Weed Science 2013 61:146–153

Hydrothermal Emergence Model for Ripgut Brome (*Bromus diandrus*)

Addy L. García, Jordi Recasens, Frank Forcella, Joel Torra, and Aritz Royo-Esnal*

A model that describes the emergence of ripgut brome was developed using a two-season data set from a no-tilled field in northeastern Spain. The relationship between cumulative emergence and hydrothermal time (HTT) was described by a sigmoid growth function (Chapman). HTT was calculated with a set of water potentials and temperatures, iteratively used, to determine the base water potential and base temperature. Emergence of ripgut brome was well described with a Chapman function. The newly-developed function was validated with four sets of data, two of them belonging to a third season in the same field and the other two coming from independent data from Southern Spain. The model also successfully described the emergence in different field management and tillage systems. This model may be useful for predicting ripgut brome emergence in winter cereal fields of semiarid Mediterranean regions.
Nomenclature: Ripgut brome, *Bromus diandrus* Roth.
Key words: Chapman function, great brome, hydrothermal time, sowing delay, tillage systems.

Emergence is considered the most important event in the life of an annual species because it determines subsequent survival and success of the plant (Forcella et al. 2000). The ability to predict weed emergence could enhance crop management, facilitating implementation of more effective strategies by optimizing the timing of weed control (Leblanc et al. 2004; Myers et al. 2004); this is becoming increasingly relevant for growers because of current pressure to reduce chemical input or to adopt nonchemical methods (Grundy et al. 2000). Emergence of several weed species can be predicted using modeling techniques (Colbach et al. 2005). A principal goal of emergence modeling for wild species is to predict germination timing under fluctuating field conditions (Meyer and Allen 2009). Seed germination and emergence are strongly influenced by soil temperature and water potential, and they can be predicted by using modeling techniques based on hydrothermal time (Bair et al. 2006; Haj Seyed Hadi and Gonzalez-Andujar 2009). Hydrothermal time mechanistically relates the weed seed bank to seedling emergence using soil microclimate simulations (Spokas and Forcella 2009).

Temperature, when converted to thermal time, or growing degree days (GDD), has been used to predict seedling emergence. The use of average air or soil temperature above a specified threshold is accumulated over days until weed emergence (Royo-Esnal et al. 2010a). Hydrothermal time is a GDD-like measurement that accumulates when daily average soil water potentials and temperatures are greater than threshold values below which seedling emergence cannot occur (Schutte et al. 2008). According to Forcella et al. (2000), hydrothermal time (HTT) models are frequently better for predicting emergence than GDD.

The modeling of emergence of winter weeds from arable land should be especially valuable for climatic conditions of Mediterranean-type environments, where initial weed emergence and crop sowing are governed by the timing of precipitation in autumn, and later emergence is likely to be regulated by soil temperature in addition to soil moisture (Kleemann and Gill 2006).

Models, as those based on hydrothermal time, have been used to predict the emergence of several winter cereals weeds, oat (*Avena sterilis* ssp. *ludoviciana*) (Leguizamón et al. 2005) and *Galium* species (Royo-Esnal et al. 2010a), under the climatic conditions of dry-land agricultural systems of Spain. In the last decades, the adoption of continuous winter cereal production and the implementation of conservation agriculture techniques, such as direct drilling, have turned ripgut brome (*Bromus diandrus* Roth) into one of the most important weeds in these cereal systems (Riba and Recasens 1997). Although implementation of models that predict the emergence of *Bromus* species could have great implications for integrated weed management programs, no model has been developed yet.

In no-till systems the absence of soil disturbance permits the seeds to remain near the soil surface, which is a more favorable condition for seedling establishment of some species. Furthermore, some seeds of ripgut brome may be dormant (Gill and Carstairs 1988; Kleemann and Gill 2006; Kon and Blacklow 1989), and those low percentages that remain in the soil from one season to the next could hinder control methods. In this sense, chemical control of ripgut brome is more restricted and difficult than for other weeds because herbicides effective against ripgut brome usually damage the crop as well (Peeper 1984).

Accordingly, in this scenario, new strategies are needed to manage ripgut brome populations in reduced tillage systems that currently are being adopted in northeastern Spain. For example, delay of sowing date is one of the most practical methods that can be used by growers, as it effectively controls weeds that emerged in October and early November (Cirujeda et al. 2008). However, its efficacy depends on the climatic conditions during autumn, mainly rainfall regimes and soil temperature, and on subsequent emergence of seedlings from the remaining soil seed bank.

To improve these strategies and obtain more effective management, models capable of providing information about the timing of emergence as functions of soil moisture and soil temperature may be useful. Consequently, the objectives of this research were to develop a hydrothermal time seedling emergence model for ripgut brome using data derived from observations in rain fed winter cereals, and to validate and apply the model with independent data from other growing seasons.

Materials and Methods

Experimental Site. Field experiments were conducted from autumn to spring 2008 to 2009, 2009 to 2010, and 2010 to

DOI: 10.1614/WS-D-12-00023.1
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2011 in an experimental cereal field that was managed since 2006 to 2007 under no-tillage. The field was located in Agramunt, Lleida, in northeastern Spain (41°48′N, 1°07′E). The soil was a Fluventic Xerocrept (100 to 120 cm deep), with 30.1% sand, 51.9% silt, 17.9% clay, 2.3% organic matter, and pH of 8.5.

Experimental Designs. Two experiments were used to first develop the model for the emergence of ripgut brome and its validation, and second for the practical application with different field and soil management systems. The first experiment (trial 1) consisted in a randomized complete block design with three replications. Plot size was 6 by 50 m. One factor was considered, the cereal sowing date. The first sowing date (F1) had been on October 20, 19, and 14; the second sowing date (F2) on November 7, 12, and 18; and the third sowing date (F3) on December 12, 3, and 13 in 2008, 2009, and 2010, respectively. Barley (*Hordeum vulgare* L.) cv. 'Sunrise' and 'Hispanic' were sown in 2008 and wheat (*Triticum aestivum* L.) cv. 'Bokaro' and 'Artur Nick' in 2009 and 2010. Each year, crops were sown at 180 kg·seed ha^{-1} (400 to 450 plants·m^{-2}). Sowing was performed with a no-till disc drill in rows 19 cm apart. Plots were sprayed with glyphosate (Roundup Plus) at 540 g ai ha^{-1} one to six days before each sowing date (October 14, 16, and 13 in F1; November 6, 4, and 12 in F2; and December 5, 2, and 9 in F3, in 2008, 2009, and 2010, respectively). In 2008 to 2009, a POST tank mix of isoproturon plus diflufenican (1243 + 69 g·ha^{-1}) was applied in February. In 2009 to 2010 POST weed control was accomplished by iodosulfuron-methyl sodium plus mesosulfuron-methyl-sodium (3 + 15 g ai ha^{-1} plus wetting agent). In 2010 to 2011, broadleaf and grass weeds were controlled POST by tribenuron-methyl plus metsulfuron-methyl(10 + 5 g·ha^{-1} plus wetting agent) in March. Iodosulfuron-methyl sodium plus mesosulfuron-methyl-sodium (3 + 15 g ai ha^{-1} plus wetting agent) was applied February 9 in F1 (tillering) and April 13 in F2 and F3 (2 to 5 leaves). Fertilizer was applied each year in February to March at 150 kg N-32% ·ha^{-1}.

The second experiment (trial 2) also consisted of a randomized complete block with three replications. This experiment was designed to study three different soil management systems: subsoiler (SS), chisel plough (ChP), and moldboard plough (MbP). The sowing date in this experiment corresponds each year to the second sowing dates of trial 1. Crop type and sowing density were the same as in trial 1, except in 2009 to 10 in which was sown barley cv. 'Hispanic'.

Weed emergence was estimated in each plot in ten permanent quadrats, each 0.1 m^2. After each sowing date, destructive counting of seedlings started and continued weekly until the end of May, except for the third season in trial 1, when counting of seedlings began in mid September (F0), before sowing, and ended in April.

Weather Data. Daily rainfall and maximum and minimum air temperatures were obtained from a standard meteorological station located at the experimental fields.

Model Development. The model was developed with data from F1 in seasons 2008 to 2009 and 2009 to 2010. Simulated soil temperatures (thermal time, TT) and water potentials (hydrotime, HT) were used to calculate hydrothermal time (HTT) based on the equation described by Roman et al. (2000):

$$HTT = \sum (HT \times TT) \quad [1]$$

where HT = 1 when $\psi > \psi b$, otherwise HT = 0; and TT = $T - Tb$ when $T > Tb$, otherwise TT = 0. ψ is the daily average water potential in the soil layer from 0 to 5 cm; ψb is the base water potential for seedling emergence; T is the daily average soil temperature in the soil layer from 0 to 5 cm and Tb is the base temperature for seedling emergence (Martinson et al. 2007; Royo-Esnal et al. 2010a). With this formula, growing degree-days are accumulated only when the water potential and temperature conditions were higher than the base water potential and base temperature. The HTT was estimated using the Soil Temperature and Moisture Model (STM^2) (Spokas and Forcella 2009). STM^2 requires as input daily maximum and minimum air temperatures and daily precipitation, along with information on the geographical location and soil texture and organic matter. HTT were accumulated over days beginning on the date when the main rainfall occurred prior to the first sowing date. The base water potential and base temperature were determined iteratively calculating HTT using a set of water potentials (−2.0 MPa to −0.5 MPa, at −0.1 MPa intervals) and temperatures (0 to 2 C at 1C intervals). Namely, the scale of HTT was changed by modifying the ψb and the Tb until the highest accuracy was obtained for the relationship between HTT and cumulative emergence of ripgut brome. Typically, ripgut brome emergence begins mid- to late summer, but because all emerged seedlings were killed before sowing, hydrothermal time was calculated from the first autumn rains each year.

The functional relationship between cumulative emergence and HTT was described by a sigmoid equation with the best fit. A Chapman equation was used,

$$y = K(1 - [\exp\{-bx\}])^a \quad [2]$$

where y is the percentage of emergence, x is time expressed as HTT, and K, b, and a are empirically derived constants. K is the maximum percentage of emergence recorded, b is the rate of increase and a is a shape parameter. Fitting of the Chapman function for cumulative emergence was performed using SAS 9.1 (PROC NLIN; SAS Institute Inc., Cary, NC, USA). Model parameters were further adjusted by nonlinear least-squares regression and the goodness of curve fitting by contrast of joint hypothesis ($P < 0.05$).

Cumulative Emergence Model Validation and Readjustment. In the third season (2010 to 2011), emergence data of ripgut brome were also taken before the first sowing date in trial 1 (described as F0). For this reason, the model developed for describing the emergence of ripgut brome was validated with these data (F0), as well as with F1 in 2010 to 2011 and data from Cao et al. (2011), obtained in two other localities of Huelva (South of Spain) in 2005 to 2006 and 2006 to 2007. Agreement between predicted and actual emergence values was determined with the root-mean-square error (RMSE):

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} (x_i - y_i)^2} \quad [3]$$

where x_i represents actual cumulative percent emergence, y_i is predicted cumulative percent emergence, and n is the number a)

b)

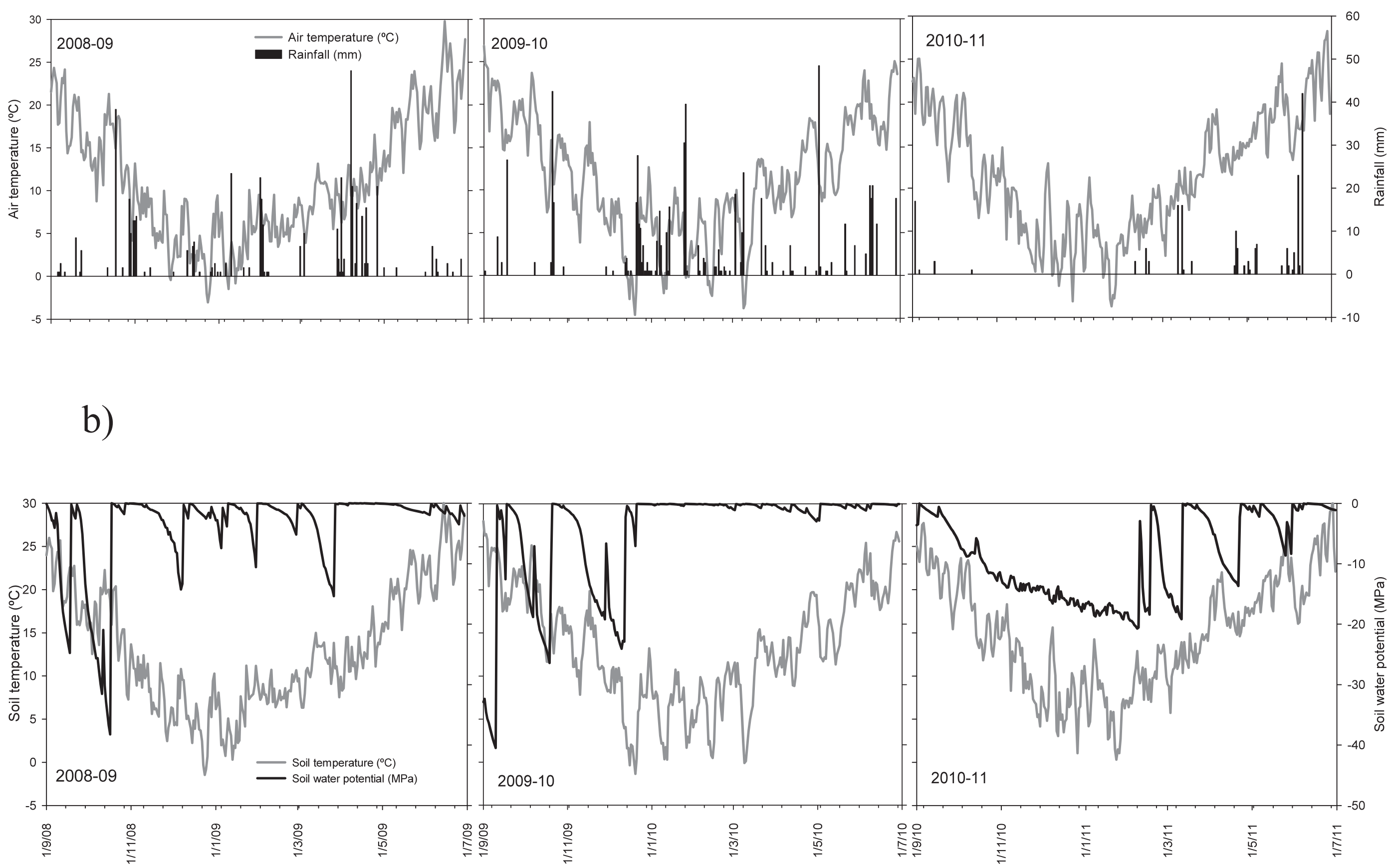

Figure 1. (a) Air temperature (C) and rainfall (mm). (b) Soil temperature (C) and soil water potential (MPa) in the first five cm of depth for seasons 2008 to 2009, 2009 to 2010 and 2010 to 2011.

of observations (Mayer and Butler 1993). RMSE provided a measurement of the typical difference between predicted and actual values in units of percentage seedling emergence. The RMSE ranges to evaluate the accuracy of the model are based on Royo-Esnal et al. (2010b): < 5, excellent prediction; 5 to 10, very good prediction; 10 to 15, good prediction; > 15, insufficient prediction. When RMSE were not optimally described by these models (RMSE$>$15) the Chapman equation was modified by adding a lag-phase (z):

$$y = K(1 - [\exp\{-bx - z\}])^{a} \qquad [4]$$

The lowest RMSE values indicated that the emergence model fit had been optimized.

Cumulative Emergence Practical Model Application. Different sowing dates (F2 and F3 in trial (1) and types of tillage (SS, ChP, and MbP in trial (2) of the three growing seasons were used to evaluate the practical application of the emergence model defined above.

Correction factors were calculated to adjust the cumulative emergence in F2 and F3. Both factors consider prior emergence during the F1. The corrections were 69% and 92% for F2 and F3, respectively, and they represent the percentages of seedling emergence that were eliminated with the delay of the sowing date through seedbed preparation. The correction factor 69% was also used in trial 2 as the crop was sown on the same date as in F2 in trial 1 each year.

Results

The three seasons differed considerably in terms of rainfall (Figure 1a), which represents an ideal situation for development of robust microclimate-based models, but not in temperature. Figure 1b represents the soil temperature and soil water potential in the first 5 cm of depth, calculated with the STM[2] using daily maximum and minimum air temperature (represented as mean air temperature in Figure 1a) and rainfall. Total rainfall from September to harvest (June) in 2008 to 2009 was 500 mm, while in 2009 to 2010 it was 637 mm, and in 2010 to 2011 only 190 mm. Besides the rainfall quantity, number of rainy days also differed between the three seasons (64 in 2008 to 2009, 77 in 2009 to 2010, and 27 in 2010 to 2011, Figure 1a), which is reflected in the soil water potential as long wet or dry periods (Figure 1b). The first season, the average of autumn-winter precipitation was 234 mm (October to February), which fell mainly in October (84 mm). Spring was rainy, with 155 mm between April and May (150 mm in April). In the second season, autumn-winter was wetter (357 mm), while spring was dryer than the previous season (85 mm). In these two seasons there had been short drought periods that are reflected in the soil water potential (Figure 1b). Finally, in 2010 to 2011 autumn-winter resulted extremely dry (13 mm), which decreased considerably the soil water potential, while spring was rainy (156 mm between March and June). For modeling purposes, such great natural variability in magnitudes

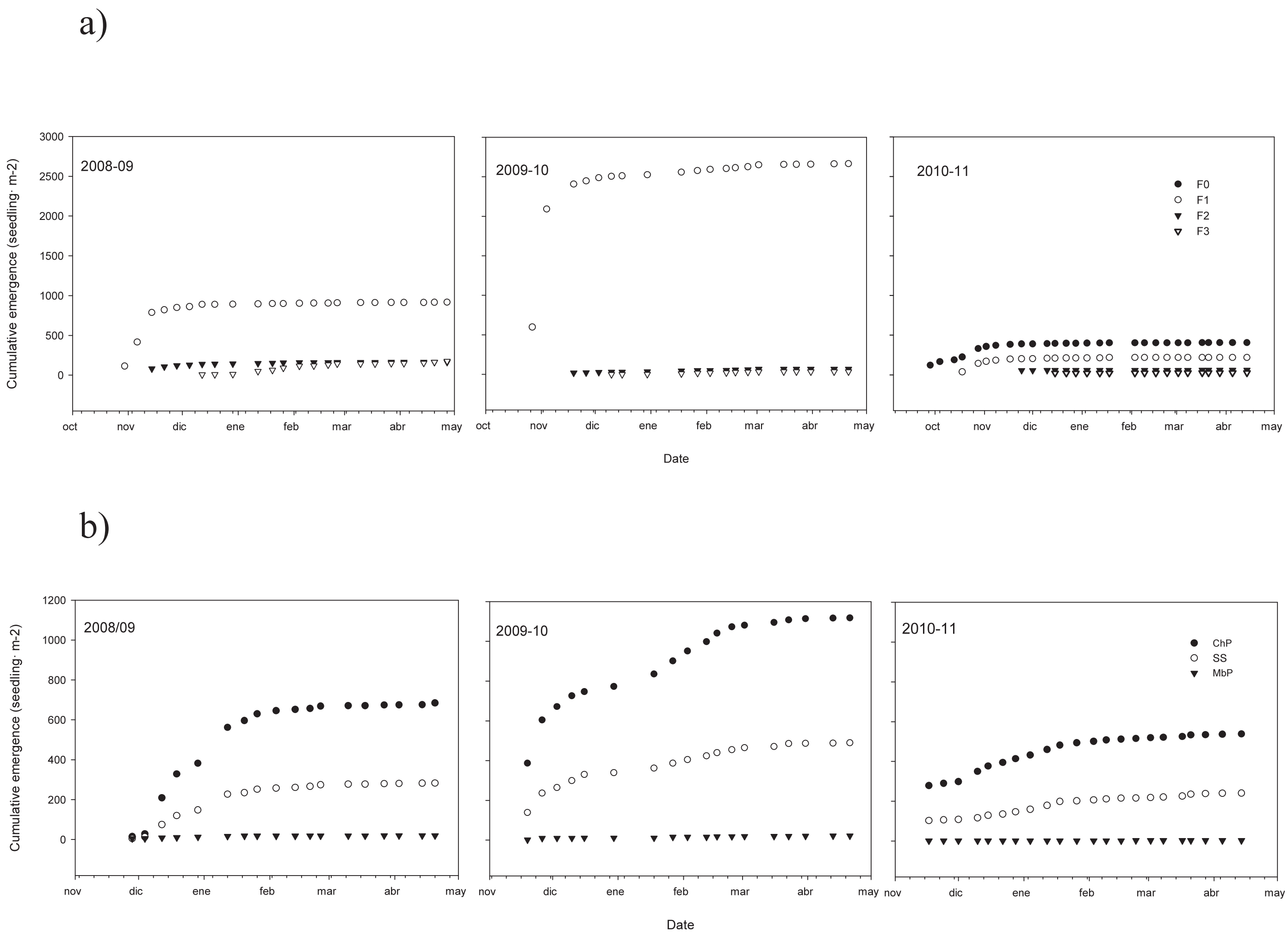

Figure 2. Cumulative emergence of ripgut brome (seedling·m^{-2}) in (a) three sowing dates (F0 = previous to first sowing date, F1 = first sowing date, F2 = second sowing date, and F3 = third sowing date) and in (b) three different soil managements throughout the three growing seasons (ChP = chisel plow, SS = subsoiler, and MbP = moldboard plow).

of driving variables is highly desirable. In the three years, the average winter air temperature (December through February) was 4 C. Overall, the soil and air temperature did not vary significantly from each other as the depth at which soil temperature had been calculated (five cm) is highly influenced by air temperature.

The cumulative emergence in trial 1 was always higher in F1 than in F2 and F3. The beginning of emergence was coincident in 2008 to 2009 and 2009 to 2010 with rainfalls occurring in October. In 2010 to 2011 rainfalls in autumn only occurred in September. Each growing season shows a decreasing gradient from F1 to F3. In 2008 to 2009, the cumulative emergence of ripgut brome differed according to the delay in sowing date (Figure 2a.). Delay of sowing from F1 to F2 entailed an 82% reduction in the cumulative emergence, and 81% reduction in F1 to F3. Between F2 and F3, percentage of cumulative emergence increased by 7%. In 2009 to 2010, the emergence of ripgut brome in F1 was higher than the year before. The percentage of reduction from F1 to F2, F1 to F3, and F2 to F3 was of 98%, 99%, and 49%, respectively. In general, cumulative emergence in 2010 to 2011 was lower than in 2008 to 2009 and 2009 to 2010 for the three sowing dates, and rainfall was almost nil from October to January. Percentage reduction in cumulative emergence was 73%, 88%, and 56%, respectively, from F1 to F2, F1 to F3 and F2 to F3.

In trial 2, cumulative emergence in ChP was higher than SS and MbP in the three growing seasons and consistently lowest in MbP (Figure 2b). Cumulative emergence was higher in 2009 to 2010 than in 2008 to 2009 and 2010 to 2011. Considering that higher cumulative emergence occurred in ChP than in SS and MbP, a percentage of 100% was assigned to ChP. Accordingly, reductions in cumulative emergence were 59% in SS and 97% in MbP in 2008 to 09. In 2009 to 10 reductions reached 56% in SS and 98% in MbP, and in 2010 to 2011 they were about 48% in SS and 99% in MbP.

Seedling Emergence Model Development. The emergence model (Chapman function) calculated using data from F1 in 2008 to 2009 and 2009 to 2010 is shown in Figure 3. In both seasons, emergence was characterized by a quick flush followed by a more gradual pattern. To optimize emergence model fit, a unique base temperature and base water potential was required. The base temperature and base water potential for HTT were estimated iteratively. The best fitting T_b was determined to be 0 C and the best fitting ψ_b was -1.35 MPa (R^2 = 0.80). Estimates of the variables K, b, z, and a fitted to HTT for ripgut brome are 100, 0.013, ±55, and 21.4, respectively.

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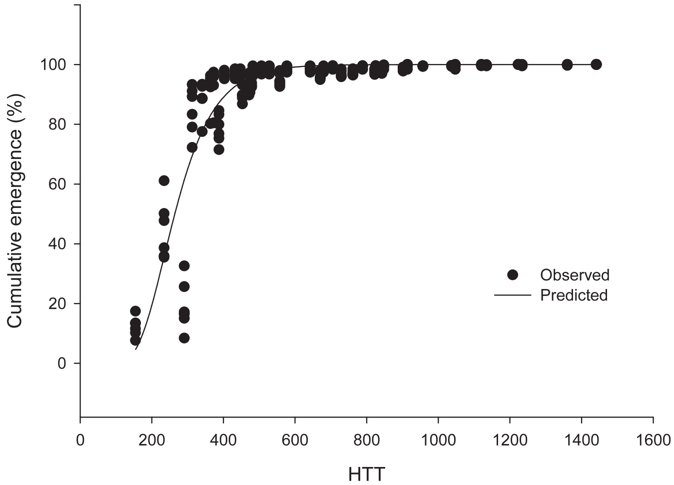

Figure 3. Observed cumulative emergence of ripgut brome in 2008 to 2009 and 2009 to 2010 and representation of the model developed with these data as a function of hydrothermal time (HTT). Emergence fitted using the Chapman function.

Seedling Emergence Model Validation. Figure 4 shows observed and predicted emergence using the Chapman function (above), based on F0 and F1 during 2010 to 2011. Both descriptions showed good fit and reasonable accuracy with predicted emergence (RMSE of 11.4 and 10.9 respectively for F0 and F1). In both cases a lag phase (*z*) was determined by repeatedly testing RMSE, with a final fix at 55 HTT. The model was also validated with emergence data from two locations in Huelva province (Figure 4c).

Practical Application. The emergence model successfully predicted the emergence of F2 and F3 from trial 1 (Figure 5) and those from SS, ChP and MbP from trial 2 (Figure 6) during the three growing seasons.

In trial 1, according to the scale established for the RMSE values, out of six simulations, two were excellent (RMSE < 5), three were very good (RMSE 5 to 10), and one was good prediction (Figure 5). In season 2008 to 2009 and 2009 to 2010, values from F3 were better described (RMSE = 2.2 and 3.3, respectively) than those from F2 (RMSE = 5.3 and 10.1, respectively). In contrast, in season 2010 to 11, F2 showed a slightly better RMSE (5.6) than F3 (7.5). Finally, for F3 values, the 2008 to 2009 growing season (RMSE = 2.2) showed the best fit (Figure 5). Thus, the model described the emergence of F2 and F3 accurately, without adding any lag-phase, however, in some cases the use of a lag phase (established at 55 HTT) improves the fit, as in F2 and F3 in 2009 to 2010.

Sowing date in the different soil management plots (trial 2) was coincident with F2 in trial 1; therefore the 69% factor correction, explained above, was applied to the emergence values. The model described emergence successfully in the three soil management systems during the three years with completely different weather situations (Figure 6). In the model application in F2 and F3 in trial 1, the use of a lag phase was not necessary because the fits were good. However, in trial 2, the use of a lag phase of 55 HTT, in 2008 to 2009 and 2009 to 2010 improved the fits. This did not happen in 2010 to 2011, when the exclusion of a lag phase was the best option for the description of emergence. The accuracy of this model developed for the emergence of ripgut brome was excellent in two situations, very good in another five and good in the last two situations. The RMSE values of this experiment ranged from 4.4 to 14.2%. ChP was generally better described in the sequence of the three seasons (2008 to 2009, 2009 to 2010, and 2010 to 2011), with RMSE values of 5.9, 6.0, and 4.4, respectively; followed by SS, 7.6, 6.1, and 5.7, respectively; and MbP, 4.1, 14.1, and 11.9, respectively) (Figure 6).

Discussion

Germination and emergence are basic processes in the survival and success of a plant (Del Monte and Dorado 2011) and the ability to predict weed emergence could enhance crop management by facilitating the implementation of more effective weed control strategies through the optimization of the timing of weed control (Leblanc et al. 2004; Myers et al. 2004). Cumulative emergence of ripgut brome in trial 1 was higher in F1 than in F2 and F3 regardless of the season. According to some reports, the first cohort of seedlings contributes more to stand biomass and subsequent seed production as well as stronger competition with associated crops, thereby having the largest contribution to the next generation (Cao et al. 2011). Total cumulative emergence was higher in 2009 to 2010 than in 2008 to 2009. The absence of a selective herbicide in barley, favored the growth and

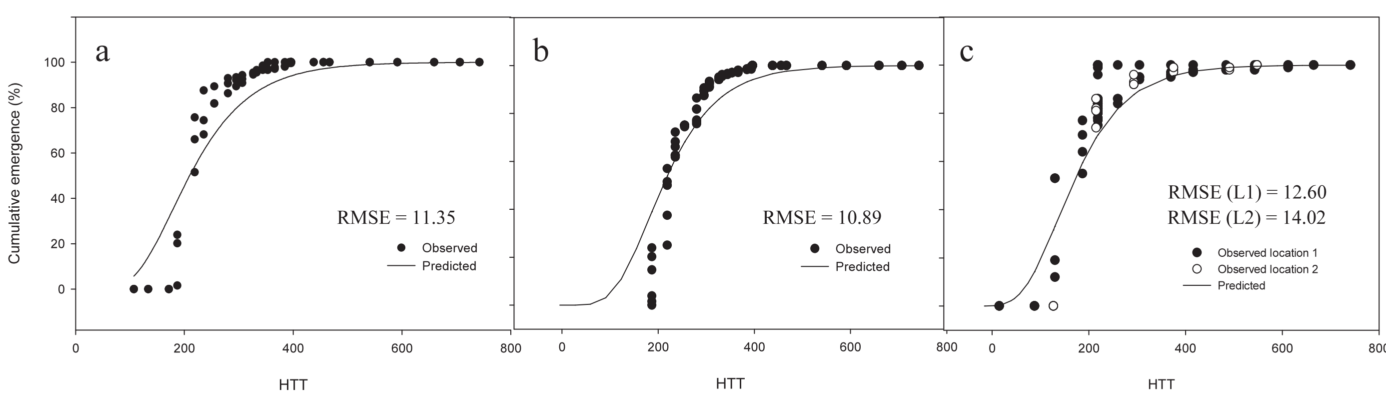

Figure 4. Model validation of cumulative seedling emergence of ripgut brome as a function of hydrothermal time (HTT) in Agramunt (Spain). (a) F0, cumulative emergence considered from September. (b) F1, cumulative emergence considered from October (sowing date). (c) Cumulative emergence using data obtained in Huelva (Cao et al. 2011) L1 = location 1 (closed circles), L2 = location 2 (open circles). The line represents predicted emergence using the model parameters listed in the text. RMSE: Root Mean Square Error.

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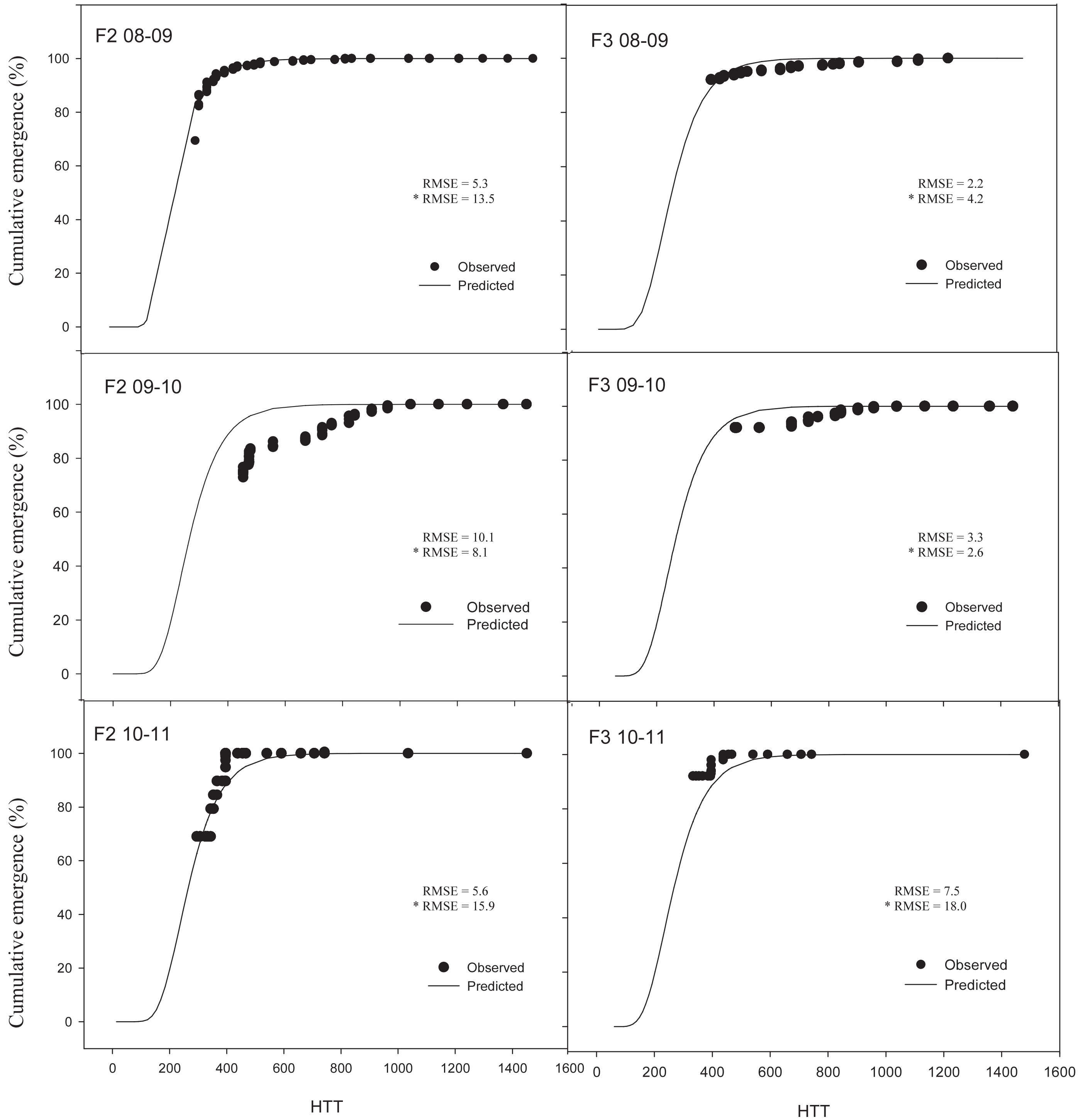

Figure 5. Hydrothermal seedling emergence model application for ripgut brome with delay of the crop sowing date in no-tillage systems in Agramunt (Spain) for three growing seasons, 2008 to 2009, 2009 to 2010, and 2010 to 2011. Root Mean Square Error is shown without (RMSE) and with the use of a lag phase of +55 HTT (*RMSE). F2, cumulative emergence (%) from November; and F3, cumulative emergence (%) from December. The line represents predicted emergence by the model developed without the lag phase. Symbols represent observed emergence.

development of ripgut brome and, therefore, its contribution to the soil seed bank was higher in the following year. The use of selective herbicides for ripgut brome control in wheat provoked a reduction of fecundity (data not shown) in 2009 to 2010. For this same reason, together with the drought suffered in autumn 2010 to 2011, a reduction of total cumulative emergence occurred that season.

Kleemann and Gill (2006) showed rapid germination of seeds of ripgut brome following initial autumn rains. In these experiments similar trends were observed, i.e., beginning of ripgut brome emergence was coincident with rainfall periods. According to Riba (1993) germination and emergence could occur under a wide period of time, ranging from late summer to mid-winter, although it is concentrated in the autumn.

In trial 2 cumulative emergence was higher in chisel plow followed by the subsoiler and moldboard plow. An explanation for this order in soil management systems is that seeds may need only a superficial covering of soil to perceive

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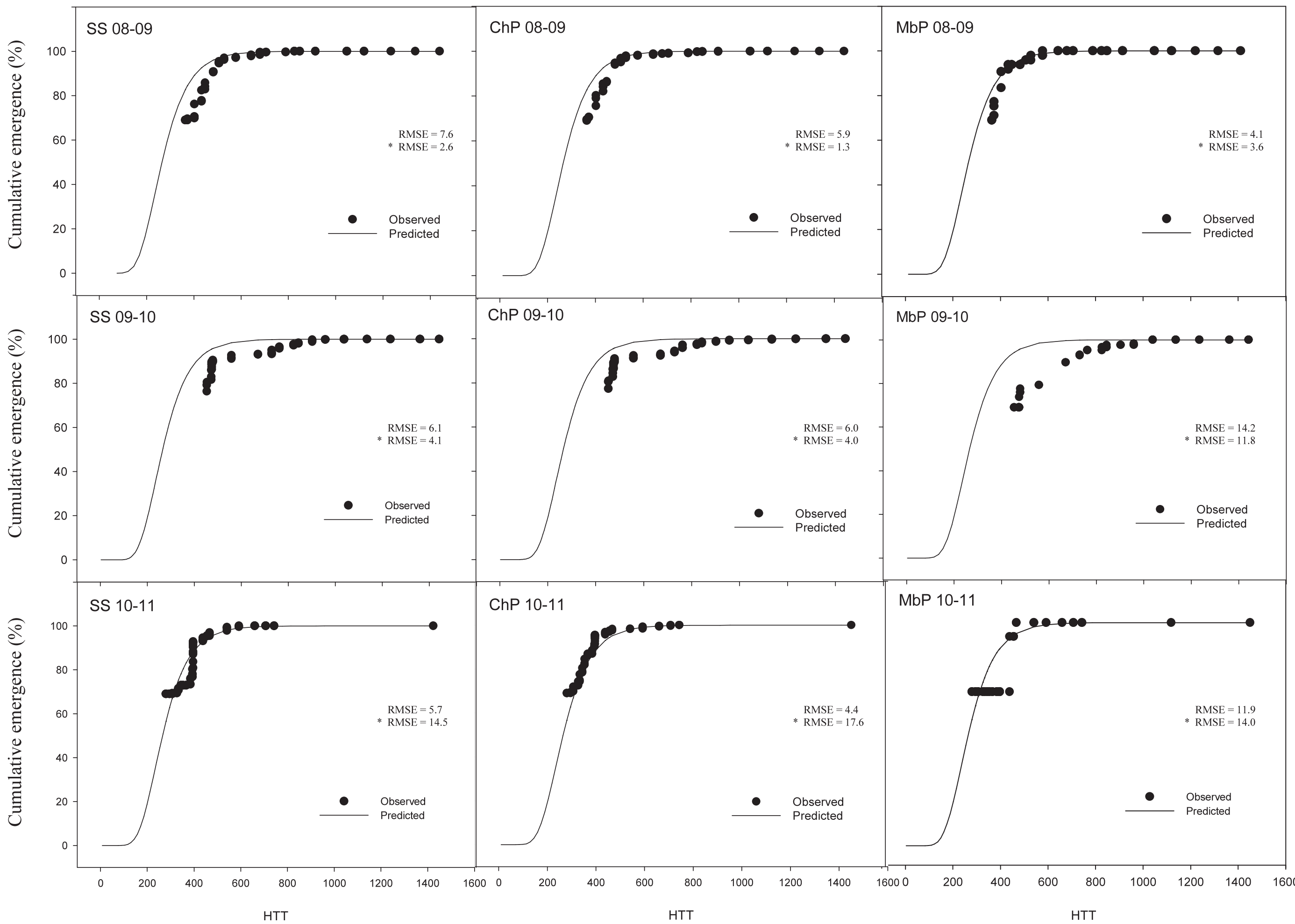

Figure 6. Hydrothermal seedling emergence model application for ripgut brome in different tillage systems (SS, ChP, MbP) in Agramunt (Spain) for three growing seasons 2008 to 2009, 2009 to 2010 and 2010 to 2011. Root Mean Square Error is shown without (RMSE) and with lag phase of +55HTT (*RMSE). Lines represent predicted emergence without a lag phase. Symbols represent observed emergence.

darkness. As long as the embryo remains buried, it is likely to germinate, and this is facilitated by the way the seed falls to the ground and can be wedged into the soil (Del Monte and Dorado 2011). Thus, the chisel plow deposits a thin layer of soil over the seeds, which allows germination. In contrast, in moldboard ploughed plots, which had the lowest cumulative emergence observed, soil inversion positioned seeds too deep to emerge. This also occurs in the related rigid brome (*Bromus rigidus* Roth) (Gleichsner and Appleby 1989).

Hydrothermal Time Seedling Emergence. Hydrothermal time emergence models that base predictions on field observations during previous growing seasons offer relatively robust predictions and with simple inputs and development (Forcella et al. 2000). The model developed in this work seems to be strong enough, as it was developed with data from two completely different seasons in terms of rainfall, and it has been validated with a third season in the same field, as well as with independent data from the south of Spain (Huelva).

The water potential with which emergence of ripgut brome was best explained was -1.35 MPa. In contrast, Del Monte and Dorado (2011) observed in a lab conditions that high germination percentages (above 75%) of ripgut brome were obtained in darkness with water potentials ≥ -0.4 MPa. Germination in the lab was significantly lower, but still appreciable at -1.25 MPa. Thus, our field- and simulation-derived value of -1.35 MPa may be deduced as the base water potential while ≥ -0.4 MPa is the optimal water potential for the germination (and emergence) of this weed. To optimize emergence model fit, a unique base water potential is required (Schutte et al. 2008). This base water potential may not be the best for any particular season, but it is the best overall for describing the three seasons with a robust model.

An advantage of the Chapman equation is the use of only three parameters that, in turn, makes it a simple model. The model predicted seedling emergence in different locations (Agramunt and Huelva) with reasonable accuracy. The RMSE values of this experiment calculated for model validation, (11.4 in F0, 10.9 in F1, and 12.6 and 14.0 in Huelva) were similar to RMSE values for model validation in other studies for common lambsquarters (*Chenopodium album*) (Roman et al. 2000), tropic ageratum (*Ageratum conyzoides* L.) (Ekeleme et al. 2005), and *Galium* spp. (Royo-Esnal et al. 2010a).

Practical Application. An interesting part of this model is that it could have been applied in other management systems (in the same locality where it was developed), which implies a wide range of situations where it probably can be used. All of the RMSE values obtained in the practical applications were below 15, indicating a very good predictive capability. The use of the lag phase in some cases further improved the fit of the model to the observed data.

The model applied to F2 and F3 in the three growing seasons showed slightly better accuracy for F3 than for F2. This could have happened because 92% of the population was destroyed by seedbed preparation and the correction factor left very low variation for K values (100%). The lack of need of a lag phase in these results is remarkable and gives a more robust basis to the model, which we believe is valid for rainfed cereal systems where sowing dates are often variable.

Ripgut brome is a common weed present in many tillage systems, although it is associated with no-till (Kleemann and Gill 2006). For this reason showing how the model predicted the emergence of ripgut brome in other soil managements was important. Therefore, the model also was applied to chisel ploughed, subsoiled and moldboard ploughed areas. In fact, the RMSE values obtained from these comparisons strengthened the perceived value of the model, as all were below 15 (without use of a lag phase). In some cases, however, the use of a lag phase did improve the fit of the model to the observed data. This might imply that the description of the emergence could still be improved, maybe with the inclusion of other factors that have not been used here, such as remnant seed dormancy alleviation. Regarding differences in accuracy of the model among tillage systems, it was somewhat less accurate in MbP than in SS and ChP. This likely happened because of the much lower seedling densities in MbP than the other soil management systems, with a corresponding decrease in reliability of the MbP data.

To summarize, soil temperature and soil moisture seem to be the determinant factors driving emergence of ripgut brome, as they are in other weeds (Forcella et al. 2000; Roman et al. 2000; Royo-Esnal et al. 2010a). With these two factors, a model that describes the emergence of this weed was developed and demonstrated to be robust and reliable, as it was validated with four different data sets and put into practice in five management systems (two sowing delays and three soil tillage practices) over three years. The model can be used henceforth to improve control and management of ripgut brome.

Acknowledgments

This work was supported by the Ministerio de Educación y Ciencia de España (AGL2007-60828 and AGL2010-22084-C02-01). It also was supported by a PhD student grant from the Universitat de Lleida. Special thanks to Cristina Maján, Noemí Pacheco Antón and Núria Moix for their help during the experimental work, and to Dr. Carlos Cantero and Carlos Cortés, from the Department of Crop and Forest Science at the University of Lleida. The first author thanks the Universitat de Lleida for the grant during the predoctoral stay in the U.S.A. The first author also thanks Valentina Atanackovic Xavier Solé-Senan and Alejandro Juárez for their help and constructive comments on the first version of abstract. Finally, we kindly thank Dean Peterson and Jim Eklund for their support and help during our stay in Morris, Minnesota.

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Received February 24, 2012, and approved May 17, 2012.