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Modeling Weed Emergence in Italian Maize Fields

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A hydrothermal time model was developed to simulate field emergence for three weed species in maize (common lambsquarters, johnsongrass, and velvetleaf). Models predicting weed emergence facilitate well-timed and efficient POST weed control strategies (e.g., chemical and mechanical control methods). The model, called AlertInf, was created by monitoring seedling emergence from 2002 to 2008 in field experiments at three sites located in the Veneto region in northeastern Italy. Hydrothermal time was calculated using threshold parameters of temperature and water potential for germination estimated in previous laboratory studies with seeds of populations collected in Veneto. AlertInf was validated with datasets from independent field experiments conducted in Veneto and in Tuscany (west central Italy). Model validation resulted in both sites in efficiency index values ranging from 0.96 to 0.99. AlertInf, based on parameters estimated in a single region, was able to predict the timing of emergence in several sites located at the two extremes of the Italian maize growing area.

Nomenclature: common lambsquarters, *Chenopodium album* L.,CHEAL; johnsongrass, *Sorghum halepense* L. Pers, SORHA; velvetleaf, *Abutilon theophrasti* Medik., ABUTH.

Key words: Hydrothermal time, emergence prediction, modeling, weed control.

Integrated Weed Management, a basic component of Integrated Pest Management, has the objective of developing effective weed control systems and efficient use of herbicides. Although PRE herbicides are often considered fundamental in weed management, as they are often applied without regard for the density and botanical composition of weed communities (Lemieux et al. 2003), some applications may not be necessary (Swanton and Weise 1991). A possible alternative is POST weed management that entails waiting until weeds have emerged, evaluating their density and competitiveness, predicting the crop yield loss they could cause, and then deciding if a chemical or mechanical control is required. Systematic PRE applications can therefore be replaced by a targeted POST control (Lemieux et al. 2003). However, the knowledge of weed emergence is paramount for specific POST control. The major cause of poor POST weed control is improper application timing, which can be either too early or too late (Battla and Benech-Arnold 2007). If the control is too early, the flushes of emergence that take place after the application are not affected by the herbicide action, while if it is too late, weeds become less sensitive to the herbicide due to their larger size and moreover they could have already caused yield losses. Predictive weed emergence models can estimate, in a given moment of the crop cycle, the percentage of weeds that have already emerged and the successive seedling emergence dynamics. Therefore, they may be useful to achieve well-timed and efficient POST applications. The agronomic importance of knowing weed emergence patterns has been recognized for many years (Buhler et al. 2000; Forcella et al. 2000; Masin et al. 2005), and several studies have been conducted on weed emergence dynamics with various approaches (Grundy 2003). Significant progress has recently been made in the development of predictive models (Colbach et al. 2007; Dorado et al. 2009; Leguizamon et al. 2005). Both mechanistic and empirical approaches have been used to forecast weed emergence and both present advantages and disadvantages (Grundy 2003). There is no universal best approach to create an accurate model, since it depends on many factors, such as application area/areas, local climatic characteristics, cultivation practices, and uses of the model (research or production). A commonly used approach is the hydrothermal time concept (Alvarado and Bradford 2002; Gummerson 1986), based on the idea that seeds need a certain amount of hydrothermal time to germinate. Hydrothermal time is accumulated according to a comparison between daily soil conditions (temperature and water potential) and specific biological thresholds for seed germination (base temperature and water potential).

In the Italian maize-growing region, crops are not always irrigated, so periods of water deficiency may affect weed seed germination. In these conditions, hydrothermal time models, which consider both soil temperature and water potential, seem to be the most adequate to predict emergence with some degree of accuracy (Masin et al. 2010a). The objective of this study was to construct and evaluate a hydrothermal time model to predict the emergence of three important weeds in Italian maize fields: velvetleaf, common lambsquarters, and johnsongrass. The validation of the model was conducted in two regions: the one where the model was created (Veneto) and a region (Tuscany) at the other extreme of the main area where maize is grown in Italy. This was done to evaluate the possibility of extending the model, created using datasets from a single region, to all the regions where maize is grown in Italy without recalibration. This hypothesis was proposed because Masin et al. (2010b) reported homogeneous values of base temperature and water potential for local populations of the three species present in the two regions.

Materials and Methods

Experimental Sites. Eight field experiments were conducted from 2002 to 2008 in three localities in the northeastern Po Valley (northeast Italy): at Montemerlo (2002, 2003, and 2005) in a silty clay loam soil, at Carbonara (2006 and 2007) in a silty clay loam soil, and at Legnaro (2006, 2007, and 2008) in a loam soil (creation dataset). In all the experimental sites, seedbed preparation was done according to local

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practices: primary tillage consisted of fall moldboard plowing and spring harrowing. Maize was sown in late winter (March) in some experiments and in mid-spring (traditional sowing) in others. Rows were spaced 0.75 m apart. In the Montemerlo and Carbonara experiments, the crop was irrigated if required to avoid yield losses (irrigation timing and amounts were considered in the model).

In all the experimental sites, weed emergence was monitored in 33 fixed sampling areas (0.3 by 0.3 m) positioned on the soil in the interrow. Weed seedlings in these areas were counted, classified, and removed weekly until the end of the growing season. The emergence data obtained from each of the 33 areas of each experiment were summed for each date and cumulated to obtain the emergence dynamics. The emergence dynamics of the eight experiments were used to create an emergence predictive model (creation dataset) for velvetleaf, common lambsquarters, and johnsongrass (seedlings from seeds).

Three other experiments were conducted following the same method at Legnaro in 2010 and at Pisa from 2007 to 2008. This latter site was chosen because it is located in Tuscany at the southwestern extreme of the Italian maize-growing area. The emergence data obtained from these three experiments were used to validate the model (validation dataset).

The climate of all experimental sites in both regions is subhumid. The sites in Veneto are less than 50 km apart and have almost the same climatic conditions. Average annual rainfall is about 850 mm and fairly uniformly distributed throughout the year. Average annual temperature of the area is 12.2 C, with temperature increases from January (average minimum: −1.5 C) to July (average maximum: 27.2 C). Pisa has average annual rainfall of about 930 mm, mainly during the spring and fall. Average annual temperature is 15.0 C, with temperature increases from January (average minimum: 3.2 C) to July (average maximum: 28.0 C).

Weather Monitoring. Average daily precipitation and air temperature were collected during the experiments from ARPA (Regional Environmental Protection Agency of Veneto) meteorological stations located less than 5 km from the experimental sites in Veneto and at the on-farm weather station in Tuscany. Average daily air temperature and precipitation were used to simulate soil temperature and soil water potential at a depth of 5 cm by the Soil Temperature and Moisture model (STM^2) (Spokas et al. 2007, http://www.ars.usda.gov). This model has been used successfully to predict the soil microclimate used as input for weed emergence modeling and other applications (Royo-Esnal et al. 2010; Spokas and Forcella 2009). Soil temperature and water potential were monitored from the sowing date onwards at Carbonara in 2009 (with a proper experiment, not repeated at Montemerlo because the soil is the same as at Carbonara), at Pisa in both experimental years 2007 to 2008 and in all years at Legnaro. Temperature was measured using four mini loggers HOBO (Pendant data logger HOBO UA-001-08, Onset Computer Corporation, Bourne, MA) buried 5 and 10 cm deep. Soil water potential was monitored using water moisture probes (253-L Watermark Soil Matric Potential, Campbell Scientific Inc., Shepshed, U.K.) buried at a depth of 10 cm (to obtain accurate measurement of soil moisture it was decided to bury the sensors only at the lower depth) and connected to an external data logger (External data logger HOBO 4-Channel U12-008, Onset Computer Corporation, Bourne, MA). The data loggers took readings of soil temperature and water potential every 2 h. The recorded values were used to test the STM^2 model simulation and to calibrate the model for the simulation of temperature and water potential where they were not directly measured.

Table 1. Densities of the three species of interest in all the experimental sites.

Sites	ABUTH	CHEAL	SORHA
	(p m^{-2})		
Creation dataset			
Montemerlo 2002	0.0	26.7	144.4
Montemerlo 2003a	0.0	15.6	0.0
Montemerlo 2003b	43.0	0.0	3.0
Montemerlo 2005	0.0	263.9	174.4
Carbonara 2006	460.0	27.8	92.2
Carbonara 2007	276.6	86.2	115.4
Legnaro 2006	0.0	84.4	520.0
Legnaro 2007	5.1	11.8	3.7
Legnaro 2008	84.2	60.9	64.0
Validation dataset			
Legnaro 2010	11.1	52.5	10.1
Pisa 2007	10.9	0.0	0.0
Pisa 2008	0.0	68.8	19.1

Hydrothermal Time and Model Creation. The model developed in this study is based on the hydrothermal time concept (Alvarado and Bradford 2002; Gummerson 1986). According to this approach, all species accumulate hydrothermal time in proportion to soil temperature only when soil water potential is above a base value. This base value of water potential increases linearly as temperature rises above the optimum temperature (T_o) until it reaches 0 Megapascal (MPa) at a temperature defined as the ceiling temperature (Bradford 2002). The hydrothermal time (HT_i) is calculated as a combination of soil temperature and soil water potential as follows:

$$HT_i = n * \max(Ts_i - T_b, 0) + HT_{i-1} \qquad [1]$$

when $Ts_i < T_o$: $n = 0$ if $\Psi s_i \leq \Psi_b$, $n = 1$ if $\Psi s_i > \Psi_b$; and when $Ts_i > T_o$: $n = 0$ if $\Psi s_i \leq \Psi_b + K_t (Ts_i - T_o)$, $n = 1$ if $\Psi s_i > \Psi_b + K_t (Ts_i - T_o)$; Ts_i and Ψs_i are the average daily soil temperature and water potential at 5 cm depth, T_b and Ψ_b are the base temperature and base water potential, T_o is the optimum temperature, and K_t is the slope of the relationship between Ψ_b and Ts_i in the supra-optimal temperature range. Base thresholds of the three species were calculated with previous laboratory experiments (for details see Masin et al. 2010b) (Table 1). Accumulation of HT starts from the spring tillage date for seedbed preparation.

Cumulative emergence (CE) is expressed by a Gompertz function, as follows:

$$CE = 100\exp(-a\exp(-bHT)) \qquad [2]$$

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

The values of T_o and K_t were estimated by systematically varying in an iterative way until the best simulations were obtained for each species. Initially, hydrothermal time was recalculated for different values of T_o and with $K_t = 0$, then K_t was varied incrementally to find the combination between the values of K_t and T_o giving the least squares best fit. Weed emergence recorded at Montemerlo (2002, 2003, and 2005),

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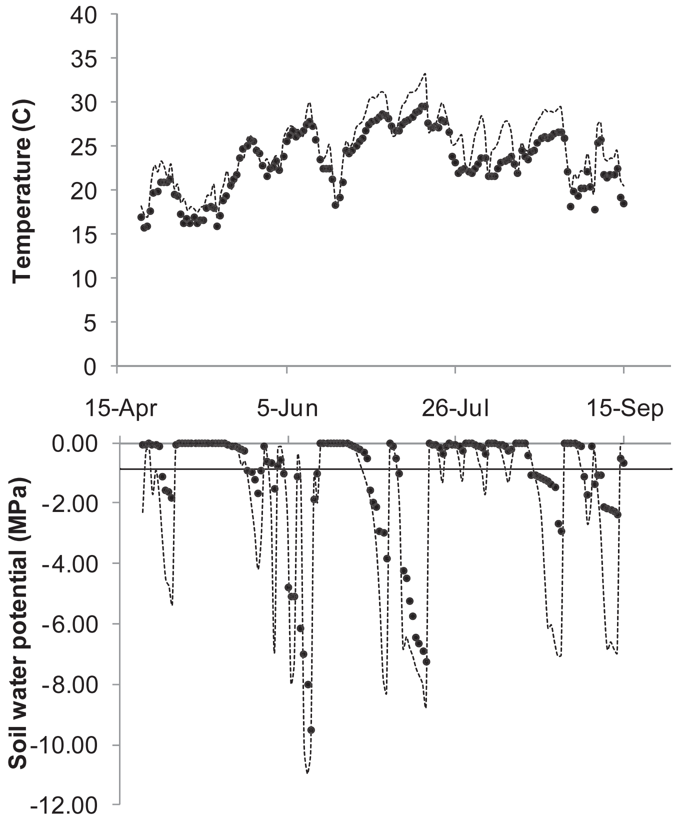

Figure 1. Measured (black circles) and estimated (dashed lines) soil temperature at 5 cm depth and soil water potential at 10 cm depth (r = 0.95 for temperature, r = 0.85 for water potential, P $<$ 0.001). The horizontal solid line in the soil water potential graph indicates the base water potential value (−0.96 MPa) of common lambsquarters.

Carbonara (2006 and 2007), and Legnaro (2006, 2007, and 2008) and soil temperature and soil water potential at 5 cm estimated by STM^2 were used to estimate K_t, T_o, and the coefficients a and b of the Gompertz function. The created model will henceforth be called "AlertInf."

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

$$EF = \frac{\sum_{i=1}^{n} \left(O_i - \overline{O}\right)^2 - \sum_{i=1}^{n} \left(P_i - O_i\right)^2}{\sum_{i=1}^{n} \left(O_i - \overline{O}\right)^2} \qquad [3]$$

where P_i is the predicted value, O_i the observed value, and $\bar{O}$ the mean of observed values. The value of EF can range from 1 downwards. An EF value of 1 would mean that the model produced exact predictions.

Validation of the Weed Emergence Model with Independent Dataset. In order to validate the model, datasets of weed emergence collected in experiments conducted at Pisa in 2007 (only velvetleaf) and 2008 (common lambsquarters and johnsongrass) and at Legnaro in 2010 (all three species) were used.

The daily average values of soil temperature and soil water potential were those estimated by STM^2 at a depth of 5 cm. The model was also validated at Pisa to verify its transferability to a region with a different climate without recalibrating it. In this way, it was verified if the same biological parameters (T_b, Ψ_b, K_t, and T_o) and Gompertz coefficients (a and b) estimated in Veneto were usable in another location at the other extreme of the Italian maize-growing region. Simulated emergence from AlertInf was compared with observed emergence data obtained at Legnaro and at Pisa using the model EF.

Table 2. Biological parameters for the calculation of the hydrothermal time and a and b coefficients of the Gompertz function used for modeling cumulated emergence. T_b and Ψ_b estimated by Masin et al. (2010b).

Species	T_b	T_o	Ψ_b	K_t	a	b
	——— (C) ———		(MPa)			
ABUTH	3.9	25	−0.78	0.10	10.28	0.02
CHEAL	2.6	23	−0.96	0.20	3.56	0.01
SORHA	11.8	24	−0.78	0.30	4.72	0.03

Results and Discussion

STM^2 Model Validation. In the field used for the weed emergence model creation, STM^2 simulated the soil environment with a certain accuracy, indeed the correlation of measured daily average soil temperatures and soil water potentials with daily average values estimated with STM^2 resulted in $r > 0.94$ for temperature and r ranged from 0.65 to 0.82 for water potential (P $<$ 0.001). Figure 1 shows the comparison between simulated and observed soil temperatures and soil water potentials at Legnaro during 2010 growing season, one of the sites and years used for the validation of the model. Soil temperatures were overestimated by the model as from July, when no more weed emergences were observed; therefore, this incorrect estimation does not influence emergence simulations. The model underestimates the low values of soil water potential when it decreases quickly (the example of the base water potential of common lambsquarters is shown in Figure 1). Nevertheless, it is important to note that the periods of water stress (when the soil water potential is below the base value and hydrothermal time accumulation stops) calculated with the observed or predicted daily water potential values coincide.

Weed Emergence Model Creation. The densities of the three studied species were very different from one experiment to another (Table 1). Parameters a and b of the Gompertz function and the input variables T_o and K_t are shown in Table 2 together with base temperatures and base water potentials determined by Masin et al. (2010b), which were also used for AlertInf parameterization. The resulting T_o of the three species were from 23 to 25 C. These values were essentially in agreement with those reported in the literature for common lambsquarters (Bouwmeester and Karssen 1993; Roman et al. 1999) and velvetleaf (Leon et al. 2004), while Benech-Arnold et al. (1990) stated that the interval 30 to 36 C was the optimum temperature for germination for an Argentinean population of johnsongrass. This dissimilarity may be a consequence of genetic differences between the two studied populations of johnsongrass that have such a different origin. The model adequately described the cumulated emergence in the experiments used for its creation, and even if there is a certain variability of between 20 and 80% of emergence prediction of johnsongrass, the EF values of the simulation are high (0.93 to 0.97) (Figure 2).

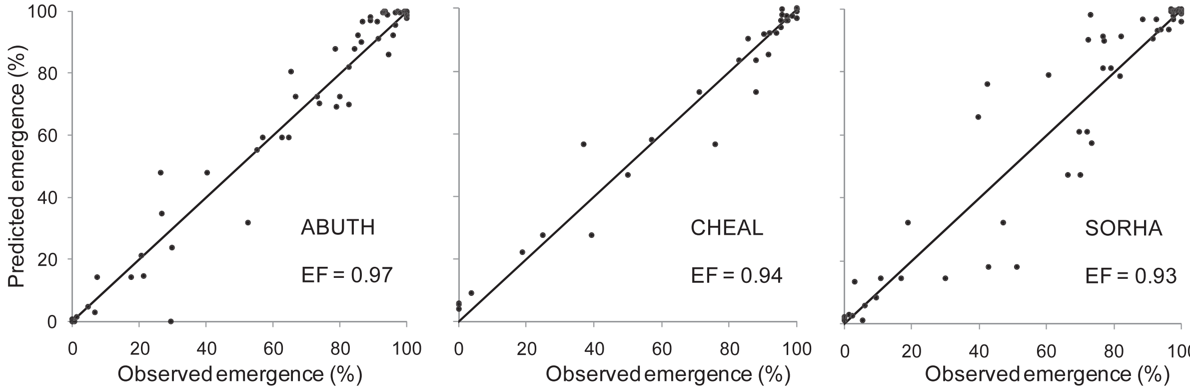

Figure 2. Observed vs. predicted cumulated weed emergence (creation datasets) for the three species and relative efficiency index (EF) values.

Validation of the Weed Emergence Model with Independent Datasets. Model simulations of emergence in 2010 at Legnaro and 2007 to 2008 at Pisa (validation dataset) resulted in EF values ranging from 0.96 to 0.99 (Figure 3), AlertInf prediction showed one pause in emergence at the end of April at Legnaro for all species. In correspondence to this pause, the model underestimated the percentage of cumulated emergence in velvetleaf and johnsongrass, and overestimated it

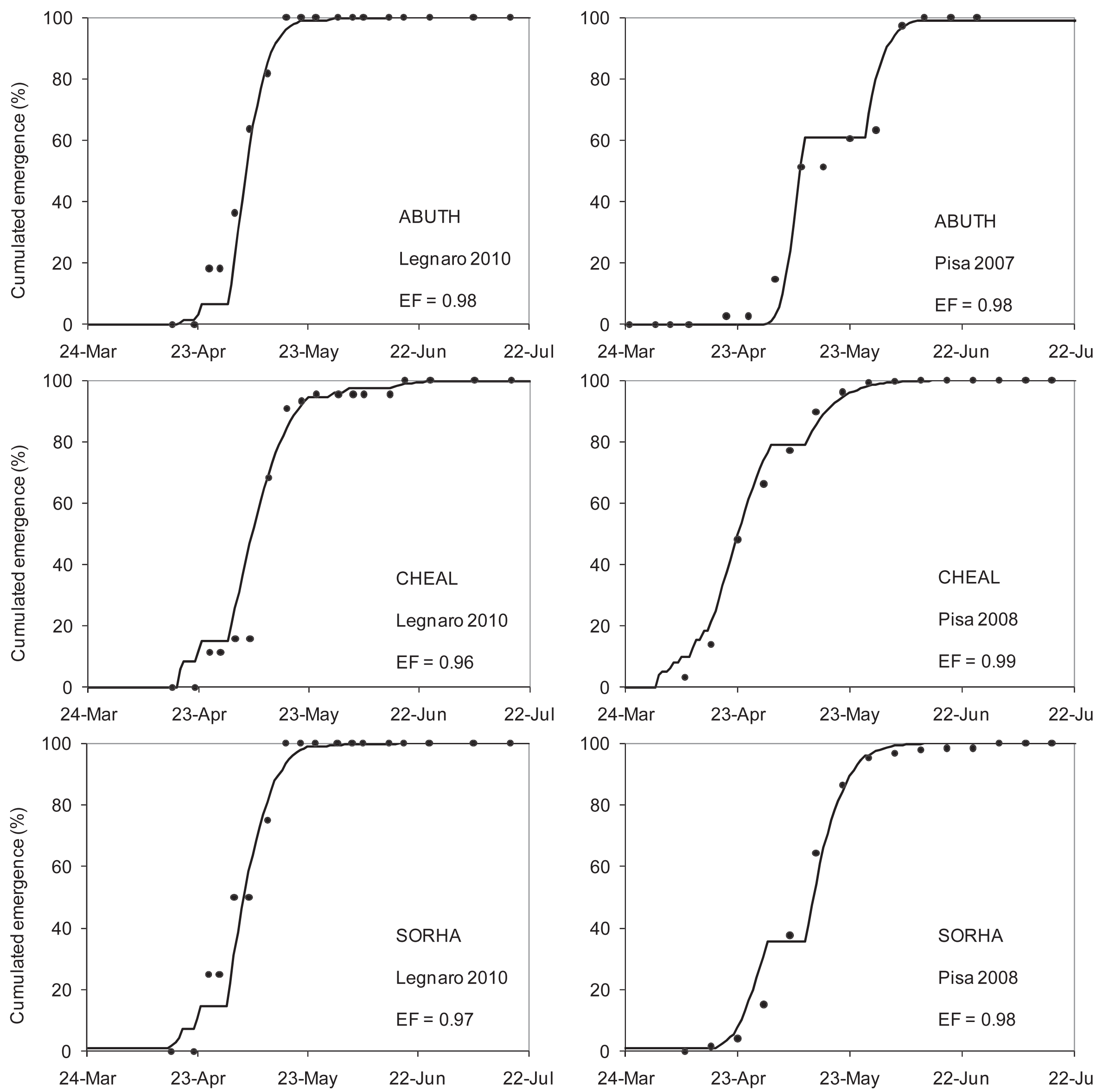

Figure 3. Cumulated emergence predicted using AlertInf (solid line), and observed (black circles) in three experiments conducted at Legnaro in 2010 and at Pisa in 2007 and 2008 (validation datasets).

in common lambsquarters. The second pause between May 3 and 7 present in the real emergence pattern of common lambsquarters and johnsongrass was not predicted by the model. This incorrect estimation is difficult to explain given that the analysis of soil temperature and soil water potential showed that neither the estimated nor the measured values of these two parameters were below the threshold on those 5 d (Figure 1). Hydrothermal time was therefore accumulated during this period, and consequently emergence percentage was supposed to increase, as for velvetleaf. Nevertheless, even if the estimation did not predict the second pause, all the simulations were satisfactory both statistically (high EF) and practically (for practical applications of the model).

It is very interesting that the simulation at Pisa, a different site from those used to create the model, was satisfactory, as shown by the high EF values (0.98 to 0.99). The simulated emergence was delayed in comparison with the real dynamics at the beginning of emergence for velvetleaf in 2007, and in advance by some days at the beginning of emergence for common lambsquarters and johnsongrass in 2008. However, for practical purposes (i.e., for timing stale seedbed preparation), estimation errors of a few days at the beginning of emergence could be acceptable. The more relevant error was in the simulation of johnsongrass emergence. AlertInf anticipated and overestimated the initial flush of emergence and then reported a pause in correspondence to 36% of emergence that was not present or maybe began later and lasted for less time in the real emergence pattern of this species. This incorrect prediction causes an estimation error of more than 20% of cumulated emergence, i.e., on April 30 the real emergence was 15% but the model estimated a much higher value (36%). A similar pause is also evident in the simulation of the emergence pattern of common lambsquarters. However, this pause could not be confirmed in the real emergence dynamics due to lack of data for this species in that period.

In conclusion, even if there were some errors of simulation, the predicted emergences of all three species showed high EF values in both sites considered for the validation. Results were accurate not only statistically, but also from a practical point of view. In general, AlertInf showed difficulties in accurately forecasting the onset of emergence, which is a critical period only for implementing weed control practices such as stale seedbed preparation but not for the use of POST control, which is applied later in the growing season. In fact, it usually suggested that farmers apply POST herbicides when most of the weeds have emerged (70 to 80% of emergence) (WeedCast Version 4.0 Documentation). In all the model validations (species and sites), the dates corresponding to this percentage of emergence were accurately estimated (the maximum difference was 2 d, an acceptable error for practical use). Another example can be made analyzing the predicted percentage required for optimizing weed control using rotary hoeing or first interrow cultivation according to the Oriade and Forcella (1999) indications. They observed that the more consistent efficacy of rotary hoeing could be obtained at 30% emergence of the species with higher density (in their experiments green foxtail, *Setaria viridis* L. Beauv.) and first interrow cultivation at 60%. AlertInf was also able to accurately predict these dates for optimizing those practices in all species and both sites. As previously said, for practical purposes the more relevant error of the model was in predicting the emergence of johnsongrass in Pisa. In this case the prediction of the date when johnsongrass reached 30% of emergence (for a hypothetical rotary hoeing), was 5 d in advance of the real date (the model estimated April 30 and the real 30% was reached on May 4).

These satisfactory results obtained with the model validation at Pisa and Legnaro lead to the conclusion that AlertInf created using a dataset collected in Veneto can be used to predict velvetleaf, common lambsquarters, and johnsongrass emergence not only in this region but also throughout the Italian maize-growing area.

Since 2008, a simplified version of AlertInf has been available on the website of the ARPAV Agrobiometeorology Unit (www.arpa.veneto.it) (Masin et al. 2010a). The response of the users is considered to be positive due to the high number of recorded visits to the AlertInf webpage throughout the growing season (about 2000 hits during 2010 growing season). Similar predictive models for weed emergence in arable fields accessible through interactive computer software are also being used by farmers and crop advisors in the United States (Archer et al. 2001) and Australia (Walsh et al. 2002), with positive feedbacks. The improved version of AlertInf described in this article has demonstrated the ability to predict emergence of the three studied species with good accuracy. The current objective is to improve this new version of the model by adding other species and then make it accessible to farmers and advisors through interactive computer software or information in bulletins distributed by extension services.

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Literature Cited

Alvarado, V. and K. J. Bradford. 2002. A hydrothermal time model explains the cardinal temperatures for seed germination. Plant Cell Env. 25:1061–1069.

Archer, D. W., F. Forcella, J. J. Eklund, and J. Gunsolus. 2001. WeedCast Version 4.0. http://www.ars.usda.gov/services/software/software.htm. Accessed: February 1, 2011.

Battla, D. and R. L. Benech-Arnold. 2007. Predicting changes in dormancy level in weed seed soil banks: implications for weed management. Crop Prot. 26:189–197.

Benech-Arnold, R. L., Ghersa, C. M., Sanchez, R. A., and Insausti, P. 1990. A mathematical model to predict *Sorghum halepense* (L.) Pers. seedlings emergence in relation to soil temperature. Weed Res. 30:90–99.

Bouwmeester, H. J. and C. Karssen. 1993. Seasonal periodicity in germination of seeds of *Chenopodium album* L. Ann. Bot. 72:463–473.

Bradford, K. J. 2002. Applications of hydrothermal time to quantifying and modeling seed germination and dormancy. Weed Sci. 50:248–260.

Buhler, D. D., M. Liebman, and J. J. Obrycki. 2000. Theoretical and practice challenges to an IPM approach to weed management. Weed Sci. 48:274–278.

Colbach, N., B. Chauvel, C. Gauvrit, and N. M. Munier-Jolain. 2007. Construction and evaluation of ALOMYSYS modelling the effects of cropping systems on the blackgrass life-cycle: from seeding to seed production. Ecol. Model. 201:283–300.

Dorado, J., E. Sousa, I. M. Calha, J. L. Gonzalez-Andujar, and C. Fernandez-Quintanilla. 2009. Predicting weed emergence in maize crops under two contrasting climatic conditions. Weed Res. 49:251–260.

Forcella, F., R. L. Benech-Arnold, R. Sanchez, and C. M. Ghersa. 2000. Modeling seedling emergence. Field Crop Res. 67:123–139.

Grundy, A. C. 2003. Predicting weed emergence: a review of approaches and future challenges. Weed Res. 43:1–11.

Gummerson, R. J. 1986. The effect of constant temperatures and osmotic potential on the germination of sugar beet. J. Exp. Bot. 37:729–741.

Leguizamon, E. S., C. Fernandez-Quintanilla, J. Barroso, and J. L. Gonzalez-Andujar. 2005. Using thermal and hydrothermal time to model seedling emergence of *Avena sterilis* ssp *ludoviciana* in Spain. Weed Res. 45:149–156.

Lemieux, C., L. Vallee, and A. Vanasse. 2003. Predicting yield loss in maize fields and developing decision support for post-emergence herbicide applications. Weed Res. 43:323–332.

Leon, R. G., A. D. Knapp, and M.D.K. Owen. 2004. Effect of temperature on the germination of common waterhemp (*Amaranthus tuberculatus*), giant foxtail (*Setaria faberi*), and velvetleaf (*Abutilon theophrasti*). Weed Sci. 52:67–73.

Loague, K. and R. E. Green. 1991. Statistical and graphical methods for evaluating solute transport models: overview and application. J. Cont. Hydrol. 7:51–73.

Masin, R., G. Cacciatori, M. C. Zuin, and G. Zanin. 2010a. AlertInf: emergence predictive model for weed control in maize in Veneto. It. J. Agromet. 1:5–9.

Masin, R., D. Loddo, S. Benvenuti, M. C. Zuin, M. Macchia, and G. Zanin. 2010b. Temperature and water potential as parameters for modeling weed emergence in central-northern Italy. Weed Sci. 58:216–222.

Masin, R., M. C. Zuin, D. W. Archer, F. Forcella, and G. Zanin. 2005. WeedTurf: a predictive model to aid control of annual summer weeds in turf. Weed Sci. 53:193–201.

Oriade, C. and F. Forcella. 1999. Maximizing efficacy and economics of mechanical weed control in row crops through forecasts of weed emergence. J. Crop Prod. 2:189–205.

Roman, E. S., A. G. Thomas, S. D. Murphy, and C. J. Swanton. 1999. Modeling germination and seedling elongation of common lambsquarters (*Chenopodium album*). Weed Sci. 47:149–155.

Royo-Esnal, A., J. Torra, J. Antoni Conesa, F. Forcella, and J. Recasens. 2010. Modeling the emergence of three arable bedstraw (*Galium*) species. Weed Sci. 58:10–15.

Spokas, K. and F. Forcella. 2009. Software tools for weed seed germination modeling. Weed Sci. 57:216–227.

Spokas, K., F. Forcella, D. Archer, D. Peterson, and S. Miller. 2007. Improving weed germination models by incorporating seed microclimate and translocation by tillage. Proc. Weed Sci. Soc. Am. 44:60.

Swanton, C. J. and S. F. Weise. 1991. Integrated weed management: the rationale and the approach. Weed Technol. 5:657–663.

Walsh, M., F. Forcella, D. Aecher, and J. Eklund. 2002. WEEDEM: turning information into action. Pages 446–449 *in* H. S. Jacob, et al. 2002. Proceedings of the 13th Australian Weeds Conference, Perth, Western Australia.

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