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An Analysis of the Exponential Family Models to Predict Yield Loss of Safflower (*Carthamus tinctorius* L.) Challenged with Water Stress and Redroot Pigweed (*Amaranthus retroflexus* L.)

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ABSTRACT

The performance of different yield loss models from an exponential family was evaluated in safflower-redroot pigweed systems in two field experiments conducted during 2007 and 2008 growing seasons at the research field of Agricultural College of Shiraz University, Iran. The yield loss of safflower was recorded as relative yield loss in experimental plots laid out in split plot design with three replicates. Three different irrigation treatments were allocated to the main plots and consisted of full irrigation or 100% field capacity (FC), 75% FC, and 50% FC, while five weed densities (0, 3, 6, 9, and 12 weeds m^{-2}) were assigned to the sub-plots The Logistic and Gompertz models and a user defined Power-Exponential model were fitted to the data to relate crop yield loss to the weed densities under different water stress conditions. The Power-Exponential model was chosen as the best fit to the data with statistically acceptable model diagnostics. Logistic and Gompertz models showed good fit to the observed data, but underestimated the yield loss under three levels of irrigation. Model performance in all cases was influenced by water stress as models generally showed greater constant and systematic biases under severe water stress (50% FC). Model parameters were used to explain the impact of water stress in crop/weed system. The exponential family models globally performed better over common empirical models such as Spitters, Kropff and Lotz and Cousens models.

Keywords: Gompertz, Logistic Model diagnostics, Water stress, Weeds, Yield loss.

INTRODUCTION

Crop loss assessment due to weed competition is the quantification of the relationship between yield of the crop and yield loss predictors such as weed density, weed relative leaf area, dry mass, fresh mass, soil cover, etc. Among different approaches of yield loss evaluation, the mechanistic approach, where applicable, is superior and consists of developing models by starting with a theory of how a physiological phenomenon or process occurs. In the empirical approach a model is developed to describe an observed process or a relationship between variables by means of accepted statistical principles. Schabenberger and Pierce (2002) believe inevitable and large dependence on empiricism in modeling has resulted in the development of narrow classes of models with very specific assumptions. The reliability of these models is determined according to the biological assumptions they are based on and, as a result, in practice, modeling often involves both mechanistic and empirical approaches and is called semi-empirical approach.

A number of semi-empirical models, i.e. Cousens, Kropff and Lotz, and Spitters models, referred to as "common empirical models" in this article, have been widely

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used to evaluate crop losses caused by weeds (Table 1). Cousens (1985) showed a rectangular hyperbola relationship between yield loss and weed density as the explanatory variable. Cousens models yield loss as a reciprocal function of weed density with parameters "*I*", the slope of the curve as an indicator of the outcome of weed crop competition, and "*A*", as the curve asymptote, which is the limit of the loss function when weed density approaches infinity (Equation (1), Table 1). Field validation studies have shown strong violations of this relationship between sites and years, even for the same crop weed combination (Fischer *et al.,* 2004; Pester *et al.,* 2000; Lindquist *et al*., 1996; Zimdahl, 1980).

Not only the individual plants are affected by competition at the population level, but dry matter production is also largely determined by available resources, thus, the prediction of yield loss based on weed density, as proposed by Cousens model, does not appear biologically adequate. To better appreciate the competition process and to improve the predictability of yield loss models, more complex models were developed. In further studies, a semi-empirical model was developed for early prediction of crop loss by weed competition (Kropff *et al*., 1995; Kropff and Spitters,

Table 1. Four contemporary semi-empirical models widely used to estimate yield loss[a] (Y_L or W^{1}) of the crop challenged by weed competition[b] expressed as crop and weed density (N_C & N_W) or relative leaf area (L_W).

Model	Equation of the model	Parameters	developer
Cousens Eq. (1)	$Y_L = IN_w(1+\frac{IN_w}{A})$	I= Curve slope A= Curve asymptote	Cousens, 1985
Kropff and Lotz, Eq. (2)	$Y_L = \left(\frac{qL_w}{\left[1 + \left(\frac{q}{m}\right) - 1\right]L_w}\right)$	*q*= Relative damage coefficient *m* = Maximum yield loss	Kropff and Spitters, 1991
Spitters, 1983 Eq. (3)	$W^{-1} = b_{co} + b_{cc}N_c + b_{ci}N_w$	b_{co}= The actual reciprocal of individual-crop plant seed yield or biomass without competition b_{cc}= Intraspecific competition index of crop, b_{ci}= Interspecific competition index of crop and weed	Spitters, 1983
Spitters, 1983(reduced version) Eq. (4)	$W^{-1} = b_{co} + b_{ci}N_w$	b_{co}= The actual reciprocal of individual-crop plant seed yield or biomass without competition b_{ci}= Interspecific competition index of crop and weed	Spitters, 1983

[a] Y_L is crop yield loss under field conditions affected from competition with weed and is estimated by: $Y_L = 1 - \left(\frac{Y_{CW}}{Y_{CM}}\right)$, where *YL*= Relative yield loss, Y_{CW}= Crop yield in competition with weed and Y_{CM}= Crop yield in a weed free condition. W^{1}= Reciprocal of individual crop plant seed yield or biomass,

[b] L_w,= The Relative leaf area of the weed, calculated from the following equation, $L_W = \left(\frac{LAI_{weed}}{(LAI_{crop} + LAI_{weed})}\right)$, where LAI_{weed} and LAI_{crop} are leaf area indices of weed and crop respectively.

1991; Kropff, 1988). The new ecophysiological model has also been supported by analyses of model for weed-crop competition and validation results of hyperbolic yield loss weed-density model. This model describes the relationship between yield loss and relative weed leaf area shortly after crop emergence using two parameters, the "relative damage coefficient", *q,* as a main model parameter and the "maximum yield loss", *m,* (Equation (2), Table 1).

In further elaboration of crop loss models, leaf area was employed as a predictor of yield loss, considering the fact that it reflects both weed density and relative time of weed emergence and may account for both weed density and age (Kropff and Spitters, 1991). It was shown that relative weed leaf area is a preferred explanatory variable over plant density, particularly for a multiple spatiotemporal scale data series (Lotz *et al*., 1996). The reciprocal of individual-plant biological yield or seed yield expressed as a linear function of weed density as predictor was also attempted as a semi-empirical estimator of weed relative competitive ability (Spitters, 1983) (Equation (3), Table 1)**.** Equation (3) reduces to a reduced version (Equation (4), Table 1) where the intra-specific competition of crop (b_{cc}) isn't practically calculable owing to fixed crop density. The Gompertz model of the exponential family has been used to describe the effect of increasing lengths of weed-free period on yield (Ratkowsky, 1990). Similarly the Logistic model has also been used to explain the effect of increasing duration of weed infestation on the yield. These two well-known models of the exponential family have been extensively used to determine the critical period for weed control (CPWC) (Knezevic *et al*., 2002). Despite the wide use of these two models, to our knowledge, they have never been used to directly relate yield as a percentage of the weed-free control to weed density.

Although safflower is considered a crop plant sensitive to water stress (Bassil and Kaffka, 2001), it is usually grown on dry lands or under dry farming conditions with various levels of water stress. Reliable prediction of the yield loss of safflower under simultaneous challenge of water deficit and weed competition would support proper decisions on weed and water management to minimize the yield losses. Water shortage was shown to aggravate the reliability of predictions of Cousens, Spitters, and Kropff and Lotz models with generally larger constant and systematic biases at 50% field capacity irrigation (Hamzehzarghani *et al.,* 2010). Accordingly, under dry farming of safflower, models with an improved performance over frequently used empirical models are required. The objective of this study was to evaluate the performance of models from the exponential family (Equations (6-8)) in safflower-redroot pigweed systems and their comparison with commonly used yield loss empirical models.

MATERIALS AND METHODS

Data on safflower yield was produced in two trials conducted at research field of Agricultural College of Shiraz University (ACSU) in the 2007 and 2008 growing seasons in Iran. The research site (ACSU) is located at Badjgah (29° 32' N, 52° 35' E, alt. 1,810 m) with hot and dry summers and cold and rainy winters. The research area was cultivated and sown with safflower (*Carthamus tinctorius* L.) cv. Esfehan, a cultivar widely grown in Shiraz region at density of 30 plants m^{-2} in early May 2007 and 2008. There were eight rows (5m long each) per plot and rows were 50 cm apart. The redroot pigweed seeds were simultaneously sown with safflower at 10 cm horizontal distance from safflower rows and, at the four-leaf stage, thinned to obtain 0, 3, 6, 9, and 12 plants m^{-2} weed densities. The plots were fertilized with urea (175 kg N ha^{-1}) on 17th of May and 20th of June and super phosphate (100 kg P_2O_5 ha^{-1}) on 17th of May in both years of study. Furrow irrigation was applied to irrigate the plots. The experimental plots were 4 by 5 m, laid out according to split plot design with each treatment replicated three times. Three different irrigation treatments served as the main plots as follows: full irrigation (100% field capacity, FC) and decreasing soil moisture content in root depth to 75% FC and 50% FC. Irrigation interval was set at 10 days for all treatments. Subplots (4 by 5 m) consisted of five weed densities (0, 3, 6, 9, and 12 weeds m^{-2}). The required irrigation water at each level was estimated by sampling soil of the experimental plots at three depths intervals (0-15, 15-45, and 45-75 cm) every 10 days at the time of irrigation and determining soil moisture content by a gravimetric method. For each soil depth interval, percentage of soil moisture was determined and irrigation depth was calculated by replacement of the percentage of volumetric moisture in the following equation:

$$\mathrm{D} = \frac{\sum (FCi - \theta_i)\Delta z}{100} \qquad (5)$$

Where, *D*= Depth of irrigation water required (cm), FC*i*= Field capacity moisture at each of the three soil depths intervals of i_{1-3} (cm^3 cm^{-3}), θi= Measured soil moisture at the three depths intervals of i_{1-3} (cm^3 cm^{-3}), and Δz is 15 cm, 30 cm, and 30 cm, respectively, for the three sampling depths intervals (cm).

To measure the LAI of safflower and the redroot pigweed, 10 plants were sampled from each plot at 4 and 7 weeks after planting (WAP) in both years of the experiment. Green leaf area of all leaves was measured using a leaf area meter (Model Delta-T, Delta-T Devices, UK). In September, the middle 1.5 m of the two central rows of each plot was harvested manually when seed moisture content dropped to 14%. The safflower grain yield was determined after oven drying for 48 h at 75 °C.

The Gompertz (Equation (6)), Logistic (Equation (7)) and the power-exponential (Equation (8)) models used in this study were as follows:

$$L = \exp(-B\exp(-kw)) \qquad (6)$$

$$L = 1/(1+\exp(-[B+kw])) \qquad (7)$$

$$L = \exp(B + kw^{0.5}) \qquad (8)$$

Where, *L* and *w* are yield loss and weed density and *B* and *k* are the constants and the slope parameters of exponential family models, respectively. The yield loss models (Equations (6-8)) were fitted to the data of the grain yield and LAI using Proc Nlin (nonlinear procedure) of the statistical software SAS 8 (SAS, 1999). Gauss-Newton method was used for parameter estimation in optimization procedures. Model performance of the exponential family models was evaluated by comparing their F-statistic values ($P< 0.05$), coefficient of determination (adjusted R^2), root mean square error (RMSE), and along with inspection of residual plots (Schabenberger and Pierce, 2002). To compare reliability (precision and accuracy) of the models, agreement analysis was conducted to help identify the best model. Reliability is defined as the extent to which the same measurements obtained under different conditions (include using different models) yield similar results (Madden *et al.,* 2007). Precision was estimated by calculation of Pearson correlation coefficient as a measure of degree of variability between model predicted and actual yield loss values. Accuracy is the measure of closeness of the best fitting line and the perfect fitting line (i.e. predicted=actual). To evaluate the precision and accuracy of the models in their predictions, estimate of Lin's concordance correlation coefficient ($\mathrm{r_c}$) for each model was calculated (Meek *et al.,*, 2009; Madden *et al.*, 2007) using the following equation:

$$r_c = \frac{2s_{UW}}{(\overline{U} - \overline{W}) + s_U^2 + s_W^2} \qquad (9)$$

Equation 9 can be written as $r_c = rC_b$, in which r is the usual Pearson Correlation Coefficient (a measure of precision) and

C_b is an indication of difference between the best fitting line ($U = \beta_0 + \beta_1 W$) and the perfect agreement (concordance) line ($U = W$) (Lin 1989). The parameter C_b can be written as $C_b = 2/(\upsilon + 1/\upsilon + u^2)$, where $\upsilon = \sigma_U / \sigma_W$ (systematic bias) and $u = (\mu_U - \mu_W)/\sqrt{\sigma_U \sigma_W}$ (scaled constant bias). If $r_c = 1$, there is a perfect agreement between the predicted (U) and the actual (W) values, meaning that the model is both precise (r= 1) and accurate ($C_b = 1$). Any deviations from $r_c = 1$ can be the result of $r < 1$ and/or $C_b < 1$. Departure of r_c from unity as a result of $r < 1$ indicates variability about the best fitting line. Since C_b involves more than just the constant bias, it is considered a generalized bias. A "$C_b < 1$" indicates evidence of systematic bias ($\upsilon < 1$) and/or constant bias ($u \neq 0$).

RESULTS AND DISCUSSION

The models used to describe the relationship between the crop yield loss and the weed density under different water stress conditions showed a relatively satisfactory fit to the data with significant F values. A summary of estimates of model diagnostics and parameters for all three models from the exponential family is shown in Tables 2 and 3. RMSE of the models ranged from 0.000 to 0.009 (0.001 to 0.008 for common empirical models) and their adjusted R-squares varied from 0.736 to 0.988 (0.72 to 0.96 for common empirical models) (Table 3). The overall fit of the exponential family models to the data was generally better than the common empirical models. Systematic biases of the exponential family models was in opposite direction as compared to the common empirical models (i.e. $\upsilon \geq 1$ / $\upsilon \leq 1$ for the exponential/common empirical models), however, the magnitude of departure from unity of the systematic bias was globally smaller for the exponential models. Similar trend was observed when constant biases of the two groups of models were compared. These models showed trivial negative constant bias ($u < 0$) while the common empirical models had positive constant bias ($u > 0$), i.e. opposite directions with slightly stronger biases for the common empirical models. Positive/negative constant biases indicate consistent over/under-prediction of yield loss while a systematic bias smaller/larger than unity is a sign of smaller/larger variability in the predicted values over the observed values. Although the models precision and accuracy were generally poorer under more intense water shortages (50% FC), their behavior was relatively consistent across years in each irrigation treatment (Table 3).

Model comparisons based on model diagnostics including F-test, Adj-R^2, RMSE, reliability analysis, and inspection of residual plots showed that, among the exponential family models, power-exponential model was the most accurate and precise predictor of yield loss (Table 3, Figures 3). This model had the lowest RMSE (0.0000 - 0.0060 compared with 0.0010 - 0.0076 and 0.0015 - 0.0099 for the other two models), and the highest concordance correlation coefficient (0.927-0.994 compared with 0.807-0.984 and 0.859-0.977 of the other two models). Compared with Spitters model that was recognized the best model among common empirical models in a similar study (Hamzehzarghani *et al.*, 2011, In Press), power-exponential model was even more accurate and precise. The fact is that a smaller RMSE for Spitters model does not necessarily indicate better model performance for Spitters when compared with other models. One major feature of Spitters model is that, unlike the other models that relate relative yield loss to weed density, it relates the reciprocal of individual crop plant seed yield or biomass (as a measure of yield loss) to weed density. A consequence of reciprocal transformation of the response variable i.e. individual crop plant seed yield, is the use of considerably smaller transformed observed yield losses for model fitting, which results in

Table 2. Estimates of parameters of exponential family (Logistic, Gompertz and a power exponential) models under different water stress regimes in two consecutive growing seasons.

Year	IR[a]	Parameters							
		Estimate	*SEM*[b]	95% *CL*[c]		Estimate	*SEM*	95% *CL*	
		Logistic[*] $L = 1/(1+\exp(-[B+kw]))$							
		B				*k*			
1	1	-1.826	0.111	-2.065	-1.586	0.184	0.013	0.156	0.212
	2	-1.826	0.109	-2.061	-1.591	0.184	0.013	0.156	0.212
	3	-0.955	0.167	-1.315	-0.595	0.133	0.023	0.084	0.182
2	1	-1.701	0.141	-2.006	-1.397	0.188	0.017	0.151	0.225
	2	-1.372	0.222	-1.852	-0.892	0.181	0.030	0.117	0.246
	3	-0.932	0.167	-1.293	-0.570	0.163	0.025	0.110	0.216
		Gompertz $L = \exp(-B\exp(-kw))$							
		B				*k*			
1	1	2.133	0.105	1.905	2.360	0.114	0.007	0.100	0.129
	2	2.133	0.103	1.911	2.355	0.114	0.006	0.101	0.128
	3	1.355	0.130	1.075	1.634	0.097	0.015	0.065	0.129
2	1	2.020	0.138	1.722	2.318	0.121	0.009	0.101	0.142
	2	1.763	0.204	1.321	2.204	0.129	0.018	0.090	0.168
	3	1.356	0.128	1.079	1.633	0.123	0.016	0.089	0.158
		Power-Exponential $L = \exp(B + kw^{0.5})$							
		B				*k*			
1	1	-2.313	0.067	-2.458	-2.169	0.512	0.022	0.464	0.559
	2	-2.314	0.063	-2.449	-2.179	0.512	0.021	0.468	0.556
	3	-1.432	0.102	-1.652	-1.212	0.285	0.035	0.209	0.361
2	1	-2.173	0.097	-2.382	-1.965	0.492	0.032	0.424	0.561
	2	-1.785	0.159	-2.128	-1.443	0.399	0.053	0.285	0.514
	3	-1.394	0.099	-1.608	-1.181	0.307	0.034	0.233	0.380

[a] Irrigation 1, 2, and 3 are 50%, 75% and 100% of field capacity, respectively.
[b] Standard Error of Mean.
[c] 95% Confidence limits of parameter estimates.

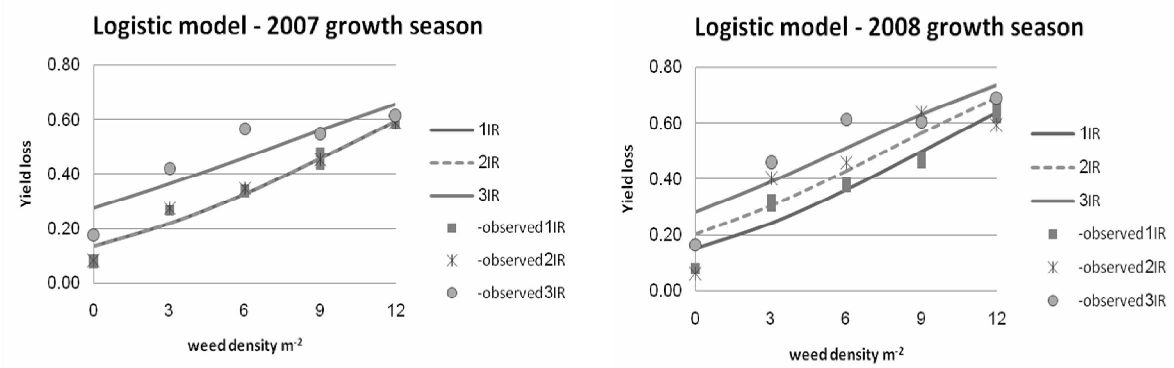

Figure 1. Relationship between yield loss of safflower and redroot pigweed density (m^{-2}) under three irrigation regimes in two successive growing seasons (2007/8 and 2007/8), both fit to Logistic model and observed data are shown.

Table 3. Diagnostics of three different models from exponential family used for predicting safflower yield loss under different irrigation regimes.

Year	Irrigation[1]	*Pr> F*[b]	*RMSE*[c]	Adj. R^2	*CCC*[d]	Precision (r)	Accuracy (cb)	*U*[e]	*V*[f]
					Logistic				
1	1	<.0001	0.0015	0.951	0.976	0.977	0.999	-0.017	1.046
	2	<.0001	0.0015	0.953	0.977	0.978	0.999	-0.016	1.045
	3	<.0001	0.0070	0.736	0.859	0.870	0.987	-0.030	1.171
2	1	<.0001	0.0028	0.922	0.962	0.964	0.998	-0.018	1.065
	2	<.0001	0.0099	0.774	0.880	0.890	0.989	-0.050	1.153
	3	<.0001	0.0071	0.799	0.896	0.902	0.993	-0.038	1.116
					Gompertz				
1	1	<.0001	0.0011	0.966	0.984	0.984	0.999	-0.009	1.028
	2	<.0001	0.0010	0.968	0.985	0.985	1.000	-0.009	1.028
	3	<.0001	0.0058	0.780	0.887	0.892	0.994	-0.025	1.112
2	1	<.0001	0.0022	0.939	0.970	0.971	0.999	-0.011	1.046
	2	<.0001	0.0076	0.826	0.912	0.917	0.995	-0.040	1.092
	3	<.0001	0.0055	0.843	0.923	0.925	0.998	-0.031	1.064
					Power-Exponential				
1	1	<.0001	0.0000	0.986	0.994	0.994	1.000	-0.006	1.018
	2	<.0001	0.0000	0.988	0.994	0.995	1.000	-0.005	1.017
	3	<.0001	0.0040	0.865	0.930	0.937	0.992	-0.017	1.133
2	1	<.0001	0.0010	0.969	0.985	0.986	0.999	-0.010	1.036
	2	<.0001	0.0060	0.863	0.927	0.938	0.988	-0.033	1.162
	3	<.0001	0.0040	0.892	0.944	0.950	0.994	-0.018	1.113

[a] Water stress levels: IR1, IR2 and IR3 are100, 75 and 50 % field capacity respectively.
[b]Test H_0: Lack of association between yield loss and weed density.
[c] Root Mean Squared Error.
[d] Concordance Correlation Coefficient.
[e] Scaled constant bias as an indicator of location shift.
[f] Systematic bias as an indicator of scale shift.

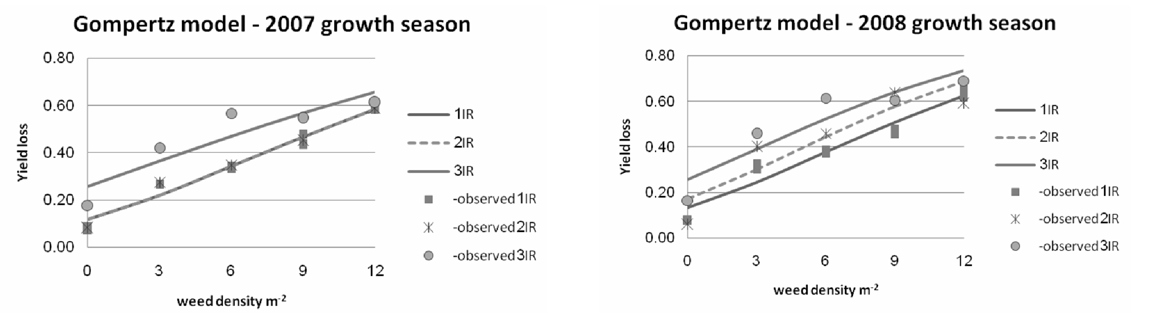

Figure 2. Yield loss of safflower as a function of redroot pigweed density (m^{-2}) under three irrigation regimes in two successive growing seasons (2006/7 and 2007/8). Fit to Gompertz model and observed data are shown.

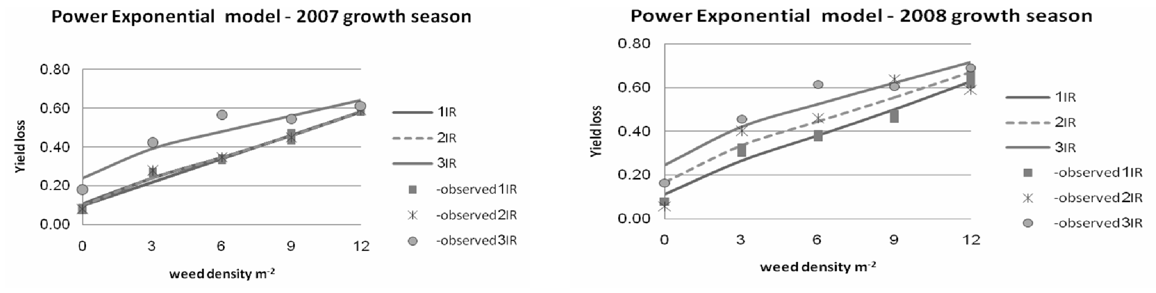

Figure 3. Yield loss of safflower as a function of redroot pigweed density (m^{-2}) under three irrigation regimes in two successive growing seasons (2006/7 and 2007/8). Observed data as well as predictions of power exponential model are shown.

calculation of an artificially smaller RMSE. Therefore, the reliability of the Spitters model is overestimated, therefore, when comparing this model with other models, great caution must be practiced.

As was expected, model parameters did not show any significant difference across years of study because the monthly precipitations and average temperatures were very similar to their long term values at field sites throughout the growing seasons across the years of study. The behavior of power-exponential model was very reliable in the experiment data space as it predicted the crop yield loss across all levels of irrigation equally well. The Power-exponential model reproduced the yield loss values at 50% irrigation treatment with very small systematic (1.017 to 1.162) and constant (-0.018 to -0.033) biases. This indicates that the power-exponential model was adequately robust and the precision of its predictions was not affected by the level of irrigation as much as the predictions of the other two exponential family models and common empirical models were (Table 3). As evidenced by inspecting all model diagnostics (Table 3), performance of the exponential model was slightly poorer at higher water stress levels regardless of the year of study and/or the model used (Table 3, Figures 1-3).

Under no water stress condition, the Power-Exponential model was the best in predicting the yield loss (u= -0.008, υ=1.027), followed by Gompertz (u= -0.010, υ=1.037), and Logistic (u= -0.018, υ=1.056) models (bias values are two-year means), which clearly shows that the Power-Exponential model performed batter than Gompertz, Logistic, and the common empirical models, except Cousens model. The latter model had a slightly lower constant bias (u= -0.005, υ= 1.067), even though its substantially higher systematic bias underlined its inadequacy. Cousen model was shown to be nearly the poorest predictor of yield loss under moderate to severe water stress conditions (u> 0.17, υ< 0.74) (Table 4).

The Power-Exponential model remained the best fit to the yield loss data produced under moderate water stress condition (u= -0.019, υ= 1.089), followed by Gompertz (u= -0.25, υ= 1.060) and Logistic (u= -0.034, υ= 1.099) models (Table 4) with comparably smaller systematic bias for Gompertz model under moderate water deficit. The predictability of Spitters model from common empirical models could be compared to the best fit (the Power-Exponential model). However, because yield loss values used to fit Spitters model were transformation of the real values (reciprocal of individual plant yield or biomass), the Power-Exponential model is preferable because it is more realistic than the Spitterz model as the yield data are used to build the model directly and without any manipulation.

A similar trend in the performance of the models used in this study was observed under severe water stress. The Power-Exponential model had the lowest two-year mean of constant bias (u= -0.017) compared with Gompertz (u= -0.028) and Logistic (u= -0.034) models. Comparison of the two-year means of systematic biases of the three exponential

Table 4. A summary of agreement statistics (constant and systematic biases) of the two main groups of models under three different irrigation treatments.

model group	model	Systematic bias (υ)			Constant bias (u)		
		100% FC[a]	75% FC	50% FC	100% FC	75% FC	50% FC
Exponential family models	Power-Exponential	1.027	1.089	1.123	-0.008	-0.019	-0.017
	Gompertz	1.037	1.060	1.088	-0.010	-0.024	-0.028
	Logistic	1.027	1.089	1.123	-0.008	-0.019	-0.017
Common Empirical models[c]	Spitters	0.869	1.037	0.873	0.098	0.000	0.100
	Kropff and Lotz 4WAS[b]	0.899	0.885	1.089	0.097	0.080	0.000
	Kropff and Lotz 7WAS	0.886	0.891	0.729	0.077	0.075	0.171
	Cousens	1.067	0.730	0.733	0.000	0.171	0.171

[a] Field Capacity.
[b] Weeks after sowing.
[C] Data on common empirical models is unpublished data.

models also revealed that the Gompertz and Power-Exponential models (υ= 1.088 and 1.123, respectively) performed equally well followed by Logistic (υ= 1.440) model. Systematic biases of the Power-Exponential and Gompertz models were very close under severe water stress conditions, although Gompertz model showed a slightly smaller systematic bias than the Power-Exponential model.

Presence of weeds can significantly reduce crop yield and the magnitude of this effect greatly depends on the critical period during which the crop is challenged by the weed and the level of key environmental factors. As such, water stress is one of the most important key factors that challenges farmers in dry regions. Semi-empirical models developed by Cousens, Kropff and Lotz, and Spitters have been widely used to evaluate crop losses caused by weeds, however, their predictions are not reliable when crop-weed system is under water stress conditions (Hamzehzarghani *et al.*, 2010). As seen in the scatter plot of yield loss versus weed density under different irrigation regimes (Figures 1-3), the plots are concave towards the weed density axis particularly in moderate weed densities under severe water deficit (IR50%). Variance component decomposition using Proc nlmixed of SAS also showed a highly significant interaction between irrigation and weed density, supporting a significant departure in curvature under IR50%. Unlike the equation of rectangular hyperbola, the curvature of the exponential family models is more manageable through either manipulation of the slope parameter or transformation of the predictor. Log or square root transformations of predictor can correct the curvature and has the advantage that the response variable remains unchanged and, thus, allows comparison of the goodness of fit statistics of different models. On the other hand, the absolute rate of increase in yield loss increases more rapidly under more severe water deficit. As a result, it is reasonable to expect a better fit for Logistic, Gompertz, or even a more flexible exponential model to the data of water stressed weed-crop systems. Although Logistic and Gompertz models have been widely used to estimate the critical period of weed control (Van Acker *et al.*, 1993; Hall *et al.*, 1992), to our knowledge, they have not been used for direct estimation of yield loss in weed-crop systems.

In this study, we showed that, with very few exceptions, exponential family models predicted the yield loss of safflower better than the common empirical models when challenged by both redroot pigweed competition and water stress (Table 4). The common empirical models are not robust enough to perform equally well under conditions different from those they were developed, conceivably because they are not developed under stressful conditions such as water deficit. In view of model diagnostics and residual plots (Table 3, Figures 1-3), the Power-Exponential model had the best fit to the yield loss data even under high water stress conditions, because it reduced the systematic bias observed in other models by simultaneously decreasing/increasing the yield loss curve slope at extreme/moderate weed densities due to square root transformation of the predictor variable. In both years of study, under 50% FC irrigation in weed free plots, average yield of the plots cultivated with safflower was significantly lower than those under 75% FC and 100% FC. The highest yield was recorded in 100% FC - weed free plots in both years. The results of agreement analysis also supported these findings where larger deviations of systematic bias from unity and greater constant biases under more intense water stress conditions were observed (Tables 3 and 4). A unique advantage of the exponential family models is that the relationship between yield loss and weed density in the data space is well explained using the same two parameters i.e. constant and slope parameters, for all models. Therefore, it is reasonable to assume that each of these two parameters represents a biological function and, therefore, it is relevant to compare performance of the models according to their parameters. Constant parameter (B) can be considered to represent the effect of water stress on competition and *k* represents the magnitude of impact of water stress at various weed densities i.e. water stress × weed competition interaction. According to the best fit (Power-Exponential model), at severe water stress (50% FC), the constant parameter (B) showed a significant increase of 58.7% over the control (no water stress) (Table 3), indicating an increased yield loss due to increased weed competition under more severe water stress conditions. The difference in "*B*" between moderate water stress and no water stress treatments was negligible and statistically insignificant (Table 3). Thus "*B*" parameter can be presumed as an index of water deficit sensitivity of the weed/crop system that determines the outcome of crop/weed competition and a greater value of "*B*" indicates a higher sensitivity of the weed/crop system to water stress. Also, under severe water stress conditions, intensified weed competition has a minor impact on yield loss compared with no water stress conditions (Table 3). Larger values of "*k*" indicate greater water stress×weed competition interaction effect, which suggests a steeper loss curve slope under intensified water stress conditions. Similar inferences could be extracted from the results of parameter estimates of Gompertz and Logistic models (Table 3).

Stressful levels of environmental factors such as temperature, light, and water directly affect weed/crop competition. Most of the knowledge produced on the effects of environmental stress on weed/crop competition has come from experiments in greenhouses and growth chambers (Patterson, 1995) where the environment can be relatively controlled. Environmental variations have always been blamed for causing inconsistencies in the results of field experiments repeated over time. At least, part of these inconsistencies can also be attributed to incorrect design of experimental studies and inappropriate selection of statistical models that are to fit to the data (Onofri *et al.*, 2009). The usefulness of the models is anticipated when they are appropriately parameterized and evaluated with local field data generated under local conditions (McDonald and Riha, 1999). Development of a more flexible modeling approach using equations with a shape parameter that enable modeling crop losses in different weed-crop systems due to weed competition and/or various stresses, such as water stress, is of prime importance. Water stress, in particular, not only determines the intensity of competition between an individual crop plant and another individual of the same crop, but also affects the growth and development of the individual competing weeds. One of the important keys of any successful weed management program aiming to minimize crop losses is sufficient knowledge on the impact of water stress on weed-crop response. Weed competition with crop for water results in a reduction in the amount of water available for crop growth and may thus intensify the crop water stress (Patterson, 1995).

The user-defined Power-Exponential model and the statistical approach we used in this study enabled us to draw relevant and consistent inferences on the influence of water stress on yield loss of safflower suffering from weed competition. Model predictions were less reliable under high water stress than moderate and no water stress. Power-Exponential model predicted the yield loss comparatively well across all irrigation treatments, whereas the other models, which showed acceptable goodness of fit statistics, had both relatively stronger constant and systematic biases under more severe water stress conditions. A significant interaction between water stress and weed competition was evidenced by variance component decomposition and was also supported by reliability analysis. Parameters of the Power-Exponential model represented biologically relevant and meaningful functions that may be used to interpret similar results for other weed/crop systems. Additional field validation study with the Power-Exponential model is required to confirm model performance in the safflower-redroot pigweed system.

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ارزیابی مدل های گروه نمایی برای پیش بینی افت عملکرد گلرنگ در ارتباط با تنش رطوبتی و علف هرز تاج خروس

ح. حمزه زرقانی و س. ع. کاظمینی

چکیده

کارائی مختلف مدل های افت عملکرد از گروه مدل ها ی نمایی در شرایط تنش رطوبتی در سیستم کاشت گلرنگ در رقابت با تاج خروس در طول دو فصل رشد در سال های ۱۳۸۷ و۱۳۸۸ در مزرعه ایستگاه تحقیقاتی دانشکده کشاورزی دانشگاه شیراز مورد ارزیابی قرار گرفت . میزان افت عملکرد گلرنگ به عنوان افت عملکرد نسبی از کرت های آزمایشی که در قالب طرح اسپلیت پلات در سه تکرار اجرا شده بود ثبت شد. تیمارها شامل تنش رطوبتی در سه سطح (۱۰۰،75 و ۵۰ درصد ظرفیت مزرعه ای) به عنوان کرت اصلی و تراکم های تاج خروس در ۵ سطح (صفر، ۳، ۶، ۹ و ۱۲ بوته علف هرز در متر مربع) به عنوان کرت فرعی بودند. مدل های لجستیک و گامپرتز ویک مدل توانی- نمایی در ارتباط با داده های افت عملکرد گیاه در شرایط تنش رطوبتی و علف هرز برازش مناسبی نشان داد. مدل توانی- نمایی به عنوان بهترین مدل شناخته شد که با داده ها برازش بسیار خوبی داشت. بر اساس داده های بدست آمده مدل لجستیک و گامپرتز هم برازش خوبی نشان داد اما در شرایط تنش رطوبتی، افت عملکرد دانه را کمتر از حد معمول تخمین زدند. کارائی مدل ها در تمام حالات تحت تاثیر تنش رطوبتی قرار گرفته به گونه ای که در شرایط تنش شدیدی رطوبتی مدل ها نااریبی ثابت و سیستماتیک بزرگتری نشان دادند. پارامترهای مدل برای تشریح تاثیر تنش رطوبتی درسیستم گلرنگ – علف هرز استفاده شد. مدل های خانواده نمایی بطور کلی نسبت به مدل های نیمه تجربی رایج مانند کازنس، اسپیترز و کراف لوتز کارائی بهتری در پیش بینی افت عملکرد دانه داشتند.