Scientific Journal of Computer Science
futuristech PT. Teknologi Futuristik Indonesia
Date of publication August 12, 2025, date of current version August 12, 2025.
Digital Object Identifier **10.64539/sjcs.v1i1.2025.34**

Article

Waiting Time Analysis of Willingness to Pay for Rice Farming Insurance Premiums Using Cox Proportional Hazard Modeling and Weibull Method

Siti Mutiah[1], Yan Nazala Bisoumi[1], Elsa Nudyawati[1], Khamidah Arsyad Daud[1], Rofiah Ainun Nisa[1], Dwi Sulistiani[1], Ihsan Fathoni Amri[2], Ariska Fitriyana Ningrum[2], Ahmed A. Mostfa[3]

[1] Department of Statistic, Universitas Muhammadiyah Semarang, Semarang 50273, Indonesia
[2] Department of Data Science, Universitas Muhammadiyah Semarang, Semarang 50273, Indonesia; ihsanfathoni@unimus.ac.id, ariskafitriyana@unimus.ac.id
[3] Department of Computer Science, College of Education, University of Al Hamdaniya, Mosul, Iraq
* Correspondence

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Abstract: Rice is a primary commodity in Indonesia's agricultural sector but is highly vulnerable to climate risks such as floods, droughts, and pest infestations. To mitigate these risks, the government, in collaboration with PT. Asuransi Jasa Indonesia (Jasindo), launched the Rice Farming Insurance Program (AUTP) in 2015. This study aims to analyze the willingness-to-pay time of farmers for AUTP premiums in Jayaraksa Village, Cimaragas Subdistrict, Ciamis Regency, using Weibull regression and Cox Proportional Hazard models. Factors such as education, secondary employment, rice production, and farming costs were examined to understand their influence on farmers' participation. Based on the analysis, the Weibull regression model, with a lower AIC value compared to Cox Proportional Hazard (270.4431 vs. 330.9111), demonstrated better performance in explaining the data. This research contributes to the development of more effective AUTP policies by identifying key factors influencing farmers' participation.

Keywords: Cox Proportional Hazard Regression; Farmers' Participation; Rice Farming Insurance; Weibull Regression; Willingness-to-Pay

1. Introduction

Rice remains the main crop and staple food source for much of the Indonesian population [1-3]. Agricultural activities, especially rice farming, are highly vulnerable to climate-related disasters [4, 5]. Risks such as flooding, drought, and attacks by Plant Pest Organisms (PPO) almost always occur during each planting season [6, 7]. Most of the land in Indonesia is utilized for agriculture [8, 9], with nearly 50% of the total workforce depending on this sector to meet their livelihood needs. If this condition persists, there are concerns that it could impact the stability of national food security, particularly in terms of rice production and availability as a staple food [10-12]. To address this issue, the government, in collaboration with PT. Asuransi Jasa Indonesia (Jasindo), has provided protection for rice farming through the Rice Farming Insurance Program (AUTP) [13-15].

The AUTP is an agricultural insurance program that has been implemented in Indonesia since 2015 [16, 17]. Agricultural insurance is a form of risk transfer that provides compensation for losses incurred in agricultural activities, ensuring the sustainability of farming businesses [18, 19]. Through this insurance, farmers receive protection against crop damage caused by floods, droughts, as well as pest and disease attacks or PPO, allowing them to receive compensation that can be used as working capital to sustain their farming operations [20-22]. The premium for the AUTP program is paid every planting season, with an amount of IDR 36,000 per hectare. In the premium payment process, the willingness of rice farmers may vary, and some farmers are unwilling to participate in the AUTP program [17, 23, 24]. There are many factors that can influence the willingness of rice farmers to pay the AUTP premium.

The factors influencing farmers' willingness to pay for Agricultural Insurance Premiums (AUTP) are not limited to economic aspects but also include social and demographic factors [25, 26]. Several studies indicate that education level, farming experience, land size, and farmers' understanding of the benefits of insurance programs can influence their decision to participate [27-29]. Agricultural insurance is a new concept for farmers; therefore, understanding how farmers perceive and evaluate the AUTP program is crucial. Farmers may have varying perceptions, which can lead to differences in behavior and decisions regarding the AUTP program [15, 30]. Additionally, farmers' trust in insurance providers and access to information about AUTP are also important variables to consider in this analysis [15, 25]. By understanding these factors, more targeted interventions can be designed to increase farmers' participation in the AUTP program. Identifying these factors can be conducted using survival analysis with the Weibull Regression and Cox Proportional Hazard Regression methods.

Previous studies on survival analysis using the Weibull regression and Cox proportional hazard regression methods have been widely conducted. For example, research Mayawi et al. (2022) [31] identified significant factors affecting the recovery time of acute myocardial infarction patients and determined the best model for recovery time in these patients at Dr. Sardjito General Hospital, Yogyakarta. Similarly [32] examined the time to failure in COVID-19 patients at Taman Husada General Hospital, Bontang. Meanwhile Azizy et al. (2023) [33] investigated the factors influencing the mortality rate of inpatient COVID-19 patients at Abdul Wahab Sjahranie General Hospital, Samarinda, in 2022.

Based on the aforementioned background, this study aims to conduct survival analysis on rice farmers in Jayaraksa Village, Cimaragas Subdistrict, Ciamis Regency. The time observed in this study refers to the duration until rice farmers are willing to pay for the AUTP premiums, while the event observed is the farmers' willingness to pay for these premiums. The influence of factors affecting this willingness is analyzed using the Weibull regression and Cox proportional hazard regression methods. The results of this study are expected to provide additional information to the government and AUTP implementers regarding the condition of farmers in the field, serving as a basis for improving policies and program implementation in the future.

2. Methods

2.1. Research Data

The data used in the study is quantitative data which is secondary data in the period of 2021. In this study, the observation unit is rice farmers in Jayakarsa Village, Cimaragas District, Ciamis Regency, West Java.

Table 1. Research Variables.

No	Variables	Description
1	X_1	Gender
2	X_2	Age
3	X_3	Marital Status
4	X_4	Last Education
5	X_5	Length of Farming
6	X_6	Other Occupations
7	X_7	Land Area
8	X_8	Rice Production
9	X_9	Farming Business Costs

2.2 Research Variables

The variables used in this study are listed in Table 1. With the dummy information in this study are:

a. Gender is grouped into 2, namely 1. male farmers and 2. female.
b. Marital Status is grouped into 2, namely 1. married and 2. unmarried.
c. Last education is grouped into 5, namely 1. no school, 2. graduated from elementary school/ equivalent, 3. graduated from junior high school/ equivalent, 4. graduated from high school/ equivalent, 5. graduated from college.
d. Other jobs are grouped into 2, namely 1. have other jobs and 2. do not have other jobs.

2.3. Testing Methods

2.3.1. Cox Proportional Hazard Regression Model

The Cox Proportional Hazard regression model is a statistical method used to analyze survival data, which is data related to the time until an event occurs, such as death or failure. This model connects the dependent variable in the form of survival time with one or more independent variables measured at the time of the study. Cox regression is modeled as [34, 35]:

$$h(t, X) = h_0(t)\psi(\beta_1 X_1), \quad t > 0 \tag{1}$$

The estimation of the regression model parameters is based on partial likelihood:

$$L(\beta) = \prod_{k \in D} \frac{\exp(x_k \beta)}{\sum_{j \in R_k} \exp(x_j \beta)} \tag{2}$$

2.3.2. Weibull Regression Model

Weibull regression is a statistical method used to model the time until an event occurs, such as a failure or death. This model is based on the Weibull distribution, which is known for its flexibility in describing various types of time data. In the Weibull regression model, the scale parameter $\lambda = f_\lambda(X; \beta)$, and the shape parameter $\alpha = f_\alpha(X; \beta)$ with the form of an exponential function $\exp(\beta X)$ [36]. The model with $\lambda = f_\lambda(X; \beta) = \exp(X\beta)$ is monly used, so the Weibull regression survival function is as follows:

$$\begin{aligned} S(t|x) &= \exp(-(f\lambda(X;\beta)t)^{\alpha}) \\ &= \exp(-\exp(X\beta)\,t)^{a} \end{aligned} \tag{3}$$

Or it can be written as:

$$S(t|x) = \exp\left[-\exp\left(\frac{y - X\beta}{\sigma}\right)\right] \tag{4}$$

What is referred to as the extreme value survival distribution function, with the location parameter being $\mu = -X\beta$ and the scale parameter σ = 1/α and its likelihood function is:

$$L(\beta,\sigma) = \prod_{i=1}^{n} f(t_i,\theta|X_i)^{\delta_i}\, S(t_i,\theta|X_i)^{1-\delta_i} \tag{5}$$

2.4. Hypothesis Testing

2.4.1. Cox Proportional Hazard Regression Hypothesis Testing

a. Simultaneous Test

Simultaneous testing was carried out using the partial likelihood ratio test method. The hypotheses analyzed in this test are [37]:

H_0 : β_i = 0, i = 1 (the treatment variable did not have a significant influence on the model).

H_1 : There's at least one $\beta_i \neq 0$, i = 1 (the treatment variable has a significant influence on the model).

The level of significance used is α = 5%.

Test criteria: If $\rho - value < \alpha$ or $G_{\text{calculated}} > X^2$ (db = 1; α), So H_0 rejected.

Conclusion: If the decision taken is to refuse H_0, then it can be concluded that there is at least one independent variable that has an influence on the dependent variable. So, the model is suitable for use.

b. Partial Test

Partial testing can use the Wald test, denoted by Z. The Z value follows a standard normal distribution and is compared with the value of $Z_{\frac{\alpha}{2}}$ from the table. The hypotheses used in this test are as follows [38]:

H_0 : β_i= 0, i = 1 (the treatment variable has a significant influence on the model).

H_1 : There's at least one β_i≠0, i = 1 (the treatment variable has a significant influence on the model).

The level of significance used is α = 5%.

Test criteria: If $\rho - value < \alpha \; or \; |Z| > Z_{\frac{\alpha}{2}}$, So H_0 rejected.

Conclusion: If the decision taken is to reject H_0, So it can be concluded that the independent variable has an effect on the dependent variable.

2.4.2. Weibull Regression Hypothesis Testing

The significance testing of parameters is conducted both partially and overall. Partial testing aims to determine the influence of each independent variable on the dependent variable, while overall testing evaluates the simultaneous influence of the independent variables and assesses the feasibility of the regression model for use.

a. Simultaneous Test

The hypothesis used in this test is [39]:

H_0 : β_i =0, i = 7 (The independent variable does not have a significant influence on the model).

H_1 : There is at least one β_i≠0, i = 7 (The independent variable has a significant influence on the model).

The level of significance used is α = 5%.

Test criteria: If $\rho - value < \alpha \; atau \; G_{\text{calculated}} > X^2(db = 1; \alpha)$, So H_0 rejected.

Conclusion: If the decision taken is to refuse H_0, then it can be concluded that there is at least one independent variable that influences the dependent variable. So, the model is suitable for use.

b. Partial Test

The hypothesis used in this test is [39]:

H_0 : β_i= 0, i = 7 (The independent variable has a significant influence on the model)).

H_1 : There is at least one, i = 7 (treatment variables have a significant influence on the model).

The level of significance used is 5%.

Test criteria: If $\rho - value < \alpha \; or \; |Z| > Z_{\frac{\alpha}{2}}$, So H_0 rejected.

Conclusion: If the decision taken is to refuse H_0 So it can be concluded that the independent variable has an effect on the dependent variable.

2.5. Determination of the Best Model

The best model can be obtained from the Akaike Information Criterion (AIC) value with backward elimination in the following equation [40]:

$$\begin{aligned} AIC &= -2\ln L\left(\dot{\beta}\right) + 2k \\ AIC &= -2\ln L\left(\dot{\theta}\right) + 2\text{k} \end{aligned} \tag{6}$$

2.6. Analysis steps

The following are the steps in the analysis carried out:

a. Collecting data on rice farmers in Jayakarsa Village in 2021.
b. Describing the data of rice farmers.

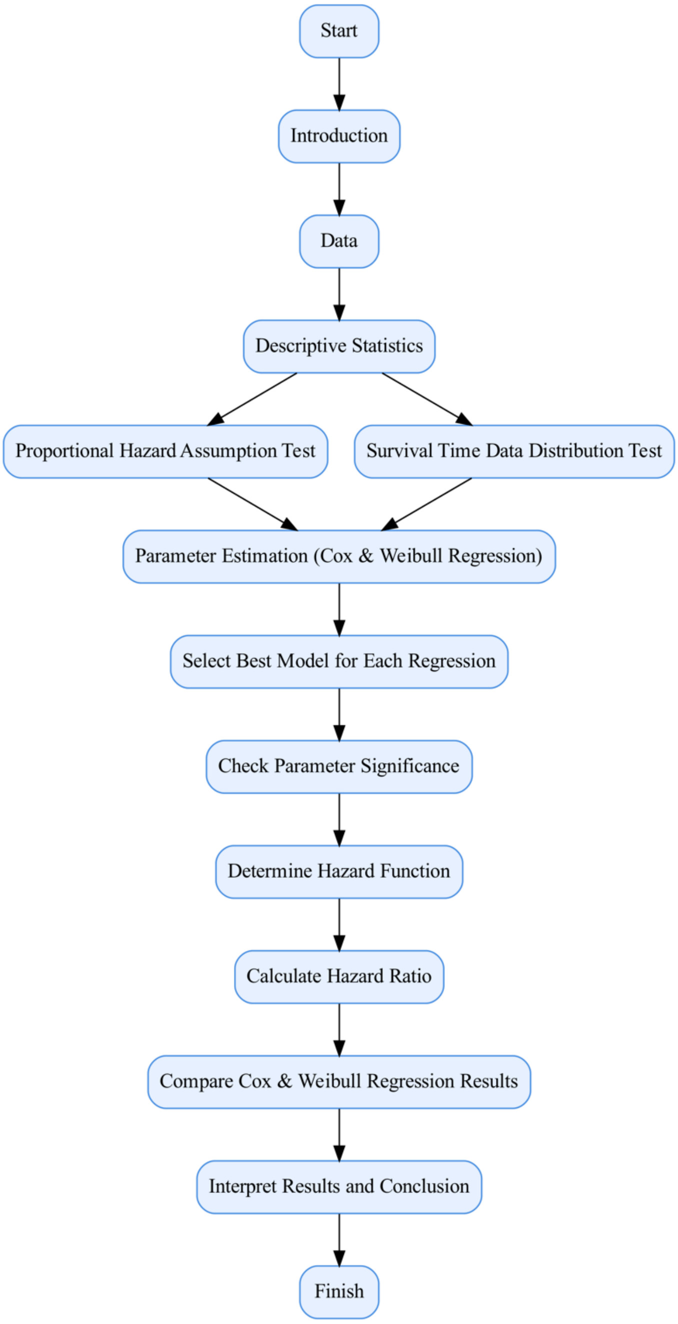

Figure 1. Research Flowchart**.**

c. Conducting analysis through the following steps:
- Testing the proportional hazard assumption.
- Testing the survival time data distribution.
- Estimating parameters in Cox proportional hazard regression and Weibull regression.
- Selecting the best model for both Cox proportional hazard regression and Weibull regression.
- Testing the significance of parameters in Cox proportional hazard regression and Weibull regression.
- Determining the hazard function for Cox proportional hazard regression and Weibull regression.
- Calculating the hazard ratio for each independent variable.
- Comparing the results of Cox proportional hazard regression and Weibull regression.

d. Drawing conclusions from the analysis results.

2.7. Research Flowchart

The flowchart of the research in this study is presented in Figure 1.

3. Results and Discussion

Based on Table 2, the average willingness to pay time is 6.24, with a median of 8.00, a maximum value of 8.00, and a minimum value of 1.00. The difference between the mean and the median indicates a potential left-skewness in the data. The average age of respondents is 61.15 years, with a median of 62.00 years and an age range between 24 and 84 years. The average farming experience is 22.92 years, with a median of 22.50 years and a range of 2 to 50 years. The close values between the mean and median for the age and farming experience variables indicate a relatively symmetrical distribution. The average land area is 0.1704 hectares, with a median of 0.1400 hectares and a range of 0.0426 to 0.7000 hectares. The average rice production is 1.555 tons, with a median of 1.200 tons and a range of 0.400 to 9.000 tons. The average farming cost is 3.056, with a median of 2.256 and a range of 0.780 to 12.800.

3.1.1. Cox Proportional Hazards Assumption Test

Hypotheses:

H_0 : The proportional hazards assumption is met (residuals are time-independent).

H_1 : The proportional hazards assumption is not met (residuals are time-dependent).

Test Criteria: Accept H_0 if the p-value > 0.05.

Table 2. Descriptive Analysis.

Variable	Mean	Median	Maximum	Minimum
Willingness-to-Pay Time	6.24	8.00	8.00	1.00
Age	61.15	62.00	84.00	24.00
Years of Farming Experience	22.92	22.50	50.00	2.00
Land Area	0.17	0.14	0.70	0.04
Rice Production	1.55	1.20	9.00	0.40
Farming Costs	3.06	2.26	12.80	0.78

Table 3. Results Cox Proportional Hazards Assumption Test.

Variable	P-Value	Decision
X_1	0.4170	Accepted H_0
X_2	0.5760	Accepted H_0
X_3	0.9530	Accepted H_0
X_4	0.0950	Accepted H_0
X_5	0.8500	Accepted H_0
X_6	0.9410	Accepted H_0
X_7	0.3250	Accepted H_0
X_8	0.7520	Accepted H_0
X_9	0.3150	Accepted H_0
Global	0.1550	Accepted H_0

Table 4. Parameter Estimation in the Initial Cox Proportional Hazards Regression Model.

Parameter	Parameter Estimation	Z	P-Value
X_1	0.35818	0.8280	0.4078
X_2	0.03101	1.3240	0.1854
X_3	-0.87868	-1.5310	0.1257
X_4	0.67182	2.6460	0.0081
X_5	0.01296	0.6350	0.5256
X_6	-1.17011	-2.8120	0.0049
X_7	2.75103	0.3100	0.7568
X_8	-0.55043	-1.4650	0.1428
X_9	0.36581	0.8020	0.4226

Likelihood ratio test = 49.11 on 9 df, $p=2\times10^{-7}$
Wald test = 50.66 on 9 df, $p=8\times10^{-8}$

3.1. Results of the Cox Proportional Hazards Regression Test

Based on Table 3, the results of the Cox Proportional Hazards assumption test indicate that the null hypothesis (H_0) states that the proportional hazards assumption is met, meaning the residuals are time-independent. According to the testing criteria, H_0 is accepted if the p-value is greater than 0.05. The test results show that all variables, namely X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, and X_9, have p-values greater than 0.05, so H_0 is accepted for each variable. Additionally, the global test provides a p-value of 0.155, which is also greater than 0.05, leading to the acceptance of H_0 overall. Therefore, it can be concluded that the proportional hazards assumption is satisfied both for each variable and globally. This indicates that the Cox Proportional Hazards model can be used in the analysis as its residuals are time-independent.

3.1.2. Simultaneous Test

Based on Table 4, the results of the Likelihood Ratio and Wald tests indicate that the tested model demonstrates very strong significance. In the Likelihood Ratio test, a p-value of 2×10^{-7} (which is very close to 0) indicates that the overall model is significant, meaning there is a significant relationship between the variables included in the model and the measured outcome. A similar finding is observed in the Wald test, with a p-value of 8×10^{-8}, which is also very close to 0, confirming that the tested model provides a significant contribution to explaining the data. Both tests consistently provide evidence that the model used is valid and relevant for the analysis.

Table 5. Results of the Partial Significance Test.

Variable	Coefficient	Z	P-Value	Decision
X_1	-0.4154	-1.2890	0.1970	Accepted H_0
X_2	-0.0118	-1.0370	0.3000	Accepted H_0
X_3	-0.9563	-2.1650	0.0304	Reject H_0
X_4	0.6405	4.3150	$1.\times10^{-5}$	Reject H_0
X_5	-0.0094	-0.7310	0.4650	Accepted H_0
X_6	-1.2407	-3.8360	0.0001	Reject H_0
X_7	3.1000	3.6040	0.0003	Reject H_0
X_8	0.2193	2.7930	0.0052	Reject H_0
X_9	0.1712	3.7980	0.0001	Reject H_0

Table 6. Parameter Estimation of the Best Cox Proportional Hazards Regression Model.

Variable	Parameter Estimation	Z	P-Value
X_4	0.3323	1.9700	0.0488
X_6	-1.4520	-3.1540	0.0016
X_8	-0.7967	-2.3760	0.0175
X_9	0.6489	3.4730	0.0005

Likelihood ratio test = 43.66 on 4 df, $p=8\times10^{-9}$
Wald test = 47.63 on 4 df, $p=1\times10^{-9}$

3.1.3. Partial Test

Based on Table 5, the variables X1, X2, and X5 have p-values greater than 0.05 (0.197, 0.3, and 0.465, respectively). This indicates that, statistically, these variables do not have a significant effect on the hazard rate. In other words, changes in X1, X2, and X5 do not significantly alter the risk of the observed event occurring in this model. The null hypothesis (no effect) is accepted for these variables. In contrast, the variables X3, X4, X6, X7, X8, and X9 show a significant influence on the hazard rate, as all have p-values less than 0.05. Specifically, variable X3, with a coefficient of -0.9563 and a p-value of 0.0304, significantly decreases the hazard rate. Conversely, X4, with a coefficient of 0.6405 and a very small p-value of 1.6×10^{-5}, significantly increases the hazard rate. Variable X6 also plays a significant role in reducing the hazard rate, with a coefficient of -1.2407 and a p-value of 0.0001. Variable X7, with a coefficient of 3.1000 and a p-value of 0.0003, significantly increases the hazard rate. X8 and X9, with coefficients of 0.21926 and 0.17119 and p-values of 0.0052 and 0.0001, respectively, also contribute significantly to increasing the hazard rate.

Table 7. Parameter Estimation in the Initial Weibull Regression Model.

Variable	Parameter Estimation	z-score	p-value
X_1	-0.1995	-0.8300	0.40772
X_2	-0.0179	-1.3700	0.17044
X_3	0.4937	1.5400	0.12439
X_4	-0.3981	-2.8300	0.00466
X_5	-0.0083	-0.7400	0.46077
X_6	0.6801	2.8300	0.00469
X_7	-180.39	-0.3700	0.71212
X_8	0.3576	1.7300	0.08282
X_9	-0.2239	-0.8900	0.37200

Table 8. Statistics of the Simultaneous Test for Weibull Regression

Statistic	Value
Log-likelihood (Model)	-126.4
Log-likelihood (Intercept)	-153.8
Chi-squared (χ^2)	54.65
Degrees of Freedom	9
p-value	1.4×10^{-8}
Iteration Newton-Raphson	6
Number of Observations (n)	100

3.1.4. Best Model

The best model selection was conducted using the forward method. The forward selection results indicate that the four predictor variables included in the best Cox proportional hazards model are the highest level of education ($X4$), other occupations ($X6$), rice production ($X8$), and farming costs ($X9$), with a p-value of 0.0002.

Based on Table 6, the parameter estimation results for the best Cox regression model provided, the Cox Proportional Hazards regression equation can be written as follows:

$$\text{h}(\,\text{t} \mid \text{X}\,) = h_0(\text{t}) \cdot \exp\,(0.3323X_4 \\ -1.452X_6 - 0.7967X_8 + 0.6489X_9) \tag{7}$$

3.2. Results of the Weibull Regression Test

3.2.1. Simultaneous Test

Based on Table 8, the log-likelihood value for the model with all predictor variables is -126.4, while the log-likelihood for the model with only the intercept is -153.8. This difference indicates that adding the predictor variables improves the model's fit to the data. The Chi-squared value for the model with 9 degrees of freedom (df) is 54.65, with a p-value of 1.4×10^{-8} (very small), leading to the conclusion that the model is statistically significant overall. This means there is sufficient evidence to state that at least one of the independent variables has an effect on the dependent variable.

Table 9. Partial Test for Weibull Regression.

Variable	Coefficient	Z-score	P-Value	Decision
X_1	0.3300	1.3300	0.1820	Accepted H_0
X_2	0.0092	1.0500	0.2947	Accepted H_0
X_3	0.7320	2.1400	0.0320	Reject H_0
X_4	-0.4680	-4.3900	1.1×10^{-5}	Reject H_0
X_5	0.0071	0.7200	0.4730	Accepted H_0
X_6	0.9290	3.6200	0.0003	Reject H_0
X_7	-2.3660	-3.4500	0.0005	Reject H_0
X_8	-0.1680	-2.7500	0.0059	Reject H_0
X_9	-0.3100	-3.6100	0.0003	Reject H_0

Table 10. Parameter Estimation of the Best Weibull Regression Model.

Variable	Parameter Estimation	Z-score	P-Value
X_4	-0.3444	-2.6100	0.0091
X_6	-0.3353	-3.0600	0.0022
X_8	0.7135	3.2400	0.0012
X_9	0.3861	1.9600	0.0496

Table 11. Statistics of the Best Weibull Regression Model.

Statistic	Value
Log-likelihood (Model)	-128.2
Log-likelihood (Intercept)	-153.8
Chi-squared (χ^2)	51.07
Degrees of Freedom	4
p-value	8.4×10^{-10}
Iteration Newton-Raphson	6
Number of Observations (n)	100

3.2.2. Partial Test

Based on Table 9, variables X1, X2, and X5 have p-values greater than 0.05 (0.182, 0.29468, and 0.473, respectively). This indicates that statistically, these three variables do not have a significant effect on the hazard rate. In other words, changes in X1, X2, and X5 do not significantly alter the risk of the observed event in this model, so the null hypothesis (no effect) is accepted for these variables. On the other hand, variables X3, X4, X6, X7, X8, and X9 show a significant effect on the hazard rate, as all have p-values less than 0.05. Specifically, X3, with a coefficient of 0.732 and a p-value of 0.032, indicates that this variable significantly increases the hazard rate. X4, with a coefficient of -0.468 and a very small p-value of 1.1×10^{-5}, significantly decreases the hazard rate. Variable X6 also has a significant effect on increasing the hazard rate with a coefficient of 0.929 and a p-value of 0.00029. Additionally, X7 (p-value = 0.00055) and X9 (p-value = 0.0003) significantly decrease the hazard rate, while X8 (p-value = 0.0059) also shows a significant effect in the same direction. Therefore, these

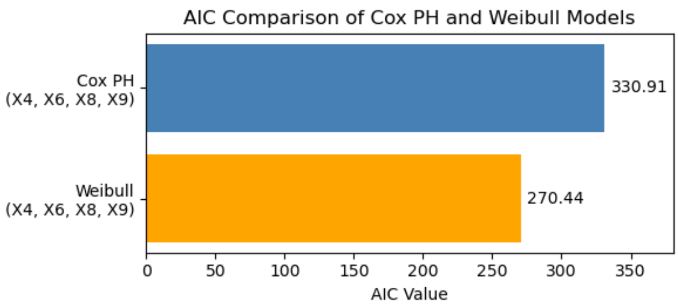

Figure 2. Comparison and selection of the best model.

significant variables should be further considered in the interpretation of the model results.

3.2.3. Best Model

In the selection of the best Weibull regression model, the stepwise method was used. The stepwise selection results show that the four predictor variables included in the best Cox proportional hazards model are the highest level of education ($X4$), other occupations ($X6$), rice production ($X8$), and farming costs ($X9$). All four variables have p-values smaller than the significance level of 0.05, so it is concluded that these four variables are included in the best Weibull regression model.

Based on Table 10, the following Weibull regression equation is obtained:

$$\lambda(t \mid X) = \lambda_0 \cdot \exp(-0.3444 \cdot X_4 - 0.3353 \cdot X_6 + 0.7135 \cdot X_8 + 0.3861 \cdot X_9) \tag{8}$$

Based on Table 11, the overall model significance test produces a very small p-value of 8.4×10^{-10}, which supports the conclusion that the model fits the data well. The convergence of the estimation algorithm within a limited number of iterations indicates the stability and reliability of the model.

3.3. Comparison and Selection of the Best Model

Based on Figure 2, the AIC value for the Weibull regression is smaller than the AIC value for the Cox Proportional Hazard regression. Therefore, it can be concluded that the Weibull regression model is better suited for the Agricultural Insurance Rice Business (AUTP) data.

4. Conclusions

Based on the analysis conducted, this study compared two survival regression models, namely the Cox Proportional Hazards model and the Weibull regression model, using the same set of variables: X4, X6, X8, and X9. The estimation results indicate that both models are capable of capturing the relationship between these variables and the time until farmers are willing to pay for agricultural insurance. However, after evaluating the models using the Akaike Information Criterion (AIC), the Weibull regression model demonstrated superior performance, with a lower AIC value of 270.4431 compared to the Cox model. This suggests that the Weibull model provides a better fit for the data and yields more accurate estimates of the timing of farmers' willingness to pay. Therefore, the Weibull model is more appropriate for supporting policy analysis and the planning of agricultural insurance programs.

5. Conflicts of Interest

The authors declare no conflicts of interest.

6. References

[1] R. Tirtalistyani, M. Murtiningrum, and R. S. Kanwar, "Indonesia Rice Irrigation System: Time for Innovation," *Sustainability*, vol. 14, no. 19, p. 12477, Sep. 2022, doi: 10.3390/su141912477.

[2] T. Sitaresmi *et al.*, "Advances in the development of rice varieties with better nutritional quality in Indonesia," *J Agric Food Res*, vol. 12, p. 100602, Jun. 2023, doi: 10.1016/j.jafr.2023.100602.

[3] Sutardi *et al.*, "The Transformation of Rice Crop Technology in Indonesia: Innovation and Sustainable Food Security," *Agronomy*, vol. 13, no. 1, p. 1, Dec. 2022, doi: 10.3390/agronomy13010001.

[4] T. D. N. Ho, J. K. M. Kuwornu, T. W. Tsusaka, L. T. Nguyen, and A. Datta, "An assessment of the smallholder rice farming households' vulnerability to climate change and variability in the Mekong delta region of Vietnam," *Local Environ*, vol. 26, no. 8, pp. 948–966, Aug. 2021, doi: 10.1080/13549839.2021.1937971.

[5] S. Weerasekara, C. Wilson, B. Lee, and V.-N. Hoang, "Impact of natural disasters on the efficiency of agricultural production: an exemplar from rice farming in Sri Lanka," *Clim Dev*, vol. 14, no. 2, pp. 133–146, Feb. 2022, doi: 10.1080/17565529.2021.1893635.

[6] R. Darma, P. O'Connor, R. Akzar, A. N. Tenriawaru, and R. Amandaria, "Enhancing Sustainability in Rice Farming: Institutional Responses to Floods and Droughts in Pump-

Based Irrigation Systems in Wajo District, Indonesia," *Sustainability*, vol. 17, no. 8, p. 3501, Apr. 2025, doi: 10.3390/su17083501.

[7] Maemunah, M. N. Y. Utomo, and R. Nur, "Development of an Agricultural Department Application to Predict Small Chili Prices," *Jurnal Teknologi Elekterika*, vol. 21, no. 2, pp. 100–110, Nov. 2024, doi: 10.31963/elekterika.v21i2.5104.

[8] Y. Ngongo *et al.*, "Land Cover Change and Food Security in Central Sumba: Challenges and Opportunities in the Decentralization Era in Indonesia," *Land (Basel)*, vol. 12, no. 5, p. 1043, May 2023, doi: 10.3390/land12051043.

[9] N. Ngadi *et al.*, "Challenge of Agriculture Development in Indonesia: Rural Youth Mobility and Aging Workers in Agriculture Sector," *Sustainability*, vol. 15, no. 2, p. 922, Jan. 2023, doi: 10.3390/su15020922.

[10] L. R. E. Malau, A. T. Darhyati, and Suharno, "The impact of climate change and natural disasters on food security in Indonesia: lessons learned on preserving forests sustainability," *IOP Conf Ser Earth Environ Sci*, vol. 886, no. 1, p. 012090, Nov. 2021, doi: 10.1088/1755-1315/886/1/012090.

[11] B. Rachman *et al.*, "Sustainability status, sensitive and key factors for increasing rice production: A case study in West Java, Indonesia," *PLoS One*, vol. 17, no. 12, p. e0274689, Dec. 2022, doi: 10.1371/journal.pone.0274689.

[12] M. Jamaludin, "Indonesia's Food Security Challenges: How Food SOE Optimizes its Role?," *Research Horizon*, vol. 2, no. 3, pp. 394–401, Jun. 2022, doi: 10.54518/rh.2.3.2022.394-401.

[13] M. A. Syah, M. Mukson, and W. Roessali, "Farmer Satisfaction Analysis on Rice Farming Insurance Program in Tegal Regency," *Agrisocionomics: Jurnal Sosial Ekonomi Pertanian*, vol. 5, no. 1, pp. 40–55, Jun. 2021, doi: 10.14710/agrisocionomics.v5i1.7361.

[14] M. I. Rachman, N. Nuryartono, B. Arifin, and T. Bakhtiar, "Optimizing crop insurance strategy as a protection tool from crop failure, due to climate change through private sector involvement," *IOP Conf Ser Earth Environ Sci*, vol. 739, no. 1, p. 012029, Apr. 2021, doi: 10.1088/1755-1315/739/1/012029.

[15] E. Ellyta, Ekawati, R. Rizieq, and M. A. Anggreni, "Analysis of farmers' perceptions of the rice farming AUTP program in Landak Regency," *IOP Conf Ser Earth Environ Sci*, vol. 951, no. 1, p. 012029, Jan. 2022, doi: 10.1088/1755-1315/951/1/012029.

[16] I. Dwijayana and S. D. W. Prajanti, "Farmer's Perception of Rice Farming Insurance Program," *Efficient: Indonesian Journal of Development Economics*, vol. 4, no. 3, pp. 1350–1360, Dec. 2021, doi: 10.15294/efficient.v4i3.46702.

[17] B. Silaban, B. Burhanuddin, and H. Harmini, "The Impact of Rice Farm Insurance on The Income of Farmers In Indonesia," *Jurnal Manajemen dan Agribisnis*, Mar. 2022, doi: 10.17358/jma.19.1.59.

[18] S. Landini and K. Noussia, "The Role of Insurance in Dealing with Disasters: The Case of Agricultural Insurance," in *Cross-Disciplinary Impacts on Insurance Law*, 2024, pp. 53–71. doi: 10.1007/978-3-031-38526-1_3.

[19] M. Robles, "Agricultural insurance for development: Past, present, and future," 2020. doi: 10.2499/9780896293830_17.

[20] R. Shofiyati, S. M. Pasaribu, M. Ardha, and Y. R. Irawan, "Climate Change Adaptation: Remote Sensing-Based Flood Crop Loss Assessment to Support Crop Insurance," in *Agriculture, Livestock Production and Aquaculture*, Cham: Springer International Publishing, 2022, pp. 167–179. doi: 10.1007/978-3-030-93258-9_10.

[21] Md. S. Hossain, "Assessing smallholder farmers' flood risk behavior and their willingness to pay for crop insurance as a risk coping strategy in northern Bangladesh," *Natural Hazards*, vol. 121, no. 4, pp. 4191–4217, Mar. 2025, doi: 10.1007/s11069-024-06958-7.

[22] Md. M. Islam, T. Ahamed, S. Matsushita, and R. Noguchi, "A Damage-Based Crop Insurance System for Flash Flooding: A Satellite Remote Sensing and Econometric Approach," in *Remote Sensing Application II*, 2024, pp. 121–163. doi: 10.1007/978-981-97-1188-8_5.

[23] I. S. Anugrah and H. H. Setiawan, "Local Wisdom-Based Food Security in Facing the Climate Crisis in Indonesia," in *Climate Crisis, Social Responses and Sustainability*, 2024, pp. 561–582. doi: 10.1007/978-3-031-58261-5_24.

[24] W. D. Prastiwi, T. Dalmiyatun, and W. Roessali, "Farmers' preference of agricultural insurance product's attributes in Pati Regency," in *The Third International Symposium on Food and Agrobiodiversity (ISFA 2021): Opportunities and Challenges of Sustainable Agriculture and Food Production during Global Pandemic*, 2023, p. 050006. doi: 10.1063/5.0106702.

[25] L. S. Ringo, H. Siregar, N. Kusnadi, and H. Harianto, "Enhancing Farmers' Insurance Literacy: Key To Improving AUTP Accessibility in Aceh Province," *Jurnal Manajemen dan Agribisnis*, vol. 22, no. 1, p. 120, Mar. 2025, doi: 10.17358/jma.22.1.120.

[26] R. Kousar, T. I. Ahmad, S. Abbas, and M. A. Bhatti, "Factors Affecting Farmers' Willingness to Pay for Agricultural Insurance: A Literature Survey (2004-2023)," *iRASD Journal of Economics*, vol. 5, no. 2, pp. 598–611, Jun. 2023, doi: 10.52131/joe.2023.0502.0149.

[27] A. Wodaju, Z. Nigussie, A. Yitayew, B. Tegegne, A. Wubalem, and S. Abele, "Factors influencing farmers' willingness to pay for weather-indexed crop insurance policies in rural Ethiopia," *Environ Dev Sustain*, vol. 27, no. 4, pp. 8951–8976, Dec. 2023, doi: 10.1007/s10668-023-04262-1.

[28] V. Hoang and V. Nguyen, "Determinants of small farmers' participation in contract farming in developing countries: A study in Vietnam," *Agribusiness*, vol. 39, no. 3, pp. 836–853, Jul. 2023, doi: 10.1002/agr.21795.

[29] D. A. Ankrah, N. A. Kwapong, D. Eghan, F. Adarkwah, and D. Boateng-Gyambiby, "Agricultural insurance access and acceptability: examining the case of smallholder farmers in Ghana," *Agric Food Secur*, vol. 10, no. 1, p. 19, Dec. 2021, doi: 10.1186/s40066-021-00292-y.

[30] O. Parmaksiz and G. Cinar, "Technology Acceptance among Farmers: Examples of Agricultural Unmanned Aerial Vehicles," *Agronomy*, vol. 13, no. 8, p. 2077, Aug. 2023, doi: 10.3390/agronomy13082077.

[31] Mayawi, Nurhayati, N. S. Laamena, A. Widyastuty, M. Salmin, and T. Talib, "Perbandingan Model Regresi Weibull and Regresi Cox Proposional Hazard(Studi Kasus Pada Pasien Infark Miokard Akut di RSUP . Dr . Sardjito Yogyakarta)," *Science Map*, vol. 4, no. 2, pp. 49–60, 2022, [Online]. Available: https://ojs3.unpatti.ac.id/index.php/sciencemap/article/view/6172

[32] S. Damayanti, T. Wuryandari, and S. Sudarno, "Perbandingan Analisis Survival Menggunakan Regresi Cox Proportional Hazard Dan Regresi Weibull Pada Pasien Covid-19 Di Rsud Taman Husada Bontang," *Jurnal Gaussian*, vol. 12, no. 3, pp. 453–464, 2023, doi: 10.14710/j.gauss.12.3.453-464.

[33] A. Azizy, Suyitno, and M. Siringoringo, "Model Regresi Cox Proportional Hazard Weibull pada Data Waktu Rawat Inap Pasien Penderita Covid-19 di RSUD Abdul Wahab Sjahranie Samarinda,"*Prosiding Seminar Nasional Matematika, Statistika, dan Aplikasinya*, pp. 143–160, 2023, [Online]. Available: https://jurnal.fmipa.unmul.ac.id/index.php/SNMSA/article/view/1179

[34] S. Sulantari and W. Hariadi, "Analisis Survival Model Regresi Cox Pada Lama Waktu Sembuh Pasien Gejala Sedang Covid-19," *Unisda Journal of Mathematics and Computer Science (UJMC)*, vol. 8, no. 1, pp. 43–54, 2022, doi: 10.52166/ujmc.v8i1.3070.

[35] R. Widyastuti, D. Wulandari, and D. Prasetyowati, "Penerapan regresi cox untuk menganalisis variabel yang berpengaruh terhadap durasi studi mahasiswa," vol. 13, pp. 88–98, 2024, doi: 10.14710/j.gauss.13.1.88-98.

[36] H. D. Panduwinata, Suyitno, and M. N. Huda, "Model Regresi Weibull Pada Data Kontinu yang Diklasifikasikan (Studi Kasus: Indikator Pencemaran Air BOD di DAS Mahakam Tahun 2016)," *Jurnal Eksponensial* , vol. 13, pp. 123–130, 2022.

[37] T. Wuryandari, Danardono, and Gunardi, "Model Regresi Cox Proporsional Hazard pada Data Durasi Proses Kelahiran dengan Ties," *Statistika*, vol. 9, no. 1, pp. 47–55, 2021, doi: https://doi.org/10.26714/jsunimus.9.1.2021.47-55.

[38] A. S. Khinanti, S. Sudarno, and T. Wuryandari, "Model Regresi Cox Proportional Hazard Pada Data Ketahanan Hidup Pasien Hemodialisa," *Jurnal Gaussian*, vol. 10, no. 2, pp. 303–314, 2021, doi: 10.14710/j.gauss.v10i2.30958.

[39] Hasmiati, Suyitno, and Y. N. Nasution, "Model Regresi Weibull Pada Data Waktu Rawat Inap Pasien Penderita Penyakit Jantung Koroner Dengan Event Kematian Di Rsud Abdul Wahab Sjahranie Samarinda," *Prosiding Seminar Nasional Matematika, Statistika, dan Aplikasinya*, pp. 369–376, 2022.

[40] W. W. Cahyani and F. Rakhmawati, "Analisis Survival Menggunakan Regresi Weibull Pada Laju Kesembuhan Pasien Jantung Koroner Survival Analysis Using Weibull Regression on the Recovery Rate of Coronary Heart Patients," vol. 9, no. 2, pp. 39–45, 2024, doi: https://doi.org/10.26740/sainsmat..v9n2.p39-45.