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A thermal time model for optimising herbicide dose in maize

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Abstract

Maize is sown in Iran from mid-April to early September. Weather, weed flora and crop growth stage all vary over this time span, which changes herbicide efficacy. To avoid any excessive or inadequate usage of herbicide, we propose an empirical model that predicts the optimum dose based on the thermal time accumulated by maize after sowing. We planted maize in May and August in 2016 and 2017, arranged in a split-plot design with four replications. Main plots were herbicide timing ranging from 2 to 8 leaves of maize, and sub-plots were herbicide dose. Weed response to herbicide dose was parameterised using the standard dose–response model against thermal time (TT) of application. The parameter W_0 weed fresh weight (WFW) in plots not treated with herbicide increased linearly, ED50 (the dose to decrease W_0 by 50%) increased exponentially, and *b* (the slope of the curve at linear decrease) decreased exponentially with TT. We replaced the parameters by their specified function of change over TT resulting in a combined model, which predicts WFW from herbicide dose and application time. A hyperbolic model described the yield loss as a function of WFW. We included this relationship in a more developed model, which predicts per cent yield loss based on herbicide dose and application TT. The model performed well over validation tests with $R^2 \geq 0.90$. We recommend an early herbicide application not later than 600 TT after maize sowing that allows reduced dose, as we found a steady decrease in herbicide efficiency with delaying application time.

KEYWORDS

application timing, dose optimisation, empirical model, herbicide dose, yield loss

1 | INTRODUCTION

Knowing the optimal time for herbicide application is an important component of integrated weed management programmes (Tursun et al., 2016), as it allows for reduced dose application and can avoid excessive usage of chemicals with their associated negative environmental side effects (Lodovichi et al., 2013). There are many studies on how to achieve optimal timing of herbicide application (Johnson and Norsworthy, 2014; Lodovichi et al., 2013; Williams and Harvey, 2000) for maximum efficiency when integrated with row spacing (Bell et al., 2015; Johnson and Hoverstad, 2002), tillage (Mangin et al., 2017), stale seedbed (Coleman et al., 2015) or sowing time (DeWerff et al., 2015). Applying herbicides too early may result in the lack of control of weed flushes that emerge after application (Gower et al., 2002), while a delayed application may cause noticeable yield loss due to an extended period of weed interference (Loux et al., 2011). Therefore, herbicide timing is crucial for efficient weed control. Zhang et al. (2013) showed that a timely application of nicosulfuron in maize (*Zea mays* L.) can reduce the required dose by 67% and 33% for the control of broad-leaved and grass weeds respectively. Although some studies emphatically state the importance of herbicide application time to achieve maximum efficacy, few models aim at predicting the optimal timing. There are models for recommending herbicide dose based on weed biomass (Sarani et al., 2016), density (Moon et al., 2014) and relative leaf area (Oveisi et al., 2013), but not on the timing of application. Sarani et al. (2016) developed a model to assess dose based on application thermal time for *Bromus japonicus* L. (Japanese brome) control in wheat, but to our best knowledge, no other studies exist that use this approach.

Maize is a major summer crop in Iran with a sowing time from mid-April to early September. Conventional crop rotation in the area used in this study includes mainly wheat (*Triticum aestivum* L.)-maize, oilseed rape (*Brassica napus* L.)-maize and fallow-maize. In a fallow-maize crop rotation, maize is planted in early to mid-spring, while for wheat-maize or oilseed rape -maize rotations, the maize sowing time is delayed to August or early September. Within this wide time span, the weather becomes hotter and drier, and the weed flora composition and abundance change. Furthermore, the sensitivity to herbicide dose varies for both weeds and maize, as the uptake, translocation and activity of herbicides change over time (Varanasi et al., 2016). Thus, optimal dose cannot be a fixed value because of these variations.

Nicosulfuron (SC 40 and OD 40) is used for weed control in maize. This product is a dual purpose herbicide that controls a wide range of grass and certain broad-leaved weeds. However, some broad-leaved weeds including *Xanthium strumarium* L. (rough cocklebur) and *Abutilon theophrasti* L. (velvetleaf) are not controlled by nicosulfuron (Baghestani et al., 2013). One method to overcome the incomplete control of broad-leaved weeds is to apply nicosulfuron as a tank-mix with a post-emergence broad-leaved herbicide such as bromoxynil + MCPA (EC 400) (Mamnoei and Baghestani, 2014).

To achieve a general model for optimising herbicide dose in maize that is planted from early spring to late summer, we specifically ask the following questions: (a) how does a multi-species weed population respond to herbicide dose over various application times? (b) do the dose–response parameters follow a certain trend over application times? (c) is there a consistent model, which over various planting times, could explain the maize yield as affected by weeds?

To address the above questions, we planted maize in May and August two conventional planting times of maize. Based on a previous assessment, the field seed bank included high populations of annual species such as *Chenopodium album* L. (common lambsquarters) as an early emerging species and *Solanum nigrum* L. (black nighshade) and *Heliotropium europaeum* L. (common heliotrope) that emerge from mid to late summer (Pourmorad Kaleibar, 2019). To both optimise and minimise effective herbicide dose, we set out to develop an empirical model that predicts optimum dose based on maize thermal time after sowing.

2 | MATERIALS AND METHODS

2.1 | Field experiments

Four field experiments were conducted at the research farm of the Department of Agronomy and Plant Breeding, University of Tehran, Karaj, Iran (35°34′ N, 50°11′ E, altitude 1,361 m). This region is characterised by a cold semi-arid climate. Monthly temperature and precipitation during the maize growing season for the two sowing times in 2016 and 2017 are shown in Figure 1. Experimental treatments were arranged in a split-plot design based on randomised complete blocks with four replications (blocks). Each block comprised four main plots that each measured 23 m in length by 5 m in width. Four herbicide application times, according to maize growth stages (2–3, 3–4, 4–6 and 6–8 leaves), were assigned to main plots. Five sub-plots, placed within each main plot, each measured 3.75 m by 5 m consisted of five herbicide doses 0, 25%, 50%, 75% and full recommended dose of a tank-mix of nicosulfuron (40 OD, 40 g a.i. L-1, Bisterfeld) and bromoxynil + MCPA (Bromicide MA®, 400 EC, 400 g a.i. L-1, Nufarm). There was a one-metre buffer between sub-plots to avoid herbicide drift while applying. We sowed five rows of maize in each sub-plot with a row spacing of 75 cm.

We chose two dates for maize sowing, early-May and mid-August, which are the two traditional sowing times of first and second planting of maize in the region, and experiments were conducted in the same way in 2016 and 2017.

Soil type, assessed on March 28th, was a loam-clay with 28.6% sand, 40% silt, 31.4% clay, 0.6% organic matter and a pH of 7.1. A mouldboard plough followed by a disc was used to prepare the seedbed in early spring. Plots were irrigated using the drip tape method. Based on soil analyses, 250 kg/ha nitrogen as urea (%46 N) was broadcasted as topdressing at canopy closure and the beginning of silking stages of maize. The maize hybrid Single-Cross 704 (Sabz Avaran Moghan Co.) was manually sown at the density of 80,000 plants/ha on May 8th and August 15th in 2016, and May 10th and August 12th in 2017. To verify the uniformity of weed distribution in the fields, weed density and species composition were evaluated before applying herbicides. For this, two 0.5 m by 0.5 m quadrats were placed randomly between crop rows in each sub-plot and the weeds were counted by species.

Herbicide was sprayed using a backpack sprayer fitted with an 8,004 even flat fan nozzle and adjusted to a pressure of 210 kPa and application volume of 250 L/ha. Weed density and fresh weight by species were measured four weeks after herbicide application. All weeds from three randomly placed quadrats (0.75 m × 1 m) within each sub-plot were harvested from at the soil surface, placed in paper bags, and after counting, the fresh weight of each species was assessed. At the end of the growing season, maize was removed by hand from a 2 m^2 area of each plot and the grain yield was measured. We calculate per cent yield loss (%YL) of each treatment as follows:

$$\%\,YL = \frac{Y_{wf} - Y}{Y_{wf}} \times 100 \qquad (1)$$

where Y_{wf} is the yield of weed-free and Y represents the yield of treatment.

2.2 | Model development

We used data from the first planting date (May 8th) in 2016 for model development and parameterisation. The change in weed fresh

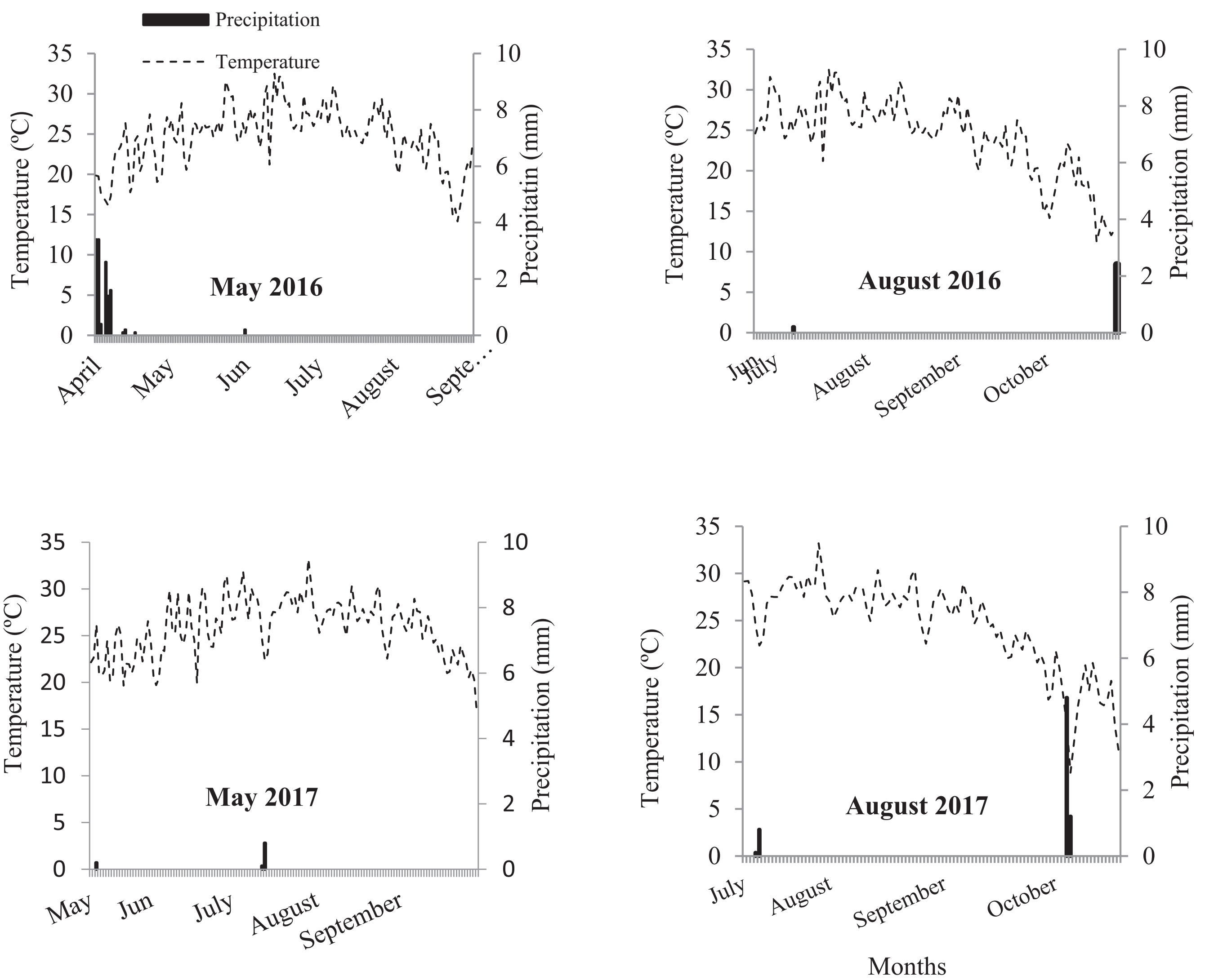

FIGURE 1 Monthly average daily air temperature and precipitation at the study site for May 2016, August 2016, May 2017 and August 2017, that is during the maize growing season in the two years of experiments

weight (WFW) treated by herbicide dose (D) was described as follows (Seefeldt et al., 1995):

$$\mathrm{WFW} = \frac{W_0}{1 + \left(\frac{D}{\mathrm{ED50}}\right)^b} \tag{2}$$

where W_0 is the upper asymptote that represents WFW with no herbicide application, ED50 represents the dose to reduce W_0 by 50%, and b denotes the slope of the curve.

We calculated cumulative thermal time (TT) from maize sowing date to each herbicide application time as follows:

$$\mathrm{TT} = \sum (T_{\mathrm{ave}} - T_b) \tag{3}$$

where T_{ave} is the average daily soil temperature (0–5 cm depth) that was recorded using data-loggers established at the climatology station located at the research farms, and T_{b} is the base temperature for maize germination that was set at 10°C (Gesch and Archer, 2005).

We parameterised Equation 2 for each herbicide application time and regressed the estimated parameters against TT. Parameter W_0 increased linearly as follows:

$$W_0 = y_{0\mathrm{w}} + A_{\mathrm{w}} \times \mathrm{TT} \tag{4}$$

where $y_{0\mathrm{w}}$ is the initial weed fresh weight at first herbicide application time, and A_{w} represents the coefficient of increase in weed fresh weight per TT.

ED50 increased exponentially with TT as follows:

$$\mathrm{ED50} = A_{\mathrm{e}} \times (b_{\mathrm{e}})^{\mathrm{TT}} \tag{5}$$

where A_{e} is the least ED50 with the first application, and b_{e} is the rate of ED50 change within exponential raise with increasing TT.

Parameter b decreased exponentially as follows:

$$b = y_{0\mathrm{s}} + \exp(-\mathrm{TT}) \tag{6}$$

where y_{0s} is an initial negative parameter that decreases with increasing TT.

Parameters W_0, ED50 and b in Equation 2 were replaced by Equations 4–6 in a combined model with five parameters that predict WFW from herbicide dose and application TT:

$$\mathrm{WFW} = \frac{y_{0w} + A_w \times \mathrm{TT}}{1 + \left(\frac{D}{A_e \times (b_e)^{\mathrm{TT}}}\right)^{(y_{0s} + \exp(-\mathrm{TT}))}} \tag{7}$$

A two-parameter hyperbolic function (Cousens, 1985) was used to describe the general relationship between *%YL* and WFW:

$$\%\mathrm{YL} = \frac{\mathrm{cc} \times \mathrm{WFW}}{1 + \left(\left(\frac{\mathrm{cc}}{\mathrm{m}}\right) \times \mathrm{WFW}\right)} \tag{8}$$

where cc is an estimate of the competition coefficient for weeds and m represents the maximum %YL occurring at the highest WFW.

Replacing WFW in Equation 8 by Equation 7 leads to a more developed model that uses the two inputs of herbicide timing and dose to predict *%YL*. As the parameter A_w was not significant and had no effect on model predictions (using sensitivity analysis, data not shown), it was eliminated from the model (9) to simplify the model:

$$\%\mathrm{YL} = \frac{\mathrm{cc} \times \frac{y_{0w} + \mathrm{TT}}{1 + \left(\frac{D}{A_e \times (b_e)^{\mathrm{TT}}}\right)^{(y_{0s} + \exp(-\mathrm{TT}))}}}{1 + \left(\left(\frac{\mathrm{cc}}{\mathrm{m}}\right) \times \left(\frac{y_{0w} + \mathrm{TT}}{1 + \left(\frac{D}{A_e \times (b_e)^{\mathrm{TT}}}\right)^{(y_{0s} + \exp(-\mathrm{TT}))}}\right)\right)} \tag{9}$$

Model (9) can be rearranged to give the minimum dose required to restrict weed competition as follows:

$$D = \exp\left(\frac{\ln\left(\left(\frac{(\mathrm{m} \times (\mathrm{cc} - \%\,\mathrm{yl})) \times (y_{0w} + \mathrm{TT})}{\%\,\mathrm{yl} \times \mathrm{m}} - 1\right) \times \left(A_e \times (b_e)^{\mathrm{TT}(y_{0s} + \exp(-\mathrm{TT}))}\right)\right)}{(y_{0s} + \exp(-\mathrm{TT}))}\right) \tag{10}$$

2.3 | Statistical analysis

A mixed model was used to analyse the main effects of herbicide application time (main plots) and dose (sub-plots) and their interactions. Planting times, herbicide timing and dose were considered as fixed effects in the model, whereas years were considered as random effects. The mixed model analysis was performed in R-studio version 1.1.453 (https://rstudio.com/products/rstudio/download/) using package 'lme4' (Bates et al., 2018). As the data had a normal distribution (Shapiro–Wilk test), no data transformation was required. Sigma Plot 14 was used for linear and non-linear regression analysis. Model fit was assessed using the lack of fit test, root mean square of error (RMSE), adjusted *R*-squared (R^2_{adj}) and the standard error of parameter estimates. More complex models were compared to their predecessors using corrected Akaike information criterion (AIC_C) as follows (Burnham and Anderson, 2002):

$$\mathrm{AIC_c} = \mathrm{AIC} + \frac{2K(K+1)}{n-k-1} \tag{11}$$

where AIC is the Akaike information criterion, *K* represents the number of estimated parameters included in the model, and n indicates the number of data points. The AIC (Burnham and Anderson, 2002) is calculated according to:

$$\mathrm{AIC} = -2(\text{log-likelihood}) + 2K \tag{12}$$

Although the best model is a model that has the smallest AICc value, delta-AICc values (Δ_i) that are pivotal for ranking the models according to their ability in fitting were also calculated as follows:

$$\Delta_i = \mathrm{AIC_{Ci}} - \mathrm{AIC_{Cmin}} \tag{13}$$

where AIC_{Cmin} denotes the minimum of the AIC_C values for the models. The delta-AIC_C values above 10 show that the model with bigger AICc has relatively little support (Burnham and Anderson, 2002).

TABLE 1 Weed density by species in the weed-infested (untreated) plots at canopy closure of maize in experimental fields. The numbers in parenthesis give the standard error of the means calculated from 60 quadrats

	Density (plant/m^2)			
Weed species	May 2016	August 2016	May 2017	August 2017
Amaranthus retroflexus L.	24 (4.13)	37 (3.71)	64 (9.19)	21 (2.80)
Amaranthus blitoides S. Wats	0	0	0	30 (5.06)
Chenopodium album L.	71 (10.96)	25 (3.41)	0	27 (9.01)
Solanum nigrum L.	42 (7.73)	142 (18.26)	51 (13.25)	128 (22.86)
Heliotropium europaeum L.	0	27 (11.94)	29 (5.69)	0
Other weed species	38 (6.80)	9 (1.12)	7 (1.63)	29 (7.20)
Total weed density	175 (16.16)	240 (11.59)	151 (14.91)	235 (7.77)

2.4 | Model validation

To test model performance, we fitted model (9) to data from August 2016, May 2017 and August 2017. As the input variables, herbicide dose was the same for all data sets, while TT for herbicide application was different for planting times. The predictions and observations were compared on an XY scatter plot evaluating point distributions around the bisector line. Root mean squared error and R^2 were used to summarise the errors.

3 | RESULTS

3.1 | Model parameterisation

The annual weed species *C. album*, *Amaranthus retroflexus* L. (redroot pigweed), *A. blitoides* S. Wats. (prostrate pigweed), *S. nigrum* and *H. europaeum* were the most abundant weed species across the experimental plots (Table 1).

For each herbicide application time, we fitted Equation (2) to WFW as a function of herbicide dose (Figure 2, Table 2). W_0 and ED50 estimates increased while *b* decreased with delaying herbicide application. The linear, exponential growth and exponential decay functions fitted the estimated parameters for W_0, ED50 and *b* (respectively) when plotted against application time (TT) (Figure 3). Therefore, we replaced W_0, ED50 and *b* in Equation 2 by Equations 4–6, accordingly. The result was Equation 7 that includes 5 parameters and predicts WFW using herbicide dose and time.

Parameter estimates summarised in Table 3 suggest that y_{0w} of 449.76 (±0.87) g/m^2 increases at a rate of 4.29 (±0.31) g per TT (d °C) (parameter A_w) if no herbicide is applied. Model (7) predicts a 1% (±0.00, parameter b_e) increase in ED50 with per unit thermal time delay in herbicide application (Figure 4).

The WFW in the hyperbolic relationship of %YL vs. WFW (Figure 5) was replaced by Equation (7) and led to the final model (Equation 9) for predicting %YL from herbicide dose and application time (Figure 6, Table 4). Model comparison (AICc) confirmed a significant advantage ($p < 0.01$) of model (9) to model (8) by evaluating the number of parameters, sum of square of errors and the degree of freedom of errors (Table 5).

Model (9) predicts that %YL increases by 4.52% (±0.00) with per gram increase in WFW (parameter *cc*). In weed-infested plots that received no herbicide dose, the maximum yield loss was estimated at 65.30% (±4.97) (parameter *m*).

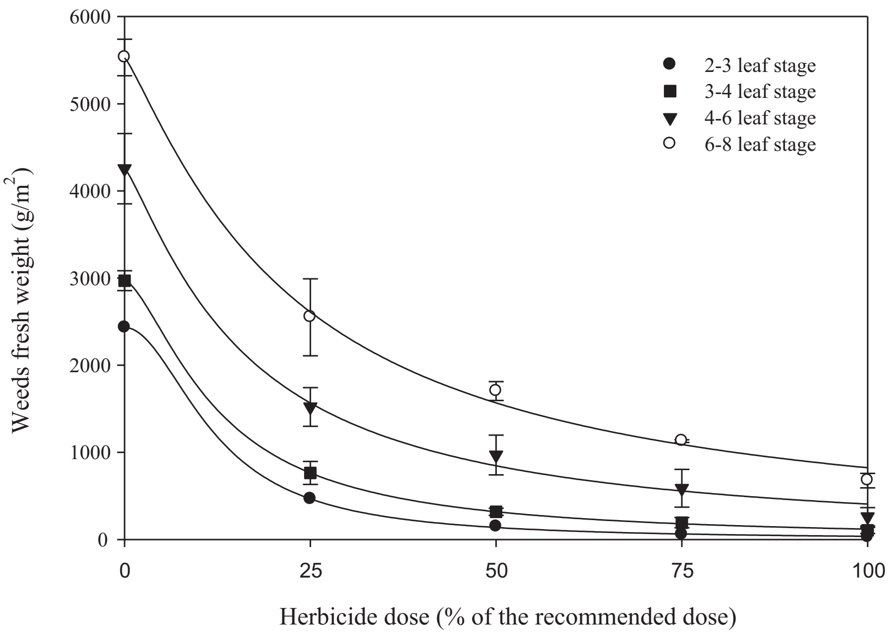

FIGURE 2 Relationships between weed fresh weight and herbicide dose applied at different maize growth stages. The standard dose–response model (Equation 2) was fitted to data from May 2016

TABLE 2 Parameter estimates of dose–response model (Equation 2) fitted to weed fresh weight treated with tank-mix of nicosulfuron and bromoxynil+MCPA at different application times in May 2016. The numbers in parenthesis give the standard error of the means

Herbicide application time (maize growth stage)	Parameter estimates				
	W_0	ED50	*b*	R^2_{adj}	RMSE
2–3 leaves	2,432.00 (11.45)	12.00 (0.53)	1.98 (0.09)	0.99	0.01
3–4 leaves	2,970.00 (13.53)	12.50 (0.41)	1.52 (0.05)	0.99	0.02
4–6 leaves	4,254.00 (14.37)	16.00 (2.84)	1.23 (0.21)	0.99	0.03
6–8 leaves	5,527.00 (15.73)	23.00 (2.42)	1.17 (0.14)	0.99	0.10

Abbreviations: *b*, the slope of the curve at linear part; ED50, required dose to decrease W_0 by 50% (% of the recommended dose); R^2_{adj}, adjusted *R*-squared; RMSE, root mean square of error; W_0, weed fresh weight with no herbicide application (g/m^2).

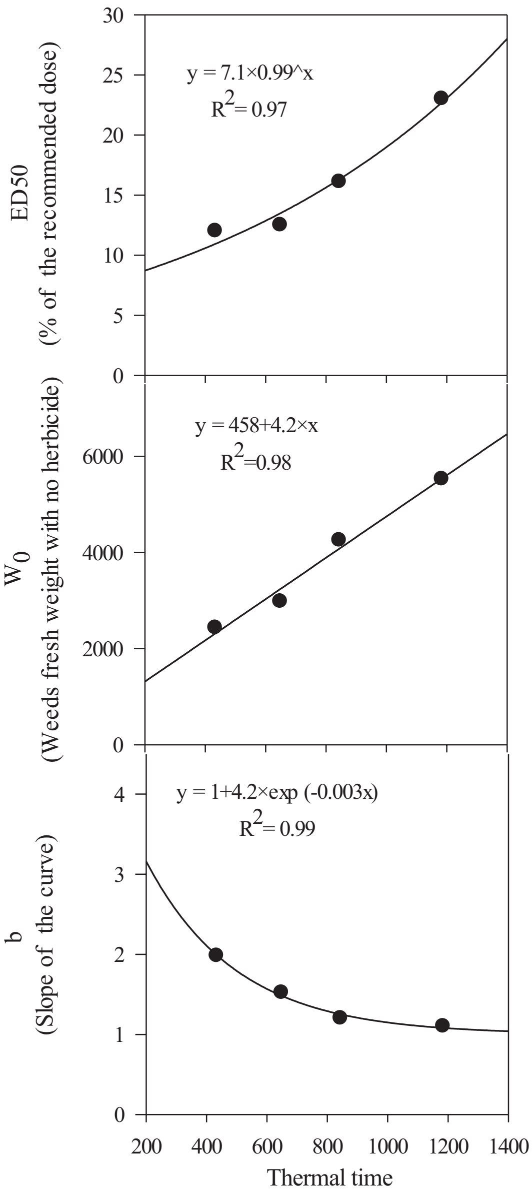

FIGURE 3 Relationships between parameters W_0, ED50 and b with increasing thermal time at different maize growth stages assessed in May 2016

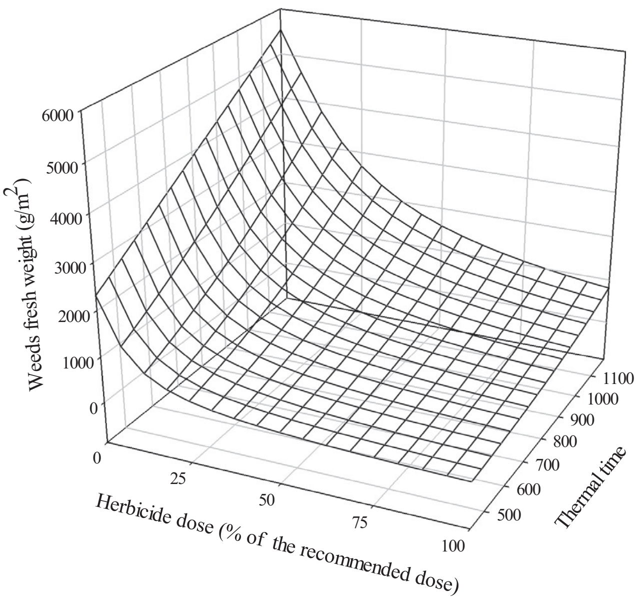

FIGURE 4 Predicted fresh weight of weeds as affected by herbicide dose and timing by fitting Equation 7 to data from May 2016

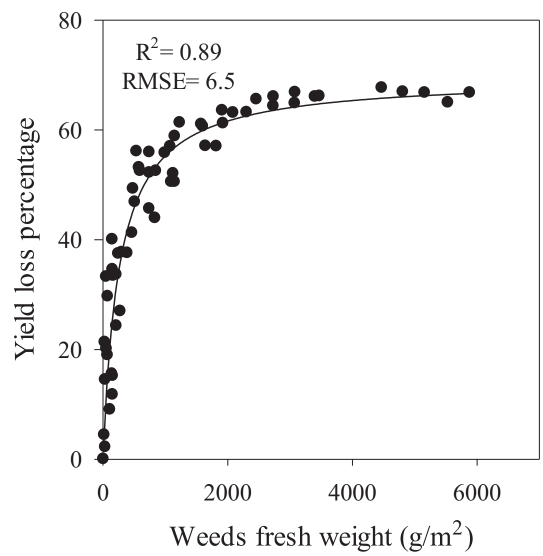

FIGURE 5 Yield loss predictions with weed fresh weigh obtained by fitting Equation 8 to data from May 2016

TABLE 3 Parameter estimates from Equation 7 fitted to weed fresh weight data against varying herbicide dose and timing in May 2016. The numbers in parenthesis give the standard error of the means

Parameter estimates						
y_{0w}	A_w	A_e	b_e	y_{0s}	R^2_{adj}	RMSE
449.76 (0.87)	4.29 (0.31)	4.24 (1.46)	1.00 (0.00)	1.22 (0.13)	0.95	0.03

Abbreviations: A_e, the least ED50 occurs with the first application (% of the recommended dose); A_w, the coefficient of increase in weed fresh weight per TT; b_e, the rate of ED50 change within exponent raise with increasing TT; R^2_{adj}, adjusted R-squared; RMSE, root mean square of error; y_{0s}, an initial negative parameter that decreases with increasing TT; y_{0w}, is the initial weed fresh weight at first herbicide application time (g/m^2).

Although delayed application of herbicide significantly decreased the efficacy of lower doses, the recommended dose effect was not affected by application time (Figure 6). Model (10) suggests that to maintain YL%, less than 5%, 73% and 95% of the recommended dose must be applied, respectively, for application times of 2–3 and 6–8 leaf stage of maize (Figure 7).

3.2 | Model validation

As shown, weed populations were different (Table 1) both between May and July 2016 and 2017, which was also reflected in variation in the predicted potential yield loss by weeds (parameter *m*). However, model (9), parameterised from a single dataset, still performed well in predicting YL% ($R^2 \geq 0.90$; Figure 8). Maize and weeds in May and August plantings are grown under different temperatures, precipitation levels, relative humidity and day length. The model performed consistency over different planting times and years confirming its practicality and generality for deciding herbicide dose in maize.

4 | DISCUSSION

Maize is grown in many countries with different climates (Ranum et al., 2014), and many weeds, both annuals and perennials, are likely to infest maize fields (Glowacka, 2011). Thus, weed management programmes in maize should be effective over a wide range of weed floras and across different periods with diverse environmental temperature, soil moisture and air humidity regimes. Herbicides will continue to be an important tool for weed control in maize, and to deal with variable target plants, multi-purpose herbicides or herbicide mixtures are available as options. However, herbicide efficiency is not constant as it is highly dependent on environmental and biological factors. Over time, there are sources of variability that affect the susceptibility of weeds to herbicides. Early emerged species become larger with more developed protective tissues,

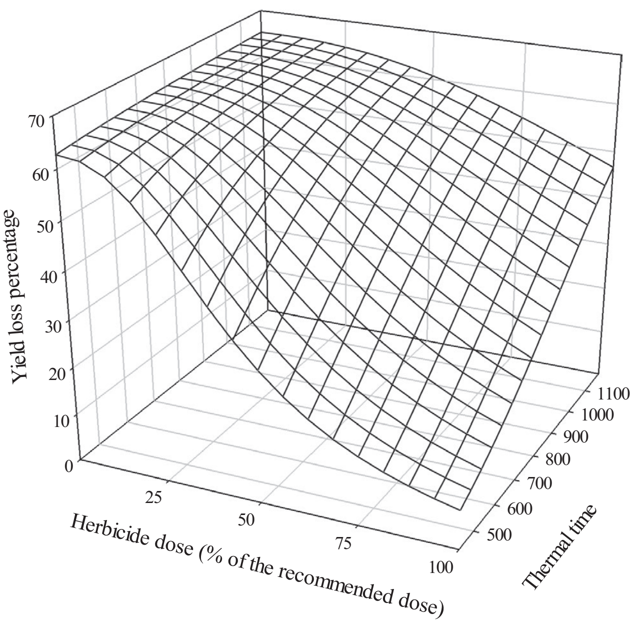

FIGURE 6 Predictions of maize yield loss by fitting Equation 9 to data from May 2016. Herbicide timing and dose are model independent variables

TABLE 4 Parameter estimates from Equation 9 fitted to the percentage loss of the maize grain yield against different herbicide doses and timings in May 2016. The numbers in the parenthesis give the standard error of the means

Parameter estimates							
y_{0w}	A_e	b_e	y_{0s}	cc	m	R^2_{adj}	RMSE
450.00 (0.00)	4.30 (0.17)	1.00 (0.00)	2.39 (0.25)	4.52 (0.00)	65.30 (4.97)	0.92	0.05

Abbreviations: A_e, the least ED50 occurs with the first application (% of the recommended dose); b_e, the rate of ED50 change within exponent raise with increasing TT; cc, competition coefficient for weeds; m, maximum yield loss percentage occurs at highest weed fresh weight; R^2_{adj}, adjusted *R*-squared; RMSE, root mean square of error; y_{0s}, an initial negative parameter that decreases with increasing TT; y_{0w}, the initial weed fresh weight at first herbicide application time (g/m^2).

TABLE 5 Summary of non-linear regression analysis and corrected Akaike information criterion to compare models for weed fresh weight (Equations 2 and 7) and the grain yield loss of maize (Equations 8 and 9) in May 2016

	Residuals		Number of	Test statistic			
Model	*df*	SS	parameters	Lack of fit	AIC_C	Comparision	Δi
Equation 2	48	4,363,320	12	ns	705.58	Equation 2 vs Equation 4	11.44
Equation 7	55	5,059,965	5	ns	694.14		
Equation 8	50	2,298	10	ns	246.23	Equation 5 vs Equation 6	27.18
Equation 9	54	1765	6	ns	219.05		

Abbreviations: AIC_C, corrected Akaike information criterion; ns, non-significant; Δi, delta-AIC_C values.

getting more woody, waxy and with a thicker cuticle, which reduces herbicide uptake (Riemens et al., 2008). Also, lower growth rate and photosynthetic activity in older plants result in less herbicide uptake and translocation (Reinhardt, 2019). Concurrently, weed species with more prolonged dormancy or higher temperature requirement are adapted to germinate and emerge later in the season when hotter, drier conditions may also affect the activity of herbicides. The changes in weed species and growth stages, and environmental conditions lead to variable herbicide dose responses with time. Our research questions set out to quantify and model this change in herbicide efficacy over time in terms of the impact on weeds and crop yield. Firstly, we showed clear variability of weed species and their response to herbicide doses over time. Secondly,

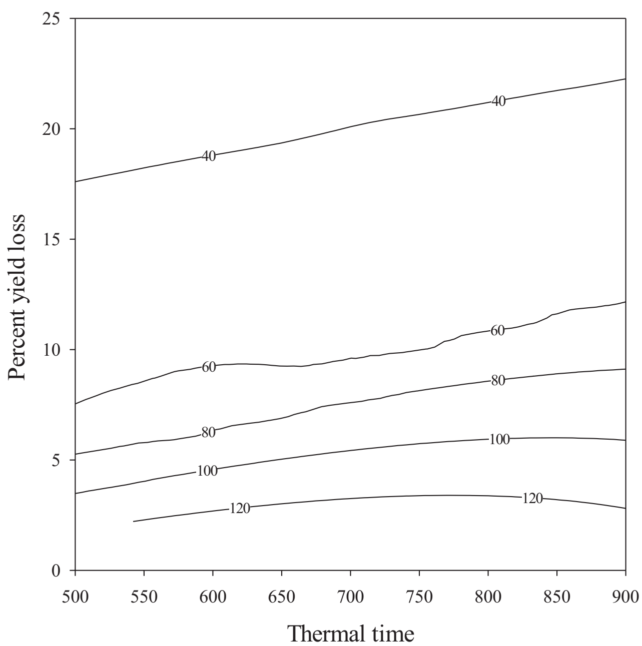

FIGURE 7 Dose predictions obtained by fitting Equation 10 to data from May 2016. Herbicide timing and acceptable yield loss of maize are model independent variables

the changes in dose–response parameters over time were described by Equations 4–6. Finally, fitting model 9 to data of maize yield with herbicide time and dose allowed us to identify the various parameter values estimated over maize planting time and year.

Despite the various sources of variability, model 9 was successful in recommending the required dose based on application time. There are important practical applications of this result. First, many studies emphasise the importance of herbicide timing for an efficient application (Gower et al., 2003; Williams and Harvey, 2000); therefore, any change in optimum time may change the herbicide effect and accordingly requires a different dose to achieve optimal weed control. To our best knowledge, except a model that recommends herbicide dose for *B. japonicus* control based on thermal time of application (Sarani et al., 2016), there is no model that recommends dose based on herbicide application time. Some models predict weed emergence patterns and determine a suitable time for herbicide application. For instance, a predictive model for emergence (WeedTurf) has been reported to determine the proper timing of herbicide application to control summer annual weed species in turf (Masin et al., 2005). Lodovichi et al. (2013) also predicted the emergence pattern of *Avena fatua* L. (wild oat) in wheat to determine the optimal application timing of herbicides within a growing season, but no recommendation of herbicide dose is included. Therefore, the current study model is the first one recommending herbicide dose based on application thermal time after maize sowing. The applicability of the model is further enhanced because we used a herbicide mixture that can control both grass and broad-leaved species at the recommended dose. The tank-mix of nicosulfuron with bromoxynil + MCPA was highly efficient in weed control, as the values of ED50 especially at early applications were lower than 15%. Baghestani et al. (2013) also showed that the ED50 values of tank-mix nicosulfuron and bromoxynil + MCPA were significantly lower than those of individual applications of either nicosulfuron or bromoxynil + MCPA. There might be some synergic effects that increase the herbicide dose effects on broad-leaved weeds (Hennigh et al., 2010). The tank-mix application can also help to avoid

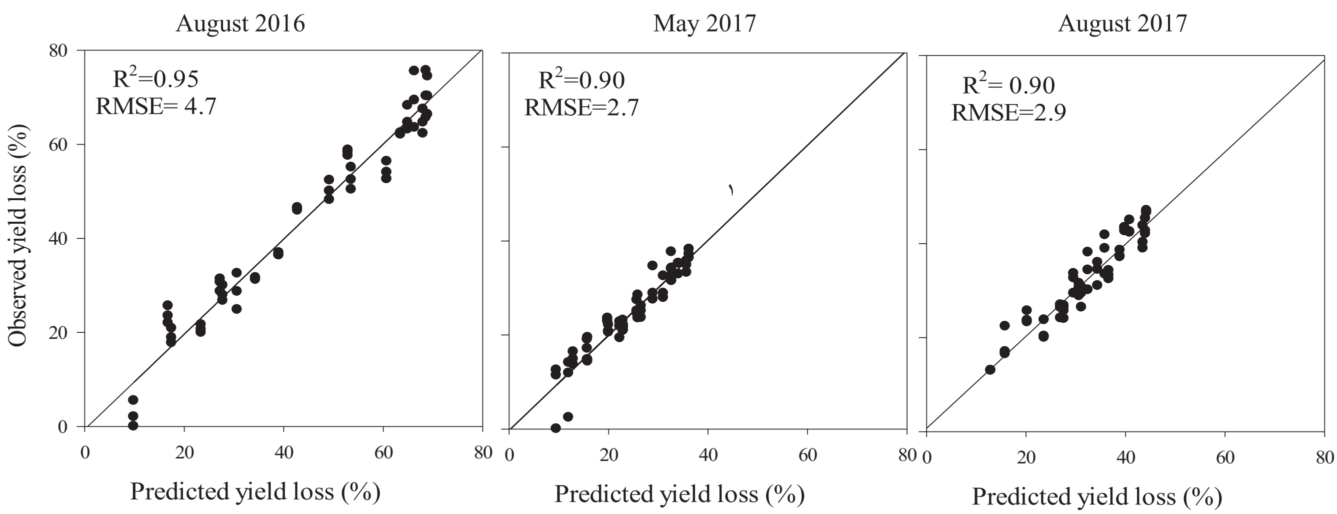

FIGURE 8 Model performance validation by fitting Equation 9 to independent data obtained from August 2016, May 2017 and August 2017

the evolution of herbicide resistant weeds (Baghestani et al., 2013). The main asset of our model is in avoiding herbicide overuse. While the conventional method relies on the label-recommended dose, irrespective of application time, the current study model recommends the herbicide dose according to the timing of application, which in most cases leads to a reduced rate of herbicide with the optimised time.

Many factors contribute to the severity of yield loss from weed interference across sites and years. Generally, maize suffered more yield loss from weeds at the second planting date. Due to a shorter growing season and lower growing degree days (GDD) in the second planting date, maize is expected to have a lower relative growth rate and weed interference tolerance (Williams and Lindquist, 2007). Furthermore, some species such as *S. nigrum* and *Amaranthus* spp. are thermophiles and profit from the increased soil temperatures associated with the late sowing date of maize (De Mol et al., 2015).

Plant fresh weight has been used in several studies (Isaacs et al., 2006; Kieloch and Domaradzki, 2011) for evaluating herbicide effect, but less often than dry weight. We found weed fresh weight to be a more accurate measure for assaying herbicide effect. Normally, fresh weight and dry weight are highly correlated, while with herbicide application, plants become drier with increasing herbicide effect. When fresh plants are compared, the difference between herbicide treated plants and unsprayed ones is more obvious, while drying them eliminates early difference among plants.

Here, we developed a simple empirical model that proved a high performance over fields with various weed species and ambient environment and that can indicate herbicide dose with two input variables of application time and allowed predicting yield loss. This quantitative framework will assist practitioners in deciding on herbicide dose. Optimising herbicide dose can alleviate both negative economic and environmental impacts of chemical weed control.

PEER REVIEW

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REFERENCES

Baghestani, M.A., Zand, E., Lotfi-Mavi, F., Mamnoie, E. & Sharifi Zive, S.H. (2013) Study of the possibility of tank-mix application of Nicosulfuron+Rimsulfuron (Ultima®) with Bromoxynil+MCPA (Bromicide MA®) for weed control in corn. *Iranian Journal of Crop Sciences*, 15, 166–180 (In Persian).

Bates et al., 2018Bates, D., Maechler, M., Bolker, B., Walker, S., Christensen, R.H.B., Singmann, H. et al (2018) *Package 'lme4'*. Version, 1, 17.

Bell, H.D., Norsworthy, J.K., Scott, R.C. & Popp, M. (2015) Effect of row spacing, seeding rate, and herbicide program in glufosinate-resistant soybean on Palmer amaranth management. *Weed Technology*, 29, 390–404.

Burnham, K.P. & Anderson, D.R. (2002) *Model selection and multi model inference: a practical information-theoretic approach*, 2nd edition. New York, NY: Springer.

Coleman, L.B., Chaudhari, S., Jennings, K.M., Schultheis, J.R., Meyers, S.L. & Monks, D.W. (2015) Evaluation of herbicide timings for Palmer amaranth control in a stale seedbed sweetpotato production system. *Weed Technology*, 30, 725–732.

Cousens, B.R. (1985) A simple model relating yield loss to weed density. *Annals of Applied Biology*, 107, 239–252.

De Mol, F., Von Redwitz, C. & Gerowitt, B. (2015) Weed species composition of maize fields in Germany is influenced by site and crop sequence. *Weed Research*, 55, 574–585.

DeWerff, R.P., Conley, S.P., Colquhoun, J.B. & Davis, V.M. (2015) Weed control in soybean as influenced by residual herbicide use and glyphosate-application timing following different planting dates. *Weed Technology*, 29, 71–81.

Gesch, R.W. & Archer, D.W. (2005) Influence of sowing date on emergence characteristics of maize seed coated with a temperature-activated polymer. *Agronomy Journal*, 97, 1543–1550.

Glowacka, A. (2011) Dominant weeds in maize (*Zea mays* L.) cultivation and their competitiveness under conditions of various methods of weed control. *Acta Agrobotanica*, 64, 119–126.

Gower, S.A., Loux, M.M., Cardina, J. & Harrison, S.K. (2002) Effect of planting date, residual herbicide, and post-emergence application timing on weed control and grain yield in glyphosate-tolerant Corn (*Zea mays*). *Weed Technology*, 16, 488–494.

Gower, S.A., Loux, M.M., Cardina, J., Harrison, S.K., Sprankle, P.L., Probst, N.J. et al (2003) Effect of postemergence glyphosate application timing on weed control and grain yield in glyphosate-resistant corn: results of a 2-yr multistate study1. *Weed Technology*, 17, 821–828.

Hennigh, D.H., Al-Khatib, K. & Tuinstra, M.R. (2010) Postemergence weed control in acetolactate synthase–resistant grain sorghum. *Weed Technology*, 24, 219–225.

Isaacs, M.A., Hatzios, K.K., Wilson, H.P. & Toler, J. (2006) Halosulfuron and 2, 4-D mixtures' effects on common lambsquarters (*chenopodium album*) 1. *Weed Technology*, 20, 137–142.

Johnson, D.B. & Norsworthy, J.K. (2014) Johnsongrass (*Sorghum halepense*) management as influenced by herbicide selection and application timing. *Weed Technology*, 28, 142–150.

Johnson, G.A. & Hoverstad, T.R. (2002) Effect of row spacing and herbicide application timing on weed control and grain yield in corn (*Zea mays*). *Weed Technology*, 16, 548–553.

Kieloch, R. & Domaradzki, K. (2011) The role of the growth stage of weeds in their response to reduced herbicide doses. *Acta Agrobotanica*, 64, 259–266.

Lodovichi, M.V., Blanco, A.M., Chantre, G.R., Bandoni, J.A., Sabbatini, M.R., Vigna, M. et al. (2013) Operational planning of herbicide-based weed management. *Agricultural Systems*, 121, 117–129.

Loux, M.M., Dobbels, A.F., Johnson, W.G. & Young, B.G. (2011) Effect of residual herbicide and postemergence application timing on weed control and yield in glyphosate-resistant Corn. *Weed Technology*, 25, 19–24.

Mamnoei, E. & Baghestani, M.A. (2014) Evaluating effect of mixing Nicosulfuron (cruz®) and Bromoxynil +MCPA herbicide (Bromicide MA®) to weeds control in corn fields of Jiroft. *Iranian Journal of Plant Protection*, 28, 211–219 (In Persian).

Mangin, A.R., Hall, L.M., Schoenau, J.J. & Beckie, H.J. (2017) Influence of tillage, vertical seed distribution, and pyroxasulfone application timing and rate on control of wild oat (*Avena fatua* L.). *Canadian Journal of Plant Science*, 98, 601–608.

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

Moon, B.C., Kim, J.W., Cho, S.H., Park, J.E., Song, J.S. & Kim, D.S. (2014) Modelling the effects of herbicide dose and weed density on rice-weed competition. *Weed Research*, 54, 484–491.

Oveisi, M., Mashhadi, H.R., Yousefi, A.R., Alizade, H., Baghestani, M.A. & González-Andújar, J.L. (2013) Predicting maize yield in a multiple species competition with *Xanthium strumarium* and *Amaranthus* *retroflexus*: Comparing of approaches to modeling herbicide performance. *Crop Protection*, 45, 15–21.

Pourmorad Kaleibar, B. (2019) *Modelling herbicide application timing and dose in accordance to weeds emergence patterns in maize*, PhD thesis. University of Tehran, Tehran, Iran.

Ranum, P., Peña-Rosas, J.P. & Garcia-Casal, M.N. (2014) Global maize production, utilization, and consumption. *Annals of the New York academy of sciences*, 1312, 105–112.

Reinhardt, C. (2019) Why herbicides are most effective on young weeds: production. *FarmBiz*, 5, 30–31.

Riemens, M.M., Duec, T. & Kempenaar, C. (2008) Predicting sublethal effects of herbicides on terrestrial non-crop plant species in the field from greenhouse data. *Environmental Pollution*, 155, 141–149.

Sarani, M., Oveisi, M., RahimianMashhadi, H. & Alizadeh, H. (2016) Modelling interactive effects of herbicide application timing and dose for the control of *Bromusjaponicus* in wheat in an arid environment. *Weed Research*, 56, 50–58.

Seefeldt, S.S., Jensen, J.E. & Fuerst, E.P. (1995) Log-logistic analysis of herbicide dose-response relationships. *Weed Technology*, 9, 218–227.

Tursun, N., Datta, A., Sakinmaz, M.S., Kantarci, Z., Knezevic, S.Z. & Chauhan, B.S. (2016) The critical period for weed control in three corn (*Zea mays* L.) types. *Crop Protection*, 90, 59–65.

Varanasi, A., Prasad, P.V. & Jugulam, M. (2016) Impact of climate change factors on weeds and herbicide efficacy. *Advanced in Agronomy*, 135, 107–146.

Williams, B.J. & Harvey, R.G. (2000) Effect of Nicosulfuron timing on wild-proso millet (*Panicum miliaceum*) control in sweet corn (*Zea mays*). *Weed Technology*, 14, 377–382.

Williams, M.M. & Lindquist, J.L. (2007) Influence of planting date and weed interference on sweet corn growth and development. *Agronomy Journal*, 99, 1066–1072.

Zhang, J., Zheng, L., Jäck, O., Yan, D., Zhang, Z. & Gerhards, R. (2013) Efficacy of four post-emergence herbicides applied at reduced doses on weeds in summer corn (*Zea mays* L.) fields in North China Plain. *Crop Protection*, 52, 26–32.

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