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CROP PRODUCTION

Prediction of Italian ryegrass (*Lolium multiflorum* L.) emergence using soil thermal time

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ABSTRACT. Italian ryegrass (*Lolium multiflorum* L.) is a highly competitive weed widely disseminated worldwide that affects both summer and winter crops. The development of predictive emergence models can contribute to optimizing weed management. The aim of this study was to develop and validate an empirical emergence model of Italian ryegrass based on soil thermal time. For model development, cumulative emergence in two locations was obtained, and the model was validated with data collected in an experiment conducted independently. Three commonly used emergence models were compared (Gompertz, Logistic, and Weibull). The relationship between emergence and soil thermal time was described best by the Gompertz model. The Gompertz model predicted Italian ryegrass emergence start at 300 thermal time (TT), reaching 50% emergence at 444 TT, and 90% at 590 TT. Model validation performed well in predicting Italian ryegrass emergence and proved to be efficient at describing its emergence. This is a potential predictive tool for assisting farmers with Italian ryegrass management.

Keywords: Gompertz model; logistic model; Weibull model; soil temperature; weed management.

Introduction

Italian ryegrass (*Lolium multiflorum* L.) is a weed that is widely disseminated worldwide (United States Department of Agriculture [USDA], 2019). Due to its robustness, it is able to withstand high variations in environmental conditions in its growth (Bond, Eubank, Bond, Golden, & Edwards, 2014). Italian ryegrass is a highly competitive weed that can affect both winter and summer crops. In both wheat and corn, the reduction in grain yield can reach 60% (Scursoni, Palmano, De Notta, & Delfino, 2012; Nandula et al., 2014). Among the characteristics that favour its infestation are its high fecundity (3000 to 7000 seeds per plant) and seed dormancy. Dormancy is a very important strategy for weeds, as it allows the seeds to germinate only under specific conditions and during specific periods of the year that favour plant development. This strategy strengthens the infestation and promotes species perpetuation (Egley, 2017).

To trigger the germination process, seeds must be in optimal physiological condition and the environment must have favourable conditions of temperature, light, and water availability (Tozzi et al., 2014). Therefore, the initiation and the constancy of emergence may change year after year. This variation hinders weed management, since in many cases there is no predictability of events. The use of mathematical models to predict seedling emergence is one way to determine under which environmental conditions the seed would be most likely to germinate. Models can be used as tools for decision-making and to optimize the use of management strategies (González-Andújar, Chantre, Morvillo, Blanco, & Forcella, 2016).

Recruitment is an important demographic event in the cycle of plant. Emergence timing determines survival and reproductive success (Lewandrowski, Erickson, Dixon, & Stevens, 2017). Mathematical models describing emergence flushes can be classified as mechanistic and empirical (Zambrano-Navea, Bastida, & Gonzalez-Andujar, 2013; González-Andújar et al., 2016). Mechanistic models require knowledge of biophysical processes that drive germination and are complex to study. These models require a deep understanding of seed dormancy regulation, germination requirements, and seedling growth. Conversely, empirical models can be developed without the level of detail required in mechanistic models by monitoring

seedling emergence over time and relating this to the appropriate thermal, hydrothermal, and photo hydrothermal time (Yousefi, Oveisi, & Gonzalez-Andujar, 2014; Royo-Esnal, Necajeva, Torra, Recasens, & Gesch, 2015).

Empirical models have been developed to predict seedling emergence in different weed species (González-Andújar et al., 2016). Izquierdo, Bastida, Lezaún, Sánchez del Arco, and Gonzalez-Andujar (2013) developed and validated a model to predict the emergence of *Lolium rigidum* in winter cereals in a Mediterranean climate, but no model for *L. multiflorum* has been developed. The ability to predict Italian ryegrass emergence could enhance crop management by facilitating the implementation of more effective weed control strategies through the optimization of the timing of weed control. To date, there is no decision-aiding tool that can provide precise information to farmers for predicting Italian ryegrass emergence in any crop. The objective of this study was therefore to develop and validate an empirical emergence model of Italian ryegrass based on the soil thermal time.

Material and methods

Study sites

Field experiments were conducted in two stages. The first was performed between April and June 2016, in post-harvest soybean fields at Mariópolis (26°19'S 52° W) and Pato Branco (26°10'S 52° W; Southwest Region in Paraná State, Brazil). Soil characteristics are presented in Table 1.

Table 1. Soil texture and chemical attributes.

Soil texture			Chemical attributes		
First stage					
Properties (%)	Mariópolis	Pato Branco	Properties (%)	Mariópolis	Pato Branco
Clay	58	55.7	MO[1]	4.6	49.3
Sand	2.5	3.0	P[2]	8.9	1.3
Silt	39.5	41.3	K[3]	0.3	0.7
			CTC[4]	17.8	17.6
			pH[5]	5.2	5.6
			H+AL[6]	9.0	5.3
Second stage					
Properties (%)		Pato Branco	Properties (%)		Pato Branco
Clay		55.7	MO[1]		49.6
Sand		3.0	P[2]		8.9
Silt		41.3	K[3]		0.7
			CTC[4]		13.8
			pH[5]		4.8
			H+AL[6]		5.8

[1] Organic matter (g dm^{-3}); [2] Phosphorus (mg dm^{-3}); [3] Potassium (cmol$_c$ dm^{-3}); [4] Cation Exchange capacity; [5] Soil pH; [6] Exchangeable acidity (cmol$_c$ dm^{-3}).

In both sites, 10 permanent quadrats (0.5 x 0.5 m) were randomly positioned in an area of 100 m². Seedlings of Italian ryegrass were counted weekly and removed from the soil, until no new seedlings were observed. Soil temperature was recorded with four sensors buried at a 5 cm depth connected to data loggers (Decagon Devices Em 50®) randomly distributed in the sampling areas. The precipitation and minimum and maximum soil temperature data of each site during the experimental period are presented in Figure 1a and 1b.

In stage two, an experiment for model validation was conducted between July and September 2018 in a farming field at Pato Branco. The selected area had a low level of infestation with *Lolium* spp., and 90 days prior to sowing, vegetation was eliminated with a soil cultivator (L90 Lavrale®). At each new emergence, the seedlings were eliminated with the herbicides paraquat + diuron (400 + 200 g ha^{-1}). In 16 micro plots of 0.25 m^2 (0.5 x 0.5). 50 Italian ryegrass seeds were sown and covered with a 1 cm layer of soil. The Italian ryegrass seeds used in stage two were collected from different farming areas in the Southwestern Region of Paraná. The emergence was monitored every three days until no new emerging seedlings were observed.

Statistical analysis and model development

The data collected in 2016 season were submitted to an analysis of variance (p ≤ 0.05) to verify whether there was any difference between the locations, using the ExpDes.pt package (Ferreira, Cavalcanti, & Nogueira, 2018), available for the R platform (R Core Team, 2018).
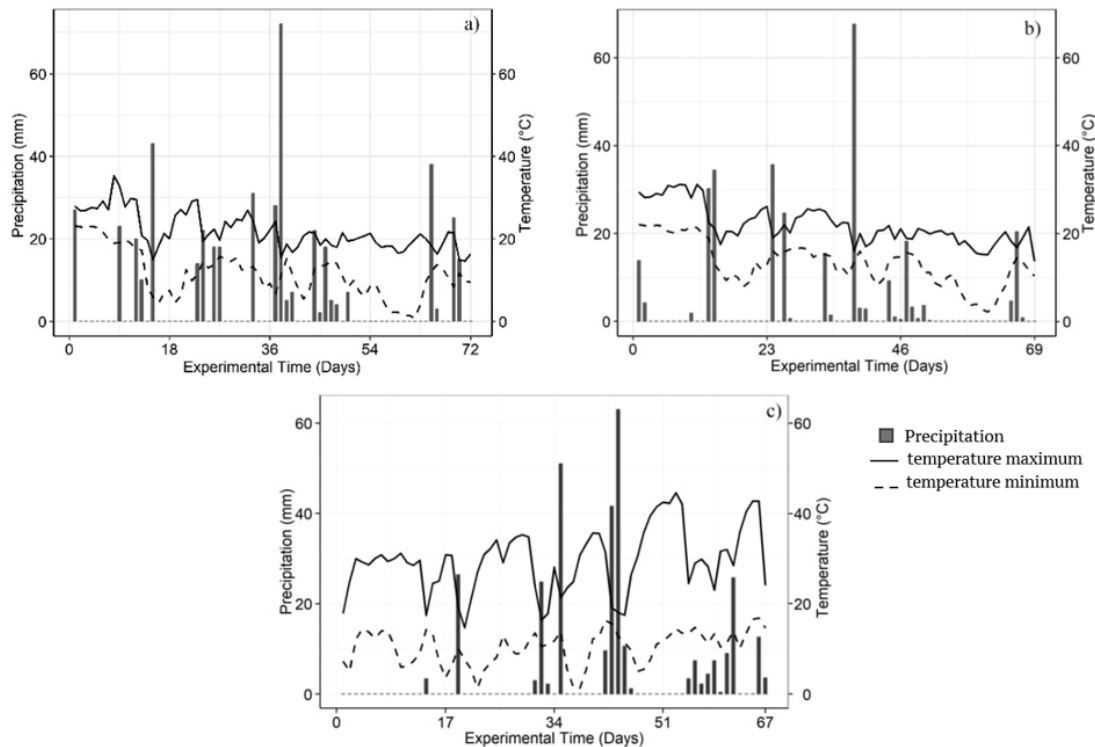
Figure 1. Precipitation, maximum and minimum soil temperature during the experimental periods in 2016 in Mariópolis (a) and Pato Branco (b) and 2018 in Pato Branco (c).

Source: Sistema Meteorológico do Paraná [Simepar] (2019).

The cumulative thermal time (TT) in degrees day was calculated using Equation 1.

$$TT = \sum_{i=1}^{n}(Tmean - Tbase) \tag{1}$$

where: n is the number of days after sowing, $Tmean$ is the average daily soil temperature (°C), and $Tbase$ is the lowest temperature (°C) at which germination can occur. The base temperature used was 1.9°C (Tribouillois, Dürr, Demilly, Wagner, & Justes, 2016).

To describe the accumulated emergence, the Logistic, Gompertz and Weibull models, commonly used in the literature, were fitted (González-Andújar et al., 2016).

Gompertz

$$Ei = K \, exp(-exp(-b(TT - m))) \tag{2}$$

Logístic

$$Ei = K / (1 + exp(-b(TT - m))) \tag{3}$$

Weibull

$$Ei = K \, (1 - exp(-\left(b(TT - m)\right)^c)) \tag{4}$$

where: Ei (%) represents the percentage of cumulative predicted emergence, K is the maximum emergence predicted by the model (the value was set at 100%), b is the rate of increase in emergence, m is the point of inflection on the x-axis, and c is the factor that determines the asymmetry and kurtosis of the distribution.

Model parameters were estimated with the 'nls' library in the program R by means of nonlinear regression analyses (RStudio Team, 2016). Multiple initial values were used to ensure that the solution was global rather than local. Model selection was performed using the corrected Akaike information criterion (AICc) (Burnham, Anderson, & Huyvaert, 2011). The goodness of fit was determined by the residual-mean-square error (RMSE) (where the lowest value indicates the best fit) and the adjusted determination coefficient (R^2). The graphs were constructed using the GGplot2 package (Wickham, 2016), available for the R platform.

Model Validation

Model validation was performed with independent data collected at Pato Branco. The accuracy of the model was evaluated by comparing the predicted and observed values. Four validation methods were used to verify the quality of the fit: the adjusted regression coefficient (R^2), the modelling efficiency (ME), coefficient of error (CE), and coefficient of model determination (CD).

ME is a dimensionless statistic that resembles Pearson's correlation coefficient (Loague & Green, 1991),

$$ME = 1 - \frac{\sum(yi - \bar{y})^2 - \sum(\hat{y}i - \bar{y})^2}{\sum(yi - \bar{y})^2} \qquad (5)$$

where: yi is the ith value observed, $\hat{y}i$ is the ith value predicted by the adjusted regression line, $\bar{y}$ is the arithmetic mean of the observed values. In a perfect fit, ME would have a value equal to 1. The lower boundary is negative infinity, and if ME is lower than zero, the model-predicted values are worse than the observed mean.

CE is a relative measurement of the mean of the absolute differences, which is expressed as a proportion of the values observed in the mean (Yang, Greenwood, Rowell, Wadsworth, & Burns, 2000),

$$EC = \frac{(1/n)\sum|yi - \hat{y}i|}{\bar{y}}, \qquad (6)$$

where: yi, $\hat{y}i$, and $\bar{y}$ are described as above, and n is the number of observations. The value of 0 for the EC represents a perfect fit between the predicted and observed values.

The CD indicates the total proportion of variation of the observed data explained by the predicted data (Loague & Green, 1991),

$$CD = \frac{\sum(yi - \bar{y})^2}{\sum(\hat{y}i - \bar{y})^2} \qquad (7)$$

where yi, $\hat{y}i$ and $\bar{y}$ are described as above. As with ME, a perfect fit would equal 1. The value of CD > 1 indicates that the data are overestimated by the model, while CD < 1 indicates that the data are underestimated.

Results and discussion

On average, 149 seedlings·m^{-2} in Mariópolis and 174 seedlings·m^{-2} in Pato Branco were recorded in 2016. No statistical difference was observed in seedling emergence in both locations (p < 0.05) (Figure 2a), and the data were pooled to fit the model. In the 2018 season, 38 seedlings·m^{-2} in Pato Branco were recorded.
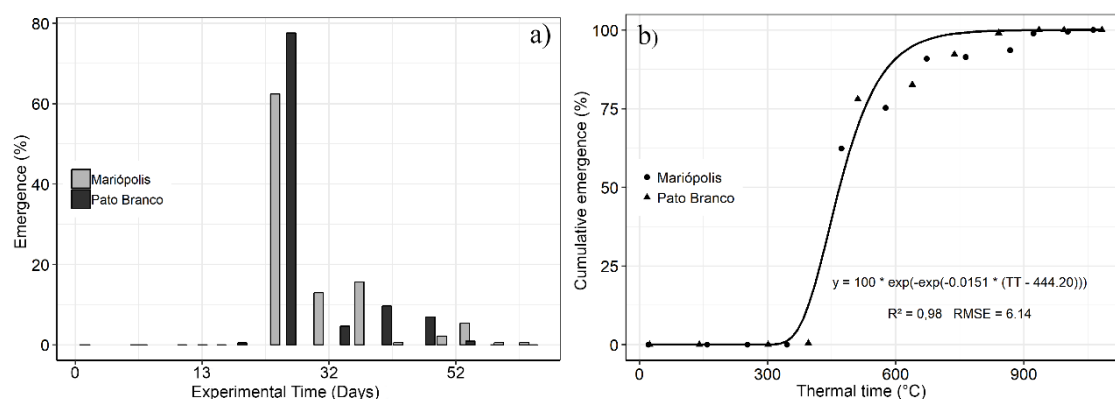

Figure 2. (a) Emergence of Italian ryegrass for each locality. (b) Cumulative seedling emergence as predicted by the Gompertz model. Data collected from the experiment conducted in the 2016.

The Gompertz model presented the lowest AIC$_c$ (Table 2) and was, therefore, chosen as being the most plausible one to explain the relationship between the emergence of Italian ryegrass and thermal time. Similar results were also reported by Izquierdo et al. (2013) with *L. rigidum*.

Table 2. Corrected Akaike information criterion (AICc) for Gompertz, Logistic and Weibull models.

Model	AICc
Gompertz	88.16*
Logistic	97.18
Weibull	146.94
*Lower value is better.	

The Gompertz thermal time model presented a good fit to the data (R^2 = 0.98; RMSE = 6.14) and was accurate in explaining cumulative emergence (Table 3). According to this model, the seedlings emergence starts at 300 thermal time (TT), reaching 50% at 444 TT and 90% at 590 TT (Figure 2b). These values are higher than that observed for *L. rigidum*, in which the soil thermal sum required to reach 90% of emergence is between 229 and 390 TT (Hadi & González-Andújar, 2009; Izquierdo et al., 2013). In fact, variability between species and environments is expected when studying weed emergence, due to the different thermal requirements between species and the different management systems in each field. Dorado, Sousa, Calha, González-Andújar and Fernández-Quintanilla (2009), when assessing the emergence of 10 weed species in different environments, observed that the thermal requirement to obtain 90% of the emerging seedlings can range from 208 to 2744 TT.

Table 3. Parameters values and performance of the Gompertz model (Standard error in parenthesis).

Parameters			RMSE	R^2
k	*B*	*m*		
100.00	0.0151 (0.002)*	444.20 (8.65)*	6.14	0.98

*Significant at p < 0.05; RMSE: root mean square error.

The model was validated with an independent data set collected at Pato Branco in 2018. The relationship between the seedling emergence observed and that predicted by the Gompertz model showed good correspondence (R^2 = 0.97) (Figure 3). The values of ME and CE were 0.97 and 0.08 respectively, indicating that the predicted data were very similar to the observed data. The value of CD (1.07) indicates that the model may slightly overestimate seedling emergence. In fact, the values observed in each method were close to the expected, confirming that the model describing Italian ryegrass seedling emergence well.
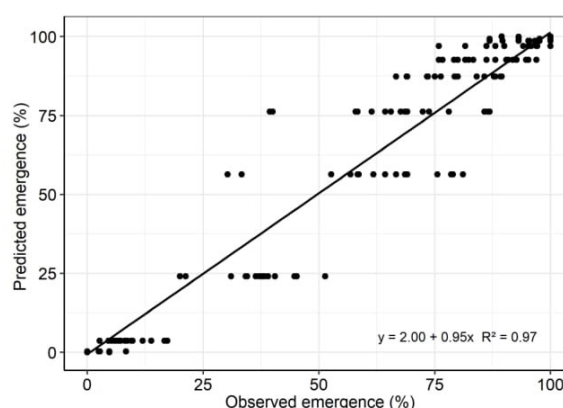

Figure 3. Validation of the Gompertz model of Italian ryegrass seedling emergence. Data collected from the experiment conducted in 2018.

Previous modelling studies have described the emergence of *Lolium rigidum* seedlings in a Mediterranean climate (Hadi & González-Andújar, 2009; Izquierdo et al., 2013), but there is no model for Italian ryegrass under temperate and humid subtropical climate conditions, as is the case of the south region of Brazil. The development of predictive models to describe seedling emergence has been the main objective in seeking more efficient management strategies for weed control. From the results of this work, it is considered that a single application of post emergence herbicide at a specific time could control most of the plants. In fact, the model can also support the use of pre-emerging herbicides, because it is possible to apply the herbicide covering the largest number of seedlings using an emergence probability. In Brazil, Italian ryegrass populations have been characterized as being resistant to herbicide inhibitors of EPSPs, ALS, and ACCase. Fortunately, there is still no recorded case of Italian ryegrass being resistant to the pre-emerging herbicides most commonly used for the management of the species (e.g., trifuralin and metolachlor). The application of more efficient management strategies to these plants could delay the evolution of resistant populations.

Studies that evaluate the emergence of Italian ryegrass show that the process occurs mainly in the first half of the autumn (Maia, Maia, Bekker, Berton, & Caetano, 2008). It is believed that it occurs in this period due to the seeds primary dormancy being terminated in the after-ripening period, when they are exposed to high temperatures during the summer (Ichihara, Yamashita, Sawada, Kida, & Asai, 2009). The results observed with the experiments conducted in 2016 support this statement. In the 2016 trials, it was observed

that the distribution of rainfall was similar in both locations, showing that the soil presented favourable conditions of moisture for the beginning of the germination process. In this case, it is assumed that the limiting factor for triggering the germination process is the thermal accumulation of the soil. As demonstrated by Çabej (2012), temperature is considered to be the main factor regulating seed dormancy and germination in temperate climate environments.

A model based only on soil thermal accumulation can be effective in describing seedlings emergence in different species (Dorado et al., 2009; Yousefi et al., 2014). However, some aspects should be considered when working with empirical models to describe that emergence. The counting date should start from a specific period. In this work, the accounting in 2016 was initiated at the harvest of the predecessor crop of the area (soybean), as described by Gardarin, Dürr, and Colbach, (2012). Researchers have suggested that the beginning of accounting should start with the soil preparation, or the planting of a new crop (Masin, Loddo, Benvenuti, Otto, & Zanin, 2012; Yousefi et al., 2014), which provides a direct comparison for the emergence time between weed and crop. Atypical climatic conditions can also impact the outputs generated by the model. Some studies developed with *Abutilon theophrasti* have shown that the thermal requirements of seeds from North America and the Mediterranean (Spain and Portugal) are different (Myers et al., 2004; Dorado et al., 2009). This could be affected by the environmental conditions under which the experiments were conducted, the soil management strategy, and the genetic characteristics of the seeds. In this work, both experimental sites in 2016 belonged to the same climatic region, which may have contributed to the accuracy of the model. Therefore, for better comprehension of Italian ryegrass seedling emergence, more work should be conducted with data collected in different environments, so that it is possible to recognize patterns more easily to develop more general models.

The Gompertz model was appropriate for describing Italian ryegrass seedling emergence as a function of thermal time. The validation tests demonstrated a good correspondence between the observed and predicted data. Empirical predictive emergence models can be incorporated into decision support systems as a decision-making tool for integrated weed management (González-Andujar et al., 2010). This can contribute to more efficient and sustainable weed management, as well as reducing the occurrence of herbicide resistance.

Conclusion

The proposed emergence model accurately describes the emergence pattern of Italian ryegrass as a function of thermal time. The model was validated with an independent data set. It can be concluded that the proposed thermal time model is robust enough to be used as a predictive tool to describe the emergence of Italian ryegrass and can be used as a decision tool for optimization of weed management strategies.

Acknowledgements

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