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Evaluation of Weed Emergence Model AlertInf for Maize in Soybean

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AlertInf is a recently developed model to predict the daily emergence of three important weed species in maize cropped in northern Italy (common lambsquarters, johnsongrass, and velvetleaf). Its use can improve the effectiveness and sustainability of weed control, and there has been growing interest from farmers and advisors. However, there are two important limits to its use: the low number of weed species included and its applicability only to maize. Consequently, the aim of this study was to expand the AlertInf weed list and extend its use to soybean. The first objective was to add another two important weed species for spring-summer crops in Italy, barnyardgrass and large crabgrass. Given that maize and soybean have different canopy architectures that can influence the interrow microclimate, the second objective was to compare weed emergence in maize and soybean sown on the same date. The third objective was to evaluate if AlertInf was transferable to soybean without recalibration, thus saving time and money. Results showed that predictions made by AlertInf for all five species simulated in soybean were satisfactory, as shown by the high efficiency index (EF) values, and acceptable from a practical point of view. The fact that the algorithm used for estimating weed emergence in maize was also efficient for soybean, at least for crops grown in northeastern Italy with standard cultural practices, encourages further development of AlertInf and the spread of its use.

Nomenclature: Common lambsquarters, *Chenopodium album* L., CHEAL; barnyardgrass, *Echinochloa crus-galli* (L.) Beauv., ECHCG; johnsongrass, *Sorghum halepense* (L.) Pers, SORHA; large crabgrass, *Digitaria sanguinalis* (L.) Scop., DIGSA; velvetleaf, *Abutilon theophrasti* Medik., ABUTH; maize, *Zea mays* L.; soybean, *Glycine max* (L.) Merr.

Key words: Hydrothermal time, modeling, predicting weed emergence dynamics, weed control.

Knowledge on the emergence pattern of the main weed species in a crop is critical for devising weed control plans. Because the timing of weed emergence relative to that of the crop strongly influences crop-weed competition, information on weed emergence dynamics can be used to optimize the removal strategies to avoid yield losses (Benjamin et al. 2010; Grundy 2003). The importance of knowing and predicting weed emergence has been recognized for many years and several studies have been conducted to model weed emergence (Colbach et al. 2007; Dorado et al. 2009; Myers et al. 2004). The introduction of such models in decision-support programs can reduce herbicide use and weed control costs compared with standard management practices (Forcella et al. 2000). Proper timing of weed control is particularly important, given the increasing frequency of POST control in maize and especially in soybean. These models provide the percentage of cumulated emergence reached every day by weed species, and farmers can use this information to select the best timing of mechanical or chemical control (Alvarado and Bradford 2002; Archer et al. 2001; Chantre et al. 2012; Masin et al. 2011). AlertInf (Masin et al. 2012) is one of these weed emergence predictive models, and was recently developed for three important weed species in Italian maize fields: common lambsquarters, johnsongrass, and velvetleaf. The model is based on the hydrothermal time concept (Bradford 2002; Gummerson 1986), in which the combination of soil temperature and soil water potential is the main factor driving germination and emergence processes. In order to evaluate the interest in and use of the model by farmers and advisors, a simplified version of AlertInf (that uses rainfall instead of soil water potential) has been made available on the Web site of the ARPAV Agrobiometeorology Unit (www.arpa.veneto.it) (Masin et al. 2010a). The high number of recorded visits to the model Web page (about 2000 hits during the 2010 growing season) suggested a positive response from the users. Nonetheless, one of the limits to its use is the low number of weed species included. In fact, the higher the number of simulated species,

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the more information is provided by the model on the total field infestation present in the field, making the model more flexible and useful for the farmers. Consequently, it is of great interest to extend the weed species list. Modeling the emergence dynamics of selected species with AlertInf requires many years of emergence observations in the field to estimate the parameters of the model equation (i.e., a Gompertz function) and laboratory experiments to estimate the germination threshold parameters (base temperature and base water potential for seed germination) for each species or, more properly, for each ecotype, needed to calculate the hydrothermal time. Studies on threshold parameters for germination reported very different values for populations of the same species growing in diverse geographic locations, showing that the thresholds may differ among ecotypes (Forcella et al. 2000; Gardarin et al. 2010; Loddo et al. 2013; Steinmaus et al. 2000). Nevertheless, a recent study (Masin et al. 2010b) reported that threshold parameters did not differ between two ecotypes of various weed species collected in two extreme regions of the main maize-growing area in Italy. The same values may therefore be adopted for these parameters throughout the Italian maize-growing area without estimating specific thresholds for each ecotype. This conclusion was of some importance because the laboratory experiments to obtain the threshold parameters are very time and resources consuming.

Because the main weed species in maize are also common in other summer crops in Italy, the same threshold parameters for weed germination can be applied. But crops have different spatial arrangements, plant development, canopy structure, and cultural practices, and this may affect weed recruitment, development, and competition with the crop differently (Baumann et al. 2001; Hock et al. 2005; Knezevic et al. 2002; Mohler 1996; Sweeney et al. 2008). Emergence of weeds may be somewhat inhibited as a crop canopy expands and as the growing season progresses because of the changing of the underlying soil microclimate (Forcella et al. 2000). The main factors are soil temperature, soil water potential, and light quality (Norsworthy 2004). Even if the use of hydrothermal time in the models accounts for the differences in the soil temperature and soil water potential, soil thermal amplitude and light quality have effects that are difficult to consider in models, also because they are not well understood (Forcella et al. 2000) and very variable among weed species. In fact, studies on effects of light and diurnal temperature fluctuations on seed germination reported that these parameters inhibit the germination of some species and are ineffective, or sometimes even a stimulant, on others (Batlla et al. 2000; Huarte and Benech Arnold 2003; LeBlanc et al. 2002). As a consequence, it is necessary to conduct specific experiments in order to determine whether weed emergence dynamics are the same in different crops and, if so, to recalibrate the model for each crop.

The aim of this study was to improve and generalize AlertInf use by fulfilling three objectives. Given that the last version of AlertInf included three weed species (common lambsquarters, johnsongrass, velvetleaf), the first objective of this study was to add another two important species for maize in Italy, barnyardgrass and large crabgrass, by calculating the biological parameters required by the model (model extension). In Italy maize and soybean grow in the late spring and summer, but maize is traditionally sown about 1 mo before soybean (in April and in May, respectively). In addition, as reported by Vina et al. (2011), the two crops have contrasting canopy architectures (spherical vs. planophile leaf angle distribution) and leaf structures (monocotyledon vs. dicotyledon). With these facts taken into consideration, the second objective of the study was to compare weed emergence in maize and soybean sown on the same date between late April and mid-May (comparison of weed emergence). According to the results of the comparison experiments, the hypothesis was advanced that weeds have the same emergence dynamics in maize and soybean, and consequently the third objective was to evaluate if AlertInf, created for weed species in maize, was transferable to soybean without recalibration, saving time and money (model validation).

Materials and Methods

Model Extension for Barnyardgrass and Large Crabgrass in Maize. Field experiments were conducted from 2005 to 2012 in three localities in the northeastern Po Valley (northeast Italy): at Montemerlo (2005), Carbonara (2007 and 2012), and Legnaro (from 2006 to 2010 and 2012) (Table 1, extension data set in maize) in different soil types (Table 2). The sites are less than 50 km apart and have almost the same subhumid climatic conditions. Average annual temperature of the area is 12.2 C, with temperature increases from January (average minimum: −1.5 C) to July (average

Table 1. Observed densities (plants m^{-2}) of the five species considered by AlertInf in all the experiments, in maize and soybean.

Experiments: data sets, crops, and sites	Sowing date	ABUTH	CHEAL	DIGSA	ECHCG	SORHA
Extension data set in maize						
Montemerlo 2005	March 13			–	11.1	
Carbonara 2007	March 14			–	17.0	
Carbonara 2012	April 26			–	23.3	
Legnaro 2006a[a]	April 13			–	52.5	
Legnaro 2006b	April 13			–	56.6	
Legnaro 2007a	March 22			127.2	–	
Legnaro 2007b	May 11			135.4	–	
Legnaro 2008	April 28			18.9	–	
Legnaro 2009	May 12			7.3	12.0	
Legnaro 2010	April 13			21.2	–	
Legnaro 2012	May 3			56.0	33.0	
Comparison data set in maize and soybean						
Albettone 2012, maize	April 26			66.7	250.0	
Albettone 2012, soybean	April 26			61.1	236.1	
Carbonara 2012, maize	April 26					458.3
Carbonara 2012, soybean	April 26					397.2
Pozzoveggiani 2012, maize	May 4		13.0			
Pozzoveggiani 2012, soybean	May 4		11.0			
Validation data set in soybean						
Carbonara 2012	April 26					397.2
Legnaro 2011	May 5	7.7				
Legnaro 2011	May 20	8.0		60.0	73.3	
Legnaro 2012	April 19	9.0	15.5	110	75.5	35.0

[a] a, b = two different fields.

maximum: 27.2 C). Annual rainfall is about 850 mm and uniformly distributed throughout the year.

In all the experimental sites, seedbed preparation was done according to local practices: Primary tillage consisted of fall moldboard plowing and spring harrowing. Maize was sown on different dates from March to May in rows spaced 0.75 m apart. The crop was irrigated if required to avoid yield losses (irrigation timing and amounts were considered in the model).

Weed emergence was monitored in each experiment in 33 fixed sampling areas (0.3 × 0.3 m) placed at random in the interrows (avoiding passing tractor wheels) in an area of the field of about 500 m^2. Weed seedlings in these areas were counted, classified, and removed every 4 to 6 d until the end of the growing season. The emergence data obtained from each of the 33 areas were summed for each sampling date and cumulated to obtain the emergence dynamics.

The emergence data were used to estimate the parameters of the AlertInf equations for barnyardgrass and large crabgrass. AlertInf simulates emergence dynamics as a function of hydrothermal time (HT). There are various methods to calculate the HT. In AlertInf, it is considered that all species accumulate HT in proportion to soil temperature only when soil water potential is above a base value. This base value of water potential increases linearly as soil temperature rises above the optimum

Table 2. Main soil characteristics of the experimental sites.

Description	Unit	Albettone	Carbonara	Legnaro	Montemerlo	Pozzoveggiani
Sand	%	34	28	16	21	17
Silt	%	42	45	65	36	61
Clay	%	24	27	19	43	22
Texture (U.S. Department of Agriculture)[a]	Class	L	CL	SL	C	SL
pH	Unit	8	7.61	8.04	7.2	8.06
Organic matter	%	2.1	2.0	1.8	2.7	2.5
Cation-exchange capacity	mEq/100 g	17.8	20.4	14.8	22.4	14.2

[a] L = loam; C = clay, CL = clay loam; SL = silt loam.

Table 3. Model creation and AlertInf performance for barnyardgrass and large crabgrass in maize (extension data set in maize): biological parameters (*Tb*, *To*, Ψb, and *Kt*) for the calculation of the hydrothermal time (*Tb* and Ψb estimated by Masin et al. 2010b), Gompertz coefficients (*a* and *b*) for modeling the cumulated emergence, and model efficiency (EF).

	Tb	*To*	Ψb	*Kt*	Gompertz coefficient		
Species	(C)	(C)	(MPa)	(slope)	*a*	*b*	EF
DIGSA	10.3	29	−0.74	0.10	6.49	0.01	0.96
ECHCG	11.7	26	−0.97	0.10	4.17	0.02	0.91

temperature until it reaches 0 MPa at a temperature defined as the ceiling temperature. HT is calculated as a combination of soil temperature and soil water potential, as follows:

$$\mathrm{HT}_i = n * \max(Ts_i - T_b, 0) + \mathrm{HT}_{i-1}, \qquad [1]$$

where $Ts_i < To$: $n = 0$ if $\Psi s_i \leq \Psi b$, $n = 1$ if $\Psi s_i > \Psi b$; and when $Ts_i > To$: n $= 0$ if $\Psi s_i \leq \Psi b + Kt\,(Ts_i - To)$, $n = 1$ if $\Psi s_i > \Psi b + Kt\,(Ts_i - To)$; Ts_i and Ψs_i are the average daily soil temperature and water potential at 5-cm depth, *Tb* and Ψb are the base temperature and base water potential, *To* is the optimum temperature and *Kt* is the slope of the relationship between Ψb and Ts_i in the supraoptimal temperature range. Base thresholds of barnyardgrass and large crabgrass had been calculated in previous laboratory experiments (Table 3) (for details see Masin et al. 2010b). Accumulation of HT starts from the spring tillage date for seedbed preparation.

Percentage of seedling emergence (cumulated and normalized to 100%) (CE) is expressed by a Gompertz function, as follows:

$$\mathrm{CE}_i = 100\exp[-a\exp(-b\mathrm{HT}_i)], \qquad [2]$$

where *a* is related to an HT lag before emergence starts, and *b* is related to the slope of the curve.

The values of *To* and *Kt* were estimated by systematically varying in an iterative fashion until the best simulations were obtained for barnyardgrass and large crabgrass. Hydrothermal time was recalculated for different values of *To* and at first with $Kt = 0$; *Kt* was then varied incrementally to find the combination between the values of *Kt* and *To* giving the least-squares best fit.

The calculation of HT used the daily average values of soil temperature and soil water potential, which were monitored in all years at Legnaro. Temperature was measured with four HOBO mini loggers (Pendant data logger HOBO UA-001-08, Onset Computer Corporation, Bourne, MA) buried 5 and 10 cm deep. Soil water potential was monitored with the use of water moisture probes (253-L Watermark Soil Matric Potential, Campbell Scientific Inc., Shepshed, U.K.) buried at a depth of 5 cm and connected to an external data logger (external data logger HOBO 4-Channel U12-008, Onset Computer Corporation, Bourne, MA). The data-logger readings of soil temperature and water potential were taken every 2 h. In the sites where the soil microclimate was not directly measured (Montemerlo 2005 and Carbonara 2007), the Soil Temperature and Moisture model (STM^2) (Spokas et al. 2007) was used to simulate soil temperature and water potential at a depth of 5 cm (Masin et al. 2012), with the use of daily precipitation and air temperature recorded by ARPA (Regional Environmental Protection Agency of Veneto) meteorological stations located near (less than 5 km) each experimental site. The STM^2 model has already been effectively used for the simulation of soil microclimate within the seedling recruitment zone in experimental sites for the simulation of other weed species emergence in AlertInf (Masin et al. 2012), moreover Royo-Esnal et al. (2010) and Spokas and Forcella (2009) have successfully used this model to predict the soil environment for weed emergence modeling and other applications.

AlertInf performance in predicting weed emergence was evaluated with an efficiency index (EF) (Loague and Green 1991), calculated as

$$\mathrm{EF} = \left[\sum_{i=1}^{n}(O_i - \bar{O})^2 - \sum_{i=1}^{n}(P_i - O_i)^2\right] \Big/ \sum_{i=1}^{n}(O_i - \bar{O})^2, \quad [3]$$

where P_i is the predicted value, O_i the observed value, and the mean of observed values. EF ranges from 1 to negative value. An EF = 1 indicates exact predictions, and EF = 0 indicates a model of poor fit where the average value would model the relationship as well. An efficiency of lower than zero indicates that the mean value of the observed values would have been a better predictor than the model. Nevertheless, Ramanarayanan et al. (1997) suggested 0.5 as the lower range value for acceptable model prediction. Parameters of AlertInf for barnyardgrass and large crabgrass in maize (extension dataset in maize) are in Table 3.

Comparison of Weed Emergence in Maize and Soybean. In order to compare weed emergence under different canopy conditions, emergence dynamics of the five weed species simulated by AlertInf were studied in experiments where maize and soybean were sown in contiguous plots on the same date in each site (Table 1). The experiments were conducted in 2012 at Carbonara, Albettone, and Pozzoveggiani. The three sites are 20 to 30 km from Padova and have different soil types (Table 2). The experiments followed the same method as described above for the model extension in maize. For soil preparation, conventional tillage was used on both maize and soybean, consisting of fall moldboard plowing and spring harrowing. Crops were sown from late April to mid-May. Maize was sown with the same interrow as in the experiments for model extension, whereas soybean was sown in rows spaced 0.45 m apart. Nitrogen fertilizer was applied only in maize at rates of 200 kg/ha of urea nitrogen.

Daily average values of soil temperature and soil water potential were recorded at a depth of 5 cm during the crop-growing season. Weed emergence was monitored with the use of fixed sampling areas (0.3×0.3 m) placed on the soil in the interrow, as described above. The emergence data obtained from these three experiments were used to compare the emergence dynamics of the five species simulated by AlertInf in maize and in soybean.

Model Validation with Independent Data Set in Soybean. In order to verify the transferability of the model from maize to soybean, four experiments were conducted in Carbonara (2012) and Legnaro (2011 to 2012) in soybean fields with sowing dates ranging from April 19 to May 20 (Table 1, validation data set in soybean). Weed emergence dynamics of the five weed species simulated by AlertInf were monitored as previously described for the other experiments (extension data set and comparison data set).

The daily average values of soil temperature and soil water potential were recorded in all the experiments. To verify if the same biological parameters (Tb, To, Ψb, and Kt) and Gompertz coefficients (a and b) estimated in maize were usable in soybean, emergence percentage of the five weed species for all experiments was simulated with the use of AlertInf and the predictions were compared with observations. Overall AlertInf performance was evaluated with the use of EF and the mean bias error (MBE) (Willmott 1982). The MBE is related to magnitude of values under investigation and is an indication of the average deviation of the predicted from the observed values. It is calculated as

$$\mathrm{MBE} = (1/N) \sum_{i=1}^{N} (P_i - O_i), \qquad [4]$$

where N is the number of observations. When the model, on average, underestimates the observed values, MBE is negative; otherwise, it is positive (Wallach 2006).

For a detailed predicted *vs.* observed analysis, linear regression and correlation analyses (Pearson's r and Spearman correlation) were performed (StatSoft Inc. 2011) and a graphical comparison was also used to identify general agreement and trends.

Results and Discussion

Model Extension for Barnyardgrass and Large Crabgrass in Maize. The densities of barnyardgrass and large crabgrass in the sites used for the emergence model extension were very different among experiments (Table 1, extension data set). Large crabgrass density ranged from 7.3 plants m^{-2} in Legnaro 2009 to 135.4 plants m^{-2} in Legnaro 2007b, whereas the highest density observed for barnyardgrass was 56.6 plants m^{-2}. These data were used to estimate the optimal temperature for emergence of the two species. The optimal temperatures resulted as 26 and 29 C for barnyardgrass and large crabgrass, respectively (Table 3). Barnyardgrass seeds germinate over a wide range of temperatures, and many different optimal temperatures have been reported for this species in the literature: A range between 20 and 30 C was reported by Rahman and Ungar (1990) and Shipley and Parent (1991), in agreement with the result of the present study, whereas Manidool (1992) reported a higher optimum germination temperature range of 32 to 37 C. The value estimated for large crabgrass was in agreement with that reported by Zhang et al. (2012), who observed the best germination performance between 25 and 30 C. The model adequately described the cumulated emergence in the experiments used for its extension as shown by the high EF values of the simulation (0.91 and 0.96 for barnyardgrass and large crabgrass, respectively) (Table 3).

Comparison of Weed Emergence in Maize and Soybean. The densities of velvetleaf in the

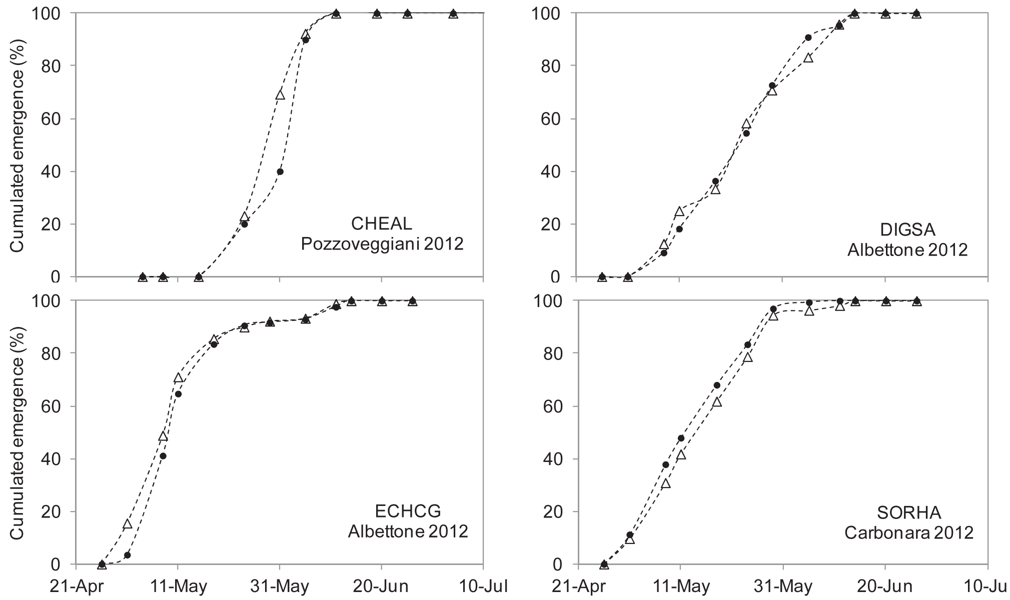

Figure 1. Observed cumulated weed emergence for four weed species in maize (triangles) and soybean (black circles) sown on the same date in each site: Pozzoveggiani May 4 (common lambsquarters), Albettone April 26 (large crabgrass and barnyardgrass), Carbonara April 26 (johnsongrass) (comparison data set).

comparison experiments was unfortunately too low in all sites to compare the emergence dynamics in maize and soybean. Therefore, only the results for barnyardgrass (in Albettone), large crabgrass (in Albettone), common lambsquarters (in Pozzoveggiani), and johnsongrass (in Carbonara) can be used for comparison (Table 1, comparison data set in maize and soybean). Results show that the observed emergence dynamics of these four weeds in maize and soybean are very similar (Figure 1) and not affected by the crop canopy differences when the two crops were sown on the same date and standard cultural practices followed. This supported the hypothesis that AlertInf could be directly used to simulate weed emergence in soybean without recalibration.

Model Validation with Independent Data Set in Soybean. The simulations of emergence of the five species in soybean performed with the use of AlertInf developed in maize (validation data set) were in general accurate, with EF index ranging from 0.93 to 0.99 for the single experiments and observed vs. predicted correlations always highly significant (Table 4, Figure 2). Even if velvetleaf was not found in the maize-soybean comparison experiments (see comparison data set in Table 1), it is interesting to see that the simulation of this species was satisfactory, as shown by the high EF values (from 0.95 to 0.98). From the graphs (Figure 3), it can be observed that the real emergence of velvetleaf in Legnaro in the 2011 second sowing date started 8 to 9 d later than the simulated emergence. This inaccuracy was observed for all other weed species in this site and year, i.e., barnyardgrass and large crabgrass. It seems that weeds have suffered a soil water potential below the threshold for germination, whereas that recorded by the moisture probes was higher, which was likely not representative of the soil water potential of the sampled areas. This could be explained by the necessity to wet the soil when the probes are installed (instruction manual of 253-L Soil Matric Potential Sensors, http://s.campbellsci.com/documents/ca/manuals/253_257_man.pdf). The consequence was that in the days soon after the soil preparation for sowing an incorrect measure of the soil water potential was recorded.

AlertInf simulation of johnsongrass emergence in soybean was very satisfactory (EF of 0.99) in Legnaro 2012, whereas in Carbonara 2012 the model underestimated the beginning of emergence and overestimated the emergence by over 50%. In particular, it seemed that the real emergence pattern was slower with a lower slope. Nevertheless, following the model simulation, the percentage of emergence is estimated only some days in advance, with a maximum of 4 d earlier on May 24, it cannot be considered a relevant error for the practical use of the information provided by the model. Furthermore, it is interesting to note that this inaccurate estimation cannot be imputed to application in soybean of a model developed in maize, because the pattern of weed emergence in maize in Carbonara

Table 4. AlertInf performance for the validation data set in soybean for the five weed species: model efficiency (EF), mean bias error (MBE), Pearson's r, and Spearman rank order correlation of the observed and predicted cumulated emergence.

Experiment	Statistic	ABUTH	DIGSA	CHEAL	ECHCG	SORHA
Carbonara 2012	No. of paired data					11
	EF					0.97
	MBE					1.02
	Pearson's r					0.99
	Spearman correlation					0.99
Legnaro 2011 First sowing	No. of paired data	15				
	EF	0.95				
	MBE	1.50				
	Pearson's r	0.98				
	Spearman correlation	0.77				
Legnaro 2011 Second sowing	No. of paired data	13	13		13	
	EF	0.97	0.98		0.93	
	MBE	1.20	−1.10		−2.13	
	Pearson's r	0.98	0.99		0.97	
	Spearman correlation	0.81	0.95		0.98	
Legnaro 2012	No. of paired data	11	17	17	17	17
	EF	0.98	0.97	0.96	0.99	0.99
	MBE	−2.88	−3.02	3.09	1.61	1.35
	Pearson's r	0.99	0.98	0.98	0.99	0.99
	Spearman correlation	0.86	0.98	0.89	0.98	0.89
All experiments	No. of paired data	39	30	17	30	28
	EF	0.97	0.97	0.96	0.96	0.98
	MBE	0.17	−1.90	3.09	−0.01	1.22
	Pearsons r	0.98	0.98	0.98	0.98	0.99
	Spearman correlation	0.80	0.95	0.89	0.91	0.94
All experiments and weeds	No. of paired data	144				
	EF	0.97				
	MBE	0.06				
	Pearson's r	0.98				
	Spearman correlation	0.89				

[a] All Pearson's r and Spearman correlations are significant ($P < 0.01$).

2012 was very similar to that in soybean, with observations almost overlapped (Figure 3, fourth graph).

The most relevant errors (more than 5 d shift) were in the simulation of common lambsquarters and large crabgrass in Legnaro 2012. For common lambsquarters, AlertInf estimated a cumulated emergence of 68% 6 d before the real emergence accumulation. This error could be relevant from a practical point of view, because it could lead to a too-early timing for POST control and consequently a consistent part of weed seedlings would emerge later and escape the treatment.

For large crabgrass, AlertInf estimated a cumulated emergence of 80% 9 d after the real emergence accumulation, which at that time actually reached more than 90% of total emergence. However, even if the error is bigger than that of common

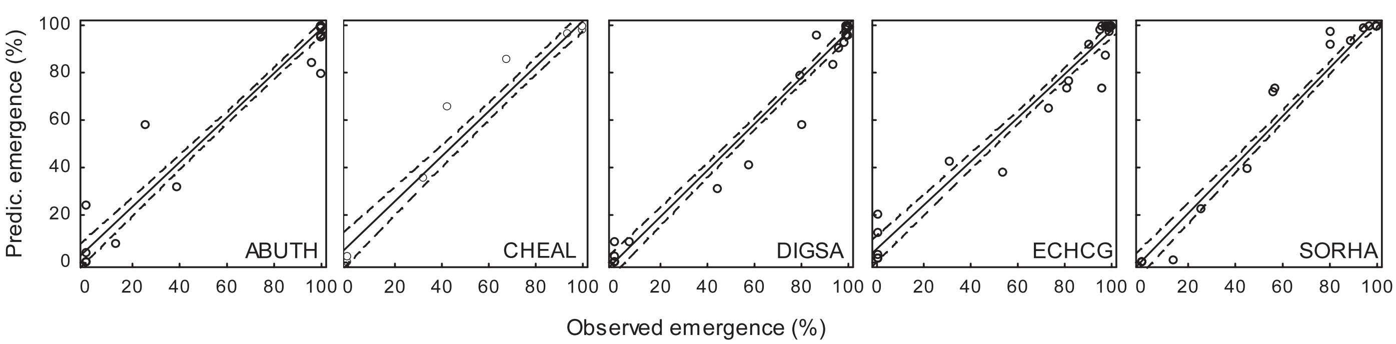

Figure 2. Predicted vs. observed weed cumulated emergence (%) for the five weed species in soybean performed with the use of AlertInf developed in maize (validation data set). Linear regression line and 95% confidence bands are indicated.

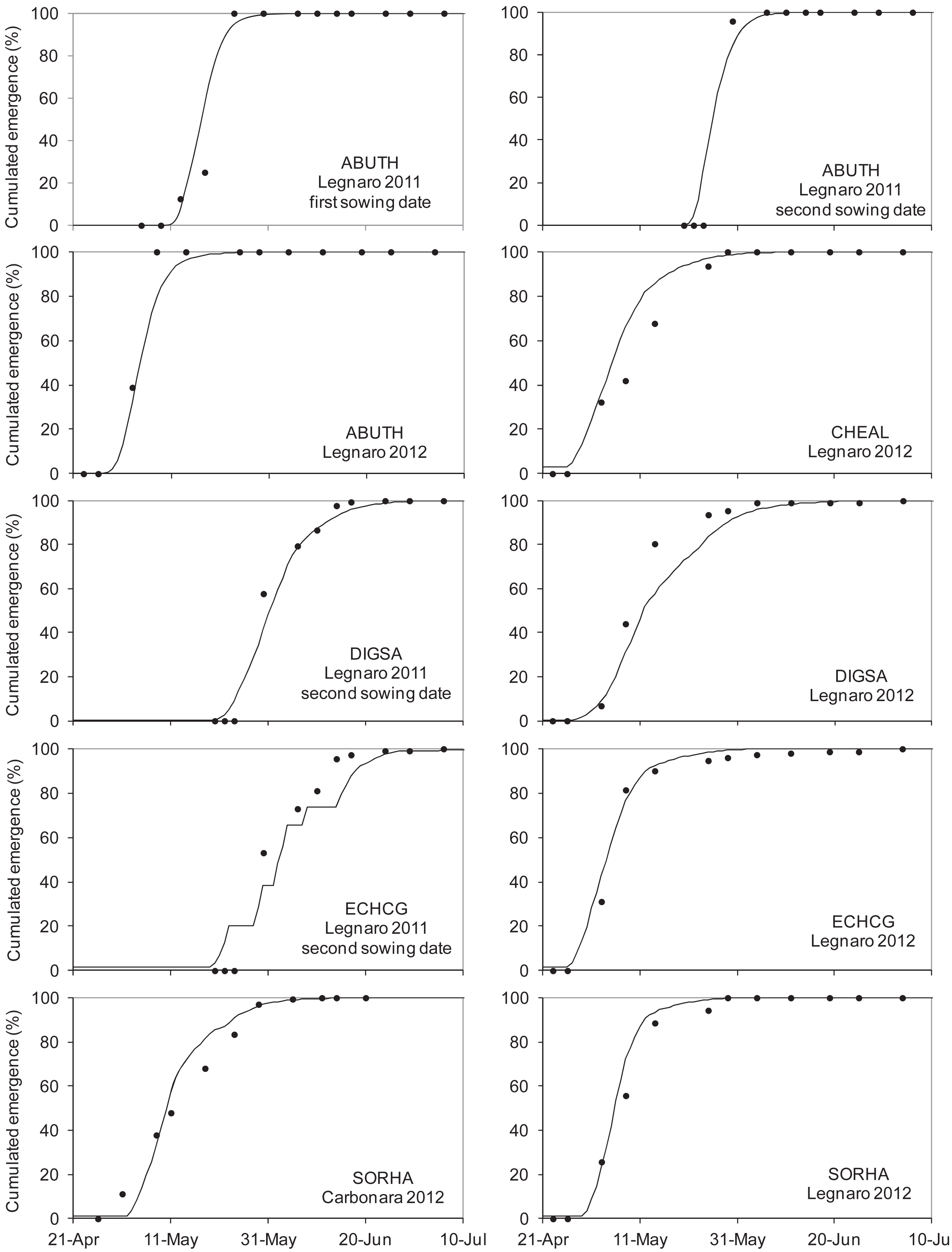

Figure 3. Cumulated weed emergence estimated with the use of AlertInf developed in maize (solid line) and emergence observations (black circles) in soybean of the five weed species in the four experiments conducted in 2011 to 2012 (validation data set).

lambsquarters, it is less important from a practical point of view. In fact when the estimation error is at high percentage of emergence (i.e., late in the season) it should not affect the timing of weed control suggested by the model, which is supposed to be done when emergence percentage is around 70% (Otto et al. 2009).

In conclusion, even if simulations were not completely accurate, emergence prediction made by AlertInf for all five species was satisfactory in all

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sites considered for the validation and, except for just two cases, acceptable also for practical purposes. This means that, even in crops such as maize and soybean, with contrasting leaf structure and canopy architecture, and different agronomic practices, the algorithm for weed emergence estimation used by AlertInf did not require recalibration of parameters, at least for crops grown in Veneto with standard cultural practices. These findings are very important, considering that recalibration of AlertInf to simulate weed emergence dynamics in soybean would require many field experiments, in different years and localities, for each weed species. Similar results were reported by Nyamusamba et al. (2008), who conducted experiments with an analogous purpose to this study. They found that the time required for common lambsquarters (as well as for redroot pigweed [*Amaranthus retroflexus* L.] and green foxtail [*Setaria viridis* (L.) Beauv.]) to reach 50% and 90% of emergence was comparable among crop species (including maize and soybean), and concluded that the same hydrothermal coefficients were adequate to predict weed emergence in several crops.

The recalibration from maize to soybean is likely not necessary because most weed species complete emergence before the different crop canopy characteristics can influence the interrow microclimate enough to change the processes of soil heating and water transfer in the seedling recruitment zone. This encourages further development of AlertInf and further studies to test its transferability to other climates and crops [e.g., sunflower (*Helianthus annuus* L.) or sugar beet (*Beta vulgaris* L.)].

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