, sending feedback to improve the network's internal parameters, and improving its performance over time.

2.3 Linear regression

Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables. It aims to find the best-fitting straight line that describes the linear relationship between the variables. (Maulud & Abdulazeez, 2020) The model assumes that the dependent variable is a linear function of the independent variables, with an additive error term. This approach is widely used in various fields, including economics, social sciences, and engineering, to analyze and predict the effects of different factors on a target variable.

2.4 Related research papers

Socio-economic Determinants of Agricultural Household Income

The socio-economic determinants of agricultural household income in Thailand are multifaceted, encompassing a range of factors related to household dynamics, the capitalist economy, and broader demographic and economic transitions. One key factor that influences agricultural household income is the expansion of the capitalist economy, which has been driven by the Green Revolution and the implementation of new socioeconomic policies since the 1960s (Podhisita, 2017). This expansion has opened up new opportunities for rural households to participate in market-oriented production, leading to a shift from subsistence farming to commercial agriculture (Podhisita, 2017). Household dynamics, including declining fertility rates and smaller household sizes, have also played a role in shaping agricultural household income.

The current study extends prior studies by narrowing its investigation to the agricultural sector in Thailand. It employs two state-of-the-art statistical modeling approaches: multiple linear regression-OLS, stepwise and back-propagation neural networks. These methods differ in their strengths and weaknesses, and thus have provided valuable insights into the relationships between socio-economic factors and agricultural household incomes.

Materials and Methods

3.1 Materials

The data applied in this study were obtained from the Household Socio-Economic Survey conducted by the National Statistical Office of Thailand. The SES is an in-depth survey that collects considerable detail on the economic activities and socio-economic characteristics of the respondents, focusing on agricultural households. The 2021 SES sampled approximately 16,253 households across Thailand, providing the analysis with a rich dataset on the conditions and difficulties of agricultural households. This broad-based dataset forms a crucial foundation for the study, shedding light on different aspects of livelihood and economic activities of interest in the agricultural sector.

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Conceptual framework

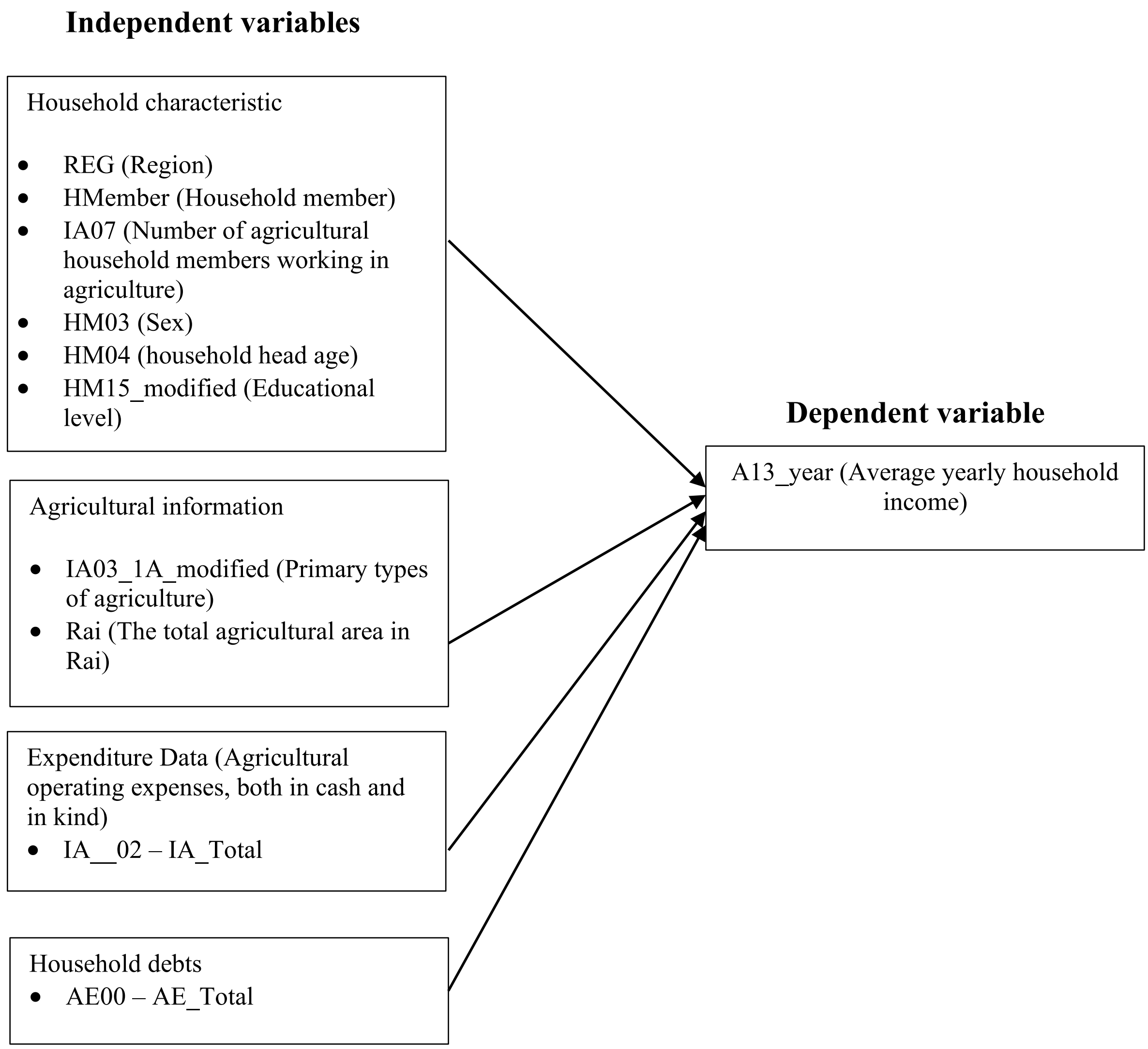

Figure 1: Conceptual framework

3.2 Methods

These descriptive statistics summarize the basic features of the dataset with an aim to discerning patterns, trends, or an overview of the variables. Then, multiple linear regression-OLS and stepwise-have been done to understand investigations and quantification of the relationship between household income and other socioeconomic factors. Lastly, artificial neural networks with backpropagation are implemented to model higher-order nonlinear relationships in the data for a deeper look at the influencing factors on income in agricultural households.

3.3 Model Specification

In this study, we compare the effectiveness of three models: the Linear Regression Models using OLS and Stepwise methods and the Backpropagation Neural Network Model. These models are used to estimate the impact of various factors on household income from agricultural production. The goal is to determine which model provides better predictive accuracy and insight into the relationships between dependent and independent variables.

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3.3.1 Linear Regression Model

The linear regression models (OLS and stepwise) are used as a baseline to estimate the relationships between household income and its independent variables. The basic form of the model remains:

$$Y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n + \epsilon_i$$

Where:

Y_i represents Average yearly household income for household i
$x_1, x_2, x_3, \cdots, x_n$ are the independent variables, including:

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Household debts
β_0 is the intercept.
$\beta_1, \beta_2, \beta_3, \cdots, \beta_n$ are the coefficients representing the effect of each independent variable on yearly household income.
ϵ_i is the error term.

3.3.2 Backpropagation Neural Network Model

The Backpropagation Neural Network (BPNN) is a type of artificial neural network that uses a supervised learning algorithm. Unlike the linear model, the neural network can capture more complex and non-linear relationships between the dependent and independent variables. The architecture of the neural network includes the following components:

Input Layer: Each independent variable (e.g., production costs, labor, capital inputs, external factors, and household characteristics) is represented as an input node. The number of input nodes corresponds to the number of independent variables.

Hidden Layer(s): The network may include one or more hidden layers, where each layer consists of several neurons. The hidden layers apply non-linear transformations to the input data using an activation function (such as ReLU or sigmoid), allowing the network to capture complex relationships between variables.

Output Layer: The output layer has one node, which represents the predicted income from agricultural activities for each household.

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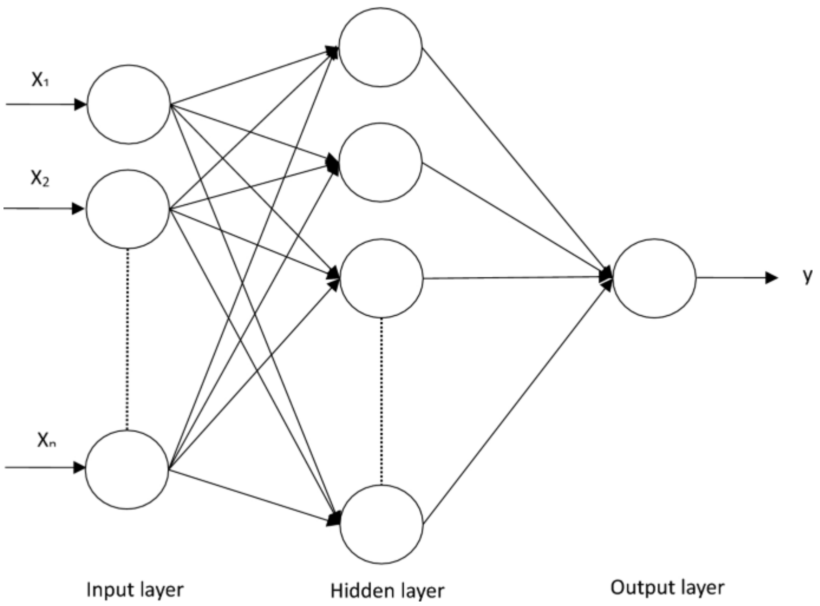

Figure 2. Backpropagation Neural Network Model
Source: Zhou et al. (2023)

The iterative process in this model, therefore, supports the capture of complex nonlinear relationships between input and output variables, making it suitable for many regression problems.

Backpropagation Algorithm: The backpropagation algorithm adjusts the weights and biases of the neural network during training. It works by minimizing the error between the predicted and actual income values through a process of forward propagation, error calculation (using a loss function like Mean Squared Error), and backward propagation of the error to update the weights.

Training and Validation: The data is split into training and validation sets. The training set is used to train the neural network, while the validation set is used to evaluate its performance and avoid overfitting.

Model Tuning: The number of hidden layers, number of neurons in each layer, learning rate, and other hyperparameters are tuned to optimize the performance of the neural network.

3.3.3 Model Comparison

To compare the performance of the Linear Regression Model and the Backpropagation Neural Network Model, the following metrics are used:

(1) Mean Squared Error (MSE): Measures the average of the squared differences between the actual and predicted values. A lower MSE indicates better model performance.

(2) R-squared (R^2): Represents the proportion of variance in the dependent variable that can be explained by the independent variables. Higher R^2 values indicate better model fit.

By comparing these two models, we aim to assess whether the added complexity of the backpropagation neural network results in significantly better predictive

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performance and understanding of the relationships between socio-economic factors and household income in agricultural production.

Empirical Results

By comparing these two models, we aim to assess whether the added complexity of the backpropagation neural network results in significantly better predictive performance and understanding of the relationships between socio-economic factors and household income in agricultural production.

4.1 Descriptive Statistics

Table 1. Descriptive Statistics (Categorial data)

Variables	Categorial data	n and Percentage
Independent variables		
Household characteristic		
REG (Region)	• Bangkok Metropolis	8 (00.05%)
	• Central region	2,508 (15.43%)
	• Northern region	4,450 (27.38%)
	• Northeastern region	6,896 (42.43%)
	• Southern region	2,391 (14.71%)
HM03 (Sex)	• Male	10,488 (64.53%)
	• Female	5,765 (35.47%)
HM15_modified (Educational level)	• No formal education or unclassified educational level	729 (4.49%)
	• Primary education	11,642 (71.63%)
	• Lower secondary education	1,436 (8.84%)
	• Upper secondary education	1,334 (8.21%)
	• Vocational Certificate	227 (1.40%)
	• Special Vocational Certificate	14 (0.09%)
	• Post-secondary Education	21 (0.13%)
	• High Vocational Certificate (Diploma)	278 (1.71%)
	• Bachelor's Degree	514 (3.16%)
	• Master's Degree	58 (0.36%)
Agricultural information		
IA03_1A_modified (Primary types of agriculture)	• crop farming	15,073 (92.74%)
	• livestock farming	830 (5.11%)
	• aquaculture	344 (2.12%)
	• others	6 (0.04%)
Household debts		
AE00 (Does your household have any debts?)	• No	5,091 (31.32%)
	• Yes	11,162 (68.68%)

Note: Total sample (n) =16,253 households

Source: 2021 Household Socioeconomic Survey conducted by the National Statistical Office of Thailand and calculated by research team

1) In 2021, the regional distribution of agricultural households (REG) was: in the Northeastern region with 6,896 households and accounted for 42.43%, followed by the largest number for the Northern region, which had 4,450 households or 27.38%, the Central, the Southern region, and Bangkok, respectively, with 2,508 households or 15.43%, 2,391 households or 14.71%, and only 8 households or 0.05%.

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2) The majority of household heads (HM03) are male, numbering 10,488 and accounting for 64.53%, while female household heads number 5,765, representing 35.47%.

3) Regarding educational level (HM15_modified), 95.51% have received some form of education, while 4.49% have not. The majority have completed primary education with a frequency of 11,642 people, which is 71.63%. It is followed by lower secondary education at 8.84% and upper secondary education at 8.21%. Further, 58 people possess a master's degree, which represents 0.36%.

4) Primary types of agriculture (crop farming, livestock farming, aquaculture) (IA03_1A_modified), it shows that the total number of agricultural households, 92.74% are farming, and farming is mainly of rice, perennial crops, vegetables, melons, tuber crops, and sugarcane. Livestock breeding accounts for 5.11%, aquaculture for freshwater and saltwater fishing makes up 2.12%, and the remaining 0.04% is other activities.

5) Household debts (AE00), we found that 68.68% of households had loans.

Table 2. Descriptive Statistics (Numerical data)

Variables	**Mean**	**Minimum**	**Maximum**	**Standard Deviation**
Dependent variable				
A13_year (Average yearly household income)	278,791.76	1,584.00	11,914,236.00	344,714.10
Independent variables				
Household characteristic				
HMember (Household member)	3.27	1.00	20.00	1.55
IA07 (Number of agricultural household members working in agriculture)	1.80	1.00	14.00	0.80
HM04 (Household head age)	58.26	16.00	99.00	12.00
Agricultural information				
Rai (The total agricultural area in Rai)[1]	15.28	0.00	1,030.00	23.91
Expenditure Data (Agricultural operating expenses, both in cash and in kind)				
IA__02 (Rent for agricultural land)	1,508.09	0.00	300,000.00	10,117.81
IA__03 (Costs for purchasing/repairing/renting tools and equipment, and renting working animals)[2]	2,527.77	0.00	2,100,000.00	21,908.53
IA__04 (Fuel, electricity, irrigation water, oil, etc.)	5,058.53	0.00	1,200,000.00	18,302.13
IA__05 (Costs for fertilizers, pesticides, fungicides, herbicides, etc.)	4,965.97	0.00	2,000,000.00	35,009.35

Variables	Mean	Minimum	Maximum	Standard Deviation
IA__06 (Costs for seeds, animal breeds)[3]	2,251.82	0.00	12,960,000.00	104,144.72
IA__07 (Costs for animal feed)[4]	5,565.55	0.00	4,500,000.00	83,456.97
IA_08 (Wages for labor)[5]	11,327.56	0.00	1,500,000.00	45,827.07
IA_09 (Other expenses)[6]	11,258.46	0.00	1,886,930.00	35,156.76
IA_Total (Total agricultural operating expenses)[7]	44,463.74	0.00	20,290,000.00	213,035.72
Household debts				
AE02 (for purchasing/renting houses and/or land)	4,006.03	0.00	1,200,000.00	30,731.36
AE03 (for education)	569.21	0.00	480,000.00	7,798.73
AE04 (for other household consumption)[8]	20,605.81	0.00	1,440,000.00	53,660.62
AE05 (for business (other than agriculture)	3,092.89	0.00	2,400,000.00	36,826.57
AE06 (for agriculture)[9]	16,022.41	0.00	3,000,000.00	60,160.18
AE07 (Other debts)[10]	206.30	0.00	693,600.00	6,645.29
AE_Total (Total household debts)[11]	44,502.65	0.00	3,084,000.00	98,644.85

Note: Total sample (n) =16,253 households
Source: 2021 Household Socioeconomic Survey conducted by the National Statistical Office of Thailand and calculated by research team

1) Annual average income of agricultural households (A13_year) has a minimum of 1,584 THB and a maximum of 11,914,236 THB per year. On average, agricultural households received an annual income of 278,792 THB. Moreover, 11,245 or 69.19% of households had incomes less than the average annual income.

2) The household size distribution (H Member) shows that 2-member households comprised the biggest proportion of 27.76%, followed by 3-member households with 24.44% and 4-member households with 19.40%. The three categories combined together make up over 71.61% of the total. In additional, there were 1,437 households consisting of a single member representing 8.84%, and 29 households that were more than 10 members and represented 0.18% of the number.

3) Number of agricultural household members working in agriculture (IA07) including operators (IA07), 2 members of most households were found to work in the

[1] A "0 Rai" response indicates either that the data is missing, or activities within agriculture do not use land.
[2] e.g., knives, hoes, shovels, tractor rental, renting cows/buffaloes, etc.
[3] Ducklings, fish fry, and other young animals) (including eggs for hatching
[4] Including seeds grown for feeding animals
[5] Including food provided for those assisting in agriculture
[6] Such as land taxes, loan interest, transportation of produce, and other expenses
[7] Calculated from IA__02 + IA__03 + … + IA__09
[8] Such as purchasing vehicles and using credit cards for goods and services
[9] Crop farming, livestock farming, aquaculture, etc.
[10] Such as guaranteed debts, fines, damages, etc.
[11] Calculated from AE02 + AE03 + … + AE0

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agricultural field, which accounts for 49.31%. The second comes households with 1 and 3 members, respectively accounting for 37.65% and 9.61%.

4) Regarding age, the household heads (HM04) were 74.84% above 50 years; minimum age is 16, while the maximum age is 99 years. Modal age is 59 years, which is 4.12%, while the average age of household heads is 58.26 years.

5) The total agricultural area in Rai (Rai) was 1,600 square meters. It is found that agricultural households have an average agricultural area of 15.28 Rai or 24,448 square meters with the largest area of 1,030 Rai or 1,648,000 square meters. Besides, 13,370 households or 82.26% were found to have agricultural land smaller than the average size.

6) Agricultural operating expenses for the last 12 months (IA__02 – IA Total) From this, it was found that average total agricultural operating expenses, both in cash and in kind, equaled 44,463.74 Baht per year. The highest expense was wages for labor, including food provided for those assisting with agriculture (IA__08), at 25.48%, followed by other expenses, such as land taxes, interest on loans, transportation of produce, and other miscellaneous costs (IA__09), at 25.32%. Animal feeds, including seeds grown for feeding animals, are constituted by IA__07, which accounted for 12.52%.

7) Total household debts (AE02 – AE_Total), we found the average total household debt was 44,502.65 Baht per year. The majority of this debt was used for other household consumption, such as purchasing vehicles and using credit cards for goods and services, accounting for 46.30%. This was followed by debt used for agricultural purposes (crop farming, livestock farming, aquaculture, etc.), which accounted for 36%.

4.2 Multiple Linear Regression Result

Table 3. Multiple Linear Regression result (n=16,253) using OLS method
Dependent variable: *A13_year (Average yearly household income)*

Independent variables	Coefficient	t statistic and significance level
Constant	-106,200.00	-5.54**
Household characteristic		
REG (Region)	15,240.00	6.20**
HMember (Household member)	40,880.00	26.90**
IA07 (Number of agricultural household members working in agriculture)	-19,490.00	-6.57**
HM03 (Sex)	-7,048.05	-1.56
HM04 (Household head age)	1,295.65	6.89**
HM15_modified (Educational level)	34,790.00	23.97**
Agricultural information		
IA03_1A_modified (Primary types of agriculture)	27,470.00	4.44**
Rai (The total agricultural area in Rai)	1,237.64	10.71**
Expenditure Data (Agricultural operating expenses, both in cash and in kind)		
IA_02 (Rent for agricultural land)	-2.05	-9.77**
IA_03 (Costs for purchasing/repairing/renting tools and equipment, and renting working animals)	-1.30	-11.76**
IA_04 (Fuel, electricity, irrigation water, oil, etc.)	0.77	4.99**
IA_05 (Costs for fertilizers, pesticides, fungicides, herbicides, etc.)	1.30	16.16**
IA_06 (Costs for seeds, animal breeds)	-0.40	-8.60**
IA_07 (Costs for animal feed)	-0.15	-3.51**

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Independent variables	Coefficient	t statistic and significance level
IA_08 (Wages for labor)	1.32	21.92**
IA_09 (Other expenses)	0.86	11.64**
IA_Total (Total agricultural operating expenses)	0.35	11.47**
Household debts		
AE00 (Does your household have any debts?)	-24,060.00	-4.81**
AE02 (for purchasing/renting houses and/or land)	0.48	5.42**
AE03 (for education)	-0.02	-0.08
AE04 (for other household consumption)	0.31	4.32**
AE05 (for business (other than agriculture)	0.05	0.62
AE06 (for agriculture)	-0.67	-9.61**
AE07 (Other debts)	0.68	2.44*
AE_Total (Total household debts)	0.83	13.52**
R-squared		0.374
Adj. R-squared		0.373
Mean Square Error (MSE)		74,424,842,411.89

Note: * indicates statistical significance at the at 0.05 level.
** indicates statistical significance at the 0.01 level.
After the t-statistic, there is significance level.

As indicated in the result of the OLS method (Table 3), the significant factors in estimating yearly average income for family and agriculture households include numbers of household members, educational level, and primary kinds of agriculture. More precisely, it shows that the number of household members has the highest degree of influence in the yearly average income. The MSE is 74,424,842,411.89 and the Adjusted R-squared is 0.373, reflects an explanatory power of approximately 37.3%.

Table 4. Multiple Linear Regression result (n=16,253) using Stepwise method
Dependent variable: A13_year *(Average yearly household income)*

Independent variables	Coefficient	t statistic and significance level
Constant	-119,400.00	-6.70**
Household characteristic		
REG (Region)	15,230.00	6.19**
HMember (Household member)	40,840.00	26.89**
IA07 (Number of agricultural household members working in agriculture)	-18,870.00	-6.40**
HM04 (Household head age)	1,304.16	6.94**
HM15_modified (Educational level)	34,960.00	24.19**
Agricultural information		
IA03_1A_modified (Primary types of agriculture)	29.170.00	4.76**
Rai (The total agricultural area in Rai)	1,285.83	11.31**
Expenditure Data (Agricultural operating expenses, both in cash and in kind)		
IA_02 (Rent for agricultural land)	-1.68	-7.25**
IA_03 (Costs for purchasing/repairing/renting tools and equipment, and renting working animals)	-1.01	-8.97**
IA_04 (Fuel, electricity, irrigation water, oil, etc.)	0.99	6.78**
IA_05 (Costs for fertilizers, pesticides, fungicides, herbicides, etc.)	1.67	23.86**
IA_07 (Costs for animal feed)	0.19	6.79**
IA_09 (Other expenses)	1.22	11.64**
IA_08 (Wages for labor)	1.68	21.92**
IA_Total (Total agricultural operating expenses)	0.35	30.94**
Household debts		
AE00 (Does your household have any debts?)	-24.800.00	-4.97**

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Independent variables	Coefficient	t statistic and significance level
AE05 (for business (other than agriculture)	-0.31	-4.97**
AE06 (for agriculture)	-1.01	-9.61**
AE_Total (Total household debts)	1.18	32.91**
R-squared	0.373	
Adj. R-squared	0.372	
Mean Square Error (MSE)	74,480,254,991.51	

Note: * indicates statistical significance at the at 0.05 level.
** indicates statistical significance at the 0.01 level.
After the t-statistic, there is significance level.

Following Table 4, by using stepwise regression, the most relevant predictors for average yearly income from the household are: household members; educational level; main kind of agriculture. Important additional variables are: head of household's age; total agricultural area. This has an R-squared of 0.373 and an Adjusted R-squared of 0.372, meaning that the model explains about 37.3% of variation in this income dataset. The MSE is 74,480,254,991.51.

4.3 Backpropagation Neural Network Model Result

With a BPNN model, we got the Feature Importance of the independent variables that are their significance or impact towards the dependent variable of interest, which, in this problem, is the average annual income for agricultural households. We find out that the most important factor toward A13_year or average annual income of the agricultural households is IA__05, which relates to the costs for fertilizers, pesticides, fungicides, herbicides, etc. The next most important ones are HM15_modified, which stands for educational level, and HMember for Household members. On the other hand, the factor with no impact on the dependent variable are HM03(Sex), IA03_1A_modified (Primary types of agriculture), AE06 (for agriculture) and IA07 (Number of agricultural household members working in agriculture). The MSE of the Backpropagation Neural Network Model was 56,492,699,868.34, the R-squared was 0.419 and the Adjusted R-squared was 0.415.

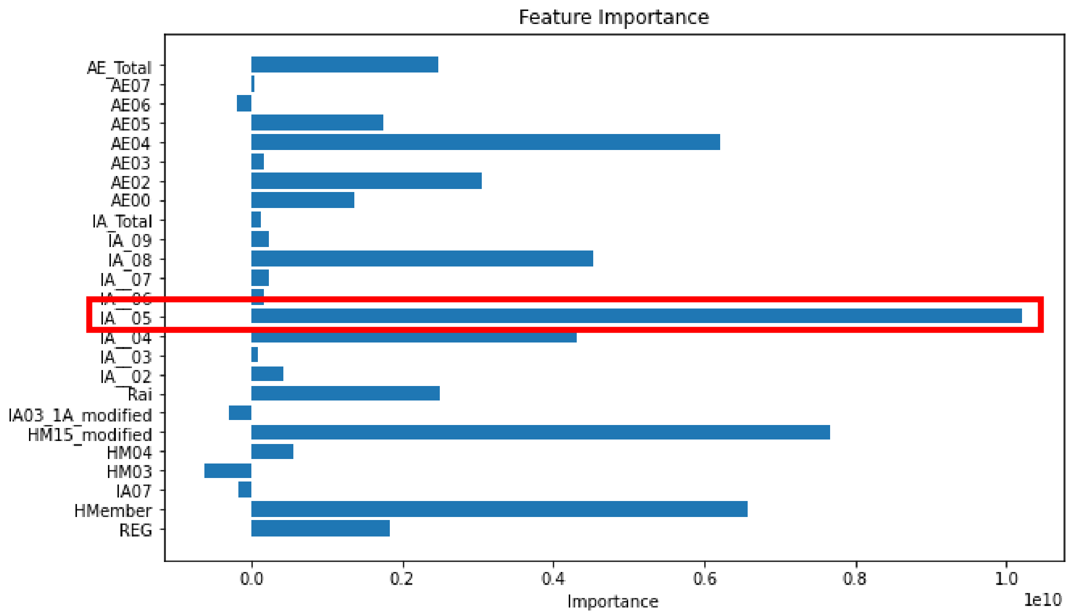

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Figure 3. Feature Importance from BPNN model
Note: MSE of Backpropagation Neural Network Model was 56,492,699,868.34, R-squared was 0.419, and Adjusted R-squared was 0.415.

4.4 Comparison of Model performance: OLS, Stepwise Linear Regression and Backpropagation Neural Network Model

Table 5. Comparison of Model Performance

Models	MSE	Adjusted R-squared
Multiple Linear Regression using OLS method	74,424,842,411.89	0.373
Multiple Linear Regression using Stepwise	74,480,254,991.51	0.372
Backpropagation Neural Network Model	56,492,699,868.34	0.415

With the evaluation metrics, it can be determined that the most effective model for predicting the average annual income in agricultural households will be the BPNN model, as this has a rather low MSE value and, simultaneously, a higher value for Adjusted R-squared compared with the OLS and Stepwise Regression models. This, therefore, shows the better prediction capability of this model. The outstanding performance of the BPNN model thus recommends its use for observing more accurate and reliable forecasts in this context.

Discussion

These results from this study give important information on factors that influence the income of agricultural households in Thailand. The findings point out that household characteristics, farm practices, and availability of resources explain household income. The poor fit of the backpropagation neural network model would suggest that even more complex statistical methods may be necessary to capture the complex relations between socio-economic factors and agricultural income.

The study also points out several implications for policy. First, the findings suggest the need for interventions that can support agricultural households, especially those with limited resources, education, and technical skills. Secondly, there is a need for policies that aim at the promotion of diversification of agricultural activities and improvement in market access for agricultural produce with a view to improving livelihoods among agricultural households. It finally underlines that challenges in the agricultural sector should be faced in respect to a changing climate and growing environmental stress.

Conclusions

This research enhances the understanding of the socio-economic factors that determine the agricultural household incomes of Thailand through underlining the importance of household size, level of education, type of agriculture, age of the household head, and total agricultural area. It further demonstrated the efficiency of the backpropagation neural network model in predicting agricultural household income. The research lays the foundation for further studies and policy interventions that seek to improve the lives of agricultural households in Thailand.

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