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Climate change impact on herbicide efficacy: A model to predict herbicide dose in common bean under different moisture and temperature conditions

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ABSTRACT

In Iran, farmers sow common bean (*Phaseolus vulgaris* L.) from mid-April to early July. We used different sowing times to mimick the changing conditions expected under climate change to assess future herbicide efficacy. Filed experiments were carried out during 2016–2018 in split plot arrangements with main plots of moisture regimes (*MR*) consisting of 100, 80, 60% of bean water requirement, and sub-plots of 0, 25, 50, 75 and 100% of the recommended dose (*RD*) of the herbicide imazethapyr. We found that 1) July plantings resulted in a higher weed biomass and a higher yield loss, 2) weed biomass under 100% *MR* was higher than with 80 and 60% *MR*, and 3) 75% of *RD* decreased weed biomass to less than 10 g m^{-2} under 100% *MR*, while with 80 and 60% *MR*, 100% *RD* could not decrease weed biomass below 100 g m^{-2}. We used a logistic model (M1) to predict weed biomass (*W*) changes with herbicide dose (*D*) at each *MR%*. Parameter W_0 (weed biomass with no herbicide application) showed a linear increase with increasing moisture, while ED_{50} (the dose to reduce W_0 by 50%) and *B* (the slope parameter) decreased. We replaced W_0, ED_{50} and *B* with their linear relationships vs. *MR%* and obtained a more developed model (M2) that describes *W* with changing *D* and *MR%*. We then used M2 as a sub-model in a hyperbolic model for predicting *D* with any given *MR%*. The model suggests higher herbicide doses with delayed sowing time and lack of moisture. However, the economic and environmental impacts and high phytotoxic effect on crops prohibits higher herbicide doses demanding an integrated weed management approach to alleviate the reduced herbicide efficacy under future climate conditions.

1. Introduction

Climate change is bringing hotter and drier summers to many areas including western Asia, Europe and North America (Krysanova et al., 2010). Common bean (*Phaseolus vulgaris* L.) is a major summer crop in Iran with a planting area of 108621 ha (Agricultural statistics, 2017) and is sown from mid-April to early July, during which air and soil moisture, sun irradiance, and temperature are greatly changing (https://www.amar.org.ir/english/Statistics-by-Topic/Climate-and-Environment). Although tillage, crop rotation, increased planting density and more competitive cultivars are used, herbicide use most often remains an inevitable practice to control weeds in bean (Procópio et al., 2009; Abtew et al., 2016; Vidal et al., 2016). Environmental conditions before, during and after herbicide applications is known to significantly affect herbicide performance and adverse environmental conditions are the major cause of herbicide inconsistency (Stewart et al., 2010; Varanasi et al., 2016).

Presently, we are observing some kind of acclimation, with phenological adjustments and population shifts in response to climatic change in the agricultural area (Peters et al., 2014; Uleberg et al., 2014; Way and Yamori, 2014). Photosynthesis can function without harm between 0 and 30 °C in cold-adapted plants that are active in winter and early spring, or grow at high altitude and latitude (Yamori et al., 2014), between 7 and 40 °C in plants from equitable habitats (e.g., warm season crops), and between 15 and 45 °C in plants from hot environments, such as tropical or summer species (Slot and Winter 2017; Mau et al., 2018). As other physiological processes, photosynthesis shows an optimum temperature and a linear decrease with supra optimal temperatures.

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Optimum and ceiling temperatures significantly differ between bean and its common weeds such as *Solanum nigrum* L., *Amaranthus retroflexus* L., or *Echinochloa crus-galli* (L.) P. Beauv. The current increase in temperature could decrease bean growth rate by one-third to one-half especially with late sowing times (Beebe et al., 2011; Stefanov et al., 2011), while, a 2–5 °C increase may favor the weed species (Korres et al., 2016; Nguyen et al., 2017). Therefore, under future climate conditions, we face stronger and more tolerant weeds competing with a more sensitive and weaker crop.

Water stress will also increase with warmer climate. Plants with a water deficit adopt a variety of strategies including a reduced leaf area (Aroca, 2012) and the stretching and growth of the plant (Kooyers, 2015), changing the shoot/root ratio (Ahmadi et al., 2018), leaf shedding and leaf rolling (Aroca, 2012), changing leaf angle (Ghanbari et al., 2013) and cuticle thickening (Aroca, 2012). Increases in Abscisic acid (ABA) (Wilkinson et al., 2012), osmotic adjustment (Blum, 2017), reduced rate of photosynthesis, transpiration and stomatal conductance (Pinheiro and Chaves, 2011) are additional physiological changes of plants under water stress.

It is hypothesized that, for a summer crop such as bean, a delayed sowing time can provide conditions like those predicted with climate change, as average temperature increases by at least 3 °C, RH% decreases, and evaporation increases. This will deplete soil water content and water will rapidly become unavailable for plants (Arredondo et al., 2020). Insufficient soil moisture reduces herbicide activation and phytotoxicity, therefore, weed control is greatly influenced by complex interactions between soil physical properties and soil moisture (Sebastian et al., 2017). The reduced herbicide performance with low moisture was also shown for post emergence herbicides (Jain et al., 2014). Increased temperature and lack of moisture cause molecular,

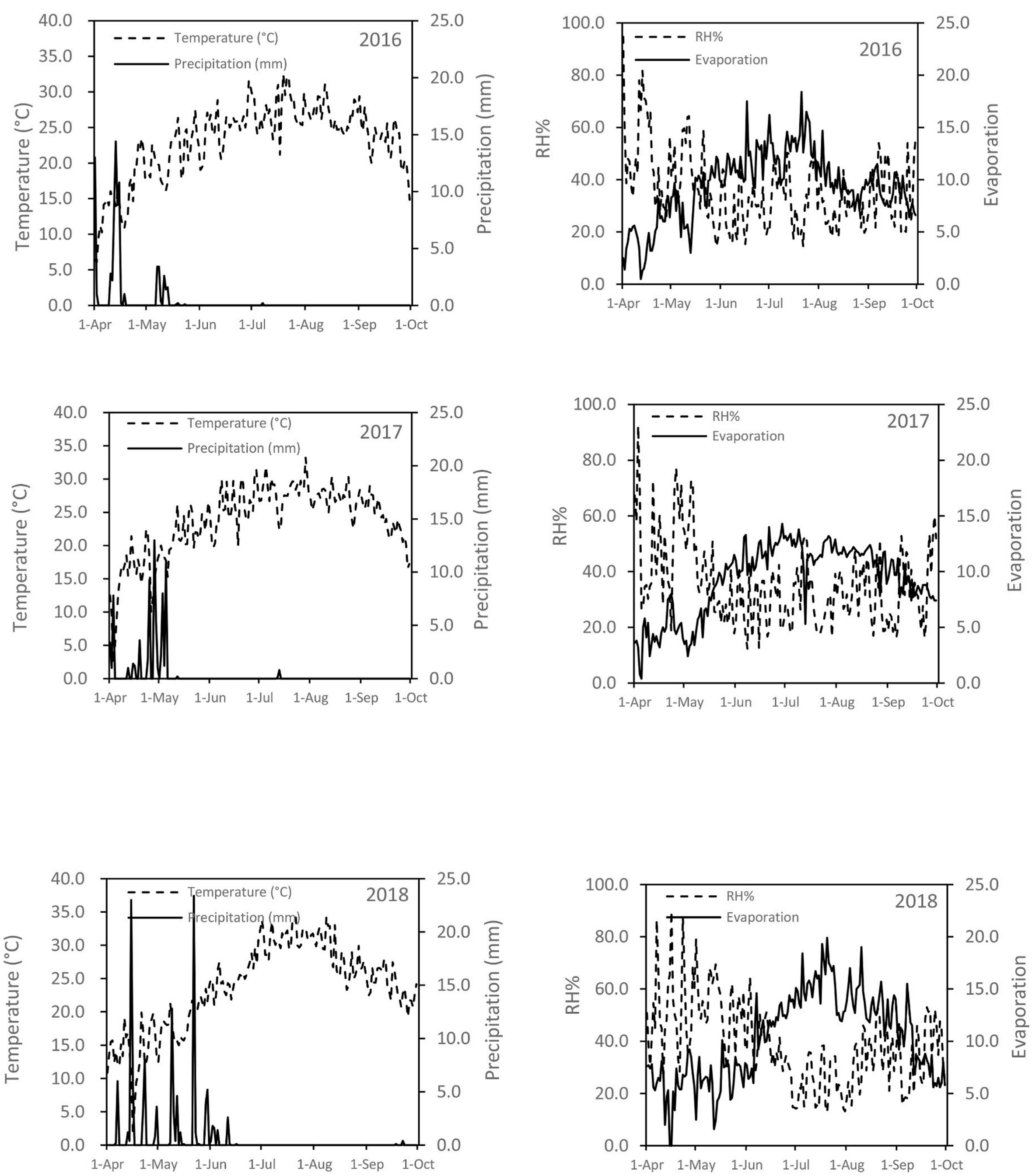

Fig. 1. Mean daily temperature, precipitation, relative humidity (RH%) and Evaporation at the experimental site in the 2016, 2017 and 2018 growing seasons.

biochemical, morphological and physiological changes in plants that are found to significantly alter herbicide effect (Ziska, 2016).

Here, we specifically ask: 1. how does the weed's impact differ between two planting dates of May and July that respectively represent current and future climate conditions? 2. How does low soil moisture for bean affect herbicide dose efficiency on crop and weeds? and 3. how does it change between May and July planting dates with different changing environmental factors such as temperature, RH%, and evaporation?

We also develop and validate a model using the experimental data to describe soil moisture effects on herbicide efficacy, and to adjust the recommended herbicide dose with climate change impacts.

2. Materials and methods

2.1. Field experiments

We carried out field experiments during 2016, 2017 and 2018 at the Research Station of the College of Agriculture and Natural Resources, University of Tehran at Karaj, Iran (35.7499° N, 50.9029° E). To simulate bean growing under climate change conditions, we chose the two planting times May as the present condition, and July to mimic a warmer environment that is predicted to happen in 20–30 years from now.

We sowed common bean on May 1st, and July 4th in 2016 and 2017, and on April 26th and July 1st in 2018, in line with the sowing period for bean in the region. The two fields assigned to the planting dates were established alongside each other and randomly attributed. Thirty years average temperature in Karaj is 21/9 (High/Low C°) in April, 27/15 C° in May and is 36/22 C° in July, the average precipitation is 38, 19, and 5 mm, and the average RH% is 45, 42 and 37%. (https://www.amar.org.ir/english/Statistics-by-Topic/Climate-and-Environment). The average rainy days for April and May are 4 days, but none for July (Fig. 1). Based on this, we chose the July planting date to mimic warmer and drier environmental conditions as expected under climate change.

The experiments were carried out in a split plot lay out with three replications (blocks). Each block measuring 61 m in length by 5 m in width comprised 3 main plots measuring 20.5 m by 5 m and 2-m intervals were made between main plots to avoid leak water. We assigned three moisture regimes of 60, 75, 90 mm of the accumulated evaporation, equivalent respectively to 100, 80, 60% of bean water requirement to the main plots. Sub-plots measured 3 m by 5 m were herbicide doses of 0, 25, 50, 75 and 100% of the recommended dose (1 L per ha) of imazethapyr (commercial name: Pursuit, 10% SL, BASF with active ingredient of imidazolinone 100 g/l). As herbicide may cause damage to bean with insufficient moisture and high temperature, a hand weeded plot was also included within each main plot to measure potential bean yield at each sowing date or watering regime (at least four times weeding over the growing season depending on the weed infestations). We put a half meter distance between sub-plots to minimize herbicide drift. Twelve soil samples (four samples from each block) were also taken using a probe from a depth of 20 cm for characterizing soil physical and chemical properties (Table 1).

The soil was disked and leveled to reach a uniform texture in mid-April (soil characteristics shown in Table 1). We also harrowed the soil to smoothen it before the July planting date.

Seeds of common been (cv. Akhtar, with a standing growth type) were sown by hand at 5 cm depth in a flat seedbed with 0.5 m between rows and 0.3 m distance within rows. We used a drip tape system for irrigation, and the moisture regimes were applied from two the leaf stage of bean onwards. We calculated the water requirement of common bean during the growing period (https://www.fao.org/3/u3160e/u3160e04.htm) used the following formula (Fao.org):

$$\text{ETcrop} = \text{kc} \times \text{Eto} \tag{1}$$

where ETcrop is the water requirement of a given crop in mm per unit of time e.g. mm/day, mm/month or mm/season and kc is the crop factor. For Eto calculation, we used a Class A evaporation pan installed next to the experimental filed. The pan evaporation rate i.e., Epan (mm/24 h) multiplied by a Pan Coefficient (Kpan) as follows:

$$\text{ETo} = \text{Epan} \times \text{Kpan} \tag{2}$$

We used an average of 0.70 for the Kpan. A season average crop factor (kc) of 0.79 was also used for common bean (Fao.org), allowing to calculate the water requirement for common bean per day. We also installed a water meter on each main pipe that branched out to each main plot and irrigation was applied according to the calculated water requirement.

The herbicide was sprayed at the four-leaves-stage of bean using a backpack sprayer fitted with an 8004 even flat fan nozzle and adjusted at a pressure of 210 kPa and application volume of 250 L/ha.

In 2016 and 2017, we evaluated the infestations of weeds throughout the experimental fields by counting weed density by species (Table 2) in three randomly placed quadrats of 0.5 m width by 1 m length within plots before herbicide application. As the experimental field was used for weed competition and herbicide effect studies for the past 10 years, the weed distribution was acceptably homogenous. However, in 2018 we had to transfer the experiment to a farm with a rather heterogeneous weed infestations, seeds of *Chenopodium album* L. and *S. nigrum* were additionally sown by hand at a density of 20 plants m^{-2} to ensure a multi-species establishment of the C_3 and C_4 weeds for both April and July planting. In all three years, we measured weed biomass five to six weeks after herbicide application simultaneously with common bean canopy closure (12 expanded leaves stage of bean). Weeds were harvested by cutting at the soil surface (again from three randomly placed quadrats of 0.5 m width by 1 m length within each plot), placed in paper bags and weighted after oven drying at 72 °C for 48 h. At the end of the growing season, bean was harvested by hand from a 2 m^2 area of each sub-plot and the grain yield was measured. We calculated percent yield loss (*%YL*) due to weed competition as follows (Gharde et al., 2018):

$$\%YL = \frac{WF_y - WC_y}{WF_y} \times 100 \tag{3}$$

where WF_y is the bean yield (t h^{-1}) in the hand weeded weed-free plot and WC_y (t h^{-1}) represents the bean yield in the weed infested plot.

Table 2
Parameter estimates by fitting Eq. (2) to May 2016 data of weed biomass (Y axis) vs. herbicide dose (X axis) for each moisture regime (*MR%*).

Moisture regimes	Parameter estimates			R^2_{adj}	RMSE
	W_0 (g m^{-2})	ED_{50}	B		
100% MR	317 (4.8)	37.5 (1.2)	−7 (0.7)	0.99	8.4
80% MR	290 (5.4)	62.9 (2.5)	−6.1 (1)	0.98	13
60% MR	210 (6)	80.7 (14)	−3.1 (1.3)	0.93	12

W0, weed biomass with no herbicide application; ED_{50}, the herbicide dose for 50% reduction in weed biomass; *B*, the slope of the curve.

Table 1
Physico-chemical soil characteristics of the experimental field measured on March 20th, 2016. Four soil samples were randomly taken within each block (12 samples in total).

Soil texture	pH	Organic matter%	Ec (ds/m)	K (mg/kg)	P (mg/kg)	N (mg/kg)	Sand (%)	Silt (%)	Clay (%)
sandy clay loam	7.5	0.77	1.23	0.075	60.8	112.84	29.45	40	30.55

2.2. Model development

For each moisture regime (*MR%*), we described herbicide dose (*D*) effect on weed biomass (*W*) using a three-parameter logistic model as follows (Kaleibar et al., 2021):

$$W = \frac{W_0}{1 + \left(\frac{D}{ED_{50}}\right)^{B}} \tag{4}$$

where W_0 is the weed biomass with no herbicide application, ED_{50} is the dose to reduce W_0 by 50%, and *B* is the slope parameter. We regressed the estimated W_0, $ED_{50,}$ and *B* with increasing *MR%* and showed that the parameter W_0 increased, and ED_{50} and *B* decreased linearly with increasing *MR%*. We replaced these three parameters with their linear relationships vs. *MR%* and obtained a more developed version of Eq. (4) that describes *W* with changing *D* and *MR%* as follows:

$$W = \frac{W_0 = b0_{w0} + b1_{w0}\ (MR\%)}{1 + \left(\frac{D}{ED_{50} = b0_{ED} - b1_{ED}\ (MR\%)}\right)^{B = b0_B - b1_B\ (MR\%)}} \tag{5}$$

where $b0_{w0}$ and $b1_{w0}$ are the intercept and the rate of W_0 change with increasing *MR%*, respectively, $b0_{ED}$ and $b1_{ED}$ are the intercept and the rate of ED_{50} change with increasing *MR%,* respectively, and $b0_B$ and $b1_B$ are the intercept and the rate of *B* change with increasing *MR%*. As formerly shown by Cousens (1985), percent yield loss (YL_w) due to weed competition increases with weed biomass (*W*) and this relationship is described using a hyperbolic function as follows:

$$YL_w = \frac{a.W}{1 + \left(\frac{a}{YL_m}\right).W} \tag{6}$$

where *a* is the competition coefficient of weed biomass, and YL_m denotes the highest yield loss that the crop may suffer from weed competition.

If we replace *W* in Eq. (6) by its prediction function i.e. Eq. (5), a combined model is obtained that predicts YL_w with *D* and *MR%*:

$$YL_w = \frac{a.\ (Eq.\ 5)}{1 + \frac{a}{YL_m}.\ (Eq.\ 5)} \tag{7}$$

A rearrangement of Eq. (6) gives *W* as follows:

$$W = \frac{YL_w}{a\left(1 - \frac{YL_w}{YL_m}\right)} \tag{8}$$

and a rearrangement of Eq. (4) gives the required dose as follows:

$$D = ED_{50}.\left(\frac{W_0}{W} - 1\right)^{\frac{1}{B}} \tag{9}$$

therefore, *D* can be calculated for a given *MR%* and *YL%* as follows:

$$D = b0_{ED} - b1_{ED}\left(MR\%\right)\left(\frac{b0_{w0} + b1_{w0}(MR\%)}{\frac{YL_w}{a\left(1 - \frac{YL_w}{YL_m}\right)}} - 1\right)^{\frac{1}{b0_B - b1_B(MR\%)}} \tag{10}$$

We used data of May planting in 2016 for the model development. The model prediction was then validated using data of July planting in 2016, May and July plantings in 2017, and April and July plantings in 2018.

2.3. Statistical analyses

Data of the three years 2016, 2017, and 2018 were subjected to a mixed model analysis of variance considering years as random effect, and planting date and herbicide dose as fixed effects. Model fit was evaluated using Lack of Fit test, root mean square of error (RMSE) and adjusted R^2. To compare model fit and performance to its predecessor, we used F-test through the model development. R-studio (version 3.3.2, R Team, 2015) were used for model fits, statistical evaluations and graphical presentation. Herbicide dose (Effective dose; ED_n) for a given percent (n) weed biomass reduction (*WR%*) was calculated using package drc (version 2.12.0, http://www.r-project.org). The ED_n value for July planting divided by the corresponding n value for the May or April planting resulted in an index for Dose Efficiency (*DE*). A *DE* value higher, lower or equal to one, respectively, indicates less, greater and equal efficiency of herbicide dose with July planting compared to May or April planting.

3. Results

3.1. Weed species and herbicide dose effects

Mixed model analysis showed significant interactions between planting date and herbicide dose (p-value <0.01) on common bean yield and weed biomass indicating a 10–20% lower herbicide effect on weed biomass depending on *MR%* (p-value< 0.05), and a higher bean yield losses with July planting (23%, averaged over years; p-value<0.05). We showed that the total weed biomass in plots with no weed control was highest at 100% *MR* followed by 80% and 60% *MR* (Fig. 2) and a higher weed biomass in July than in May planting (Fig. 2).

Weed assessments at 2–4 leaves stages of bean (before applying the treatments) from all 54 plots showed *C. album*, *Convolvulus arvensis* L., *Xanthium strumarium* L., *A. retroflexus*, *S. nigrum*, *Sonchus asper* (L.) Hill, *Datura stramonium* L., *Cirsium arvense* (L.) Scop., and *E. crus-galli* to be the dominant species in the experimental plots (seedling density >4 m^{-2}). These data were also used for an analysis of covariance to ensure that weed heterogeneity effect was not significant (p-value > 0.3).

3.2. Model parametrization

Changes in weed biomass with herbicide dose at each soil moisture regime are shown in Fig. 3, and estimated parameters value in Table 3. With increasing *MR*%, the weed biomass with no herbicide application (W_0) increased (P < 0.01), while the dose for decreasing 50% of W_0 (ED_{50}) and the slope parameter (*B*) decreased (P < 0.01). Linear model described the changes in W_0, ED_{50} and *B* (Fig. 4). Thus, higher moisture availability caused a higher weed biomass, but this was substantially reduced with lower herbicide doses. As explained in model development, a combination of Eq. (4) and linear functions shown in Fig. 3 led to Eq. (5) that described weed biomass with two variables of herbicide dose and moisture (Fig. 5). Although, 100% *MR* resulted in higher weed biomass than 80% and 60% *MR* when no herbicides were applied, 100% *MR* showed the least weed biomass using herbicide dose of more than 50% of the recommended dose (Fig. 5). Increasing dose to 75 and 100% of the recommended dose consistently decreased weed biomass in 100% *MR* to less than 10 g m^{-2}. In contrast, weed biomass in plots with 80 and 60% *MR* remained higher than 100 g m^{-2} even with full dosage of herbicide.

We then used Eq. (6) to describe the increase in *YL%* with weed biomass. Eq. (6) predicted that, at maximum, an 80% yield loss occurs with highest possible weed biomass (Fig. 6).

Continuing the model development, we fit Eq. (5) to *YL%* vs. herbicide dose and moisture regime. Model (7) with the residual degrees of freedom of 38, and mean square of error of 12.4 showed a good performance with respect to its capability of integrating moisture and herbicide dose effect on weed biomass and predicting *YL%* caused by weed competition (Table 3, Fig. 7).

3.3. Model validation

We fitted model (7) to data series obtained from experiments of July

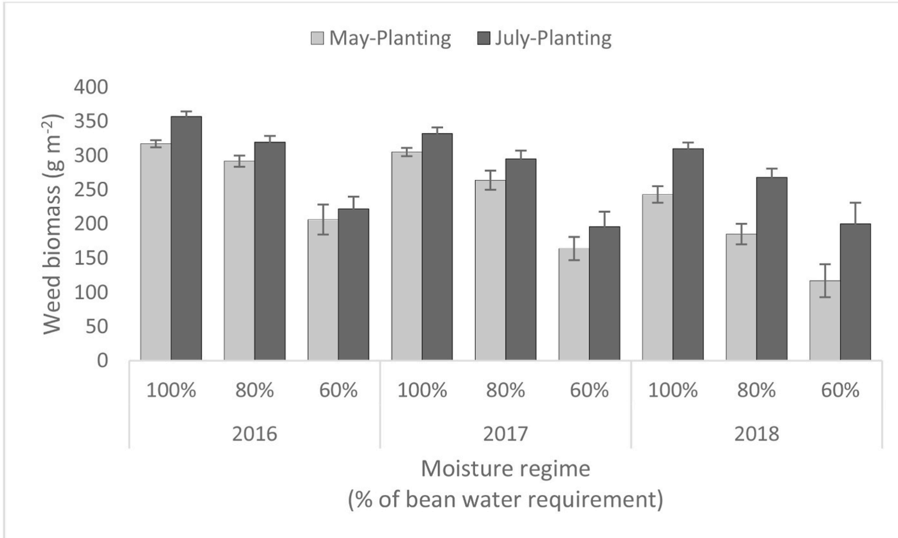

Fig. 2. Weed biomass (g m^{-2}) in weed infested control plots for May and July planting and 2016, 2017 and 2018. Error bars show the standard error of means.

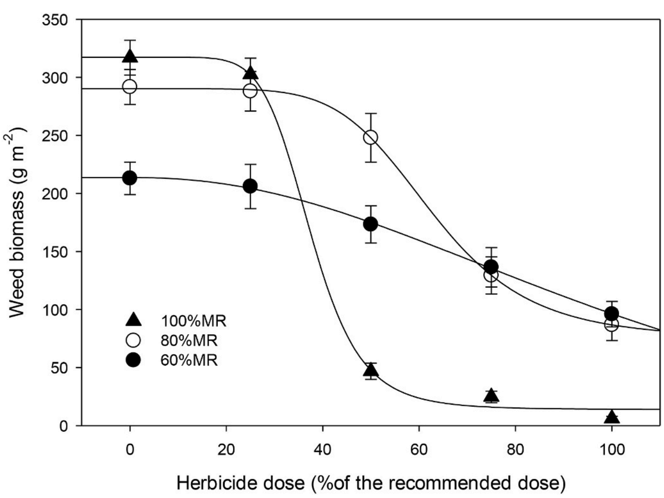

Fig. 3. Relationship between weed biomass and herbicide doses described by fitting eq. (2) at each moisture regime (*MR*%). Data from May 2016 were used for model fit.

2016, May and July 2017 and April and July 2018. Yield loss by weeds was consistently higher over years in July planting than in May or April planting (Fig. 7). With May or April planting, *YL%* in no-herbicide+100% *MR* ranged between 72 and 79% over years, while with July planting it was 86% averaged over 2016 to 2018, indicating a 10% higher *YL%*. Furthermore, with decrease in moisture from 100% *MR* to 60% *MR*, a 10% decrease occurred in *YL%* with May or April planting, suggesting that bean benefited from less weed biomass present in the plots. For July planting, decreasing soil moisture to 60% *MR* did not change *YL%* or a non-significant decrease occurred. With full rate of herbicide application in May planting, *YL%* was 10% or lower for different years, while in July planting bean suffered more than 20% *YL %*. Although, there were variations over years and sowing times in climate conditions and weed populations, and we showed inconsistency in response to soil moisture and herbicide dose for both weed biomass and bean yield over May sowing and July sowing, model (7) performed well in predicting bean *YL%* with planting dates and years (Fig. 8). Fitting Eq. (10), we obtain dose predictions at any moisture level for a given *YL%* showing increased dose requirement under low moisture conditions (Fig. 9).

3.4. *Comparing effective dose for percent weed biomass reduction*

We estimated Dose Efficiency (*DE*) for the first to ninth deciles of weed biomass reduction at each moisture level and for the two planting dates over the tree-year period from 2016 to 2018 (six data sets). We then regressed *DE* values with weed biomass reduction% and fitted three lines for the three *MR%*, which varied in slopes (p-value$<$0.05; Fig. 10). For 100% MR, from a threshold point of 35% weed biomass reduction, *DE* became greater than one; for 80% and 60% MR, it occurred at 39 and 43%, respectively. The increasing rate of *ED* was the highest in 80% MR, followed by 60% MR. In 100% MR, the slope of line was significantly lower than for 60 and 80% MR (p-value$<$0.05). Based on this, although herbicide efficiency was less affected by the planting time with 100% MR, higher doses were needed for July planting to reduce weed biomass for more than 35%. Moreover, for reducing weed biomass by 60%, the 80% MR plots require a higher dose than for 60% MR (p-value$<$0.01). In summary, July planting needed higher herbicide doses for weed control, with 80, 60, and 100% MR, respectively, showing higher to lower excessive dose requirement for weed control (p-value$<$0.01).

Table 3
Parameter estimates of model (5) fitted to the May 2016 data. The standard error of the parameter estimate is shown in the parenthesis.

Model 5	Parameter estimates								Adj-R2	RMSE
	a	$b0_{w0}$	$b1_{w0}$	$b0_{ED}$	$b1_{ED}$	$b0_B$	$b1_B$	YL_m		
	1.2 (0.07)	60 (7.3)	2.6 (0.03)	146 (9.1)	1.8 (0.01)	2.9 (0.2)	0.2 (0.01)	90 (3)	0.98	3.4

a is the competition coefficient of weed biomass, YL_m denotes the highest yield loss that the crop may suffer from weed competition, $b0_{w0}$ and $b1_{w0}$ are the intercept and the rate of W_0 change with increasing *MR%*, respectively, $b0_{ED}$ and $b1_{ED}$ are the intercept and the rate of ED_{50} change with increasing *MR%*, respectively, and $b0_B$ and $b1_B$ are the intercept and the rate of B change with increasing *MR%* (see text for further details).

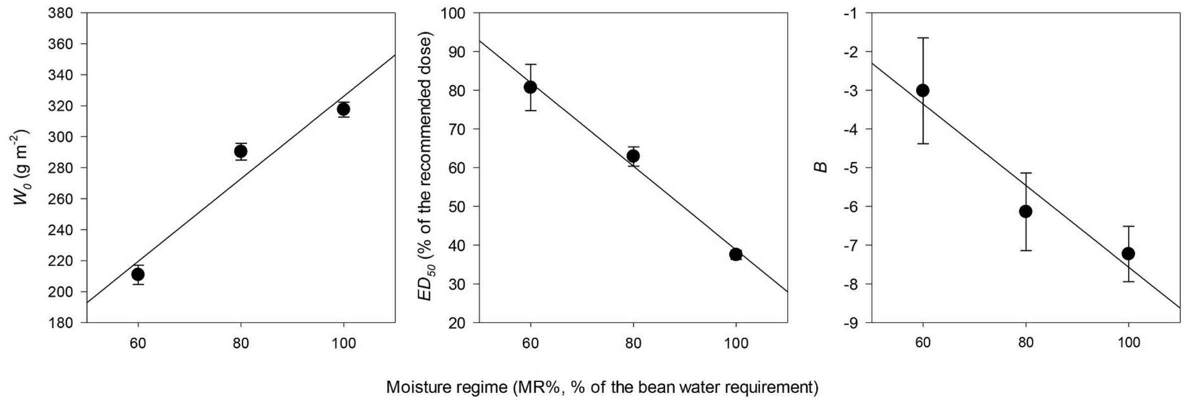

Fig. 4. Linear relationships between W_0, ED_{50}, and B (parameters estimates of eq. (2) for data of May 2016) with moisture levels ($MR\%$).

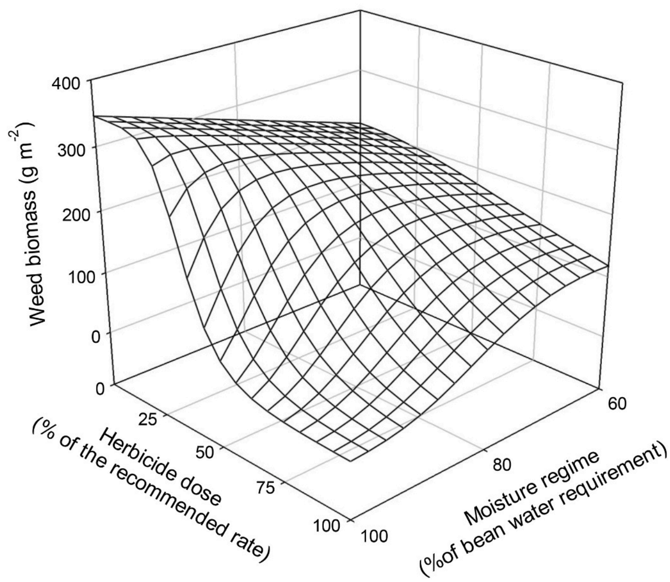

Fig. 5. Predicting weed biomass as affected by herbicide dose and moisture regime by fitting eq. (3) to data of May 2016.

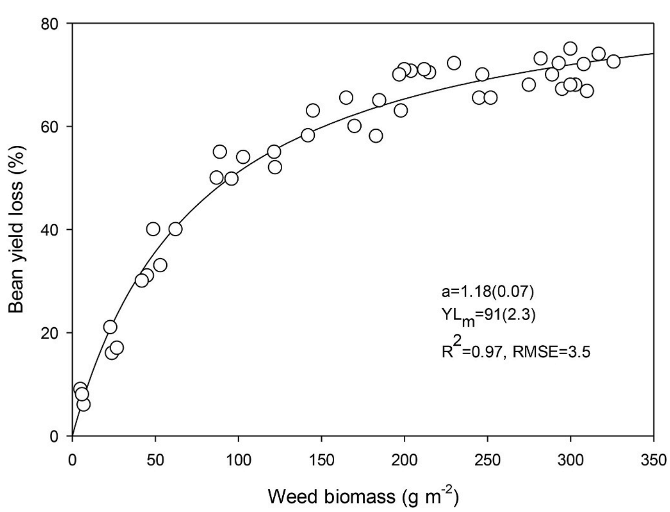

Fig. 6. Relationship between yield loss% and increasing weed biomass. Eq. (4) was fitted to data of May 2016.

4. Discussion

Herbicide efficiency is highly dependent on the environmental conditions while applying. Among effective factors, the ambient temperature and soil moisture status are known to be the most important ones (Mishra and Singh, 2011; Varanasi et al., 2016). Temperature alteration causes physicochemical effect on both herbicide activity and the reaction of the target plant (Varanasi et al., 2016). Enzymatic reactions and physiological process are affected by increasing temperature (Matzenbacher et al., 2014). We chose May and July plantings to mimic variable environments for herbicide application. As shown in Fig. 1, temperature is at least 4 °C higher in July than May or April. While, higher temperature may increase herbicide efficiency (Matzenbacher et al., 2014), we showed that herbicide effects decreased with July planting. Moreover, decreasing moisture caused more severe damage to bean yield. We showed that July plantings had higher weed biomass than May or April planting (Fig. 2). The weed species present in the experimental plots were mainly C_4, therefore, favored higher temperature to produce greater biomass (Singh et al., 2011). They are also more tolerant to water shortage (Lopes et al., 2011), and can maintain their photosynthetic potentials, while saving water via keeping their stomates semi-open (Chauhan and Abugho, 2013; Lemoine et al., 2016). Based on this, July planting is expected to suffer more from higher weed density and biomass (Byiringiro et al., 2017). A higher weed density or biomass requires higher herbicide dose to be controlled (Kim et al., 2006). We also showed increased herbicide dose requirement with July planting by comparing *DE* values between May and July planting dates (Fig. 10).

Inadequate soil moisture can decrease herbicide effect (Jursik et al., 2015; Sebastian et al., 2017). A less herbicide uptake happens with water shortage because of formation of a thicker cuticle and other protective tissues on the plant surface (Chauhan and Abugho, 2013; Franco Pinheiro et al., 2013). Yang et al. (2016) showed that lack of moisture caused an increased cuticle layer (Yang et al., 2016), therefore, less herbicide absorption. In addition, materials translocation in plant xylem or phloem is subjected to change with defensive mechanisms in plants against water shortage such as making stomata semi-open (Farooq et al., 2012; Lemoine et al., 2013; Gričar et al., 2019). We showed by *DE* comparisons that with 80%, 60% and 100% MR, higher herbicide dose was needed and this was more severe for the July planting time. For instances, Equation (10) predicted that to decrease common bean *YL%* to lower than 5%, 118, 110, 100 and 93% of the recommended herbicide dose was needed with 60, 70, 80, and 95% MR (Fig. 9), but crops tolerance to these high doses is highly questioned. Moreover, environmental side effects and economic restrictions would not allow such high herbicide doses (Norsworthy et al., 2012).

We developed an empirical model to predicting herbicide dose for controlling weeds in common bean with varying soil moisture conditions. The model showed a consistent and good performance over both

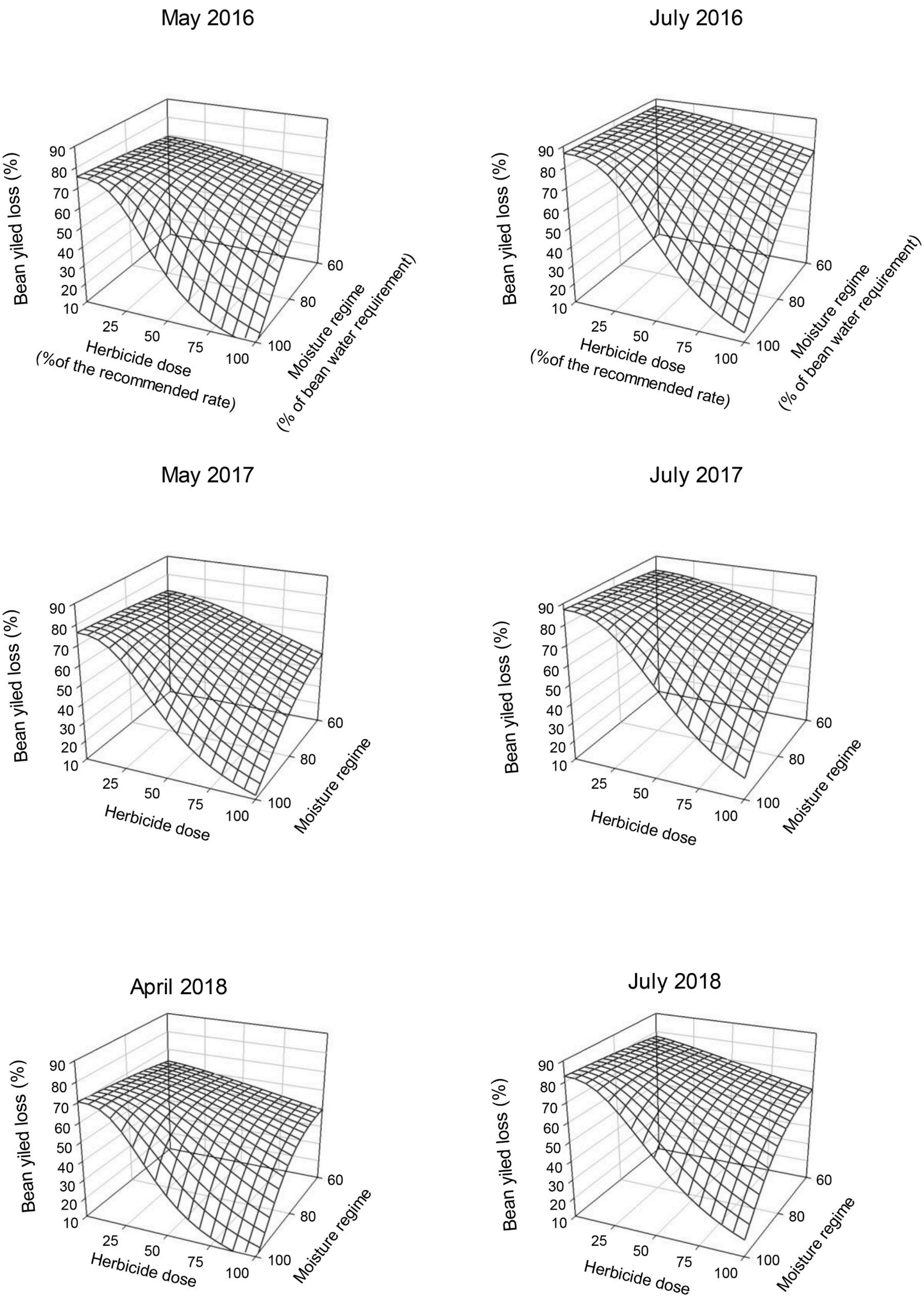

Fig. 7. Model (5) was fitted to the data of common bean vs. herbicide dose and moisture as the model inputs. Model predictions were shown for May/April and July planting for 2016, 2017 and 2018.

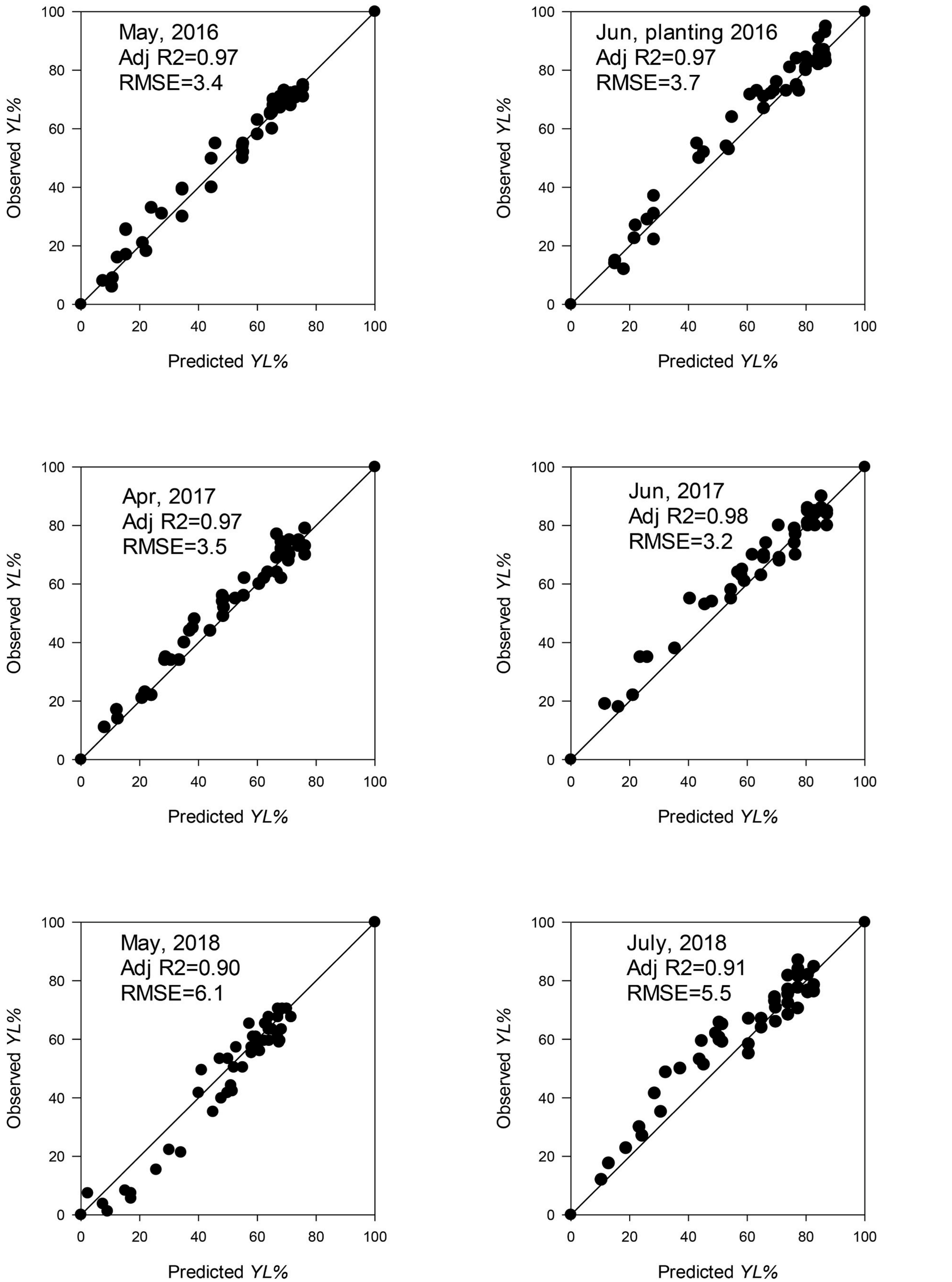

Fig. 8. Validation of model (5) in predicting bean yield loss% with the two input variables herbicide dose and moisture level. Model performance was evaluated for May/April and July planting time for 2016, 2017 and 2018 by comparing distributions of predictions and observations around the one-to-one line.

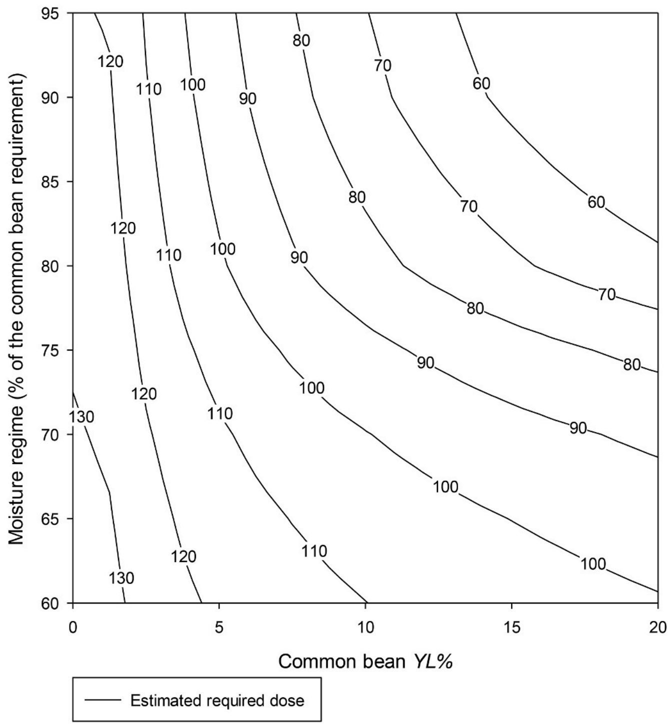

Fig. 9. Contour graph showing calculated required herbicide dose (by eq. (8)) for preventing yield loss% with soil moisture (*MR%*).

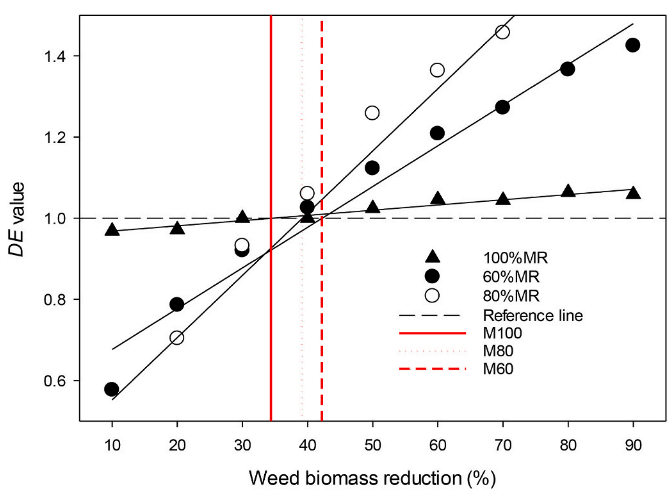

Fig. 10. Dose Efficiency (*DE*) calculated by dividing $ED_{(n)}$ values from July planting by the corresponding $ED_{(n)}$ for May/April planting for different moisture regimes (MR%). The *DE* values higher, lower and equal to one, respectively, indicate less, greater and equal efficiency of herbicide dose with July planting compared to May/April planting. Linear relationships for each *MR %* are shown as follows: 100% MR = 0.95(0.006) +0.0013(0.0001)*x, 80% MR = 0.62(0.039)+0.012(0.0007)*x, 60% MR = 0.43(0.039)+0.022(0.0007)*x.

planting times and the three-year period. To our best knowledge, no model describing interactions between herbicide dose and soil moisture conditions has been published so far.

4.1. *Growing beans under future climate conditions*

We showed that decreasing soil moisture caused a major deficit in herbicide dose effect, and bean suffered more from water shortage than weeds. The July planting time encountered higher temperatures that favored summer weeds and accordingly increased loss of bean yield. The current study model predicts a need for higher herbicide doses for weed control with delayed sowing time and lack of moisture, mimicking future climatic conditions. However, this cannot be an option, because of potential phytotoxic effects on crops and of economic and environmental restrictions for herbicide use. Increased weed biomass and competition and decreased herbicide efficiency with July planting constitutes a serious challenge for weed control with warmer and drier conditions that are predicted with climate change. Although, beans will still be irrigated, water shortage will become even more severe in the future in dry areas including the Middle East. Maintaining high soil moisture for crop production will become more challenging, thus our model predictions will become more realistic with regard to the expected reduced herbicide efficacy under water stress. Integrated weed management measures that include cultural weed control measures, such as crop rotation, choosing efficient crop sequence, seed rate and crop spacing will, therefore, become more important. Furthermore, intercropping or mixed cropping, adapted sowing time, the use of drought-tolerant crops or varieties and a smart and precise irrigation system may alleviate the reduced herbicide efficacy under future climate conditions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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