

Prediction of emergence of Flixweed (*Descurainia sophia*) and Wild Oat (*Avena fatua*) using thermal time models in Winter Rapeseed (*Brassica napus*)

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ABSTRACT

A thermal time (TT) model was developed to simulate field emergence of two weed species (flixweed and wild oat) in winter rapeseed. Practical predictive weed emergence models can provide information about timing of weed emergence. Non-linear regression models are usually able to accurately predict field emergence under specific environmental conditions. In the present study, cumulative seedling emergence in response to TT was described by the Weibull, Logistic, Gompertz, Sigmoid and Chapman functions. Some criteria were used to describe the goodness of fit of the models. These criteria included coefficient of determination (r^2_{adj}), root mean square of error (RMSE) and Akaike index (AIC). In both species (*Descurainia sophia*: RMSE= 3.65, r^2_{adj} =0.97, AIC=88.87; *Avena fatua*: RMSE= 2.59, r^2_{adj} =0.99, AIC=45.83) the seedling emergence flushes were well described with the Weibull four-parameter function. To start emergence after sowing and to reach maximum emergence, lower TT requirements were observed in *A. fatua* than in *D. sophia*. Seedling emergence increased steadily and reached from 50% to 90% of total emergence at 315 and 543 TT, respectively for *D. sophia* and 70 and 286 TT, respectively for *A. fatua*.

Keywords: *Avena fatua*, *Descurainia sophia*, Soil temperature, Weibull model.

پیش بینی سبز شدن خاکشیر (*Descurainia sophia*) و یولاف وحشی (*Avena fatua*) با استفاده از مدل های ترمال تایم در کلزای پاییزه (*Brassica napus*)

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چکیده

به منظور شبیه سازی سبز شدن دو گونه علف هرز (خاکشیر و یولاف وحشی) در مزرعه کلزای پاییزه از مدل های ترمال تایم (زمان-دما) استفاده شده است. بکارگیری مدل های پیش بینی سبز شدن علف هرز می تواند اطلاعات مناسبی را در تعیین زمان رویش علف های هرز ارائه دهد. رگرسیون های غیرخطی معمولاً قابلیت پیش بینی دقیق سبز شدن را در شرایط محیطی مختلف را دارند. در تحقیق حاضر برای تعیین درصد تجمعی سبز شدن از مدل های ترمال تایم شامل ویبول، لجستیک، گامپرتز، سیگموئید و چارمن استفاده شده است. همچنین برای تعیین نکویی برازش مدل ها از ضریب تبیین (R^2)، ریشه میانگین مربعات خطا (RMSE) و شاخص آکائیک (AIC) استفاده شد. نتایج نشان داد که در هر دو گونه مدل چهار پارامتره ویبول توانست برازش مناسبی را برای پیش بینی رویش این دو علف هرز انجام دهد. همچنین یولاف وحشی بعد از کاشت کلزا برای شروع زمان سبز شدن به دمای کمتری نسبت به خاکشیر نیاز دارد. بطوریکه برای دستیابی از ۵۰ به ۹۰ درصد سبز شدن کل به ترتیب ۳۱۵ تا ۵۴۳ درجه روز رشد برای خاکشیر و به ترتیب ۷۰ تا ۲۸۶ درجه روز رشد برای یولاف وحشی نیاز می باشد.

واژه های کلیدی: یولاف وحشی، خاکشیر، دمای خاک، مدل ویبول.

Introduction

Field emergence predictive models are essential tools for developing weed management support systems whose aims are to design sustainable weed control programs while optimizing crop yield. Such models should be able to minimize the degree of uncertainty in the estimation of the time and magnitude of seedling emergence (Forcella *et al.*, 2000). Quantitative models predicting weed emergence patterns are expected to have two important agronomic applications (Forcella, 1993). First, when coupled with models predicting crop emergence, they will allow an early estimation of crop yield loss due to weed interference (Vleeshouwers & Kropff, 2000). Weed emergence patterns concern both weed density and the timing of weed emergence, both of which strongly affect the degree of interference with crop growth. Second, they will permit a better determination of the optimal timing for both mechanical and chemical weed control (Masin *et al.*, 2012).

Mathematical models are powerful tools to evaluate changes in seed dormancy and the influences of environmental factors that modulate these changes or stimulate germination (Bradford & Nonogaki, 2007). Two approaches, an empirical model and a mechanistic model, are usually used to model seed germination and seedling emergence (Wang, 2005). Empirical models, at various levels of empiricism, can perfectly match individual data of germination overtime, but these models may need more empirical variables (Brown & Mayer, 1988). The empirical approach may be useful for a specific purpose, but it is difficult to interpret biological significance of the derived model parameters (Bradford, 1990). Empirical models have been based on the effect of soil temperature and soil

water potential to predict weed seedling emergence in agronomic systems (Chantre *et al.*, 2012a). Data for testing thermal-germination models under variable temperature regimes are limited and have been generally obtained under laboratory conditions that simulate repeating diurnal temperature patterns (Hardegree & Emmerich, 1999), or in field emergence experiments where factors other than temperature affect cumulative response (Finch-Savage *et al.*, 1998).

Parametric non-linear regression (NLR) models, based on S-shaped curves using thermal indices as explanatory variables, have been widely used for weed emergence prediction (Chantre *et al.*, 2012a). In many cases, NLR models have demonstrated adequate representations of the observed data; however, they present several major limitations (Chantre *et al.*, 2013b). Specifically, NLR models are sometimes not flexible enough to capture complex features in the explanatory variable, such as abrupt jumps or heavy tails. Moreover, observed cumulative emergence values obtained from consecutive monitoring approaches are not statistically independent. However, this is not considered explicitly in the weed science literature where fitting the model is the goal, regardless of whether the data are independent or not (Cao *et al.*, 2011).

Soil temperature, when converted to soil thermal time (TT), or growing degree days (GDD), has been used to predict seedling emergence (Norsworthy & Oliveira, 2007). In these models, average air or soil temperature above a specified threshold is accumulated over days until weed emergence (Royo-Esnal *et al.*, 2010). TT, the heat unit accumulation above a temperature threshold, is an essential component in germination modeling. One assumption of the

previous TT models is the constancy of base temperature (T_b) within a seed population. TT in emergence models has been successfully used to predict phenological development in crops and weedy species (Wang *et al.*, 2009), as well as seed germination under non water-limiting conditions (Garcia-Huidobro *et al.*, 1982; Covell *et al.*, 1986). It has also been prosperously applied in emergence models with the realization that emergence can be represented by a simple continuous cumulative sigmoidal curve, only if the upper few centimeters of field soil remain continuously moist, either through irrigation or natural rainfall (Forcella *et al.*, 2000). Gompertz, Weibull, Chapman, Richards, and Logistic functions (Brown & Mayer, 1988), in which soil TT serves as the independent variable, can represent such a curve.

Descurainia sophia and *Avena fatua* are noxious weed species distributed worldwide which cause severe yield and quality losses in cereal and oil seed crops (Holm *et al.*, 1977; Blackshaw, 1989). Several empirical NLR models were developed specifically for predicting *D. sophia* and *A. fatua* field emergence (Chantre *et al.*, 2012). These models have adequately described typical S-shaped cumulative emergence curves as a function of TT showing a good correlation between observed and predicted emergence data. The objective of this study is to develop models of seedling emergence for the *D. sophia* and *A. fatua* present in winter rapeseed crop and to examine whether GDD and soil TT are appropriate parameters for describing the timing of the emergence of their seedlings. Knowledge of this pattern will allow farmers to determine the time by which most of the weeds have already emerged and, consequently, the best time to apply a control measure.

Materials and methods

Experimental site

A Field experiment was conducted during 2014/15 in a canola field at the experimental farm of Islamic Azad University, Karaj Branch, Iran. An experimental site was under a continuing canola-corn crop rotation for more than 10 years. The site is located at latitude of 35°45' N, longitude of 51°6' E and altitude of 1313 meters above the sea level in semi-arid climate which have cold winters and warm (but not hot) and dry summers. The soil type was a silty clay (10.33% sand, 46.33% silt, 43.34% clay), with 1.18% organic matter and pH of 7.4.

Design and data collection

To prepare the field, it was irrigated before conducting the experiment and after the field got wet enough, molboard plowing was performed a few days before sowing in August, followed by a disking to slice plant residue and incorporating fertilizers into the soil. NPK fertilizers were applied at rates of 200:80:80 kg ha⁻¹, respectively. P, K and 1/3 of N were applied before sowing and incorporated. The rest of N was used at the end of rosette stage and the beginning of the flowering. Canola (cv. Okapi) was sown on September 6, 2014. Each experimental plot included 6 planting rows which were 6 m in length and 30 cm in width. Average density was 80 plants per m². Plants were irrigated every 10-12 days. *D. sophia* and *A. fatua* emergence data were recorded from sowing to harvesting of rapeseed by a one meter square quadrat. After each count, seedlings which had already emerged were removed by hand.

Weather data

Daily rainfall and maximum and minimum air temperatures were obtained from a meteorology station located 7 km away from the experimental field (Meteorological Organization of Alborz

Province). The meteorological data included temperature, rainfall, and temporal patterns as shown in Table 1. Total rainfall from sowing to harvest of canola was 248 mm. The winter was relatively cold with average temperature of -3 °C, and high rainfall (213 mm) that fell mainly in January. Spring was mild, with 93 mm rainfall between March and May. June and September had the highest temperatures, i.e. 15 and 20 °C, respectively. In contrast to the typical agronomic research where consistency in weather variables is desirable, highly contrasting weather patterns between experimental years enhanced opportunities for understanding and modeling responses of weeds to TT.

Description and parameterization of the model

Thermal time (TT) was based on the average of the minimum and maximum

daily weather temperatures (Benvenuti & Macchia, 1993) that was 2.5 °C for *D. sophia* (Cousens *et al.*, 1992) and 1 °C for *A. fatua* (Kiemnce & Mcinnis, 2002) as T_b .

As *D. sophia* and *A. fatua* mainly emerge from the top 5 cm soils (Yousefi *et al.*, 2014b), the soil temperature at this depth was chosen. Cumulative soil TT was calculated on a daily basis during the growing season as follows:

$$(1) \quad TT = \sum_{i=1}^n (T_{mean} - T_{base})$$

Where T_{mean} is the daily mean soil temperature (°C), T_{base} is the lowest temperature (°C) at which germination occurs and n is the number of days after sowing. Cumulative seedling emergence in response to TT was described by the Weibull, Logistic, Gompertz, Sigmoid and Chapman functions (Table 2).

Table 1. Meteorological data on the experimental site in 2014-15

Month	Highest temp. (°C)	Lowest temp. (°C)	Rainfall (mm)	Average relative humidity (%)	Mean monthly sunshine hours
Sep	29.4	14.2	0	36	304.2
Oct	24.1	10.4	13	44	250.1
Nov	14.9	3.4	24	56	187.2
Dec	8.9	-1.1	32	66	156.8
Jan	4.9	-5.1	44	67	166.3
Feb	7.8	-2.8	37	60	169.7
Mar	12.6	1.2	40	53	197.4
Apr	19.3	6.3	35	48	218.1
May	27.3	12.7	18	43	280.7
Jun	31.5	15.9	5	34	335.2

Table 2. The distribution models tested for the interaction of cumulative soil TT and the cumulative emergence of the *Descurainia sophia* and *Avena fatua*

Model	Function	No. of estimable parameters
Weibull	$y = a(1 - \exp(-b(x-z)^c))$ (Weibull, 1951)	4
Logistic	$y = a / (1 + (x/z)^b)$ (France and Thornley, 1984)	3
Gompertz	$y = a \exp(-\exp(-(x-z)/b))$ (Gompertz, 1825)	3
Sigmoid	$y = a / (1 + \exp(-(x-z)/b))$ (Hardegree, 2006)	3
Chapman	$y = a(1 - \exp(-bx))^c$ (Shellenberg <i>et al.</i> , 2013)	3

Where y is the cumulative percentage of emergence observed in the field experiment, a is the maximum percentage of emergence recorded, b is the rate of increase in emergence once it is initiated, x is time expressed as TT, z is the lag phase and c is a shape parameter. The number of parameters for the Weibull model was 4, while for the Logistic, Gompertz, Sigmoid and Chapman models was 3.

The fit of all the functions for seedling emergence was investigated using SAS (procedure NLIN; SAS 8.1, SAS Institute, 2008).

Validation of emergence model

In all cases goodness-of-fit between predicted and observed values was determined in accumulated percentage as a function of TT by calculating the adjusted coefficient of determination (r^2_{adj}) as a measure of the observed variability explained by the model, where by a higher value indicates a better fit. For the residual-mean-square error (*RMSE*) and Akaike Information Criterion (*AIC*) a lower value indicates a better fit.

$$(2) r^2 = 1 - \frac{\sum (y_{obs} - y_{sim})^2}{\sum (y_{obs} - \bar{y}_{obs})^2}$$

Where y_{obs} is the observed value and y_{sim} is simulated value. An r^2 value of 1 indicates a perfect fit of the model. It should be noted that the values of r^2 might be negative since simulated results are not obtained by regression.

$$(3) RMSE = \sqrt{1/n \sum_{i=1}^n (y_{obs} - y_{sim})^2}$$

Where y_{obs} represents observed cumulative percentage seedling

emergence, y_{sim} is predicted cumulative percentage seedling emergence, and n is the number of observations (Mayer & Butler, 1993). *RMSE* provides a measurement of the typical difference between predicted and actual values in units of percentage seedling emergence. The least *RMSE* value indicates that the emergence model fit has been optimized.

$$(4) AIC = n \log \left(\frac{RSS}{n} \right) + 2k$$

Where k is the number of parameters in the model, *RSS* is the residual sum of squares and n denotes the sample size.

Results

Emergence pattern

Emergence patterns of *D. sophia* and *A. fatua* are shown in Table 3. *D. sophia* seedling emergence started 63 days after sowing and showed one marked (84 days after sowing) and one short (126 days after sowing) flush. Over 66% of *D. sophia* seedlings emerged between 63 and 84 days after sowing (Fig. 1). *A. fatua* seedling emergence started very early, 14 days after sowing and showed one marked (28 days after sowing) and one short (63 days after sowing) flush (Fig. 1).

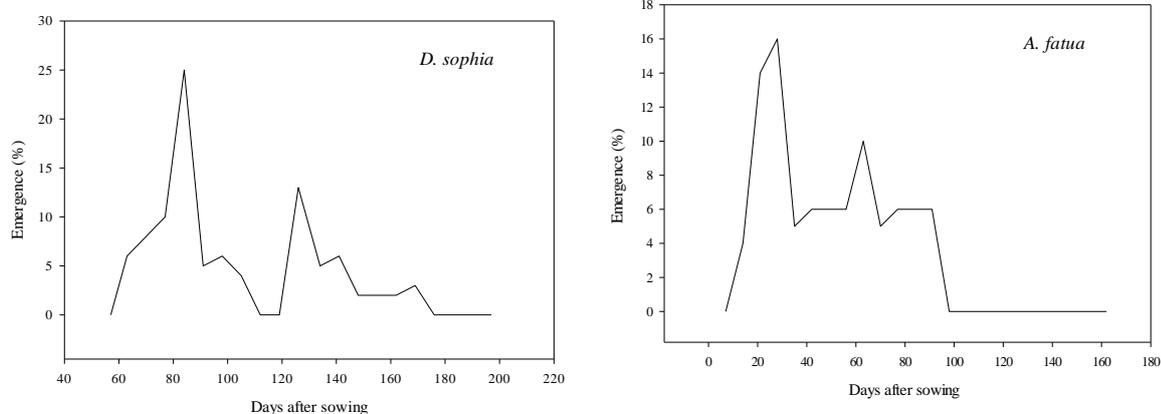


Figure 1. Relative distribution (%) of *Descurainia sophia* and *Avena fatua* seedling emergence during the experiments.

Performance of models

The parameters estimated for five distributions are shown in Table 3 for both species. For *D. sophia* and *A. fatua* there were marked differences among distributions in terms of precision, as shown by very different AIC and RMSE values. For *D. sophia*, obtained results for models showed that the Weibull model outperformed all other models based on AIC (88.87) and RMSE (3.65) measures of the training set (Table 3). The least fit was related to the Chapman distribution (AIC= 181.23; RMSE= 6.87).

A Weibull function closely fitted the observed patterns of *A. fatua* emergence (AIC= 45.83; RMSE= 2.59). The Sigmoid distribution provided the least fit (AIC= 68.98; RMSE= 4.29). In Table 2, the number of parameters of each model is presented. The Weibull function was selected as the best model for both species. It must be noted that the number of parameters in the model considerably affects model accuracy because it can effectively reduce the error function. Data regarding model and model parameters are given below.

The relationship between emergence and temperature was tested initially with the simple TT model. Estimates of the variables a , b , c and x_0 fitted to TT for both species are summarized in Table 3 and predicted and observed emergence using Weibull functions are shown in Fig. 2. According to our model, *D. sophia* and *A. fatua* emergence started at 205 and 27 TT, respectively. Afterwards, seedling emergence increased steadily and reached 50% and 90% of total emergence at 315 and 543 TT, respectively for *D. sophia* and 70 and 286 TT, respectively for *A. fatua* (Fig. 2). These TTs were recorded over 57 to 134 days and 14 to 87 days after sowing of canola for *D. sophia* and *A. fatua*, respectively (Fig. 1). All models as a function of TT might be explained with the required T_b of both species. *A. fatua* required a low temperature period to germinate. Calculation of the TT was optimal using 1 °C as a T_b for this species. Emergence predicted by the models corresponded well with the one observed through the independent experiments carried out (*D. sophia*: $r^2= 0.97$; *A. fatua*: $r^2= 0.99$) (Fig. 3).

Table 3. Parameter estimates, distribution properties and measures of goodness of fit for five statistical distributions used in thermal time (TT) modelling of *Descurainia sophia* and *Avena fatua* seed germination

Species	Model	Model parameters				AIC	RMSE
		$a \pm SE$	$b \pm SE$	$c \pm SE$	$x_0 \pm SE$		
<i>D. sophia</i>	Weibull	97.24±10.36	219.65±7.5	0.59±0.07	309.69±9.29	88.87	3.65
	Logistic	96.63±3.72	-3.76±0.45	-	291.65±11.56	124.3	4.34
	Gompertz	93.67±2.73	102.06±11.91	-	250.19±8.28	142.1	4.37
	Sigmoid	90.84±2.64	66.321±8.62	-	291.03±10.99	134.48	5.72
	Chapman	94.52±2.92	0.009±0.001	9.12±2.85	-	181.23	6.87
<i>A. fatua</i>	Weibull	98.68±2.32	86.51±6.59	0.68±0.06	72.67±30.14	45.83	2.59
	Logistic	94.67±2.17	-1.47±0.11	-	78.61±4.06	57.31	3.33
	Gompertz	93.16±1.32	64.4±6.11	-	55.59±3.74	54.73	3.15
	Sigmoid	92.52±1.71	46.94±5.92	-	82.75±5.81	68.98	4.29
	Chapman	94.8±1.19	0.01±0.001	1.12±0.11	-	48.54	2.75

SE in the table indicates standard error.

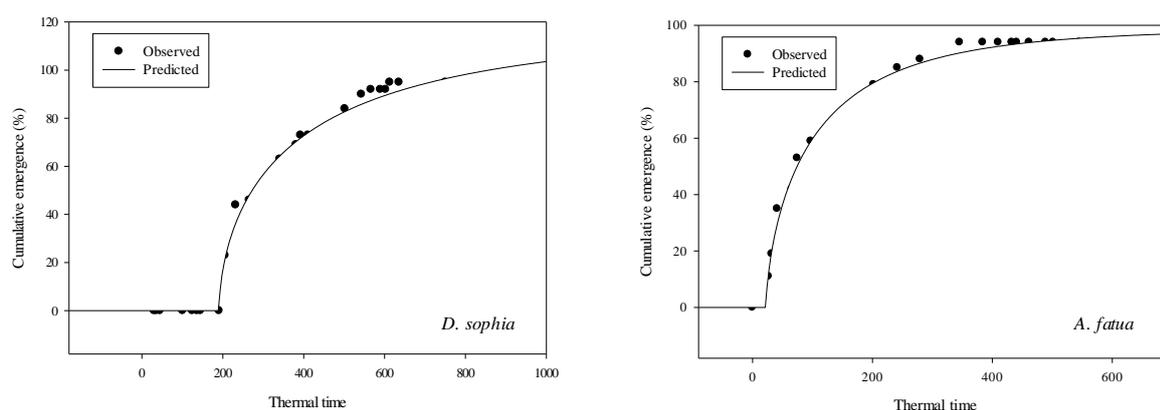


Figure 2. *Descurainia sophia* and *Avena fatua* (infesting Canola in Karaj) cumulative seedling emergence as predicted by thermal time model (TT). Observed (symbols) and predicted (lines) predicted emergence according to a Weibull function.

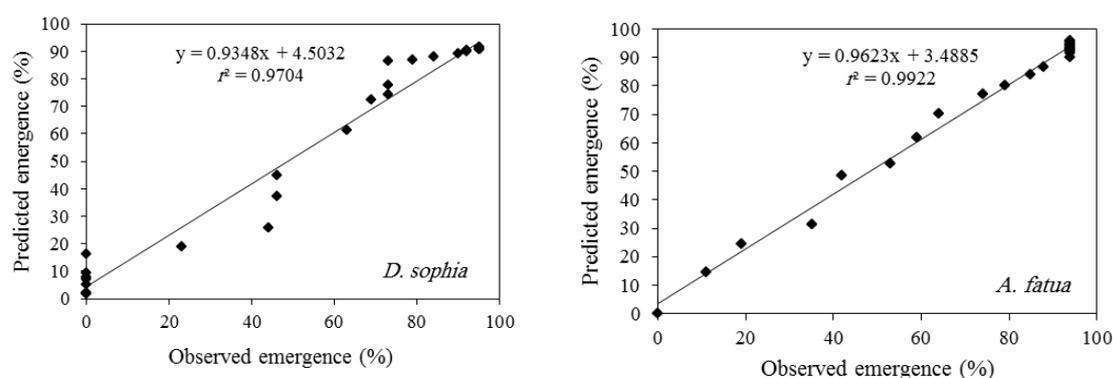


Figure 3. Seedling emergence models validation for *Descurainia sophia* and *Avena fatua* infesting canola

Discussion

In this study, *A. fatua* and *D. sophia* reached 92 and 94% of emergence 84 and 147 days after sowing, respectively (Fig. 1). *A. fatua* emergence is faster than *D. sophia*. Sharma and Vanden Born (1978) reported that cool and moist soil conditions are preferable for *A. fatua* to emerge. Karimmojeni *et al.* (2014) declared *D. sophia* seeds, buried at a depth of 10 cm, had maximum emergence (55%), 60 days after seeding. Yousefi *et al.* (2014b) in Iran found that there was 100% emergence of *A. fatua* 84 d after seeding. Ibrahim *et al.* (1995) in Pakistan claimed that *A. fatua* 100% emergence was reached 15 d after seeding. The differences in times reported for maximum emergence are likely to be due to weather conditions, management

practices and possibly dormancy (Yousefi *et al.*, 2014b). The differences between emergence patterns of *A. fatua* in semiarid conditions (Chantre *et al.* 2012a) and those studied in the present work might be attributed mainly to the effect of varying seed bank dormancy behavior due to ecological adaptations to different regional climatic conditions. Having the ability to accurately predict the timing of complete emergence for both species has practical implications for the timing of POST herbicide application and its efficacy. Many growers prefer to time the control operations in their fields as soon as there is 100% emergence for both species population. Because the model predicts 92 to 94% of emergence for the both species within a few days of observed emergence, growers and

agricultural professionals can use this tool to assist more timely and efficacious POST herbicide applications.

Models that estimate the timing of weed seedling emergence are valuable tools to optimize weed control schedules (Schutte *et al.*, 2008). Emergence is possibly the most important event of an annual plant as the time when it occurs largely determines its survival and success (Forcella *et al.*, 2000). These models adequately described the typical S-shaped curves of cumulative emergence as a function of TT showing a good correlation between observed and predicted emergence data. Conversely, in the semiarid region of Iran, *D. sophia* and *A. fatua* show an irregular seedling emergence behavior per season and a great variability per year mainly due to a highly unpredictable precipitation regime. It is also influenced by a fluctuating thermal environment and seed dormancy level variations within the population. In the present study, the Weibull model gave the most satisfactory results for both species analysed. Following this, the results of this study partially agree with those of Chantre *et al.* (2012a) who reported that the Weibull model was deemed to provide a better fit than other models for *A. fatua* seedling emergence in the region, Argentina. Results of present study confirmed the limited capability of hydrothermal time-based Weibull models to accurately predict the onset of *A. fatua* emergence time-window under semiarid conditions (Moschini *et al.*, 2011). In the same vein, Yousefi *et al.* (2013a) in a comparison of three models (Gompertz, logistic and Weibull models) on *D. sophia* found that the Weibull model gave the best fit in Iran. However, Gonzalez-Diaz *et al.* (2007) reported that the Gompertz model was deemed to provide a better fit than the other models for *A. fatua* seedling

emergence in the climatic conditions of Spain. The differences between wild oat emergence patterns in semiarid conditions (Chantre *et al.*, 2012a) and those studied in the present work might be attributed mainly to the effect of contrasting seed bank dormancy behavior due to ecological adaptations to different regional climatic conditions. Seed dormancy is a crucial mechanism to avoid germination under unfavourable environmental conditions for seedling survival which extends seed longevity in the soil (Baskin & Baskin, 1998).

Soil temperature can be used directly as a predictor of seedling emergence, or it can be converted to TT, i.e. growing-degree per days (Forcella *et al.*, 2000). Effect of temperature on seed germination has been successfully predicted and characterized by the TT model (Windauer *et al.*, 2012). This probably occurred because crop seeds are relatively homogeneous genetically, and they are typically sown directly in moist soil at precise soil depths (Forcella *et al.*, 2000). TT is the basic and most important temperature factor in plant growth and development processes (Fry, 1983) such as seed germination and seedling emergence (Elis *et al.*, 1986). TT is widely used to quantify and model seed germination (Parmoon *et al.*, 2015). The development of TT models for *D. sophia* and *A. fatua* is a major step forward in terms of improving the ability to predict the emergence and development of this species. Figure 2 illustrates the cumulative emergence patterns of both species as a Weibull function of TT. Compared with *D. Sophia*, *A. fatua* showed lower TT requirements to start emergence after sowing and to reach maximum emergence. For visible emergence to occur in the study sites, *A. fatua* and *D. sophia* require TTs of 27 (14 d after sowing canola) and 205 (63 d after

sowing canola), respectively (Figs. 1 and 2). The T_b is the minimum temperature at which the plant grows, and it varies for each weed. In growth models accumulation of TT start at a starting point, usually the T_b . According to the T_b the *A. fatua* seed emergences during the autumn-winter period are 1 and 2.5 °C for *D. Sophia*, respectively. So the cycle of *A. fatua* emergence is completed in a shorter time. The lowest developmental threshold temperature or T_b for an organism is the temperature below which development stops. *A. fatua* emerged earlier than *D. sophia* in this experiment, especially in the early sowing period (Fig. 2).

Conclusion

The increasing public awareness and concern about impacts of herbicides on

the environment, development of herbicide-resistant weeds, and the high economic cost of herbicides have augmented the need to reduce the amount of herbicides used in agriculture. Prediction of weed emergence timing would help reduce herbicide use through the optimization of the timing of weed control. It was concluded that Weibull four-parameter model could be used as a decision making tool for *A. fatua* and *D. sophia* to predict efficient management of seed emergence as well as to reduce usage of herbicides. Future research should be addressed to determine a wider validation of the models which could be valuable tools for farmers and practitioners for proper timing of control on *A. fatua* and *D. sophia* weeds.

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