Weed Science

www.cambridge.org/wsc

A hydrothermal model to predict Russian thistle (*Salsola tragus*) seedling emergence in the dryland of the Pacific Northwest (USA)

Fernando H. Oreja[1], Nicholas G. Genna[2], Jose L. Gonzalez-Andujar[3], Stewart B. Wuest[4] and Judit Barroso[5]

[1]Postdoctoral Research Associate, Oregon State University, Columbia Basin Agricultural Research Center, Adams, OR, USA; [2]Postdoctoral Scholar, Oregon State University, Columbia Basin Agricultural Research Center, Adams, OR, USA; [3]Professor of Research, Spanish National Research Council, Institute for Sustainable Agriculture, Cordoba, Spain; [4]Research Soil Scientist, USDA-ARS, Columbia Plateau Conservation Research Center, Adams, OR, USA and [5]Associate Professor, Oregon State University, Columbia Basin Agricultural Research Center, Adams, OR, USA

Research Article

Cite this article: Oreja FH, Genna NG, Gonzalez-Andujar JL, Wuest SB, Barroso J (2024) A hydrothermal model to predict Russian thistle (*Salsola tragus*) seedling emergence in the dryland of the Pacific Northwest (USA). Weed Sci. **72**: 108–112. doi: 10.1017/wsc.2023.67

Received: 23 August 2023
Revised: 22 October 2023
Accepted: 10 November 2023
First published online: 17 November 2023

Associate Editor:
Bhagirath Chauhan, The University of Queensland

Keywords:
Fallow; integrated weed management; spring wheat; soil temperature; water potential.

Corresponding author:
Fernando H. Oreja; Email: orejaf@agro.uba.ar

Abstract

Russian thistle (*Salsola tragus* L.) is among the most troublesome weeds in cropland and ruderal semiarid areas of the Pacific Northwest (PNW). Predicting *S. tragus* emergence timing plays a critical role in scheduling weed management measures. The objective of this research was to develop and validate a predictive model of the seedling emergence pattern of *S. tragus* under field conditions in the PNW to increase the efficacy of control measures targeting this species. The relationship between cumulative seedling emergence and cumulative hydrothermal time under field conditions was modeled using the Weibull function. This model is the first to use hydrothermal time units (HTT) to predict *S. tragus* emergence and showed a very good fit to the experimental data. According to this model, seedling emergence starts at 5 HTT, and 50% and 90% emergence is completed at 56 HTT and 177 HTT, respectively. For model validation, independent field experiments were carried out. Cumulative seedling emergence was accurately predicted by the model, supporting the idea that this model is robust enough to be used as a predictive tool for *S. tragus* seedling emergence. Our model can serve as the basis for the development of decision support systems, helping farmers make the best decisions to control *S. tragus* populations in no-till fallow and spring wheat systems.

Introduction

Russian thistle (*Salsola tragus* L.; syn.: *Salsola kali*) is among the most troublesome weeds in cropland and ruderal semiarid areas in the Pacific Northwest (PNW) (Beckie and Francis 2009). In dryland, this summer annual species is one of the most abundant broadleaf weeds in crops such as spring wheat (*Triticum aestivum* L.) (Young 1988), camelina [*Camelina sativa* (L.) Crantz] (Schillinger 2019), pulses, canola (*Brassica napus* L.), and mustard (*Brassica* spp.) (Nakka et al. 2019). In spring wheat, yield losses can range from 11% to 50%, depending on the amount of rainfall (Young 1988). This summer annual species emerges from March to May (Schillinger 2007), coinciding with the planting dates of spring crops or even preceding them in the region (Ogg and Dawson 1984). *Salsola tragus* is less problematic in winter crops, because they are already established when *S. tragus* emerges, reducing weed competitiveness, weed growth, and wheat yield losses (Fahad et al. 2015). Weeds that escape herbicide applications or emerge late may not be a problem for current crops but can become a severe weed problem during and after harvest (Young and Whitesides 1987), as they consume water and nutrients needed for the next crop. Furthermore, *S. tragus* control after wheat harvest in the PNW can be complicated and expensive. At that time, herbicides may be less effective due to factors like reduced active ingredient per biomass, thicker cuticles and higher wax accumulation than in younger plants (Harbour et al. 2003; Kirkwood 1999), or inadequate environmental conditions (high temperatures, low precipitation and air humidity) (Oreja et al. 2023). Therefore, the accurate daily prediction of seedling emergence is crucial for making successful management decisions regarding this weed.

For annual plants, successful establishment is critical to guarantee reproductive success (Forcella et al. 2000) and determines the intensity of the weed–crop interaction. A long emergence period with several flushes guarantees some individuals will escape from postemergence applications and mechanical controls, as well as from the effect of some residual herbicides. The late-emerging individuals are not the most important in terms of causing yield loss, but they will contribute to replenishing the seedbank for future seasons (Grundy 2003; Soltani et al. 2009). Therefore, predicting *S. tragus* emergence is critical to optimizing in-crop herbicide applications to reduce yield loss in the present season as well as potentially reduce the number of late-emerging individuals that replenish the seedbank.

Seedling emergence is the final step of several processes involving seed dormancy release, germination, and preemergence seedling growth (Forcella et al. 2000). Once *S. tragus* seeds are fully mature, they require an afterripening period to avoid germination in fall and so being killed by frost in winter. Following the afterripening period, if environmental conditions are favorable, seeds will germinate (Thorne et al. 2007). Temperature and water availability are the most important factors driving seed germination (Soltani et al. 2022). Empirical models based on accumulation of either thermal or hydrothermal time have been developed for many weed species to predict the time course of seedling emergence in crop fields. These models consider that seeds need to accumulate a certain amount of growing degree days independent of soil water availability (thermal models) or including information about soil water potential (hydrothermal models).

Effective weed management relies on applying control measures at the right time. Postemergence herbicides are most effective when applied at an early seedling stage before the plant becomes tolerant. This goal can be accomplished with the aid of predictive models of weed emergence. The objective of this research was to develop a predictive model of the seedling emergence pattern of *S. tragus* in the dryland PNW that can provide precise information to farmers and crop advisors in order to increase the efficacy of control measures targeting this species.

Materials and Methods

Site Description

Four field experiments were established at the Columbia Basin Agriculture Research Center (CBARC) (45.7196°N, 118.6235°W) in two consecutive years (2020 and 2021). The soil at CBARC was a Walla Walla silt loam (coarse-silty, mixed, superactive, mesic Typic Haploxerolls; 8% clay, 27% sand, and 65% silt) with 2.3% organic matter and a pH of 5.4. Average precipitation at CBARC is 420 mm yr^{-1}.

Model Development Experiment

In 2020, one experiment (hereafter referred as Site A) was established in a completely randomized block design with four replications. Each replication had 10 plots, each measuring 3 m by 4.5 m. Four hundred *S. tragus* seeds were sprinkled in the center of each plot on March 23, with 200 seeds (86% viability) spread in two separate 1 m^2 areas within each plot. Seeds came from *S. tragus* plants collected on October 2019 from a grower's field south of Ione, OR (45.3867°N, −119.8436°W). Seeds were stored in paper bags at room temperature (20 to 25 C) until use. Seed germination was tested in germination chambers at constant temperature (25 C) and 12-h interval of light and darkness, arranged in five replicates with 25 seeds per replicate each year. Initially, petri dishes were set up with a filter paper and water was added as required later. Germination was recorded regularly until no further seeds germinated (the incubation period did not exceed 15 d). After *S. tragus* seeds were sprinkled, spring wheat ('Ryan') was planted on March 24 in the experimental area using a no-till drill (Great Plains 606NT, Salinas, KS, USA) with 25 cm of interrow space at a seeding rate of 120 kg ha^{-1}. The experimental area was fenced to prevent tumbleweed *S. tragus* plants from blowing across the research plots. Spring wheat fertilization was conducted following standard recommendations for the region (Wysocki et al. 2007). The number of emerged seedlings was recorded every 15 d from April 7 until July 29. Data from the 10 plots per replicate were averaged, and the cumulative emergence percentage was calculated at the end of the season.

Model Validation Experiments

Also, in 2020 but in a no-till fallow field, one experiment (hereafter referred to as Site B) was conducted in a completely randomized block with four replications. Plot size was 3 m by 4.5 m. *Salsola tragus* seeds (from the same seed lot as those used in Site A) were sprinkled in the center of each plot in two 1 m^2 areas on March 5. In 2021, two experiments were conducted in fallow and spring wheat following the same experimental design and plot size as Sites A and B. Again, *S. tragus* seeds were sprinkled in the center of each plot in two 1 m^2 areas on March 13 in the fallow site (hereafter referred to as Site C) and on March 10 in the spring wheat site (hereafter referred to as Site D), at a seeding rate of 400 seeds (56% viability) per plot (200 seeds in each 1 m^2 area). Seeds came from *S. tragus* plants collected on October 2020 from a different grower's field south of Ione, OR (45.4409°N, 119.8791°W). After *S. tragus* seeds were sprinkled, spring wheat (Ryan) was planted in Site C on March 11 using the same no-till drill described for Site A at a seeding rate of 120 kg ha^{-1}. Sites B, C, and D were fenced to prevent *S. tragus* plants from rolling across the experiments and dispersing seeds across the experimental area. Fertilization of spring wheat in Site D was conducted following standard recommendations for the region (Wysocki et al. 2007). The number of emerged seedlings was recorded every 15 d in 2020, from March 31 to July 4 in site B, and weekly in 2021, from March 23 to July 13 in sites C and D, until no further seedlings were observed.

Soil Environmental Measures

Daily soil temperature and moisture were measured with 24 sensors per site located in a range of shallow soil depths varying from 0 up to 2.5 cm. Temperature was measured with calibrated thermistors, and water potential was measured with Decagon MPS6 water potential sensors (Meter Group, 2365 NE Hopkins Ct., Pullman, Washington 99163, US). Four sets of sensors (north, south, east, west) were established in each experimental site, with each set having two thermistors and four MPS6 sensors.

Soil temperature and water potential were used to calculate the hydrothermal time (θ_{HT}), expressed as C · kPa · d (degrees Celsius × kilopascal × days), being a function of hydro time ($\theta_H = \Psi - \Psi_b$) (kPa) and thermal time ($\theta_T = T - T_b$) (C), where Ψ is daily average soil water potential, Ψ_b is base water potential for seed germination expressed in kPa, T is daily average temperature at the soil surface, and T_b is base temperature for seed germination expressed in C, according to Equation 1:

$$\theta_{HT} = \theta_H \cdot \theta_T \quad [1]$$

where $\theta_H = 1$ when $\Psi > \Psi_b$, otherwise $\theta_H = 0$; and $\theta_T = T - T_b$ when $T > T_b$, otherwise $\theta_T = 0$. The Ψ_b and T_b considered for *S. tragus* were −1,000 kPa (Yousefi et al. 2020) and 4 C (Dwyer and Wolde-Yohannis 1972), respectively.

The cumulative hydrothermal time (HTT) was estimated from March 28 according to Equation 2, where d is the time period in days when HTT was computed:

$$\mathrm{HTT} = \sum(\theta_{HT}) * d \quad [2]$$

https://doi.org/10.1017/wsc.2023.67 Published online by Cambridge University Press

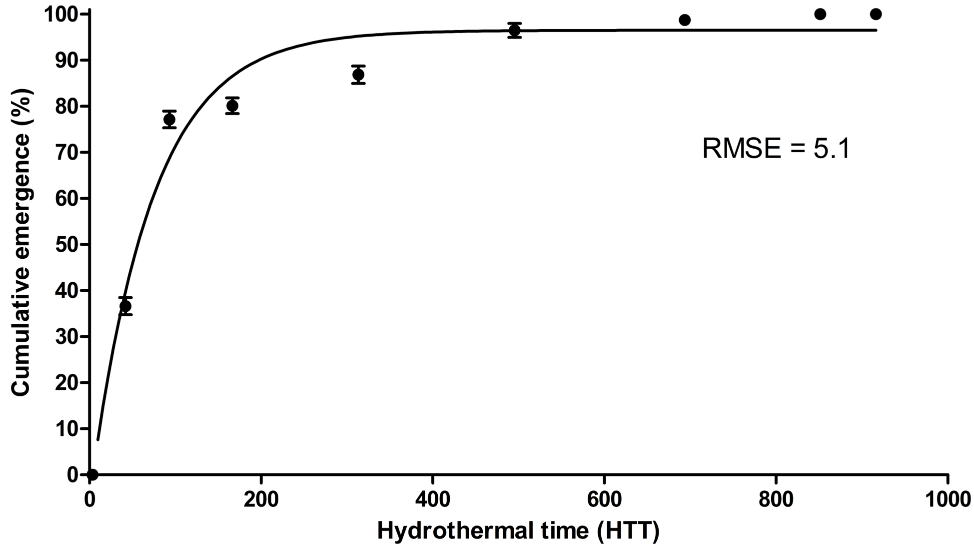

Figure 1. Observed (solid circles) and predicted (solid line) cumulative emergence (%) of *Salsola tragus* as a function of hydrothermal time (HTT) unit accumulation. Predictions are the result of the fit Weibull model to the experimental data set. Error bars on symbols are the SDs from the four replications. RMSE, root mean-square error.

Model Development

To describe the pattern of seedling emergence, percent of cumulative emergence, *E*, was related to the cumulative hydrothermal time (HTT) with a Weibull model (Gonzalez-Andujar et al. 2016; Martinson et al. 2007):

$$E = k\{1 - \exp[-b(\mathrm{HTT} - p)]\} \quad [3]$$

where *k* is the maximum emergence fraction, *b* is the slope (emergence rate), and *p* is the inflection point on the *x* axis. Model performance was assessed by calculating the root mean-square error (RMSE), sum of the residuals (SRES), and sum of the absolute residuals (SARES) (Bastida et al. 2021). These measures are defined by Equations 4 to 6, where x_i and y_i are the observed and predicted cumulative percentage emergence, respectively:

$$\mathrm{RMSE} = \sqrt{\left(\frac{1}{n}\right)\sum\nolimits_{i=1}^{n}(x_i - y_i)^2} \quad [4]$$

$$\mathrm{SRES} = \sum\nolimits_{i=1}^{n}(x_i - y_i) \quad [5]$$

$$\mathrm{SARES} = \sum_{i=1}^{n}\mathrm{ABS}\,(x_i - y_i) \quad [6]$$

ABS is absolute value of the number within parentheses and *n* is the number of observations. A scale of RMSE meaning is (Royo-Esnal et al. 2010): < 5 = excellent prediction, 5 to 10 = very good prediction, 10 to 15 = good prediction, and >15 = insufficient prediction. The SRES and SARES determine how errors in the model cancel out. If SRES is small compared with SARES, errors in the model will tend to cancel out. If SRES and SARES are large and SRES is positive, the model will tend to underestimate the observed value. However, if SRES is negative and large in comparison to SARES, then the model will tend to overestimate the observed value. Model parameters and goodness of fit were estimated by nonlinear least-squares regression using GraphPad Prism 6.0 (GraphPad Software, San Diego, CA, USA).

Model Validation

The model was validated using independent data from the described sites (B, C, and D) by comparing the observed seedling emergence and the predicted seedling emergence according to HTT, based on soil temperature and water potential measured on the sites and modeled by the Weibull function. Finally, the accuracy of the model was assessed by comparing the predicted and observed values through linear regression.

Results and Discussion

This work establishes for the first time a model for accurate prediction of *S. tragus* field emergence in the inland PNW. Our model can serve as the basis for the development of decision support systems, helping farmers to make the best decisions to control this troublesome weed in the future (Gonzalez-Andujar 2020).

The relationship between *S. tragus* cumulative emergence and cumulative hydrothermal time was well described by the Weibull model (Figure 1; Table 1). This model showed no significant bias, as indicated by SRES and SARES values (Table 1). The Weibull model has been widely used to model weed emergence due to its flexibility (Gonzalez-Andujar et al. 2016). Leguizamón et al. (2009) found a good fit of this model to describe the emergence of six summer annual grass weeds in maize (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.].

Our model was based on 7,212 *S. tragus* seedlings, counting an average of 1,803 seedlings per replication. It was validated with independent data sets and was in good agreement with the observed seedling emergence pattern in Site B ($R^2 = 0.96$), Site D ($R^2 = 0.95$), and Site C ($R^2 = 0.81$) (Figure 2). According to the model, the onset of emergence takes place at 5 HTT, and 50% and 90% emergence is reached at 56 and 177 HTT, respectively, indicating a rapid establishment of *S. tragus* in comparison with other species infesting cereals. Bastida et al. (2021) found that 50% and 90% emergence of shortspike canarygrass (*Phalaris brachystachys* Link) in wheat takes place at 108 and 160 HTT, respectively.

https://doi.org/10.1017/wsc.2023.67 Published online by Cambridge University Press

Table 1. Weibull model parameters (Equation 1) (SEs in parentheses), root mean-square error (RMSE), coefficient of determination (R^2), sum of the residuals (SRES), and sum of the absolute residuals (SARES) from the model performance.

K	*p*	*b*	R^2	RMSE	SRES	SARES
96.5 (0.83)	3.844 (1.30)	0.01396 (0.00064)	0.98	5.1	−0.12	36

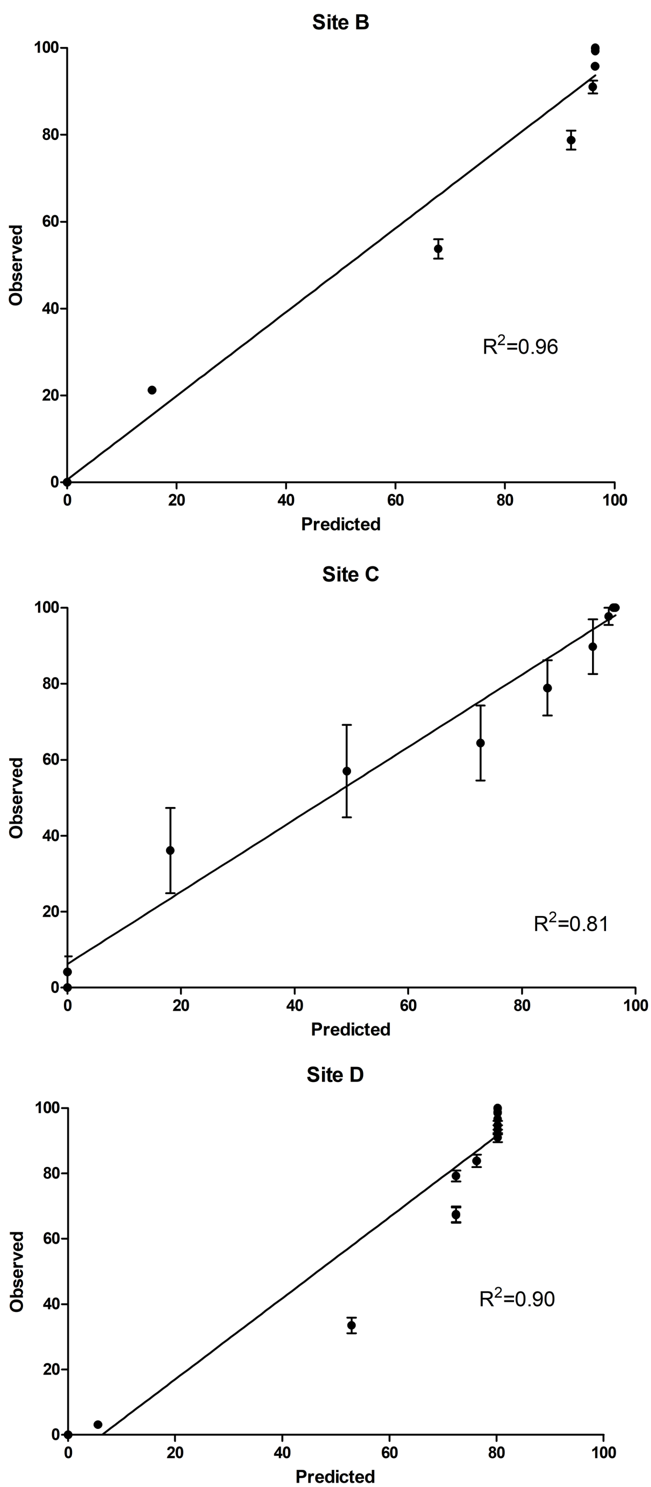

Figure 2. Validation of the Weibull model for *Salsola tragus* in Site B (fallow 2020), Site C (spring wheat 2021), and Site D (fallow 2021).

The present model can be used to design herbicide programs for wheat–fallow rotations that target high proportions of *S. tragus* seedlings in fallow fields with fewer herbicide applications than the current standard practice (three or four applications) (Kumar et al. 2017). Decreasing the number of herbicide applications will reduce the herbicide-resistance pressure and the risk of selecting for new herbicide-resistant populations (Neve et al. 2009), as well as environmental pollution (Rashid et al. 2010) and costs. Additionally, *S. tragus* has a short seed longevity. Burnside (1996) and Ogg and Dawson (1984) indicated that >99% of the seeds germinate in the first year; hence, the predictive model could help reduce the seedbank faster, by increasing the herbicide efficacy, than if the species had longer seed longevity. However, the annual emergence of *S. tragus* seedlings in calendar days can vary significantly among sites depending on environmental conditions, which can impact the effectiveness of residual herbicides in no-till fallow systems (Lyon et al. 2021). Particularly, the period between the 50% and 90% germination (more than 120 HTT units) can be wide for cool and/or dry seasons. Therefore, the model can estimate the proportion of emerged seedlings and assist in management decisions.

On the other hand, in spring wheat, no-till growers apply glyphosate before planting wheat to control emerged weeds, but in the case of *S. tragus*, most seedlings emerge after planting, thus escaping the herbicide application. Most *S. tragus* seedlings will emerge with the crop and compete for resources during and after the wheat harvest. To control *S. tragus* seedlings that emerge after seeding in spring wheat, this model can be used to apply selective herbicides in crop at the optimal HTT to minimize the number of plants competing with the crop and plants present at harvest (Young and Whitesides 1987). *Salsola tragus* can regrow after harvest, producing hundreds or thousands of seeds per plant. Consequently, reducing *S. tragus* plants present at harvest will reduce the number of seeds re-entering the soil seedbank (Oreja et al. 2023).

In recent years, there has been an increase in social demand for more sustainable management of agrosystems. In response, farmers are putting more emphasis on improving the efficiency of herbicide applications. In this study, our hydrothermal model describes the emergence of *S. tragus* with an accuracy of 81% to 96%, as demonstrated by validation tests at three different sites representing different field conditions (fallow vs. spring wheat) over two years. Future research should focus on wider model validation under different weather and soil management conditions (e.g., conventional tillage, where seeds are buried at deeper soil layers) to fine-tune the timing of control measures targeting this species (Egea-Cobrero et al. 2020).

Acknowledgments. This material is based upon work supported by the Department of Agriculture, Agricultural Research Service under Agreement No. 58-2074-2-003 (as part of the Pacific Northwest Herbicide Resistance Initiative) as well as by the USDA National Institute of Food and Agriculture through the research project No. ORE00339 (Integrated and Cooperative Russian Thistle (*Sasola tragus*) Management in the Semi-Arid Pacific Northwest).

The authors thank Jennifer Gourlie for helping in the establishment and development of the experiments and Kyle Harrison for conducting some of the farming in the experiments. We also thank John Rietmann and Keith Morter (two growers of Morrow County, OR) for allowing us to collect *S. tragus* plants from their fields to conduct this study. The authors declare no conflicts of interest.

References

Bastida F, Lezaun JA, Gonzalez-Andujar JL (2021) A predictive model for the time course of seedling emergence of *Phalaris brachystachys* (short-spiked canary grass) in wheat fields. Span J Agric Res 19(3):e10SC02

Beckie HJ, Francis A (2009) The biology of Canadian weeds. 65. *Salsola tragus* L. (Updated). Can J Plant Sci 89:775–789

Burnside OC, Wilson RG, Weisberg S, Hubbard KG (1996) Seed longevity of 41 weed species buried 17 years in eastern and western Nebraska. Weed Sci 44:74–86

Dwyer DD, Wolde-Yohannis K (1972) Germination, emergence, water use, and production of Russian thistle (*Salsola kali* L.) Agron J 64:52–55

Egea-Cobrero V, Bradley K, Calha I, Davis AS, Dorado J, Forcella F, Lindquist JL, Sprague CL, Gonzalez-Andujar JL (2020) Validation of predictive empirical weed emergence models of *Abutilon theophrasti* Medik. based on intercontinental data. Weed Res 6:297–302

Fahad S, Hussain S, Chauhan BS, Saud S, Wu C, Hassan S, Tanveer M, Jan A, Huang J (2015) Weed growth and crop yield loss in wheat as influenced by row spacing and weed emergence times. Crop Prot 71:101–108

Forcella F, Arnold RLB, Sanchez R, Ghersa CM (2000) Modeling seedling emergence. Field Crops Res 67:123–139

Gonzalez-Andujar JL (2020) Introduction to decision support systems. Pages 25–38 *in* Chantre G, Gonzalez-Andujar JL, eds. Decision Support Systems for Weed Management. Cham, Switzerland: Springer

Gonzalez-Andujar JL, Chantre GR, Morvillo C, Blanco AM, Forcella F (2016) Predicting field weed emergence with empirical models and soft computing techniques. Weed Res 56:415–423

Grundy AC (2003) Predicting weed emergence: a review of approaches and future challenges. Weed Res 43:1–11

Harbour JD, Messersmith CG, Ramsdale BK (2003) Surfactants affect herbicides on kochia (*Kochia scoparia*) and Russian thistle (*Salsola iberica*). Weed Sci 51:430–434

Kirkwood R (1999) Recent developments in our understanding of the plant cuticle as a barrier to the foliar uptake of pesticides. Pestic Sci 55:69–77

Kumar V, Spring JF, Jha P, Lyon DJ, Burke IC (2017) Glyphosate-resistant Russian-thistle (*Salsola tragus*) identified in Montana and Washington. Weed Technol 31:238–251

Leguizamón ES, Rodriguez N, Rainero H, Perez M, Perez L, Zorza E, Fernández-Quintanilla C (2009) Modelling the emergence pattern of six summer annual weed grasses under no tillage systems in Argentina. Weed Res 49:98–106

Lyon DJ, Barroso J, Thorne ME, Gourlie J, Lutcher LK (2021) Russian thistle (*Salsola tragus* L.) control with soil-active herbicides in no-till fallow. Weed Technol 35:547–553

Martinson K, Durgan B, Forcella F, Wiersma J, Spokas K, Archer D (2007) An emergence model for wild oat (*Avena fatua*). Weed Sci 55:584–591

Nakka S, Jugulam M, Peterson D, Asif M (2019) Herbicide resistance: development of wheat production systems and current status of resistant weeds in wheat cropping systems. Crop J 7:750–760

Neve P, Vila-Aiub MM, Roux F (2009) Evolutionary thinking in agricultural weed management. New Phytol 184:783–793

Ogg AG, Dawson JH (1984) Time of emergence of eight weed species. Weed Sci 32:327–335

Oreja FH, Lyon DJ, Gourlie J, Wetzel HC, Barroso J (2023) Russian thistle (*Salsola tragus*) post-harvest control and plant dispersal. Weed Technol 37:1–9

Rashid B, Husnain T, Riazuddin S (2010) Herbicides and pesticides as potential pollutants: a global problem. Pages 427–447 *in* Ashraf M, Ozturk M, Ahmad M, eds. Plant adaptation and phytoremediation. Dordrecht, Netherlands: Springer

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

Schillinger WF (2007) Ecology and control of Russian thistle (*Salsola iberica*) after spring wheat harvest. Weed Sci 55:381–385

Schillinger WF (2019) Camelina: long-term cropping systems research in a dry Mediterranean climate. Field Crops Res 235:87–94

Soltani E, Baskin CC, Gonzalez-Andujar JL (2022) An overview of environmental cues that affect germination of seeds. Seeds 1:146–151

Soltani N, Vyn JD, Sikkema PH (2009) Control of common waterhemp (*Amaranthus tuberculatus* var. *rudis*) in corn and soybean with sequential herbicide applications. Can J Plant Sci 89:127–132

Thorne ME, Young FL, Yenish JP (2007) Cropping systems alter weed seed banks in Pacific Northwest semi-arid wheat regions. Crop Prot 26:1121–1134

Wysocki DJ, Lutcher LK, Horneck DA, Hart JM, Petrie SE (2007) Winter Wheat and Spring Grains in Continuous Cropping Systems (Low Precipitation Zone): Fertilizer Guide. Corvallis: Oregon State University Extension Service. 81 p

Young FL (1988) Effect of Russian thistle (*Salsola iberica*) interference on spring wheat (*Triticum aestivum*). Weed Sci 36:594–598

Young FL, Whitesides RE (1987) Efficacy of postharvest herbicides on Russian thistle (*Salsola iberica*) control and seed germination. Weed Sci 35:554–559

Yousefi AR, Rashidi S, Moradi P, Mastinu A (2020) Germination and seedling growth responses of *Zygophyllum fabago*, *Salsola kali* L. and *Atriplex canescens* to PEG-induced drought stress. Environments 7:107