Predicting junglerice (*Echinochloa colona* L.) emergence as a function of thermal time in the Humid Pampas of Argentina

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Junglerice (*Echinochloa colona*) is one of the most important annual weeds affecting crops in Argentina. A predictive seedling emergence model based on thermal time was developed and validated. Monitoring of seedling emergence was performed weekly during the growing season in a soybean field over four years. Cumulative thermal time, expressed in growing degree days (GDD), was used as the independent variable for predicting cumulative emergence. The variations in mean air temperature between late August and early September have determined a period with a conserved pattern over the years. That period had a close linear relationship ($r^2 = 0.99$) with the beginning of seedling emergence. A double-logistic model fitted junglerice seedling emergence better than Gompertz, Logistic or Weibull functions. Model validation showed a good performance in predicting the seedling emergence ($r^2 = 0.99$). Based on findings of this study it is possible to predict junglerice emergence by air temperature and, thus, to contribute reliably to the rational management of this weed.

Keywords: double-logistic model; non-linear emergence models; air temperature; seedlings; weed management

1 Introduction

Junglerice (*Echinochloa colona* L. Link) is one of the most important annual weeds affecting several crop production systems worldwide (Valverde et al. 2000). This weed has a high fecundity, ranging from 3,000 to 7,000 seeds per plant (Parodi 1964; Chauhan 2013; Leguizamón and Echeverría 2014). The seeds have a relatively short dormancy period, ranging from 2 to 10 months (with a seed dormancy rate of 75%) (Holm et al. 1977, Valverde et al. 2000). Seed dispersion usually occur by agricultural machinery, irrigation channels, rodents, birds, and other animals (Peerzada et al. 2016) and seeds can persist up to seven years in the soil seed bank, where up to 1% can still be viable (Uremis and Uygur 2005).

In the northwest of Buenos Aires province, the production systems of extensive farming are generally characterized by no till, the use of genetically modified (GM) soybean and maize crops (glyphosate-resistant), followed by intensive use of glyphosate (Frene 2014). This context has generated a shift in the weed flora that has led to the selection of resistant weeds. The intensive use of herbicides, coupled with soybean monoculture and limited herbicide rotation, has facilitated the evolution of acetolactate synthase (ALS)-inhibiting herbicide resistance and glyphosate resistance in junglerice (Acciaresi et al. 2016, Heap 2019).

Several studies have shown that junglerice might cause significant yield losses in different crops. Chauhan and Johnson (2010) observed that the yield of a single rice plant surrounded by eight junglerice plants can be reduced by 93%. Under field conditions, junglerice at a density of 280 plants m⁻² reduced the yield of dry-seeded rice by up to 76% (Mercado and Talatala 1977). Chhokar and Balyan (1999) demonstrated that junglerice is the most dominant in weed community in soybean crop, causing yield losses of 31% at a density of 172 plants m⁻². In Argentina, a decrease in the range of 20-45% in soybean grain yield was observed when the weed reached a 25-75% relative cover (Picapietra and Ponsa 2015).

Seedling emergence is one of the most important demographic events in the cycle of an annual plant species as the emergence timing determines its survival and reproductive success (Forcella et al. 2000). Therefore, predicting the timing of weed emergence plays a critical role in scheduling weed management measures (Forcella 1998). In the last decade, important efforts have been made in the attempt to develop models to predict seedling emergence patterns for several weed species (e.g., Zambrano-Navea et al. 2013, Yousefi et al. 2014) as a fundamental step in the development of integrated weed management (IWM) strategies.

There are models that describe and predict weed emergence, either by empirical or mechanistic approaches (Forcella et al. 2000, Grundy 2003, González-Andújar et al. 2016). The latter have the potential advantage of describing the different stages in the process of seedling emergence from seed dormancy to establishment. However, these models require a deep understanding of seed dormancy regulation and knowledge of the effects of environmental factors regulating seed germination and growth of the seedlings; besides they usually require a large amount of often unavailable or difficult to gather experimental information to be developed, calibrated, and finally validated (Grundy 2003).

Empirical weather-based models are less complex than mechanistic models. These models predict seedling emergence as a function of environmental factors (temperature and/or water potential) with the final objective to provide real-time information on weed management programs (Grenón and Mansilla 2014). Thus, these empirical models could provide adequate information on the timing and duration of seedling emergence periods after sowing (Izquierdo et al. 2009). Hydrothermal time based models include both water potential and temperature (Allen et al. 2000). These models generally improve the prediction, but soil water potential is often unavailable or difficult to get for most farmers and is unnecessary in irrigated regions (Dorado et al. 2009). Temperature-based emergence models can be good predictors for weed seedling emergence (Forcella et al. 2000). Some of these models are fitted to thermal time, such as growing degree days (GDD), predicting with accuracy seedling emergence (Myers et al. 2004, De Corby et al. 2007) for the area where that model was developed (Izquierdo et al. 2009). They can also predict emergence as well as hydrothermal models for species such as *Echinochloa crus-galli* (Bagavathiannan et al. 2011).

One limitation when developing thermal models is the beginning of the count of the accumulation of growing degree days (GDD). Different criteria have been considered to determine the beginning of GDD sum, such as seed sowing (Walker et al. 2010), crop sowing (Chauhan and Johnson 2009) or a calendar date (Leguizamón et al. 2009). However, all criteria begin GDD count from a calendar day, but the temperature over years is in constant change (Nuñez et al. 2008), so this can have an important influence on the predictive capacity of the model. This is why it would be important to associate an emergence model with weather patterns not dependent on calendar dates.

It is known that daily thermal variations around 10°C increase junglerice seedling emergence (Kovach et al. 2010, Elahifard and Mijani 2014), but there are no studies that have addressed the fluctuation of mean daily temperature through the previous days to beginning of weed emergence under field conditions. This effect could be related to the winter end temperatures and its fluctuations, since it is one of the first weeds to emerge in late-winter (Picapietra and Acciaresi 2018).

Given the important impact of junglerice on soybean and maize yield in the Humid Pampean region of Argentina and the need to decrease the selection pressure of herbicide resistances, the present study aimed to develop an emergence predictive model based on the relationship between the accumulated emergence of junglerice and GDD. Such a model could contribute to optimizing the efficacy of control measures for this species. We hypothesized that the air temperature at winter ending could be related with the beginning of seedling emergence and that it is possible to develop a predictive thermal time emergence model for junglerice in soybean crop in the Humid Pampas, Argentina.

2 Material and methods

Experiments were conducted between 2013 and 2017 at the National Institute of

Agricultural Technology (Pergamino, Buenos Aires province, Argentina, 33.95°S, 60.57°W, 56 m asl). Each year, seedling emergence from a native seed population was measure between late August and late January. In the last ten years, annual mean air temperature was 16.7 ± 0.6 °C and mean rainfall was 1162 ± 308.4 mm. All temperature and rainfall data were provided by INTA Pergamino Agrometeorology station, located 70 m from the plots.

The field size was 1 hectare and the soil was a Typical Argiudoll (Soil Survey Staff 2014) with 2% organic matter. Before and during the experiment, glyphosate-resistant soybean was cultivated under no-tillage system. Crop management was the same every year. Foliar herbicides (2,4-D plus paraquat) were used in winter fallow. Soybean sowing was between October 15th and 20th, while glyphosate after soybean emergence was applied.

2.1 Determination of GDD sum beginning

A period between late August and early September where daily mean air temperature has a repeated pattern over the years was related to junglerice seedling emergence. This period is characterized by an abrupt decrease in the daily mean air temperature (between August 20th and 27th) below base temperature (T_b) of 10°C (Leguizamón and Echeverría 2014) reaching a minimum temperature (θ), followed by an increase to a thermal maximum (ψ), after which the temperature decreases variably and then junglerice emerges (λ) (Figure 1).

[Figure 1 near here]

The maximum and minimum daily temperature was recorded and growing degree days (Eq. 1) were calculated during the period as follows:

$$GDD_{\text{daily}} = (T_{\text{max}} + T_{\text{min}})/2 - T_{\text{base}} \quad (\text{Eq. 1})$$

where GDD_{daily} is the daily growing degree days, T_{max} is the maximum daily air temperature, T_{min} is the minimum daily air.

To identify the relationship between the variations of daily mean air temperature and weed emergence, two GDD accumulation periods were determined. The first (w) comprises the sum of GDDs from the moment the initial temperature below T_b is recorded (θ) up to the following maximal air temperature (ψ). The second period (z) comprises from the record of ψ up to the moment in which the first junglerice seedling emergence is recorded (λ). Thus, a linear relation was established between both periods of GDD accumulation in 2013, 2014, and 2015 (Eq. 2):

$$z = a + b * w \quad (\text{Eq. 2})$$

where z and w express the GDDs of each corresponding period.

2.2 The emergence model selection

For adjustment of the methodology an exploratory analysis was carried out in 2013. For this reason, data from this year were not used for the model development. In this way, junglerice emergence was recorded between September 2014 and January 2016, from early September to late January in each season. Emerging seedlings were counted every 10 days in four 0.25 m² permanent plots located randomly in the field. After each sampling, seedlings were carefully removed with a minimum of soil disturbance. In the following years the plots were moved to different places within the field. Data from these experiments were used for the model development.

To avoid the direct disturbance of seed drill on the plots, soybean planting was performed one meter away from the edge of the plots. Also, plots were covered with nylon bags while glyphosate was being applied for weed control on the field.

The cumulative relative emergence (EM) was obtained through the following equation (Eq. 3):

$$EM_i = \frac{\sum(x_0..x_i)}{x_t} * 100 \quad (\text{Eq. 3})$$

where EM_i is the cumulative relative emergence at time i , x_0 is the number of emerging seedlings at the beginning, x_i is the number of emerging seedlings at time i , and x_t the total sum of the seedling emergence. The GDD were also calculated (Eq. 1) for the whole period of emergence, which began at θ .

Four non-linear models with one and two inflection points (Kannien and Khawaja 1995; Grundy 2003; Hai Seyed Hadi et al. 2009; González-Andújar et al. 2016) were considered:

Logistic:
$$EM = \frac{\alpha}{1 + \gamma * e^{(-\beta * GDD)}} \quad (\text{Eq. 4})$$

Double-logistic:
$$EM = \rho + \frac{\alpha}{1 + \delta_1 * e^{(-\beta_1 * (GDD - \gamma_1))}} - \frac{\alpha}{1 + \delta_2 * e^{(-\beta_2 * (GDD - \gamma_2))}} \quad (\text{Eq. 5})$$

Gompertz:
$$EM = \alpha * e^{(-\gamma * e^{(-\beta * GDD)})} \quad (\text{Eq. 6})$$

Weibull:
$$EM = a * e^{\left(-e^{\left(-\frac{GDD - \gamma}{\beta}\right)}\right)} \quad (\text{Eq. 7})$$

where EM (%) is the cumulative relative predicted emergence; GDD is the cumulative growing degree days; α is asymptote (maximum emergence), β is slope, γ and δ are the inflection points, and ρ is the asymptotic adjust (only for double-logistic model). Maximum emergence (α) was fixed to 100 for Logistic, Gompertz and Weibull models.

2.3 Model selection and validation

Model validations were performed with independent data collected in the experiment carried out from September 2016 to January 2017 (see M&M).

The linear function (Eq. 2) validation to determine GDD sum beginning was performed by estimation of w and z values. Then, z predicted by the function and z observed in the field were compared in a confidence interval (CI) (Eq. 8) for a linear function:

$$CI_{95\%} = \hat{z} \pm t_{n-2; \frac{\alpha}{2}} \sqrt{MSE \left(\frac{1}{n} + \frac{(w_0 - \bar{w})^2}{\sum (w_0 - \bar{w})^2} \right)} \quad (\text{Eq. 8})$$

where CI is the confidence interval, $\hat{z}$ the estimated value for w_0 , t is Student's t-test, $\bar{w}$ is the mean value of w , and MSE is the mean-square error (Eq. 9).

$$MSE = \sum_{i=1}^n (\hat{z} - z_i)^2 \quad (\text{Eq. 9})$$

where $\hat{z}$ is the seedling emergence timing estimated by the model and z_i the emergence timing observed in the field.

In relation with the emergence models (Eqs. 4-7), the model selection was performed on the corrected Akaike's Information Criterion (AIC) while the goodness-of-fit measures were based on the root-mean-square error (RMSE) where a lower value indicates a better fit (Burnham and Anderson 2002; Burnham et al. 2011; Chai and Draxler 2014). Prediction accuracy was evaluated by comparing predicted versus observed values, using the regression coefficient (r^2) (Yousefi et al. 2014).

All statistical analyses were performed using the statistical package InfoStat (v2019p) (Di Rienzo et al. 2019).

3 Results

During the experiment, monthly mean air temperature was similar to the last ten years average (Figure 2), but cumulated rainfall recorded from August to January in 2014/2015 and 2015/2016 was higher than the last ten years average by 442 and 288 mm, respectively (Figure 2). Total emerged seedlings were 851, 4249 and 5587 plants m^{-2} in 2014, 2015, and 2016, respectively.

[Figure 2 near here]

3.1 Initial moment of seedling emergence estimation

Across the tested period, the mean daily temperature decreased to a minimum value (θ) below T_b on August 26, 2013, August 27, 2014, and August 24, 2015, from which GDD sum was initiated (Table 1). Furthermore, the maximum (ψ) was recorded on August 30th (2013 and 2015) and on September 5th (2014), thus determining the end of the w period. From this period, the initial emergence of junglerice (λ) was observed on September 08, 2013, September 12, 2014, and September 11, 2015, thus ending the z period.

[Table 1 near here]

An inversely proportional close relationship between GDD in z period and GDD in w period was observed (Figure 3). That is, if cumulative GDD is lower in w , due to the cold-temperate conditions typical of the region in August, a higher GDD will be needed from ψ until the junglerice emergence (z period).

[Figure 3 near here]

The fit of the linear regression established between z and w for the three evaluated time periods was significant ($p = 0.05$, $r^2 = 0.99$), for w values between 24.8

and 40.4 GDD. With the observed data from the 2016/17 period (Table 1), w reached a value of 18.9 GDD; therefore, the estimation showed a higher confidence interval (CI).

Regarding this difference in period duration, the 95% CI for z estimation, for a w of 18.9 GDD, was 61.2 ± 25.4 GDD, which means that the emergence of junglerice can occur between 35.8 and 86.6 GDD (between the 11th and 26th of September). On the other hand, the observed value in the field was 62.1 GDD, with a slightly difference of 0.9 GDD with respect to the estimated value. Therefore, the linear function could predict the initial emergence of junglerice in the field from the GDD.

3.2 Emergence model selection

From the record of minimum air temperature (θ) until the end of emergence, the GDD sum was 950 and 1090 GDD in 2014 and 2015, respectively. The four non-linear models were fitted in these periods (Table 2).

[Table 2 near here]

The best fit was obtained by the double-logistic model (DLM), with both RMSE (9.08) and AIC (842.69) lowest when compared with the other non-linear functions used in this study (Table 2). Therefore, DLM was chosen as being the most plausible model to explain the relationship between emergence of junglerice and thermal time. The predicted emergence by the DLM model showed a curve of four phases: an initial phase up to approximately 79 GDD, a second phase where the maximum slope (0.65% seedling emerged per GDD⁻¹) is reached at 123 GDD (inflection point), a third phase between 183 and 510 GDD with a slope reduction and a final phase where the function reached a plateau (> 95% cumulative emergence) (Figure 4).

[Figure 4 near here]

The relationship between the seedling emergence observed and predicted by the DLM model showed a good correspondence ($R^2 = 0.99$; Figure 5).

Therefore, it seems that the DLM thermal models proposed may be robust enough to be used as a predictive tool for seedling emergence of junglerice.

[Figure 5 near here]

4 Discussion

Differences in total number of seedlings emerged annually could be due to both intrinsic factors of the seed (i.e., dormancy) or extrinsic ones (such as soil temperature fluctuation, soil moisture, solar radiation (quantity and/or quality), air quality, seeds vertical distribution, and soil seed bank) (Benech-Arnold et al. 2000; Forcella et al. 2000; Grundy 2003; Bagavathiannan et al. 2011; Royo-Esnal et al. 2015).

On the other hand, the total rainfall in 2013 (756 mm) was lower than the average of the last ten years, and this could have an influence on the production of seeds for the following year.

4.1 Temperature as indicator of the seedling emergence beginning

It is known that several populations of junglerice increased germination rate when submitted to daily thermal variations ranging from 20 to 30 °C in diurnal fluctuation and from 15 to 25 °C in nightly ones (Kovach et al. 2010). Also, Elahifard and Mijani (2014) reported that when subjecting the seeds to daily fluctuation of 30/20 °C and 20/10 °C day/night temperature (under continuous light), one and two days were enough to observe the first germinations, respectively. This effect can explain the beginning of the seedling emergence that has been observed in this study. Also, our results can be compared with those obtained by Thompson et al. (1977), who observed that the diurnal thermal variation had a positive effect on the germination of the grass weeds *Poa annua*, and *Lolium perenne*, determining that the higher the thermal fluctuation between day and night, the higher the number of emerged seedlings.

As mentioned previously, there are many studies that show the effect of thermal fluctuation pattern in breaking the seed dormancy of weeds and in the timing of emergence. Therefore, the thermal variation observed in the present study could have conditioned the emergence pattern in association with the increased mean temperature as a determining environmental factor (related with the increased temperature in the period w of this experiment). In addition, daily mean soil temperature (5 cm below the soil surface) reached 20 °C between August 20th and 29th after winter cold temperatures were observed during the experiment. Taylorson and Dinola (1989) proposed that a small temperature increase (42 °C for half an hour) could be considered a seed dormancy-breaking mechanism in *E. crus-galli*. This effect could be associated with the behavior observed after exposure to temperatures over T_b (θ), showing that the higher the GDD sum is during w , the faster the emergence will be. Besides temperature, moisture is also an important factor that can determine emergence when it is a limiting factor, which was not the case in the current work, with an average of 755 mm of cumulated rainfall from August to January. Therefore, a thermal time model was enough to accurately fit the data.

4.2 Timing of beginning of GDD sum

Different criteria have been considered to determine the beginning of GDD sum in order to model the weed emergence pattern. Walker et al. (2010) considered the beginning of the GDD sum when junglerice seeds were sown. However, other studies used the crop sowing date such as the beginning of the GDD sum (Chauhan and Johnson 2009). On the other hand, Leguizamón et al. (2009) chose the beginning of GDD sum as a date where it is expected that the environmental factors will release seed dormancy without allowing germination. The association of beginning of GDD sum with an environmental variable (temperature) allows use for the prediction of

emergence in different years, possibly based on weather forecasts, independently of management schedule. Those practices linked to a calendar date are not uniform to the temperature pattern and GDD. That is, if 1 August is considered as the date to start the GDD accumulation (Leguizamón et al. 2009), the result would have been 136, 186, 143, and 104 GDD until the junglerice emergence for each year of study, respectively.

4.3 Fit and use of double-logistic model

While most emergence studies fitted more “simple” non-linear models (e.g., Zambrano-Navea et al. 2013), our results present a more complex pattern of emergence with more of one inflection point (Kremer and Lotz 1998). A possible explanation could be due to intrinsic factors of the seeds (e.g., the presence of different biotypes that may have different requirements) or to meteorological conditions. On this last point, the slope of EM changed at 346 GDD, coinciding with the increase in daily mean air temperature between 23.5 °C and 27.5 °C in late October - early November.

Models with double inflection points result in more interesting interpretations, which allow a better understanding of the described process (Lipovetsky 2010). Leon et al. (2005) observed that seedling emergence of *Rottboellia cochinchinensis* growing in pineapple fitted well to a biphasic emergence pattern, therefore presenting two inflection points. This complex emergence pattern can have implications for survival in highly disturbed environments such as agricultural fields (Schutte et al. 2008).

Our results highlight the usefulness of air temperature as a meteorological variable in the prediction of junglerice emergence. Also, these results agree with those obtained by Grundy and Mead (2000), who demonstrated the feasibility of using air temperature when predicting the emergence of *Stellaria media*, *Chenopodium album*, *Capsella bursa-pastoris*, *Matricaria perforate*, and *Veronica hederifolia*.

The model developed in the present study may be useful when planning the sowing of summer crops on a suitable date. Most junglerice emergence is associated with the sowing dates and the early growing stages of soybean in the Pampas region, a time during which the presence of weeds is highly relevant, due to the significant impact on grain yield (Bedmar et al. 2002). For example, when sowing occurs on approximately October 15th (when 200-250 GDD have accumulated), the emergence potential for junglerice will be 33-37%, with a lower emergence rate in the late stages of the crop cycle. If late planting date is implemented (e.g., December 15th), which represents about 770-860 GDD accumulated, the emergence potential would be 99%, and it might allow producers to control most seedlings before crop planting.

The good fit of the double-logistic model is, on one hand, an accurate method for designing management programs for this weed in the medium and long term, whereas in the short term, the model is highly valuable for decision support systems (DSS) concerning the application of weed control practices. The availability of a predictive emergence model for junglerice can ensure a rational use of herbicides that, in turn, will minimize the interference of junglerice in summer season crops in the region.

Future research should be addressed to determine a wider validation of the model since it does not consider soil and water variables, which could limit the potential use in different locations. This model would be a valuable tool for farmers' decision-making with regard to the timing of control measures for junglerice. The model may contribute to a sustainable junglerice management in Argentina soybean production system when incorporated into a DSS (González-Andújar et al. 2011).

5 Conclusion

The information in this paper shows that it is possible to develop a simple thermal time seedling emergence model for junglerice for the Humid Pampas of Argentina based on air temperature. Junglerice emergence was affected by air temperature stimuli during the last third of August, when the trending base temperature began to change. Seedling emergence in soybean stubble in late winter was well fitted with a double-logistic model and had good accuracy in predicting and quantifying junglerice emergence pattern. These predictive models might aid decisions for the timing of junglerice control. Due to the versatility of the model, it is important to highlight that it could be a reliable contribution to the rational weed management.

Geolocation information

33.9455°S, 60.5682°W

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Disclosure statement

The authors have no conflicts of interest to declare.

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Tables

Table 1. Mean daily temperature (MDT, °C) recorded in 2013, 2014, 2015 (for linear regression between both w and z periods), and 2016 (for the linear regression validation); occurrence dates of the initial minimum air temperature (θ), the following maximum air temperature (ψ), the initial emergence of junglerice (λ), and the cumulative thermal time expressed in growing degree days (GDD, GDD) for the periods w and z .

Date	MDT			
	2013	2014	2015	2016
Aug-21	-	-	-	6.6
Aug-22	-	-	-	13.6
Aug-23	-	-	-	14.3
Aug-24	-	-	9.5	14.4
Aug-25	-	-	11.0	16.6
Aug-26	2.2	-	12.0	15.6
Aug-27	5.6	5.6	13.6	10.0
Aug-28	16.5	8.0	17.9	8.4
Aug-29	19.0	11.1	20.0	7.5
Aug-30	19.3	13.4	20.5	9.3
Aug-31	17.1	14.9	18.0	11.3
Sep-01	18.2	16.0	10.4	7.0
Sep-02	14.9	16.0	13.5	6.5
Sep-03	9.8	15.7	11.6	5.4
Sep-04	10.0	16.0	13.4	5.6
Sep-05	15.9	17.5	14.2	8.1
Sep-06	18.6	13.5	14.5	9.3
Sep-07	17.0	14.5	15.2	9.6
Sep-08	18.7	17.3	15.5	11.6
Sep-09	-	15.9	10.2	16.7
Sep-10	-	10.8	10.3	17.5
Sep-11	-	12.3	6.9	20.3
Sep-12	-	12.4	-	14.5
Sep-13	-	-	-	13.0
Sep-14	-	-	-	11.8
Sep-15	-	-	-	12.1
Sep-16	-	-	-	15.9
Sep-17	-	-	-	15.8
Sep-18	-	-	-	13.1
Sep-19	-	-	-	13.2
θ	Aug-26	Aug-27	Aug-24	Aug-21
Ψ	Aug-30	Sep-05	Aug-30	Aug-25
GDD w	24.8	40.4	35	18.9
λ	Sep-08	Sep-12	Sep-11	Sep-19

GDD z	50.4	26.6	36.6	62.1
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Table 2. Parameter values and standard error for the non-linear models. Root mean square error (RMSE) and Akaike's Information Criterion (AIC) for each model. DLM: double-logistic model

	Logistic	Gompertz	Weibull	DLM	
α	100 (0)	100 (0)	100 (0)	52.04 (4.99)	
β	0.020 (0.002)	0.013 (0.001)	78.57 (5.36)	β_1	0.04 (0.02)
				β_2	-0.007 (0.003)
γ	33.21 (9.13)	6.11 (0.87)	142.24 (3.69)	γ_1	123.30 (60.34)
				γ_2	485.99 (238.78)
δ	-	-	-	δ_1	1.39 (0.68)
				δ_2	7.80 (3.88)
ρ	-	-	-	47.42 (4.05)	
RMSE	10.85	9.85	9.81	9.08	
AIC _c	873.23	850.43	850.43	842.69	

Figure legends

Figure 1. Diagram of the mean daily temperature trend between late August and early September: θ is the minimum air temperature below junglerice T_b (10°C), ψ is the following maximum air temperature, λ is the initial emergence of the first junglerice seedlings, w is the period of cumulative thermal time between θ and ψ , and z is that between ψ and λ .

Figure 2. Monthly mean air temperature (lines, $^{\circ}\text{C}$) and monthly rainfall (bars, mm) from August to January for the four years of study and last ten years average.

Figure 3. Relationship of the cumulative thermal time expressed in growing degree days (GDD, $^{\circ}\text{C day}$) between z and w periods in 2013, 2014, and 2015.

Figure 4. Cumulated emergence trend (EM, %) as a function of the thermal time expressed in growing degree days (GDD, $^{\circ}\text{C day}$) in 2014 and 2015. Double-logistic model with four stages: I- initial phase, II- higher slope, III- lower slope, and IV- 'plateau' final phase.

Figure 5. Validation of double-logistic model. EMo: observed values. EMe: estimated values. Data collected from the experiment conducted in 2016.

Figure 1

188x97mm (600 x 600 DPI)

Figure 2

182x321mm (300 x 300 DPI)

Figure 3

173x92mm (300 x 300 DPI)

Figure 4

188x96mm (300 x 300 DPI)

Figure 5

179x92mm (600 x 600 DPI)