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Common Sunflower Seedling Emergence across the U.S. Midwest

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Predictions of weed emergence can be used by practitioners to schedule POST weed management operations. Common sunflower seed from Kansas was used at six Midwestern U.S. sites to examine the variability that 16 climates had on common sunflower emergence. Nonlinear mixed effects models, using a flexible sigmoidal Weibull function that included thermal time, hydrothermal time, and a modified hydrothermal time (with accumulation starting from January 1 of each year), were developed to describe the emergence data. An iterative method was used to select an optimal base temperature (T_b) and base and ceiling soil matric potentials (ψ_b and ψ_c) that resulted in a best-fit regional model. The most parsimonious model, based on Akaike's information criterion (AIC), resulted when $T_b = 4.4$ C, and $\psi_b = -20000$ kPa. Deviations among model fits for individual site years indicated a negative relationship ($r = -0.75$; $P < 0.001$) between the duration of seedling emergence and growing degree days ($T_b = 10$ C) from October (fall planting) to March. Thus, seeds exposed to warmer conditions from fall burial to spring emergence had longer emergence periods.
Nomenclature: Common sunflower, *Helianthus annuus* L.
Key words: Abiotic influences on seed dormancy, regional environmental variation, seedling recruitment.

Weed emergence timing from the seed bank influences weed control decisions and may dictate it's competitiveness and seed production potential. Early germinating plants may be controlled with preplant weed management however if left untreated, these plants may be the most competitive with the crop (Gallandt and Weiner 2007; Sattin et al. 1996) and produce the greatest number of seed (Clay et al. 2005; Uscanga-Mortera et al. 2007). Late emerging plants, while not as competitive (Deines et al. 2004), often escape control and produce some seed to replenish the soil seed bank (Clay et al. 2005 Uscanga-Mortera et al. 2007). Mechanical weed control operations can be optimized when the length of the emergence period is known (Oriade and Forcella 1999).

Climate variability among years, even within a site, makes predicting biological events, such as germination or flower initiation, of any species tenuous at best (Alan and Wiese 1985; Baskin and Baskin 1987). Often only a few years of data are collected and phenological trends are not obvious (Wolkovich et al. 2012). One of the National Phenology Network (http://npnweb-dev.npn.arizona.edu/lilac) projects involves a system of volunteers throughout the U.S. to report on the annual flowering time of two cloned ornamental species as a common garden approach. These and other observations are being used to explore the influence of climate across the U.S. on plant phenology and animal behavior and are serving as a baseline to determine what, if any, changes occur as long term climate trends are recorded (Rosemartin et al. 2012). Perennial shrub phenology has been correlated to some weed species emergence to provide an easily observed event to link with weed control timing (Otto et al. 2007).

Growing degree day(GDD)units(thermal time)

$$GDD = \sum [(T_{\min} + T_{\max}) - T_b] \quad [1]$$

where T_{min} and T_{max} are the daily minimum and maximum temperatures, respectively, and T_b is the base temperature below which thermal time units are not accumulated, provide heat accumulation based on daily air or soil temperatures have been used to predict weed emergence, crop phenological events, and pest control timing. Myers et al. (2004) used soil degree days with a base temperature of 9 C to predict weed emergence of eight species in the northeastern United

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States. Other weed emergence research has focused on using other base temperatures (Forcella et al. 2000; Horak and Loughin 2000) or a combination of thermal time and soil water availability (hydrothermal time, HTT) to improve predictions (Bradford 2002; Davis et al. 2013; Larsen et al. 2004; Leguizamón et al. 2005; ; Roman et al. 2000; Rowse and Finch-Savage 2003). The conceptual framework underpinning using HTT, rather than relying on GDD alone, is that if soil water is not present or too limiting, seeds will not germinate (Bradford 2002; Davis et al. 2013; Forcella et al. 2000; Larsen et al. 2004; Leguizamón et al. 2005; Meyer et al. 2000; Roman et al. 2000; Rowse and Finch-Savage 2003).

Models have been developed to predict emergence patterns for several weed species (Davis et al. 2013; Forcella 1998; Grundy and Mead 2000; Grundy et al. 2003; Hardegree and Winstral 2006; Oryokot et al. 1997a, 1997b; Roman et al. 2000; Schutte et al. 2008), often within a limited geographic region. Moloney et al. (2009) summarized results of 36 common garden experiments conducted from 1998 to 2008 and reported that only 14% of these studies (five out of 36) utilized both native and invasive geographic locations. Moloney et al. (2009) suggested that emergence and growth data for a species from a range of geographic locations are critical because uncontrolled factors [such as climate (precipitation and temperature), soil type, nutrient availability, and daylength] strongly influence the outcome of the experiment and hence, the data interpretation.

The NC1191 (formerly NC1026 and NC202) Regional Research Committee focused on studies using giant ragweed (*Ambrosia trifida* L.) and common sunflower during 2007 to 2009 across the U.S. Midwest (Davis et al 2013; Wortman et al. 2012). These species were chosen because they emerge early in the season, can cause major crop yield reductions even at low densities and, although native to the midwestern U.S., have differential abundance across the region (common sunflower in the west, and giant ragweed in the east). Michigan State Extension reported that one giant ragweed plant per m^{-2} has the potential to reduce corn (*Zea mays* L.) yield by 55% and soybean [*Glycine max* (L.) Merr.] yield by 52% (http://www.msuweeds.com/worst-weeds/giant-ragweed/). In Kansas, yield losses due to common sunflower were nearly 50% in corn when the weed population was 0.25 plant per m^{-2} (Deines et al. 2004) and about 96% in soybean at densities of 4 plants per m^{-2} (Geier et al. 1996).

NC1191 regional research results that highlight giant ragweed emergence (Davis et al. 2013) and growth and fecundity similarities and differences of giant ragweed and common sunflower (Wortman et al. 2012) have been published previously. The current paper focuses on (1) determining if common sunflower emergence data from 16 site–yr across the region can be modeled with a common set of parameters, (2) defining the parameters that best fit the data, and (3) examining deviation of individual site years from the model to determine if other random effects can help explain the variation. Because the environments in the North Central region range from wet (east) to dry (west) and cold (north) to warm (south), correct interpretation of these data may enhance our understanding of weed population dynamics at both the local and regional scales and helps identify environmental variables that are responsible for response variation. Knowledge gained through this research may be used to parameterize and validate weed management decision support systems that extend basic weed biology and management information to farmers (Grundy 2003).

Materials and Methods

Seed Accessions and Site Information. Common sunflower seeds were collected from a Kansas accession (J.A. Dille, Kansas State University) in the autumn following seed maturity. These seeds were cleaned to remove chaff and light seed. Seed lots were distributed to participants and planted at field locations at Manhattan, KS (2006 to 2008); Savoy, IL (2006 to 2008); East Lansing and St. Charles, MI (2006 to 2008); Ithaca, NE (2007 to 2008); and Aurora, SD (2007 to 2008).

Soil classification, organic matter, and pH, precipitation and fall/winter spring/summer temperatures and other site information and study design are presented in Wortman et al. (2012) and Davis et al. (2013). To allow for overwintering, 100 seeds were sown during the same autumn as collection (freshly collected seed each year) into 12.5 by 12.5 cm wire baskets that were filled with the site's topsoil. Seeds were covered by 2 cm of soil, and baskets were buried so that their soil surfaces were level with the surrounding soil surface. Ambient densities of viable common sunflower seeds from each site were determined by excavating a 12.5 by 12.5 cm block of soil to the 5 cm depth, elutriating seeds, and testing for viability using a tetrazolium test (Wortman et al. 2012). In the

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spring, weekly destructive seedling sampling occurred to determine emergence timing. Seed recruitment data were adjusted for ambient density of native seed, as needed. Monitoring began as early as possible after January 1, before emergence occurred at any site, and continued throughout the summer, long after the bulk of emergence had occurred, thereby capturing all emergence events.

Soil Microclimate Conditions. Detailed information is presented in Davis et al. (2013), with the same microclimate information used for this common sunflower study. Briefly, hourly air temperatures and rainfall were collected within 10 km of each site. The Soil Temperature and Moisture Model (STM^2) (Spokas and Forcella 2009) was used to estimate daily soil temperature (T) and ψ, at 1-, 3-, and 5-cm, based on solar radiation, daily maximum and minimum air temperatures and precipitation, soil properties (sand, silt, clay, organic matter contents), longitude, latitude and site elevation (Wortman et al. 2012).

Calculating Thermal (θ_T) and Hydrothermal (θ_{HT}) Times. The GDD equation (eq. 1) was used calculate θ_T on a daily basis at depths of 1-, 3-, and 5-cm. Temperatures were similar among depths (typically within 10%, data not shown) and therefore the 1-cm depth was used in model development. Values above the T_b from each day starting on January 1 of each year (except 2006 in Kansas where seed was planted on April 13) were summed to get a running total of θ_T until the end of emergence. If the value was less than the T_b, then θ_T did not accumulate for the day. Values tested for T_b included 1, 2, 4.4, and 5 C.

The soil water potentials (ψ) at the 1-, 3-, and 5-cm depths and soil temperature calculated on a daily time-step from STM^2 model (Spokas and Forcella 2009) were used to calculate cumulative hydrothermal time (θ_{HT}) (Bradford 2002; Gardarin et al. 2010; Masin et al. 2010; Roman et al. 2000) for the season based on:

$$\theta_{HT} = \sum_{i=1}^{n} \theta_H \times \theta_T \qquad [2]$$

where i = day of year at a particular location, n = final observation day of year at a particular location, $\theta_H = 1$ when $\psi > \psi_b$, or else $\theta_H = 0$ when $\psi < \psi_b$; and $\theta_T = T - T_b$ when $T > T_b$, or if $T < T_b$ than $\theta_T = 0$. The ψ_b tested included -20000, -10000, -5000, -2500, -1000, -100 and -33 kPa. To determine if an upper limit of soil water potential (i.e., too wet soil conditions for emergence) should be included in the model, $\psi_c = -40$, -33, -10, -1, and 0 kPa were included in model development. For each site year, January 1 was treated as $\theta_{HT} = 0$ (with the exception of Kansas 2006 when θ_{HT} started on April 13). The θ_{HT} was equivalent to thermal time (unmodified by soil water) when $\psi_b = -20000$ kPa and $\psi_c = 0$.

Statistical Modeling. The approach to modeling common sunflower emergence in response to θ_{HT} is detailed in Davis et al. (2013) for giant ragweed. A nonlinear mixed effects model was fit to common sunflower emergence data using maximum likelihood methods (Pinheiro and Bates 2004). The saturated model containing fixed and random effects for all parameters of the Weibull equation was used (Brown and Mayer 1988; Ratkowski 1983; Weibull 1951). It describes cumulative data series with a flexible mathematical function such that

$$\begin{aligned} y_i &\sim (\beta_{1i} + b_{1i}) - (\beta_{2i} + b_{2i}) \\ &\times e^{\left[\left(-e^{(\beta_{3i}+b_{3i})}\right)\left(\theta_{HT_i}^{(\beta_{4i}+b_{4i})}\right)\right]} + \varepsilon_i \\ b_1 &\sim N(0,\psi), \quad \varepsilon_i \sim N(0,\sigma^2) \\ \psi &= \begin{bmatrix} \sigma_{11} & 0 & 0 & 0 \\ 0 & \sigma_{22} & 0 & 0 \\ 0 & 0 & \sigma_{33} & 0 \\ 0 & 0 & 0 & \sigma_{44} \end{bmatrix} \end{aligned} \qquad [3]$$

where i = experimental unit; y = cumulative percent emergence at a cumulative θ_{HT} value; β_1 and b_1 represent the fixed and random effects, respectively, for Asym, the upper horizontal asymptote (theoretical maximum for Y normalized to 100%); β_2 and b_2 represent the fixed and random effects, respectively, for *Drop*, the vertical distance between the upper and lower horizontal asymptotes; β_3 and b_3 represent the fixed and random effects, respectively, for *lcr*, the natural log of the rate of increase; β_4 and b_4 represent the fixed and random effects, respectively, for *pwr*, a curve shape parameter, and ε_i represents the error term (Ratkowski 1983). The advantage of a mixed model is that it contains only eight estimated parameters whereas a fixed-effects only model would overparameratize the data with $4 \times 16 = 64$ parameters. A diagonal covariance structure for the random error terms was used, as a general

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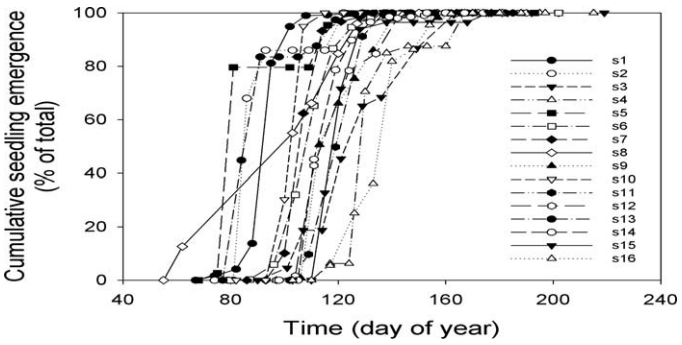


Figure 1. Common sunflower cumulative emergence during 16 site–yr–. Site–yr abbreviations: 1 to 3 = Savoy, IL, 2006 to 2008; 4 to 6 = Manhattan, KS, 2006 to 2008; 7 to 9 = East Lansing, MI, 2006 to 2008; 10 to 12 = St. Charles, MI, 2006 to 2008; 13 to 14 = Ithaca, NE, 2007 to 2008; 15 to 16 = Brookings, SD, 2007 to 2008.

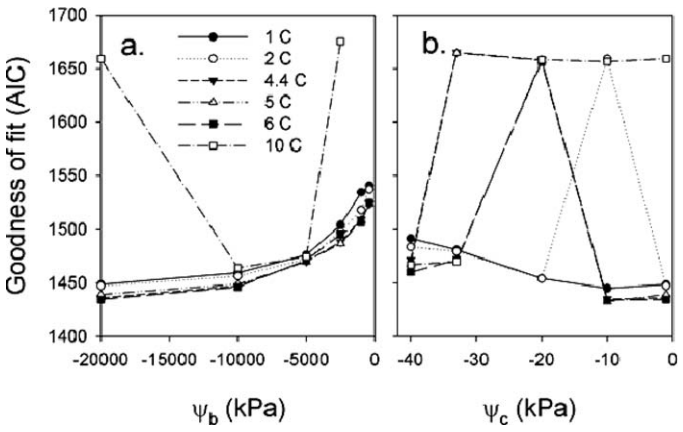


Figure 2. Results of interactive search for optimal base values for common sunflower hydrothermal time and modified Hydrothermal time. For HTT: T_b = 4.4 and ψ_b = −20000 kPa. For mHTT, T_b= 4.4, ψ_b = −20000 kPa and ψ_u = −10 kPa.

positive-definite Log-Cholesky covariance structure did not converge for these data (Pinhero and Bates 2004).

The search for optimal base values for the θ_{HT} model and model simplification were implemented using a maximum likelihood model selection approach in the nlme package of the R v.12.13.0 (R Development Core Team 2009). Parsimony of competing models was evaluated via maximum likelihood criteria, including AIC and BIC and through Akaike weights, (the probability that a given model was the best among the pool of candidate models) (Burnham and Anderson 2002). Simple and partial correlations between fitted random effects for parameters of the best seedling emergence model using θ_{HT} and environmental variables (soil T, $soil_{10}$ GDD, soil ψ, and rainfall) during overwinter seed burial and during seedling emergence were implemented in the *corpcor* package of R v12.13.0.

Results and Discussion

The most southerly location, Manhattan, KS, had the highest yearly mean low (6.5 C) and high (19 C) temperatures. Savoy, IL, was the wettest site with the mean monthly precipitation of 87 mm. The East Lansing and St. Charles, MI, sites were cooler and drier than both Manhattan and Savoy. Aurora, SD, the most northerly location, had the lowest mean average low (−0.1C) and high (12.4 C) temperatures, and was the driest site with a mean monthly precipitation of 48 mm. Other detailed site characteristics were presented in Wortman et al. (2012)

Base Values for θ_{HT} Model. Emergence by calendar days differed greatly across the region and between years (Figure 1). Iteratively fitting emergence data to the Weibull hydrothermal time model identified clear optimum values for T_b and

Table 1. Maximum likelihood selection among best nonlinear mixed effects models of common sunflower cumulative seedling emergence following a Weibull response function to hydrothermal time (T_b: 4.4 C, ψ_b = −20000 kPa).

Model	Fixed effects[a]	Random effects	d.f.[b]	AIC	BIC	LL	w_i
1	*Asym+Drop+lrc+pwr*∼1	*Asym + Drop + lrc +pwr* ∼1	9	1436	1466	−709	2.8×10^{-5}
2	*Asym+Drop+lrc+pwr*∼1	*Lrc* ∼1	6	1445	1465	−717	3.1×10^{-12}
3	*Asym+Drop+lrc+pwr*∼1	*Drop +lrc* ∼1	8	1449	1475	−716	4.7×10^{-5}
4	***Asym+Drop+lrc+pwr*∼1**	***Lrc + pwr* ∼1**	**8**	**1387**	**1413**	**−686**	**0.62**

[a] Weibull function parameters treated as fixed effects: *Asym* = upper horizontal asymptote, *Drop* = vertical difference between upper and lower horizontal asymptotes, *lrc* = ln(rate constant), *pwr* = shape parameter. The symbol ∼1 indicates that fixed effects refer to model intercepts only.

[b] Model selection criteria abbreviations: d.f. = degrees of freedom, AIC = Akaike's Information Criterion, BIC = Bayesian Information Criterion, LL = log likelihood, w_i = Akaike weights. For AIC and BIC, smaller values indicate more parsimonious models, whereas for LL, larger values indicate more parsimonious models. Akaike weights range from 0 to 1, sum to 1 for a group of candidate models, and indicate the probability that a given model represents the most parsimonious model (shown in bold) within the group.

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Table 2. Summary of random and fixed effects for the most parsimonious nonlinear mixed effects model of common sunflower cumulative seedling emergence following a Weibull response function to hydrothermal time (T_b: 4.4 C, ψ_b = −20000 kPa).

Fixed effects[a]	Coefficient	s.e.	d.f.	*t*-value	P-value	Random effects	s.d.
Asym	98	0.5	184	209	0.0001	*lrc*	9.9
Drop	102	1.5	184	28.1	0.0001	*pwr*	1.8
lrc	−19	2.7	184	7	0.0001		
pwr	3.5	0.5	184	7	0.0001		

[a] Explanation of fixed effects parameters: *Asym* = upper horizontal asymptote, *Drop* = vertical difference between upper and lower horizontal asymptotes, *lrc* = ln(rate constant), *pwr* = shape parameter. The parameters *Asym*, *Drop, lrc* and *pwr* are modeled as intercepts.

ψ_b. Of the base temperatures and water potentials used to develop the model, the lowest AIC value (i.e., best fit) occurred when T_b = 4.4 C and ψ_b = −20000 kPa (Table 1 and Figure 2a). Including a factor that represented ceiling water potential (i.e., soil too wet) did not improve the model fit at any tested temperature and, therefore, this term was not used further in model development (Figure 2b). Four potential models showing how the selection of fixed and random effects influenced AIC, Bayesian

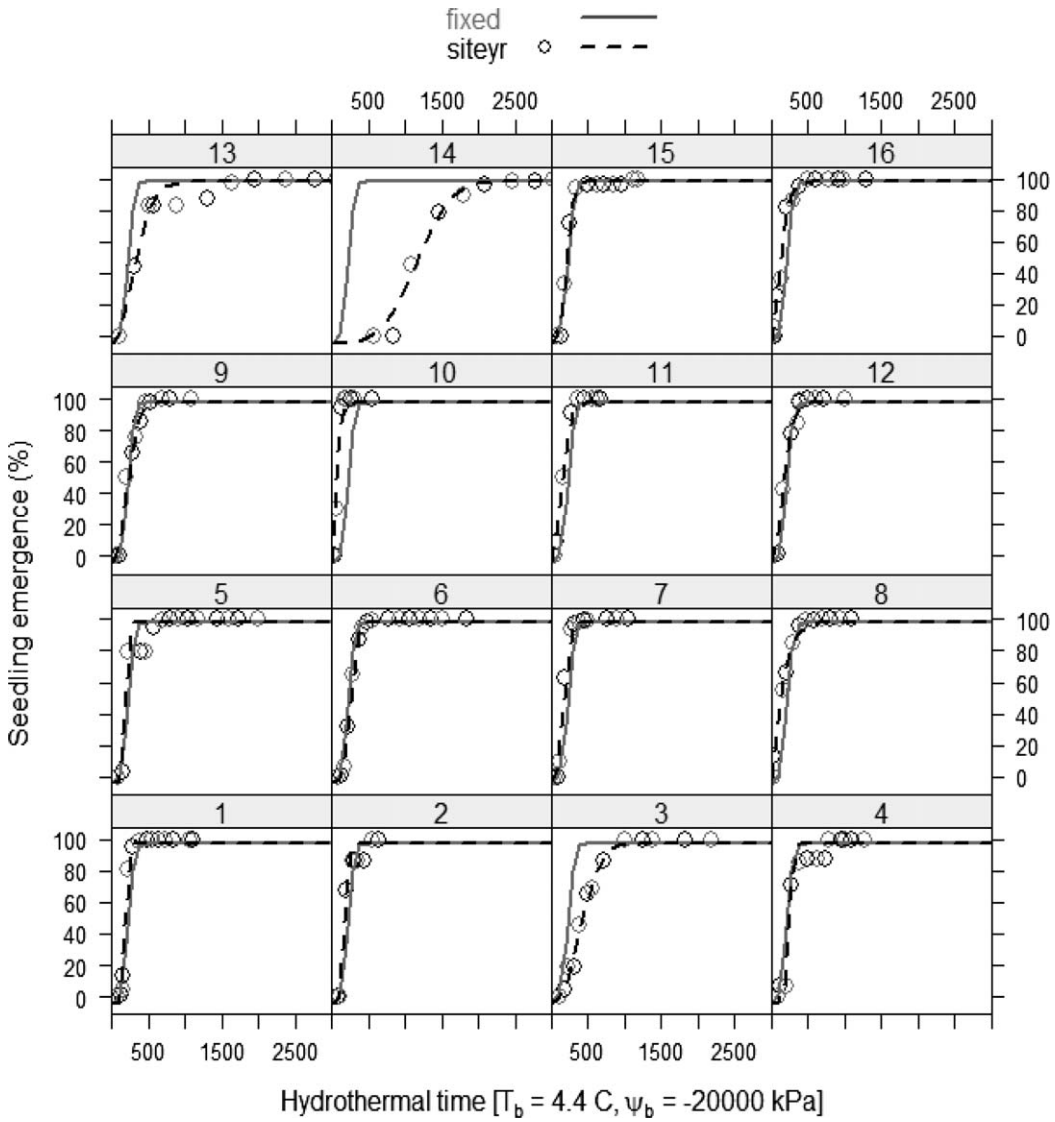


Figure 3. Best HTT model (T_b = 4.4, ψ_b = −20000 kPa,). Site year abbreviations: 1 to 3 = Savoy, IL, 2006 to 2008; 4 to 6 = Manhattan, KS, 2006 to 2008; 7 to 9 = East Lansing, MI, 2006 to 2008; 10 to 12 = St. Charles, MI, 2006 to 2008; 13 to 14 = Ithaca, NE, 2007 to 2008; 15 to 16 = Aurora, SD, 2007 to 2008. Circles indicate observed emergence for the site—yr. Solid lines represent only fixed effects and dashed lines represent when random effects of the mixed model were used.

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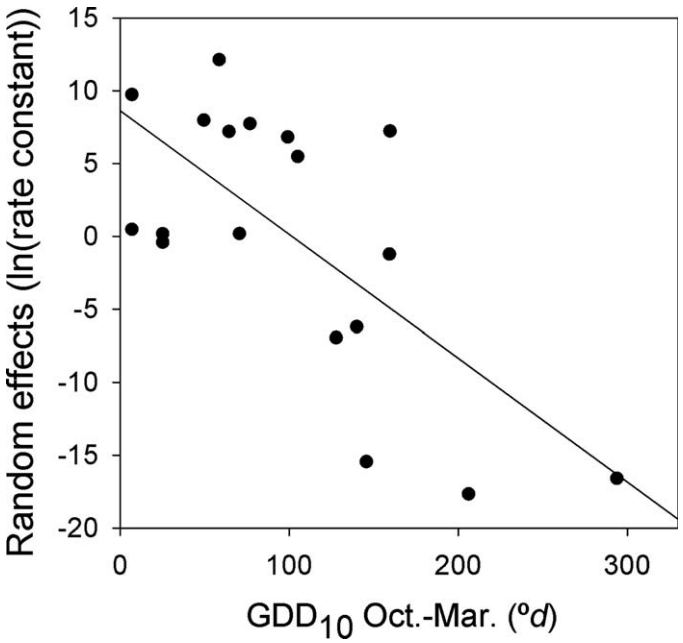


Figure 4. Random effects of ln(rate constant) for best hydrothermal time model of common sunflower seedling emergence were negatively correlated ($r = -0.75$; $P < 0.001$) with GDD_{10} from fall burial (October) to spring emergence (March).

Information Criterion (BIC), log likelihood (LL), and w_i (Akaike weights) are presented in Table 1, with coefficients for the fixed and random effects for the best fit model reported in Table 2.

The optimum value for T_b of 4.4 C (Figure 2a) for seedling emergence is lower than the base temperature ranges of 6.7 to 10 C reported for growth and development of sunflower (Archer et al. 2006; Bazin et al. 2011; North Dakota Ag Weather Network; Sadras and Hall 1988). Since different physiological processes govern seedling emergence, seed dormancy alleviation, and plant growth, differing base temperatures are not unexpected. Indeed, seedling emergence from the soil described in this study, seed dormancy alleviation (8 C, Bazin et al. 2011), and plant growth (6.7 C, ND Ag Weather Network; 8.5 C, Sadras and Hall 1988) have different optimal base temperatures.

The unexpectedly low ψ_b value (−20000 kPa) reported here is much lower than the generally accepted permanent wilting point of −1500 kPa, which helps define the amount of available water for plant growth in a soil. This does not mean that common sunflower can germinate and emerge in the absence of water, rather that emergence is not completely halted by intermittent dry periods. McDonough (1975) reported that imbibition occurred at relatively high water potentials [ranging from −400 kPa (slender wheatgrass [*Elymus trachycaulus* (Link) Gould ex Shinners]) to −1700 kPa, (downy brome (*Bromus tectorum* L.)]. However, after imbibition and germination, but prior to seedling emergence at the soil surface, the downward growing radical may precede the dehydration front permeating from the soil surface. Thus, seedlings may have access to available water deeper in the soil profile, facilitating emergence despite very low surface water potentials. In addition, large-seeded plants, like common sunflower and giant ragweed, have the reserves to support radicle growth under unfavorable conditions, more so than small-seeded species like common lambsquarters (*Chenopodium album* L.) and pigweed (*Amaranthus* spp.). This may partially explain why the base ψ value for emergence is seemingly low.

Examining the *nlme* model vs. all site years of data (Figure 3) indicates that the fixed effects (solid lines) predicted emergence very well except for site–yr3 (Savoy, IL, 2008) and 13 and 14 (Ithaca, NE, 2007 and 2008), in which the random effects (dotted lines) of the mixed model became more important for capturing observed germination patterns. Therefore, the relationship between fitted and random effects for model parameters and environmental variables (air temperature, GDD_1, $GDD_{4.4}$, GDD_{10} and precipitation) from fall burial (generally October) to March, when seedlings began to emerge, were examined. Random departures from the fixed model for *lcr* [ln(rate constant)] were strongly negatively associated ($r = -0.75$; $P < 0.001$) with GDD_{10} during the seed burial period (Figure 4). These data suggest that seeds exposed to warmer winter temperatures were less likely to emerge quickly than those exposed to colder temperatures. Indeed, sunflower seeds need an after-ripening period to alleviate dormancy (Finch-Savage and Leubner-Metzger, 2006) and warmer temperatures may not have provided the chilling needed to fully alleviate seed dormancy. The negative association between warm fall and winter conditions and seedling emergence also has been reported for giant ragweed (Davis et al. 2013), although giant ragweed emergence also was negatively influenced by fall/winter precipitation. Although we did not see a relationship with fall/winter precipitation in this study, Bazin et al. (2011) reported that the optimal temperature of domestic sunflower seed germination differed with seed moisture content with drier seed germinating at lower temperatures.

These findings suggest that common sunflower spring emergence is promoted by low temperatures

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after fall burial and can occur under drier soil conditions than giant ragweed emergence (ψ_b = −2500 kPa, Davis et al. 2013). These data may help explain why common sunflower is more problematic in the drier western regions of Kansas and less problematic in the warmer eastern regions of Illinois and Michigan. This information can be incorporated into process models to help predict emergence based on soil conditions. It is important to note that the environment during the fall and winter may be as important as spring conditions when predicting common sunflower seedling emergence.

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