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Performance of 45 Non-Linear Models for Determining Critical Period of Weed Control and Acceptable Yield Loss in Soybean Agroforestry Systems

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Abstract: A family of Sigmoidal non-linear models is commonly used to determine the critical period of weed control (CPWC) and acceptable yield loss (AYL) in annual crops. We tried to prove another non-linear model to determine CPWC and AYL in a soybean agroforestry system with *kayu putih*. The three-year experiment (from 2019–2021) was conducted using a randomised complete block design factorial with five blocks as replications. The treatments comprised weedy and weed-free periods. Non-linear models comprised 45 functions. The results show that the Sigmoidal and Dose-Response Curve (DRC) families were the most suitable for estimating CPWC and AYL. The best fitted non-linear model for weedy and weed-free periods in the dry season used the Sigmoidal family consisting of the Weibull and Richards models, while in the wet season the best fit was obtained using the DRC and Sigmoidal families consisting of the DR-Hill and Richards models, respectively. The CPWC of soybean in the dry season for AYL was 5, 10, and 15%, beginning at 20, 22, and 24 days after emergence (DAE) and ended at 56, 54, and 52 DAE. The AYL in the wet season started at 20, 23, and 26 DAE and ended at 59, 53, and 49 DAE.

Keywords: agroforestry; AYL; CPWC; *kayu putih*; non-linear models; soybean; weed-free period; weedy period

1. Introduction

A problem of soybean cultivation with non-tillage systems in rain-fed areas lies in competition for solar radiation, water, and nutrients with weeds [1–4]. In addition, weeds secrete allelopathy in the form of phytotoxins that inhibit plant growth [5,6]. Weeds can reduce soybean productivity, thus minimising the income of farmers [7,8]. Weed control is considered a critical factor in the success of soybean production. Suryanto et al. [8] reported that competition between soybeans and weeds could reduce soybean production in agroforestry systems with *kayu putih* (*Melaleuca cajuputi*) by 80.09%.

The critical period of weed control (CPWC) is defined as the maximum length of time from which the initial weeds appear, which can disturb the plant without causing a significant yield loss [9]. Only some stages of plant growth are susceptible to weed competition [10]. Weeds emerging with the crop should be removed by the V2 or V3 stage of soybean development, particularly when weeds are less than 4 inches tall, to minimise yield loss. Weeds can reduce soybean yield by 1% daily if left uncontrolled after the V2 to V3 stage of soybean growth [11]. The soybean yield in agroforestry with *kayu putih* significantly decreased when the weedy periods were conducted after 14 up to 42 days after emergence (DAE) [8].

Various methods related to integrated weed management have been developed for weed control. One of these methods is the CPWC [12]. Knowledge of the critical timing of weed removal, critical weed-free period, and subsequently the CPWC, could help producers improve their weed management strategies and prevent yield loss due to weed interference whilst reducing the amount of herbicide use.

CPWC has two components: weedy and weed-free curves. The weedy curve is the maximum amount of time that the crop can tolerate early-season weed competition before suffering from an irreversible yield reduction, whilst the weed-free curve is the minimum weed-free period necessary from the time of planting to prevent yield loss [12]. The beginning and end of the CPWC are determined by calculations using a non-linear model equation based on the level of acceptable yield loss (AYL) to predict its beginning and end [12]. CPWC has been widely used as a guideline for weed removal timing of soybean [8,9,13].

Various types of statistical methods, including multiple comparison techniques and non-linear models, have also been widely reported in the literature [9]. Non-linear models are important tools because many crop and soil processes are better represented by non-linear than linear models. The main advantages of non-linear models lie in their parsimony, interpretability, and prediction [14].

Many researchers have widely used non-linear models to estimate CPWC and AYL in various annual crop commodities. Some non-linear models used to determine CPWC include the Sigmoidal family, such as Boltzmann, Exponential, Logistic, and Gompertz models [8,12,15–21]. The development of various types of non-linear models does not dismiss the existence of other non-linear models that are substantially accurate in determining the CPWC of soybean, especially those planted amongst *kayu putih* stands.

We tried to prove another non-linear model to determine CPWC and AYL in soybean agroforestry system with *kayu putih*. The performance of different non-linear regression models on soybean planted for three years (2019–2021) in the dry and wet seasons is compared in this study. The accuracy of the best non-linear models for determining CPWC and AYL in soybean agroforestry systems with *kayu putih* is also investigated.

2. Materials and Methods

2.1. Study Site

The study was conducted in Menggoran Forest Resort, Playen District, Gunungkidul Regency, Special Province of Yogyakarta, Indonesia, in dry and wet seasons from 2019 to 2021. This area is located ±43 km south-east of Yogyakarta City (Figure 1). The altitude of the command area is ±150 m above sea level, with an average air temperature of 25.60 °C and relative humidity of 84.20%. The average rainfall is 2005 mm year^{-1}, and the soil type is Lithic Haplusterts [8,22]. The dominant annual weeds in this study consisted of *Spigelia anthelmia*, *Lindernia crustacea*, and *Eleutheranthera ruderalis*, while the perennial weeds were *Panicum distachyum*, *Panicum muticum*, and *Leptochloa chinensis*.

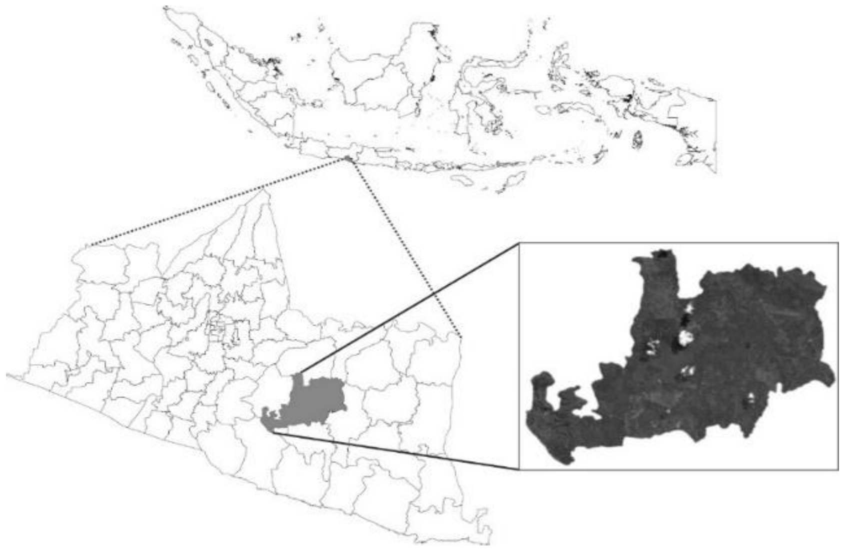

Figure 1. The geographical locations of the study area are as follows: latitude 7°57′50″ S and longitude 110°29′54″ E.

2.2. Experimental Design and Crop Management

All the trials were laid out in a randomised complete block design with five blocks as replications. The treatments included the duration of weedy (0, 7, 14, 21, 28, 35, 42, 49, 56, and 63 DAE) and weed-free (0, 7, 14, 21, 28, 35, 42, 49, 56, and 63 DAE) periods in soybean, which comprised 20 levels as illustrated in Table 1. This research was conducted during the dry and wet seasons and was repeated for three years (2019–2021).

Table 1. Weedy and weed-free periods of treatments.

Duration of Weedy and Weed-Free Periods [1]	Remarks
W—0 DAE	Weedy until 70 days after emergence (DAE)
W—7 DAE	Weedy after 7 until 70 DAE
W—14 DAE	Weedy after 14 until 70 DAE
W—21 DAE	Weedy after 21 until 70 DAE
W—28 DAE	Weedy after 28 until 70 DAE
W—35 DAE	Weedy after 35 until 70 DAE
W—42 DAE	Weedy after 42 until 70 DAE
W—49 DAE	Weedy after 49 until 70 DAE
W—56 DAE	Weedy after 56 until 70 DAE
W—63 DAE	Weedy after 63 until 70 DAE
WF—7 DAE	Weed-Free after 7 until 70 DAE
WF—14 DAE	Weed-Free after 14 until 70 DAE
WF—21 DAE	Weed-Free after 21 until 70 DAE
WF—28 DAE	Weed-Free after 28 until 70 DAE
WF—35 DAE	Weed-Free after 35 until 70 DAE
WF—42 DAE	Weed-Free after 42 until 70 DAE
WF—49 DAE	Weed-Free after 49 until 70 DAE
WF—56 DAE	Weed-Free after 56 until 70 DAE
WF—63 DAE	Weed-Free after 63 until 70 DAE
WF—0 DAE	Weed-Free until 70 DAE

[1] W: Weedy period; WF: Weed-free period.

The soybean variety used in this study was the Grobogan variety. This variety is commonly used by farmers in Indonesia and has high yields, wide stability and short age [22,23]. The seeds were obtained from the Indonesian Legumes and Tuber Crops Research Institute in Malang Regency, Province of East Java, Indonesia. The experimental plots covered an area of 20 m^2 (5 m × 4 m) between *kayu putih* stands and a harvest area of

12 m^2, excluding the border rows. The plant spacing was 40 cm × 20 cm. Pesticide and fertiliser were not used in this study. Irrigation was not performed because the field used in this study was in a rain-fed area.

2.3. Data Collection

The data collected for each treatment (duration of weed, seasons, and years) was the seed weight per plot in the harvest area (12 m^2). Seed weight per plot was weighed using a digital scale, and the moisture content was measured using a moisture tester. Seed weight per plot was converted to seed weight per hectare with a moisture content of 12% using the formula [8,22,23]:

$$\text{yield}\ (\text{tons ha}^{-1}) = \frac{10,000}{\text{HA}} \times \frac{100 - \text{MC}}{100 - 12} \times \text{Y} \tag{1}$$

where yield is the yield of soybean (tons ha^{-1}), HA is harvest area (7 m^2), MC is the seed moisture content at harvesting and Y is the seed weight at harvesting.

2.4. Statistical Analysis

The following steps were considered [14]: (i) selection of candidate models; (ii) measures of goodness-of-fit for the best non-linear models; (iii) evaluation of model assumptions, and (iv) model calibration between observed and prediction values.

2.4.1. Selection of Candidate Models

Forty-five non-linear models were used in determining the duration of weedy and weed-free periods in soybean. A general example of the non-linear model is as follows:

$$y = f(x,\ \theta) + \varepsilon, \tag{2}$$

where y is the response variable, f is the function or model, x is the input, θ denotes the estimated parameters, and ε is an error term [14].

The non-linear models used in this study were Decline, Distribution, Dose–Response Curve, Exponential, Growth, Miscellaneous, Power Law Family, Sigmoidal, and Yield-Spacing families. The non-linear equation models are detailed in Tables 2 and 3.

Table 2. Detail family of non-linear models used in this study.

Decline	Distribution	Dose–Response	Exponential	Growth	Miscellaneous	Power Law Family	Sigmoidal	Yield-Spacing Models
– Exponential Decline	– Log Normal CDF	– DR-Gamma	– Exponential	– Exponential Association 2	– Gaussian model	– Geometric	– Gompertz Relations	– Bleasdale
– Harmonic	– Log Normal PDF	– DR-Hill	– Modified Exponential	– Exponential Association 3	– Heat Capacity	– Hoerl	– Logistics	– Farazdaghi–Harris
– Hyperbolic Decline	– Normal (Gaussian) CDF	– DR-Logistic	– Natural Logarithm	– Saturation Growth Rate	– Rational model	– Modified Geometric	– Logistics Power	– Reciprocal
	– Normal (Gaussian) PDF	– DR-Probit	– Reciprocal Logarithm		– Sinusoidal	– Modified Hoerl	– Morgan Mercer Flodin (MMF)	– Reciprocal Quadratic
		– DR-Weibull	– Vapour Pressure models		– Steinhart–Hart equation	– Modified Power	– Ratkowsky	
					– Truncated Fourier Series	– Power	– Richards	
						– Root	– Weibull	
						– Shifted Power		

Table 3. Non-linear equation models used in this study.

No.	Model	Family	Equation	References
1.	Bleasdale	Yield-Spacing Models	$y = (a + bx)^{\frac{-1}{c}}$	[24]
2.	Exponential	Exponential Models	$y = ae^{bx}$	[24]
3.	Exponential Association 2	Growth Models	$y = a\left(1 - e^{-bx}\right)$	[24]
4.	Exponential Association 3	Growth Models	$y = a\left(b - e^{-cx}\right)$	[24]
5.	Exponential Decline	Decline Models	$y = q_0 e^{\frac{-x}{a}}$	[25]
6.	Farazdaghi–Harris	Yield-Spacing Models	$y = 1/(a + bx^c)$	[26]
7.	DR-Gamma	Dose–Response Models		[26]
8.	DR-Hill	Dose–Response Models	$y = \alpha + \frac{\theta x^\eta}{\kappa^\eta + x^\eta}$	[26]
9.	DR-Logistic	Dose–Response Models	$y = \gamma + \frac{1-\gamma}{1+e^{-\alpha-\beta x}}$	[26]
10.	DR-Probit	Dose–Response Models	$y = \gamma + \frac{1-\gamma}{2}\left[1 + \mathrm{erf}\left(\frac{\alpha+\beta x}{\sqrt{2}}\right)\right]$	[26]
11.	DR-Weibull	Dose–Response Models	$y = \gamma + (1 - \gamma)\left(1 - e^{-\beta x^{\alpha}}\right)$	[26]
12.	Gaussian Model	Miscellaneous	$y = ae^{\frac{-(x-b)^2}{2c^2}}$	[24]
13.	Geometric	Power Law Family	$y = ax^{bx}$	[24]
14.	Gompertz Relation	Sigmoidal Models	$y = ae^{-e^{b-cx}}$	[24]
15.	Harmonic Decline	Decline Models	$y = q_0/(1 + x/a)$	[24]
16.	Hyperbolic Decline	Decline Models	$y = q_0(1 + bx/a)^{(-1/b)}$	[24]
17.	Heat Capacity	Miscellaneous	$y = a + bx + c/x^2$	[24]
18.	Hoerl	Power Law Family	$y = ab^x x^c$	[27]
19.	Logistic	Sigmoidal Models	$y = a/\left(1 + be^{-cx}\right)$	[24]
20.	Logistic Power	Sigmoidal Models	$y = a/\left(1 + (x/b)^c\right)$	[27]
21.	Log Normal CDF	Distribution Models	$y = \frac{1}{2}\mathrm{erfc}\left(-\frac{\ln(x) - \mu}{\sigma\sqrt{2}}\right)$	[27]
22.	Log Normal PDF	Distribution Models	$y = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln(x) - \mu}{\sigma}\right)^2}$	[27]
23.	Modified Exponential	Exponential Models	$y = ae^{b/x}$	[24]
24.	Modified Geometric	Power Law Family	$y = ax^{b/x}$	[24]
25.	Modified Hoerl	Power Law Family	$y = ab^{1/x_{x^c}}$	[24]
26.	Modified Power	Power Law Family	$y = ab^x$	[24]
27.	Morgan–Mercer–Flodin (MMF)	Sigmoidal Models	$y = \frac{ab + cx^d}{b + x^d}$	[28]
28.	Natural Logarithm	Exponential Models	$y = a + b\ln(x)$	[27]
29.	Normal (Gaussian) CDF	Distribution Models	$y = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{x - \pi}{\sigma\sqrt{2}}\right)\right]$	[27]
30.	Normal (Gaussian) PDF	Distribution Models	$y = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x - \mu}{\sigma}\right)^2}$	[27]
31.	Power	Power Law Family	$y = ax^b$	[24]
32.	Rational Model	Miscellaneous	$y = \frac{a + bx}{1 + cx + dx^2}$	[24]
33.	Ratkowsky	Sigmoidal Models	$y = a/\left(1 + e^{b-cx}\right)$	[28]
34.	Reciprocal	Yield-Spacing Models	$y = 1/(a + bx)$	[24]

Table 3. *Cont.*

No.	Model	Family	Equation	References
35.	Reciprocal Logarithm	Exponential Models	$y = \frac{1}{a+b\ln(x)}$	[27]
36.	Reciprocal Quadratic	Yield-Spacing Models	$y = 1/\left(a + bx + cx^2\right)$	[24]
37.	Richards	Sigmoidal Models	$y = \frac{a}{\left(1+e^{b\ -cx}\right)^{1/d}}$	[29]
38.	Root	Power Law Family	$y = ab^{\frac{1}{x}}$	[24]
39.	Saturation Growth Rate	Growth Models	$y = ax/(b + x)$	[24]
40.	Shifted Power	Power Law Family	$y = a(x - b)^c$	[24]
41.	Sinusoidal	Miscellaneous	$y = a + b\cos(cx + d)$	[24]
42.	Steinhart–Hart Equation	Miscellaneous	$y = \frac{1}{a+b\ln(x)+c(\ln(x))^3}$	[24]
43.	Truncated Fourier Series	Miscellaneous	$y = \alpha\cos(x + d)+b\cos(2x + d) + \cos(3x + d)$	[27]
44.	Vapour Pressure Model	Exponential Models	$y = e^{a+b/x+c\ln(x)}$	[24]
45.	Weibull	Sigmoidal Models	$y = a - be^{-cx^d}$	[30]

2.4.2. Measures for Goodness-of-Fit

The best amongst non-linear models was evaluated by goodness-of-fit [31]. Different statistical criteria can be used depending on the model structure to find the best model, including highest adjusted coefficient of determination $\left(R^2_{adj}\right)$, lowest root mean square error (RMSE), lowest bias-corrected Akaike information criterion (AIC_C), and lowest Bayesian information criterion (BIC) [31].

R^2_{adj} was chosen to compensate for the bias due to the difference in the number of parameters:

$$R^2_{adj} = 1 - \frac{n - 1}{n - p} * \left(1 - R^2\right), \tag{3}$$

where n is the sample size, p is the number of parameters, and R^2 is the coefficient of determination [32,33].

$$R^2 = 1 - \frac{SS_{residual}}{SS_{total}}, \tag{4}$$

where $SS_{residual}$ and SS_{total} are the sums of the square for the residual and the total, respectively [32,33].

$$RMSE = \sqrt{\frac{SS_{residual}}{n - p - 1}}, \tag{5}$$

where $SS_{residual}$ is the sum of the square for the residual; n is the number of data points, and p is the number of model parameters [31].

An AIC variant that corrects small sample sizes, namely the bias-corrected AIC (AICc) was employed to ensure fairness.

$$AIC_C = AIC + \frac{2p(p + 1)}{n - p - 1}, \tag{6}$$

where n is the sample size, p is the number of parameters, and AIC is the AIC_C [34].

$$AIC = 2p - 2\ln(L), \tag{7}$$

where p is the number of parameters and ln(L) is the maximum log-likelihood of the estimated model [35].

The BIC, which provides a high penalty on the number of parameters, was also chosen.

$$BIC = p \ln(n) - 2 \ln(L), \quad (8)$$

where p is the number of parameters; n is the sample size, and L is the maximum likelihood of the estimated model [36].

The values of R^2_{adj}, RMSE, AICc, and BIC in each non-linear model were averaged over three years based on seasons (dry and wet) and weed durations (weedy and weed-free periods).

2.4.3. Evaluation of Model Assumptions

The next step was to evaluate key model assumptions, normally distributed with a Q–Q plot and homogeneous variance with a residual versus value graph [14,37].

2.4.4. Model Calibration

The model calibration between observed and prediction values during weedy and weed-free periods in soybean used the pooled *T*-test ($p < 0.05$) [38].

2.4.5. Data Analysis

Data analysis included the following: calculation of 45 non-linear models, evaluation of model assumptions, measures of goodness-of-fit, and model calibration between observed and prediction values (weedy and weed-free periods using PROC NLMIXED and PROC TTEST in SAS 9.4 and RStudio software v. 3.6.3 R Development Core Team, respectively) with the drc and nlstools packages, and CurveExpert Professional software [9,27,39,40].

3. Results

3.1. Choose Candidate Models for Determining CPWC

The predicted data for 45 non-linear models to determine the weedy and weed-free periods in the wet and dry seasons on soybean in an agroforestry system with *kayu putih* are illustrated in Tables 4 and 5. The best fitted models were evaluated on the basis of the highest R^2_{adj}, lowest RMSE, lowest AICc, and lowest BIC. The evaluation results showed that the Weibull model was the best fitted non-linear model for determining the weedy period in the dry season. The values of R^2_{adj}, RMSE, AICc, and BIC for the Weibull model were 0.997, 1.732, 15.883, and 19.128, respectively, under the following model parameters: $a = 96.221$, $b = 88.989$, $c = 3.202 \times 10^{-3}$, and $d = -2.357$ (Table 4). Furthermore, the best fitted non-linear model for determining the weed-free period in the dry season was the Richards model with R^2_{adj}, RMSE, AICc, and BIC values of 0.996, 2.298, 19.944, and 23.708, respectively, under the following model parameters: $a = 98.525$, $b = 17.820$, $c = 0.312$, and $d = 10.223$ (Table 4).

The Dose–Response Hill (DR-Hill) and Richards models were the best fitted non-linear models for determining weedy and weed-free periods in the wet season. The values of R^2_{adj}, RMSE, AICc and BIC for the DR-Hill model were 0.997, 1.822, 16.893, and 20.238, respectively, under the following model parameters: $\alpha = 15.082$, $\theta = 72.743$, $\eta = -4.241$, and $\kappa = 37.369$ (Table 5). The values of R^2_{adj}, RMSE, AICc, and BIC for the Richards model were 0.996, 2.194, 17.464, and 21.061, respectively, under the following model parameters: $a = 97.432$, $b = 420.280$, $c = 7.172$, and $d = 233.497$ (Table 5).

Table 4. Goodness-of-fit of non-linear models for the weedy and weed-free periods in the dry season.

No.	Models	Periods [1]	Goodness-of-Fit			
			R^2_{adj}	RMSE	AICc	BIC
1.	Bleasdale	W WF	0.946 0.952	8.143 7.348	44.091 42.035	52.018 49.529
2.	Exponential	W WF	0.933 0.952	7.607 6.873	40.851 38.819	48.092 45.628
3.	Exponential Association 2	W WF	0.000 0.966	32.789 5.796	70.070 35.411	83.550 41.523
4.	Exponential Association 3	W WF	0.956 0.974	7.340 5.397	42.015 35.863	49.500 42.065
5.	Exponential Decline	W WF	0.946 0.952	7.617 6.873	40.876 38.819	48.122 45.628
6.	Farazdaghi–Harris	W WF	0.991 0.957	3.246 6.951	25.697 40.925	30.163 48.180
7.	DR-Gamma	W WF	0.986 0.000	4.099 33.528	30.361 72.395	35.585 86.167
8.	DR-Hill	W WF	0.000 0.991	37.861 3.490	77.570 29.890	92.334 34.974
9.	DR-Logistic	W WF	0.000 0.000	73.558 77.572	88.109 89.172	104.131 105.216
10.	DR-Probit	W WF	0.000 0.000	73.558 77.572	88.109 89.172	104.131 105.216
11.	DR-Weibull	W WF	0.000 0.000	73.558 77.572	88.109 89.172	104.131 105.216
12.	Gaussian	W WF	0.983 0.987	4.125 3.813	30.487 28.913	35.733 33.832
13.	Geometric	W WF	0.967 0.936	5.973 7.949	36.015 41.731	42.280 49.159
14.	Gompertz Relation	W WF	0.000 0.983	31.328 4.427	71.038 31.902	84.698 37.343
15.	Harmonic Decline	W WF	0.859 0.872	12.326 11.199	50.503 48.585	59.836 57.518
16.	Hyperbolic Decline	W WF	0.969 0.978	6.192 4.925	38.613 34.032	45.394 39.874
17.	Heat Capacity	W WF	0.957 0.984	7.270 4.334	41.822 31.477	49.266 36.841
18.	Hoerl	W WF	0.990 0.973	3.101 5.483	24.783 36.181	29.113 42.447
19.	Logistic	W WF	0.843 0.987	12.427 3.829	52.545 28.999	62.331 33.932
20.	Logistic Power	W WF	0.992 0.968	2.710 5.973	22.085 37.890	26.039 44.505
21.	Log Normal CDF	W WF	0.000 0.000	68.807 72.642	84.895 85.979	100.613 101.690
22.	Log Normal PDF	W WF	0.000 0.000	64.208 66.136	83.573 84.103	99.144 99.595
23.	Modified Exponential	W WF	0.512 0.888	22.901 10.521	62.891 47.336	74.936 55.992

Table 4. *Cont.*

No.	Models	Periods [1]	Goodness-of-Fit			
			R^2_{adj}	RMSE	AICc	BIC
24.	Modified Geometric	W	0.640	19.688	59.869	71.269
		WF	0.931	8.268	42.515	50.113
25.	Modified Hoerl	W	0.972	5.903	37.657	44.246
		WF	0.982	4.560	32.493	38.043
26.	Modified Power	W	0.946	7.617	40.876	48.122
		WF	0.952	6.873	38.819	45.628
27.	MMF	W	0.996	2.097	19.414	23.035
		WF	0.980	4.721	33.189	38.870
28.	Natural Logarithm	W	0.863	10.852	47.956	56.725
		WF	0.832	12.840	51.320	60.857
29.	Normal (Gaussian) CDF	W	0.000	68.807	84.895	100.613
		WF	0.000	72.701	85.996	101.709
30.	Normal (Gaussian) PDF	W	0.000	61.212	82.556	98.006
		WF	0.000	65.515	83.914	99.383
31.	Power	W	0.731	15.178	54.666	64.924
		WF	0.968	5.586	34.675	40.642
32.	Rational Model	W	0.996	2.323	21.748	25.658
		WF	0.995	2.608	24.065	28.268
33.	Ratkowsky	W	0.982	4.223	30.962	36.291
		WF	0.987	3.829	28.999	33.932
34.	Reciprocal	W	0.859	50.503	50.503	59.836
		WF	0.873	11.199	48.586	57.519
35.	Reciprocal Logarithm	W	0.641	19.634	59.814	71.202
		WF	0.958	6.449	37.547	44.092
36.	Reciprocal Quadratic	W	0.996	2.311	18.904	22.466
		WF	0.995	2.435	21.532	25.443
37.	Richards	W	0.995	2.379	22.222	26.194
		WF	0.996	2.298	19.944	23.708
38.	Root	W	0.512	22.901	62.892	74.937
		WF	0.888	10.521	47.336	55.992
39.	Saturation Growth Rate	W	0.438	24.580	64.308	76.648
		WF	0.966	5.794	35.405	41.516
40.	Shifted Power	W	0.918	10.010	48.219	57.046
		WF	0.978	4.925	34.032	39.874
41.	Sinusoidal	W	0.994	2.694	24.711	29.031
		WF	0.992	3.191	28.099	32.885
42.	Steinhart–Hart Equation	W	0.957	7.236	41.729	49.154
		WF	0.980	4.721	33.189	38.870
43.	Truncated Fourier Series	W	0.000	73.623	90.870	107.092
		WF	0.000	79.345	92.368	108.695
44.	Vapour Pressure Model	W	0.954	6.726	40.266	47.386
		WF	0.981	4.560	32.493	38.043
45.	Weibull	W	0.997	1.732	15.883	19.128
		WF	0.993	3.113	27.601	32.308

[1] W: Weedy period; WF: Weed-free period.

Table 5. Goodness-of-fit of non-linear models for the weedy and weed-free periods in the wet season.

No.	Models	Periods [1]	Goodness-of-Fit			
			R^2_{adj}	RMSE	AICc	BIC
1.	Bleasdale	W WF	0.931 0.961	8.188 6.741	44.200 40.311	52.151 47.435
2.	Exponential	W WF	0.947 0.961	7.533 6.305	40.653 37.095	47.853 43.547
3.	Exponential Association 2	W WF	0.000 0.966	29.249 5.858	67.786 35.625	80.828 41.780
4.	Exponential Association 3	W WF	0.961 0.969	6.183 5.970	38.585 37.882	45.361 44.496
5.	Exponential Decline	W WF	0.931 0.961	7.659 6.305	40.985 37.095	48.254 43.547
6.	Farazdaghi–Harris	W WF	0.992 0.960	2.861 6.796	23.171 40.475	27.272 47.634
7.	DR-Gamma	W WF	0.987 0.000	3.526 34.020	27.351 72.687	32.074 86.509
8.	DR-Hill	W WF	0.997 0.993	1.822 3.115	16.893 27.618	20.238 32.328
9.	DR-Logistic	W WF	0.000 0.000	69.330 75.296	86.925 88.576	102.844 104.562
10.	DR-Probit	W WF	0.000 0.000	69.330 75.296	86.925 88.576	102.844 104.562
11.	DR-Weibull	W WF	0.000 0.000	69.330 75.296	86.925 88.576	102.844 104.562
12.	Gaussian	W WF	0.981 0.987	4.790 29.496	33.478 29.496	39.261 34.513
13.	Geometric	W WF	0.956 0.947	6.119 7.319	36.498 40.079	42.858 47.154
14.	Gompertz Relation	W WF	0.000 0.983	35.125 4.423	73.326 31.885	87.396 37.323
15.	Harmonic Decline	W WF	0.842 0.883	11.615 10.894	49.314 48.033	58.383 56.844
16.	Hyperbolic Decline	W WF	0.965 0.980	5.845 4.810	37.458 33.563	44.007 39.315
17.	Heat Capacity	W WF	0.965 0.983	5.861 4.384	37.515 31.705	44.076 37.110
18.	Hoerl	W WF	0.992 0.975	3.116 5.403	24.877 35.888	29.221 42.095
19.	Logistic	W WF	0.859 0.961	13.186 6.740	53.731 40.309	63.781 47.433
20.	Logistic Power	W WF	0.992 0.966	3.037 6.242	24.363 38.772	28.632 45.571
21.	Log Normal CDF	W WF	0.000 0.000	64.852 70.469	83.711 85.372	99.298 101.014
22.	Log Normal PDF	W WF	0.000 0.000	58.588 63.230	81.680 83.204	97.021 98.586
23.	Modified Exponential	W WF	0.884 0.888	10.860 10.661	47.971 47.600	56.744 56.315

Table 5. *Cont.*

No.	Models	Periods [1]	Goodness-of-Fit			
			R^2_{adj}	RMSE	AICc	BIC
24.	Modified Geometric	W WF	0.608 0.927	18.314 8.618	58.421 43.346	69.506 51.125
25.	Modified Hoerl	W WF	0.952 0.983	6.845 4.379	40.618 31.684	47.811 37.085
26.	Modified Power	W WF	0.931 0.961	7.659 6.305	40.985 37.095	48.254 43.547
27.	MMF	W WF	0.996 0.978	2.296 5.410	21.519 38.656	25.399 45.431
28.	Natural Logarithm	W WF	0.892 0.808	10.797 13.928	47.854 52.947	56.601 62.841
29.	Normal (Gaussian) CDF	W WF	0.000 0.000	64.852 70.567	83.711 85.400	99.298 101.045
30.	Normal (Gaussian) PDF	W WF	0.000 0.000	58.407 65.701	81.617 83.971	96.950 99.447
31.	Power	W WF	0.760 0.966	16.086 5.838	55.827 35.558	66.342 41.699
32.	Rational Model	W WF	0.996 0.996	2.453 2.323	22.839 21.748	26.894 25.681
33.	Ratkowsky	W WF	0.982 0.987	4.725 3.824	33.205 28.973	38.938 33.902
34.	Reciprocal	W WF	0.842 0.883	11.615 10.894	49.314 48.033	58.383 56.844
35.	Reciprocal Logarithm	W WF	0.620 0.961	18.032 6.304	58.112 37.091	69.129 43.542
36.	Reciprocal Quadratic	W WF	0.993 0.996	2.573 2.194	21.051 20.608	24.871 24.430
37.	Richards	W WF	0.997 0.996	2.125 2.194	19.971 17.464	23.658 21.061
38.	Root	W WF	0.481 0.888	21.063 10.661	61.219 47.600	72.909 56.315
39.	Saturation Growth Rate	W WF	0.413 0.966	22.400 5.847	62.450 35.597	74.402 41.746
40.	Shifted Power	W WF	0.901 0.980	9.842 4.810	47.882 33.563	56.635 39.315
41.	Sinusoidal	W WF	0.989 0.993	3.960 3.0819	32.415 27.403	38.003 32.080
42.	Steinhart–Hart Equation	W WF	0.939 0.980	7.744 4.774	43.087 33.411	50.799 39.134
43.	Truncated Fourier Series	W WF	0.000 0.000	69.928 76.577	89.841 91.658	105.995 107.926
44.	Vapour Pressure Model	W WF	0.970 0.983	6.056 4.379	38.169 31.682	44.861 37.083
45.	Weibull	W WF	0.998 0.994	1.839 0.9972	17.073 25.140	20.436 29.485

[1] W: Weedy period; WF: Weed-free period.

3.2. Evaluation of Model Assumptions

The best non-linear model chosen to determine CPWC and AYL must fulfil normal distribution and homogeneous variance assumptions. The analysis results of the Q–Q plot graph show that all selected non-linear models had normally distributed data (Figure 2A–D). Analysis of the homogeneous variance using a residual versus value graph revealed that all selected non-linear models had homogeneous variance (Figure 3A–D). The results of the assumption test demonstrate that the selected non-linear model candidate fulfilled all assumptions and can thus be used to determine CPWC and AYL.

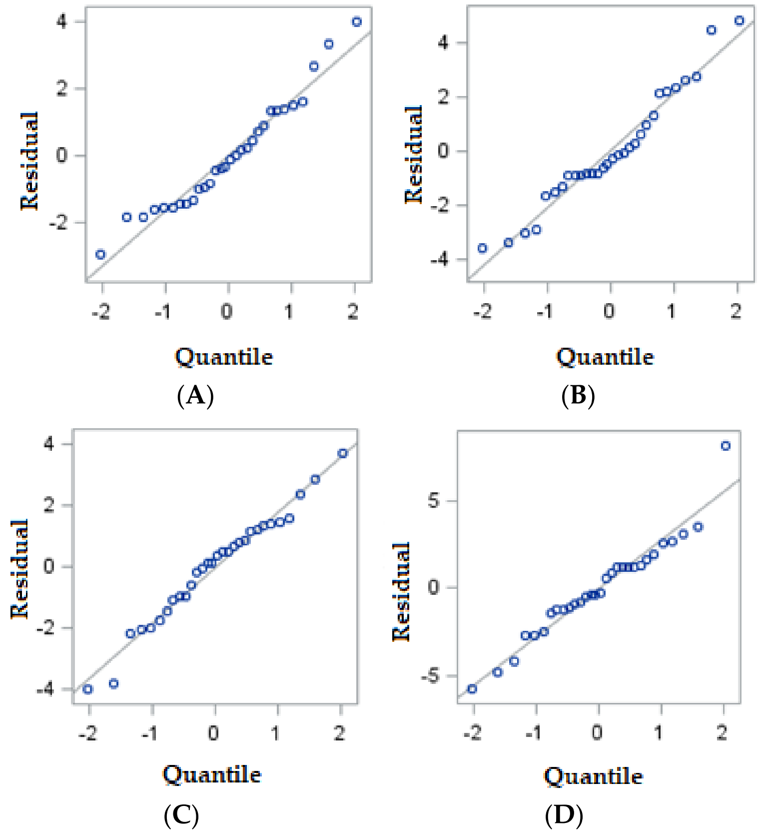

Figure 2. Q–Q plot to evaluate the assumption of normally distributed variance. (**A**) Weedy period in the dry season using the Weibull Model. (**B**) Weed-free period in the dry season using the Richards model. (**C**) Weedy period in the wet season using the DR-Hill model. (**D**) Weed-free period in the wet season using Richards model.

3.3. Model Calibration

Comparing the observed versus predicted values in the weedy and weed-free periods in the dry and wet seasons used the pooled *T*-test ($t < 0.05$). The observed and predicted values using the Weibull model showed no significant difference ($t < 0.998^{ns}$) based on the pooled T-test in the weedy period (Figure 4A). The same result was found in the weed-free period with the predicted value of the Richards model, and no significant difference ($t < 0.999^{ns}$) was observed (Figure 4B). A similar trend was also obtained in the wet season between the observed versus predicted values in the weedy period (DR-Hill model) and weed-free period (Richards model), which revealed no significant difference ($t < 0.999^{ns}$ and $t < 0.999^{ns}$) (Figure 4C,D). Overall, the four selected non-linear models satisfy the aforementioned assumptions and are feasible to use.

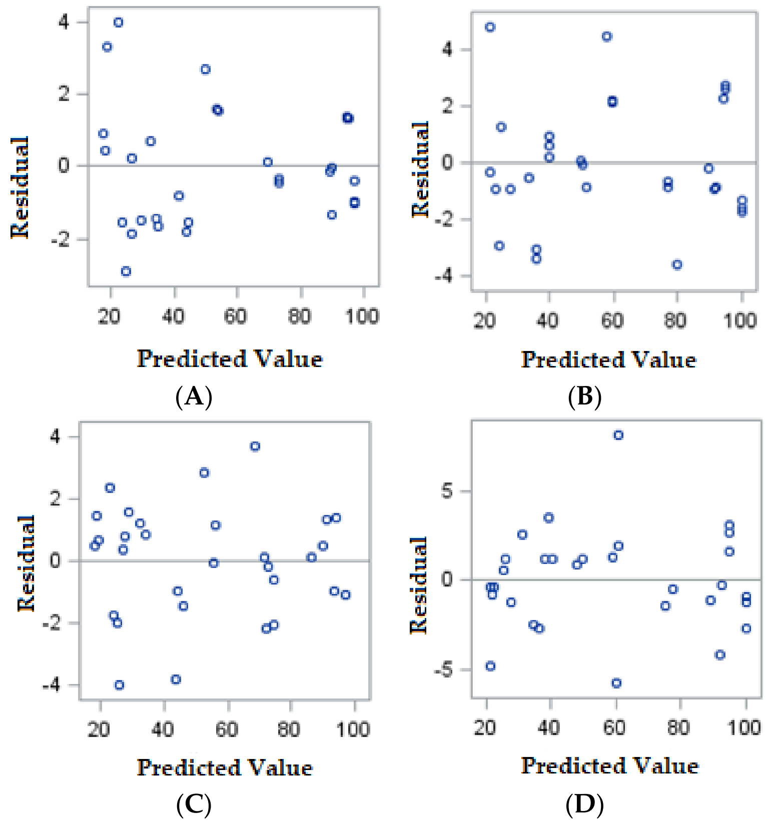

Figure 3. Residual versus value graph to evaluate the assumption of homogeneous variance. (**A**) Weedy period in the dry season using the Weibull model. (**B**) Weed-free period in the dry season using the Richards model. (**C**) Weedy period in the wet season using the DR-Hill model. (**D**) Weed-free period in the wet season using the Richards model.

3.4. Predicted AYL Based on the Best Fitted Model

Weed control throughout the season (dry and wet) demonstrated yield loss below 5% AYL. The CPWC of soybean in the dry season for AYL was 5, 10, and 15%, which began at 20, 22, and 24 days after emergence (DAE), respectively, and ended at 56, 54, and 52 DAE (Figure 5 and Table 6). The AYL in the wet season began at 20, 23, and 26 DAE and ended at 59, 53, and 49 DAE (Figure 6 and Table 6).

Table 6. Critical period of weed control (CPWC) in soybean yield for acceptable yield loss (AYL) based on days after emergence (DAE).

AYL (%)	Dry Season		Wet Season	
	Beginning	End	Beginning	End
5	20	56	20	59
10	22	54	23	53
15	24	52	26	49

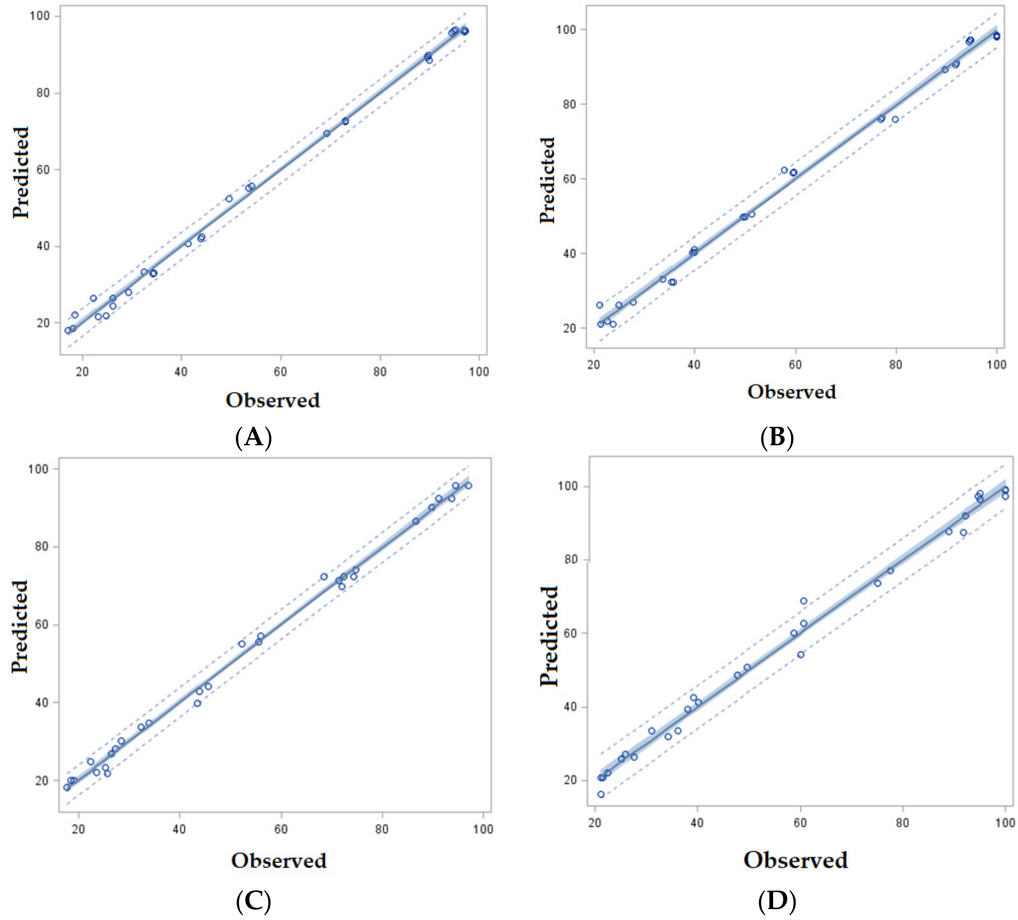

Figure 4. Comparison of observed versus predicted values of relative yield (% of weed-free) of soybean in agroforestry system with *kayu putih*. (**A**) Weedy period in the dry season using the Weibull model. (**B**) Weed-free period in the dry season using the Richards model. (**C**) Weedy period in the wet season using the DR-Hill model. (**D**) Weed-free period in the wet season using the Richards model.

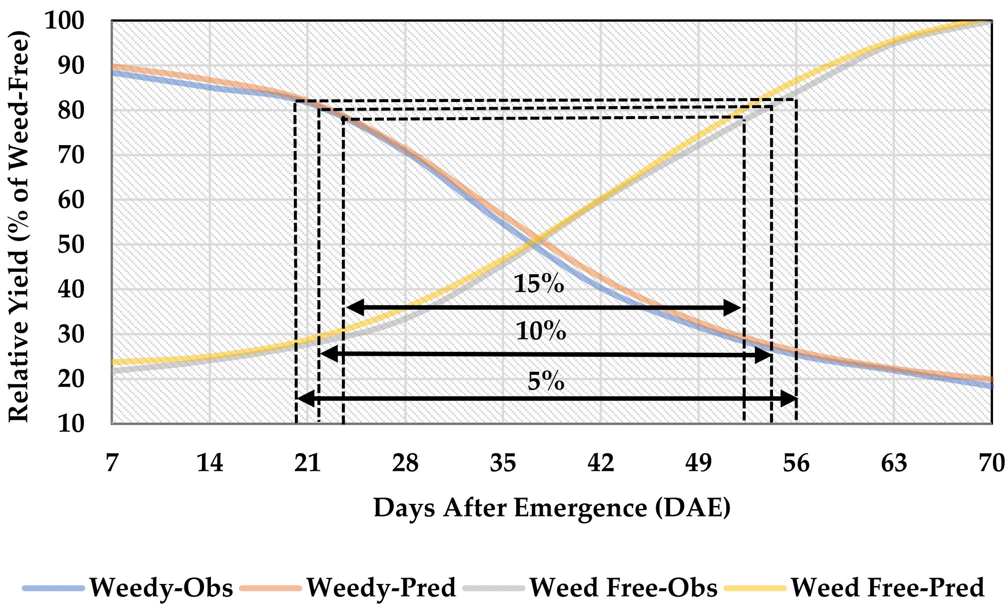

Figure 5. Relative yield (% of weed-free) of soybean in agroforestry system with *kayu putih* as influenced by increasing weedy and weed-free periods (expressed in DAE) in dry season. The weedy period used the Weibull model, whilst the weed-free period used the Richards model.

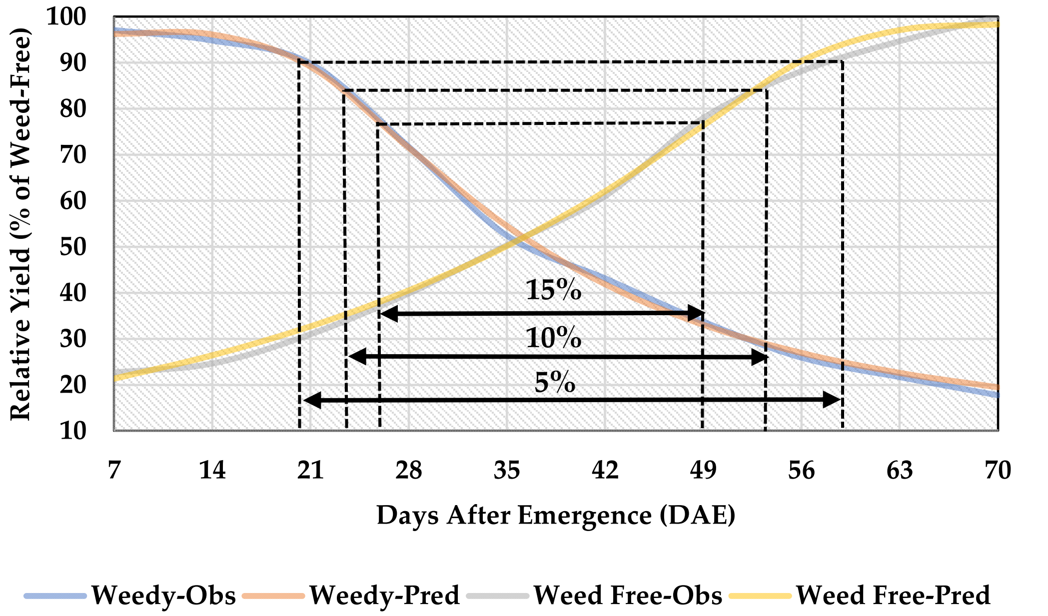

Figure 6. Relative yield (% of weed-free) of soybean in agroforestry system with *kayu putih* as influenced by increasing weedy and weed-free periods (expressed in DAE) in wet season. The weedy period used the Dose–Response Hill (DR-Hill) model, whilst the weed-free period used the Richards model.

4. Discussion

The advantage of using a non-linear regression model lies in its stronger prediction compared to polynomials, especially outside the observed data range (extrapolation) [14]. Compared with a linear model, a non-linear model has an unbiased least squares estimator, minimum variance, and normally distributed estimator [28]. The best fitted non-linear model to determine the weedy and weed-free periods in the CPWC and AYL was selected on the basis of the highest R^2_{adj}, lowest RMSE, lowest AIC_C, and lowest BIC [26,34,41,42].

R^2 is not used to measure goodness-of-fit for non-linear models. R^2 represents the percentage of variability in Y, which has been explained by the fit regression model ranging from 0% to 100%. This value is used to provide prediction limits for new observations [43]. A wide error exists in the non-linear regression where R^2 is used to decide on the fit of the non-linear model. R^2 is effectively utilised to indicate the proportion of variation explained by the linear model, whilst R^2 does not have a definite meaning for non-linear regression models [28,33,42,43].

AICc and BIC are measured to assist in selecting model candidates [35,36]. The best model demonstrates the lowest AICc and BIC based on the aforementioned criterion. This criterion considers the proximity of the point to the model and the number of parameters used by the model. AICc is designed to compare the performance of models that have been fitted to the data through maximum likelihood estimation [34]. Bauldry [44] showed that BIC can be used to select the model with more parsimonious criteria than complex models.

The results of the current study indicate that the Weibull, DR-Hill, and Richards models are the best for predicting weed and weed-free periods in the wet and dry seasons. All selected non-linear models fulfilled the assumptions set, namely normal distribution and homogeneous variance, as indicated by the absence of outliers and extreme data [14].

The Weibull and Richards models belong to the Sigmoidal family, whilst the DR-Hill curve is included in the Dose–Response Curve (DRC) family. The Sigmoidal family is often used to describe plant height, weight, leaf area index, seed germination as a function of time, N application rate, and herbicide dose [45]. The Sigmoidal family is also used as a 0–1 modifier in process-based models to include moisture availability, soil pH, soil N transformation processes, and a breaker function in studies assessing plant photoperiodic sensitivity [46].

The Weibull model has never been used in selecting CPWC and AYL. However, this model is widely utilised in agriculture, forestry, and livestock research to explain growth models. The Weibull model is also recommended for studies related to growth (plants and animals) because it has a smaller additive term error compared with that of Gompertz and Richards models [47]. Mahanta and Borah [48] used the Weibull model to explain the growth of trees. The Weibull model was also utilised to calculate the height increase of the *Pinus radiate* [49]. The application of the Weibull model can help more accurately describe the macromineral requirements of laying hens compared with the Logistics and Gompertz models [50]. Weibull is the best model amongst other non-linear models for broiler and Japanese quail growth. This model is also the most suitable, but has poor logistics [51].

The Richards model is widely used by researchers to determine CPWC for various annual crops, and such determination is possible because this model is direct and has remarkable flexibility and accuracy [52]. Suryanto et al. [8] used the Richards model to estimate the increasing duration of the weedy period in soybeans. The Richards model can also be used to predict CPWC and AYL. Teleken et al. [53] revealed that a modified Richards model could more accurately predict isothermal and non-isothermal microbial growth in food products compared with other models.

Dose–Response Curve (DRC) are widely used in several sciences (medicine, biology, and chemistry). This model is widely utilised in plant growth analysis to assess the effect of toxicity or dose of fertiliser [54]. Knezevic and Datta [9] and Tursun et al. [21] reported a recent development regarding the use of DRC in determining CPWC and AYL. This finding is due to the rapid development of software, especially R Software, which can estimate DRC, including the drc package (dose–response curve) [37].

DR-Hill, which belongs to the family of DRC, was considered in this study to be best to determine the weedy period in the wet season. The DR-Hill model has been widely used in biochemistry and pharmacology to describe the binding of ligands to macromolecules as a function of ligand concentration. The DR-Hill model is also used in biology to model the regulation of gene transcription [55]. The use of the DR-Hill model concerning the determination of CPWC and AYL was not observed. This finding is novel because the DR-Hill model is one of the best non-linear models for CPWC and AYL estimation.

The CPWC of soybean in the dry season for AYL was 5, 10, and 15%, and began at 20, 22, and 24 DAE and ended at 56, 54, and 52 DAE. The AYL in wet season began at 20, 23, and 26 DAE and ended at 59, 53, and 49 DAE. The critical period for soybeans against weeds generally begins when soybeans are at 20 DAE and ends at 59 DAE. Soybeans enter the pre-flowering phase (V3) to seed filling (R3) during this time. Limited environmental factors (soil moisture, nutrients, and sunlight) in these critical phases reduce soybean yields [56]. Various environmental conditions between the wet and dry seasons cause differences in soybean AYL. Suryanto et al. [8] stated that competition between soybeans and weeds was influenced by the dry weight of weed, weed heterogeneity, and soil moisture availability.

5. Conclusions

The Sigmoidal and Dose–Response Curve (DRC) families were the most suitable for estimating CPWC and AYL. The best fitted non-lienear model for weedy and weed-free periods in the dry season used the Sigmoidal family consisting of the Weibull (R^2_{adj} = 0.997; RMSE = 1.732; AICc = 15.883; BIC = 19.128) and Richards (R^2_{adj} = 0.996; RMSE = 2.298; AICc = 19.944; BIC = 23.708) models, while in the wet season the best fits were obtained using the DRC and Sigmoidal families consisting of the DR-Hill (R^2_{adj} = 0.997; RMSE = 1.822; AICc = 16.893; BIC = 20.238) and Richards (R^2_{adj} = 0.996; RMSE = 2.194; AICc = 17.464; BIC = 21.061) models, respectively. A comparison between the observed versus predicted values in the weedy and weed-free periods in the dry and wet seasons showed no significant differences. The CPWC of soybean in the dry season for AYL was 5, 10, and 15%, and began at 20, 22, and 24 DAE and ended at 56, 54, and 52 DAE. The AYL in the wet season started at 20, 23, and 26 DAE and ended at 59, 53, and 49 DAE.

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References

1. Abbas, A.; Khaliq, A.; Saqib, M.; Majeed, M.Z.; Ullah, S.; Haroon, M. Influence of tillage systems and selective herbicides on weed management and productivity of direct-seeded rice (*Oryza sativa*). *Planta Daninha* **2019**, *37*, 1–15. [CrossRef]
2. Hosseini, S.Z.; Firouzi, S.; Aminpanah, H.; Sadeghnejhad, H.R. Effect of tillage system on yield and weed populations of soybean (*Glycine max* L.). *An. Acad. Bras. Ciências* **2016**, *88*, 377–384. [CrossRef] [PubMed]
3. Swanton, C.J.; O'Sullivan, J.; Robinson, D.E. The critical weed-free period in carrot. *Weed Sci.* **2010**, *58*, 229–233. [CrossRef]
4. Travlos, I.S.; Cheimona, N.; Roussis, I.; Bilalis, D.J. Weed-species abundance and diversity indices in relation to tillage systems and fertilization. *Front. Environ. Sci.* **2018**, *6*, 11. [CrossRef]
5. Bastiaans, L.; Kropff, M.J. Weed competition. In *Encyclopedia of Applied Plant Sciences: Crop Systems*, 2nd ed.; Thomas, B., Murray, B.G., Murphy, D.J., Eds.; Academic Press: New York, NY, USA, 2017; Volume 3, pp. 473–478.
6. McLeod, R. *Annual Costs of Weeds in Australia*; eSYS Development Pty Limited: Sydney, NSW, Australia, 2018; pp. 9–14.
7. Shrestha, A.; Thapa, B.; Devkota, M.; Subedi, R. Comparative efficiency of different weed management practices on yield and economic in summer maize in Dang. *Adv. Crop. Sci. Tech.* **2018**, *6*, 2.
8. Suryanto, P.; Tohari, S.E.; Putra, E.T.S.; Kastono, D.; Alam, T. Estimation of critical period for weed control in soybean on agro-forestry system with *kayu putih*. *Asian J. Crop Sci.* **2017**, *9*, 82–91. [CrossRef]
9. Knezevic, S.Z.; Datta, A. The critical period for weed control: Revisiting data analysis. *Weed Sci.* **2015**, *63*, 188–202. [CrossRef]
10. Zandoná, R.R.; Agostinetto, D.; Silva, B.M.; Ruchel, Q.; Fraga, D.S. Interference periods in soybean crop as affected by emergence times of weeds. *Planta Daninha* **2018**, *36*, e018169361. [CrossRef]
11. Hartzler, R. Is Your Weed Management Program Reducing Your Economic Return? Iowa State University: Ames, IA, USA, 2003. Available online: http://extension.agron.iastate.edu/weeds/mgmt/2003/economics.shtml (accessed on 9 February 2022).
12. Knezevic, S.Z.; Evans, S.P.; Blankenship, E.E.; Van Acker, R.C.; Lindquist, J.L. Critical period of weed control: The concept and data analysis. *Weed Sci.* **2002**, *50*, 773–786. [CrossRef]
13. Hendrival, W.; Zurrahmi; Abdul, A. Critical period for weed control competition in soybean. *Floratek J.* **2014**, *9*, 6–13.
14. Archontoulisa, S.V.; Miguez, F.E. Nonlinear regression models and applications in agricultural research. *Agron. J.* **2014**, *107*, 786–798. [CrossRef]
15. Cardoso, G.D.; Alves, P.L.C.A.; Severino, L.S.; Vale, L.S. Critical periods of weed control in naturally green colored cotton BRS Verde. *Ind. Crops Prod.* **2011**, *34*, 1198–1202. [CrossRef]
16. Singh, M.; Bhullar, M.S.; Chauhan, B.S. The critical period for weed control in dry-seeded rice. *Crop Prot.* **2011**, *66*, 80–85. [CrossRef]
17. Singh, M.; Bhullar, M.S.; Chauhan, B.S. Relative time of weed and crop emergence is crucial for managing weed seed production: A study under an aerobic rice system. *Crop Prot.* **2017**, *99*, 33–38. [CrossRef]
18. Stagnari, F.; Pisante, M. The critical period for weed competition in French bean (*Phaseolus vulgaris* L.) in Mediterranean areas. *Crop Prot.* **2011**, *30*, 179–184. [CrossRef]

19. Seyyedi, S.M.; Moghaddam, P.R.; Mahallati, M.N. Weed competition periods affect grain yield and nutrient uptake of black seed (*Nigella Sativa* L.). *Hortic. Plant J.* **2016**, *2*, 172–180. [CrossRef]
20. Tursun, N.; Datta, A.; Tuncel, E.; Kantarci, Z.; Knezevic, S.Z. Nitrogen application influenced the critical period for weed control in cotton. *Crop Prot.* **2015**, *74*, 85–91. [CrossRef]
21. Tursun, N.; Datta, A.; Sakinmaz, M.S.; Kantarci, Z.; Knezevic, S.Z.; Chauhan, B.S. The critical period for weed control in three corn (*Zea mays* L.) types. *Crop Prot.* **2016**, *90*, 59–65. [CrossRef]
22. Alam, T.; Kurniasih, B.; Suryanto, P.; Basunanda, P.; Supriyanta; Ambarwati, E.; Widyawan, M.H.; Handayani, S.; Taryono. Stability analysis for soybean in agroforestry system with kayu putih. *SABRAO J. Breed. Genet.* **2019**, *51*, 405–418.
23. Alam, T.; Suryanto, P.; Handayani, S.; Kastono, D.; Kurniasih, B. Optimizing application of biochar, compost and nitrogen fertilizer in soybean intercropping with kayu putih (*Melaleuca cajuputi*). *Rev. Bras. Cienc. Solo* **2020**, *44*, 1–17. [CrossRef]
24. Kuri-Morales, A.; Rodríguez-Erazo, F. A search space reduction methodology for large databases: A case study. In *Advances in Data Mining: Theoretical Aspects and Applications*; Carbonell, J.G., Siekmann, J., Eds.; Springer: Leipzig, Germany, 2007; pp. 204–205.
25. Satter, A.; Iqbal, G.M. Decline curve analysis for conventional and unconventional reservoirs. *Reservoir. Eng.* **2016**, 211–232. Available online: https://www.researchgate.net/publication/314643400_Decline_curve_analysis_for_conventional_and_unconventional_reservoirs (accessed on 20 June 2022).
26. Ritz, C.; Baty, F.; Streibig, J.C.; Gerhard, D. Dose-response analysis using R. *PLoS ONE* **2015**, *10*, e0146021.
27. Hyams, D.G. CurveExpert Professional Documentation. Available online: https://www.curveexpert.net/docs/curveexpert/pro/pdf/CurveExpertProfessional.pdf (accessed on 9 February 2022).
28. Ratkowsky, D.A. *Handbook of Nonlinear Regression Models*; Marcel Dekker: New York, NY, USA, 1990; pp. 123–147.
29. Richards, F.J. The quantitative analysis of growth. In *Plant Physiology*; Steward, F.C., Ed.; Academic Press: New York, NY, USA, 1969; pp. 3–76.
30. Weibull, W. A statistical distribution function of wide applicability. *J. Appl. Mech.* **1951**, *18*, 293–297. [CrossRef]
31. Wallach, D. Evaluating crop models. In *Working with Dynamic Crop Models: Evaluations, Analysis, Parameterization, and Applications*, 1st ed.; Wallach, D., Makowski, D., Jones, J., Eds.; Elsevier: Amsterdam, The Netherlands, 2006; pp. 11–53.
32. Anderson-Sprecher, R. Model comparisons and R-square. *Am. Stat.* **1994**, *48*, 113–117.
33. Kvalseth, T.O. Cautionary note about R^2. *Am. Stat.* **1985**, *39*, 279–285.
34. Burnham, K.P.; Anderson, D.R. *Model Selection and Inference: A Practical Information-Theoretic Approach*, 2nd ed.; Springer: New York, NY, USA, 2003; pp. 271–273.
35. Akaike, H. A new look at the statistical model identification. *IEEE Trans. Autom. Control.* **1974**, *19*, 716–723. [CrossRef]
36. Schwarz, G. Estimating the dimension of a model. *Ann. Stat.* **1978**, *6*, 461–464. [CrossRef]
37. Ritz, C.; Streibig, J.C. *Nonlinear Regression with R*; Springer: New York, NY, USA, 2008; pp. 4–6.
38. Bhattacharyya, M. To pool or not to pool: A comparison between two commonly used test statistics. *Int. J. Pure Appl. Math.* **2013**, *89*, 497–510. [CrossRef]
39. SAS Institute Inc. *Step-by-Step Programming with Base SAS® 9.4*, 2nd ed.; SAS Institute Inc.: Cary, NC, USA, 2013.
40. Baty, F.; Ritz, C.; Charles, S.; Brutsche, M.; Flandrois, J.P.; Delignette-Muller, M.L. A toolbox for nonlinear regression in R: The package nlstools. *J. Stat. Softw.* **2015**, *66*, 1–21. [CrossRef]
41. Lewis, F.; Butler, A.; Gilbert, L. A unified approach to model selection using the likelihood ratio test. *Methods Ecol. Evol.* **2011**, *2*, 155–162. [CrossRef]
42. Spiess, A.N.; Neumeyer, N. An evaluation of R^2 as an inadequate measure for nonlinear models in pharmacological and biochemical research: A Monte Carlo approach. *BMC Pharmacol.* **2010**, *10*, 6. [CrossRef]
43. Draper, N.R.; Smith, H. *Applied Regression Analysis*, 3rd ed.; John Wiley & Sons, Inc.: New York, NY, USA, 1998; pp. 243–250.
44. Bauldry, S. Structural equation modeling. In *International Encyclopedia of the Social & Behavioral Sciences*, 2nd ed.; Wright, J.D., Ed.; Elsevier: Amsterdam, The Netherlands, 2015; pp. 615–620.
45. Miguez, F.E.; Villamil, M.B.; Long, S.P.; Bollero, G.A. Meta-analysis of the effects of management factors on Miscanthus × giganteus growth and biomass production. *Agric. For. Meteorol.* **2008**, *148*, 1280–1292. [CrossRef]
46. Amaducci, S.; Colauzzi, M.; Bellocchi, G.; Venturi, G. Modelling post-emergent hemp phenology (*Cannabis sativa* L.): Theory and evaluation. *Eur J. Agron.* **2008**, *28*, 90–102. [CrossRef]
47. Dagogo, J.; Nduka, E.C.; Ogoke, U.P. Comparative analysis of richards, gompertz and weibull models. *IOSR J. Math.* **2020**, *16*, 15–25.
48. Mahanta, D.J.; Borah, M. Parameter estimation of weibull growth models in forestry. *Int. J. Math. Trends Technol.* **2014**, *8*, 158–163.
49. Colff, M.V.D.; Kimberley, M.O. A national height-age model for *Pinus radiata* in New Zealand. *N. Z. J. For. Sci.* **2013**, *43*, 1–11.
50. Sholikin, M.M.; Alifian, M.D.; Purba, F.M.; Harahap, R.P.; Jayanegara, A.; Nahrowi. Evaluate Non-Linear Model Logistic, Gompertz, and Weibull: Study Case on Calcium and Phosphor Requirements of Laying Hen. In Proceedings of the Conference Series: Earth and Environmental Science, Malang, Indonesia, 24–27 October 2020.
51. Raji, A.O.; Mbap, S.T.; Aliyu, J. Comparison of different models to describe growth of the japanese quail (*Coturnix japonica*). *Trakia J. Sci.* **2014**, *12*, 182–188.
52. Svagelj, W.S.; Laich, A.G.; Quintana, F. Richards's equation and nonlinear mixed models applied to avian growth: Why use them? *J. Avian Biol.* **2019**, *2019*, 1–8. [CrossRef]

53. Teleken, J.T.; Galvão, A.C.; Robazza, W.S. Use of modified Richards model to predict isothermal and non-isothermal microbial growth. *Braz. J. Microbiol.* **2018**, *49*, 614–620. [CrossRef]
54. Ritz, P.P.; Rogers, M.B.; Zabinsky, J.S.; Hedrick, V.E.; Rockwell, J.A.; Rimer, E.G. Dietary and biological assessment of the omega-3 status of collegiate athletes: A cross-sectional analysis. *PLoS ONE* **2020**, *15*, e0228834. [CrossRef]
55. Gesztelyi, R.; Zsuga, J.; Kemeny-Beke, A.; Varga, B.; Juhasz, B.; Tosaki, A. The hill equation and the origin of quantitative pharmacology. *Arch. Hist. Exact Sci.* **2012**, *66*, 427–438. [CrossRef]
56. Sobko, O.; Stahl, A.; Hahn, V.; Zikeli, S.; Claupein, W.; Gruber, S. Environmental effects on soybean (*Glycine max* (L.) Merr) production in Central and South Germany. *Agronomy* **2020**, *10*, 1847. [CrossRef]