**Crop-Weed Relationship Studies in Additive Design: Selecting the Top Model**

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**ABSTRACT**: Crop-weed competition is extensively studied in weed science. The additive design, where weed density varies, and the crop density is kept constant, is the most used design for competition studies. However, most crop-weed competition research is conducted by non-statisticians, which sometimes report misleading results because of lack of knowledge with this type of data analysis. The objective of this study is to demonstrate a selection of a top model for describing the crop-weed relationship in additive design to non-statisticians. We evaluated three models routinely used to interpret competition studies, including polynomial quadratic, logistic, and rectangular hyperbola. Based on statistical criteria and meaningfulness of parameters, we demonstrated the rectangular hyperbola to be the top model to describe crop-weed competition studies in additive design. Moreover, it was showed with F-test model selection that at low densities *C. benghalensis* is more competitive than *Richardia brasiliensis* in corn, but both weed species compete similarly at higher densities. In this paper, it is proposed the use of the rectangular hyperbola as a standardized model for crop-weed competition in additive design.

**Keywords**: AIC criterion, model selection, crop-weed competition, rectangular hyperbola

**Nomenclature:** *Commelina benghalensis*, *Richardia brasiliensis*

**Introduction**

Studies have described the relationship function of crop yield loss in response to weed density using additive design. Despite several review papers recommending the use of rectangular hyperbola in the weed science literature (KNEZ̆EVIĆ et al. 1995; Knezevic et al. 1994; Ritz et al. 2015; Swanton et al. 2015), there is still a distinct number of empirical models fitted for additive design studies (Silva et al. 2015; Strieder et al. 2007; Trezzi et al. 2015; Voll et al. 2002). Four major regressions curves are frequently used: linear (Figure 1A), polynomial quadratic (Figure 1B), sigmoid (Figure 1C), and rectangular hyperbola (Figure 1D).

The commonly used criteria for selection of linear and nonlinear regression models is the equation with highest R-squared (R2). The R2 tests the goodness of fit and is statistically inadequate for nonlinear model selection (Archontoulis and Miguez 2015; Zuur et al. 2007). There are several appropriate statistical criteria for selecting the best nonlinear model for datasets: Alkaike’s information criterion (AIC), Bayesian information criterion (BIC), F-test, and likelihood ratio (Anderson 2008; Lewis et al. 2011; Zucchini 2000). Non-nested models are models with different structure and parameters, in this case, the AIC and BIC are indicated for top model selection. However, F-test or any of the model selection techniques described above are applicable for nested models. Nested are models that are a special case of each other and have identical terms whereas one must have one or more extra terms.

From a practical standpoint, the top model should be selected upon a balance between statistics and biological relevance, which will help scientists answer their research questions (Archontoulis and Miguez 2015). Therefore, in crop-weed relationship studies in additive design, the model that provides a good fit and meaningful biological parameters are considered a strong candidate model.

The advances in statistical software should facilitate the use of standardized nonlinear regression analysis that could perform by non-statisticians (Knezevic et al. 2007). Here, there is a comparison of three non-nested candidate models (polynomial quadratic, logistic, and a rectangular hyperbola) for describing the crop-weed relationship. Data from an experiment of corn (*Zea mays* L.) in competition with two weed species, *Richardia brasiliensis,* and *Commelina benghalensis* was used. First, it demonstrates the selection process for the top model to describe the crop-weed relationship for each weed species. Second, it is tested the hypothesis that *C. benghalensis* and *R. brasiliensis* compete similarly with corn.

**Material and Methods**

**Plant Material**. On March 2011, inflorescences of *R. brasiliensis* were harvest on roadsides near Diamantina, Minas Gerais (MG), Brazil. Inflorescences of *R. brasiliensis* were dried at room temperature (25 °C), cleaned, and stored at 5 °C until the onset of the experiment. Ten days before the experiment began (September 2011), stolon (vegetative propagules) of *C. benghalensis* were collected in wetlands, near Diamantina, MG. Seeds of *R. brasiliensis* and stolon of *C. benghalensis* were seeded and transplanted to separate trays (1210 cm3) filled with red latosol (pH 6.1 and 1% organic matter). A single seed of glyphosate-resistant (GR) corn (AG8088) was sown in 8 dm3 plastic pots filled with the aforementioned soil source. The soil was fertilized following the local recommendations, and N was applied at 15 and 30 DAE (days after corn emergence) at a rate of 55 mg dm-3 of ammonium sulfate. Greenhouse conditions were 28/19 °C day/night, and pots were watered daily.

**Experimental procedures**. The experiment was conducted under greenhouse conditions at the Federal University of Jequitinhonha and Mucuri, MG. In this study, the additive design for competition studies was used, whereas weed densities varied, and corn density was kept constant (Swanton et al. 2015). The treatment design was a factorial with two weed species, *R. brasiliensis* and *C. benghalensis*, and five weed densities (0, 1, 2, 3, and 4 plants pot-1), in a completely randomized design with four replications.

Corn dry matter was harvested at 60 DAE from each experimental unit. Shoot biomass was oven-dried at 65 °C until reaching constant weight, and dry weight recorded. The corn dry matter (g) data (shoot) were converted into yield loss (%) compared with the corn control treatment (no weeds):

eq. (1)

where *Μ* is the mean dry mass (g) of the untreated replicates, and is the dry mass (g) of an individual treated experimental unit.

**Statistical Analysis**

Three models were fitted to yield loss data (%) in response to weed density (plants pot-1):

*Rectangular hyperbola model* proposed by (Cousens 1985):

eq. (2)

where *I* represent YL (yield loss) per unit weed density as *D* (density) approaches 0, and *A* represents YL as D approaches ∞ (or maximum expected yield loss). The rectangular hyperbola model was fitted using the *nls* function of R version 3.3.1 (R Foundation for Statistical Computing, Vienna, Austria).

*Logistic model* (four parameter log-logistic curve):

eq. (3)

where *c* is the (lower limit or YL at low weed density), *d* is the asymptote (upper limit or YL at high weed density), and *e* represents the weed density (weeds pot-2) that cause 50% yield loss (inflection point). The parameter *b* is the relative slope around the parameter *e*, and *D* is the number of weeds pot-1. Parameters for the sigmoidal model (four-parameter logistic) were estimated using the *drm* function of drc package (Ritz and Streibig 2005) in R software.

*Polynomial quadratic model* (second order):

eq. (4)

where *α* is the intercept in the y-axis (maximum YL in the absence of weed), a represents the slope of the model. The parameter b is the quadratic term of the model, and *D* is the number of weeds plot-1. The parameters for the polynomial quadratic equation were estimated using the *lm* function of R software.

**Top model selection to describe crop-weed competition.** The AICc criterion, which is indicated by non-nested model selection (Hurvich and Tsai 1991), was calculated as:

eq. (5)

where is the likelihood function and is the number of estimated parameters in the model, and *n* is the sample size of the model. The AICc is the second-order or small sample AIC (Sugiura 1978). According to the AICc criterion, the top model has the lowest AICc value. The AICc values for each model was estimated using the *AICc* command of package AICcmodavg in R software (Mazerolle 2016).

**Model selection to evaluate weed competitiveness with the crop.** Assuming that rectangular hyperbola is the top model, the impact of *R. brasiliensis* and *C. benghalensis* on corn YL is accessed through the variance-ratio or F-test performed using equation [2] (Lindquist et al. 1996). This statistical procedure evaluates the difference of residual sum squares (RSS) of nested models (Werle et al. 2014c). F-test is calculated as (Archontoulis and Miguez 2015):

eq. (6)

Where RSSFULL and RSSRED represent the minimized residual sum squares of the parameters estimated for the full (step 1) and reduced model (step 2, 3, or 4), respectively; dfFULL and dfRED represent the degrees of freedom of the full and reduced models, respectively. F-value greater than the F-critical value (P-value <0.05) indicates that two models are different. Thus, the full model should be used. F-value smaller than the F-critical value indicates that two models are not different (P-value >0.05); therefore, a model with fewer parameters (reduced model) can be used to describe the data. When P-value >0.05 we fail to reject the null hypothesis and a reduced model should be used (no difference of *I* and *A* parameter values between weed species). However, if P-value <0.05, the null hypothesis is rejected and the full model should be used (different *I* and *A* parameter values for each weed species). The F-test principle for nonlinear regression analysis was calculated for each model using *nls* *ANOVA* command in R software (Ritz and Streibig 2008).

Four major steps need to be completed to compare the parameters using this method (see supplemental file):

1) Fit Equation [2] to the data of each species individually (*R. brasiliensis* and *C. benghalensis*); this represents the full model, where four parameter values (*I* and *A* for each weed species) will be estimated.

2) Pooling the data for both species (*R. brasiliensis* and *C. benghalensis*) and fit Equation [2]. This represents the reduced model, where two parameter values (*I* and *A* for both weed species combined) are estimated for the polled data. This step will allow testing the hypothesis that *I* and *A* do not vary between species, which means that both species compete similarly with corn. If the hypothesis is accepted (P-value>0.05), stop here. Otherwise, there is two more hypothesis to be tested.

3) Fit equation [2] setting a single parameter *I*, but different *A* parameter for each species. This is a reduced model, and three parameters will be estimated. This step tests the second hypothesis, that weed species compete similarly at low densities (*I*), but different at higher densities (*A*).

4) Fit equation [2] setting a single parameter *A*, but different *I* parameters for each species. This is a reduced model, and three parameters will be estimated. This step tests the third hypothesis, that weed species compete similarly at higher densities (*A*), but different at low densities (*I*). Additional AIC was also performed for the nested model selection for confirming the F-test model selection.

**Goodness-of-fit of the models.** Root mean squared error (RMSE), model efficiency (ME), and R2 (for polynomial quadratic model only) were calculated and used to test the goodness-of-fit of non-nested and nested models (Archontoulis and Miguez 2015; Mayer and Butler 1993; Roman et al. 2000):

eq. [7]

eq. [8]

*R2* eq. [9]

where RSS and RSTare the sums of squares for the residual and total, respectively; is the number of data points; is the number of model parameters; is the observed, is the predicted, and is the mean observed value. The ME values range from -∞ and 1, with values closer to 1 indicating better predictions (Werle et al. 2014c). R2 values range from 0 to 1, and it was used only for the polynomial quadratic model, which is a form of linear regression.

**Results**

**Top model selection to describe crop-weed competition.** The retangular hyperbola model resulted in the lowest AICc (332.2), followed by a logistic model (337.6) and a polynomial quadratic model (343.1) (Table 1). The RMSE and ME resulted in similar trend for the models tested, except *R. brasiliensis* in the polynomial quadratic model (Table 1).

In the retangular hyperbola model (top model selected), four parameters were estimated, which are *I* and *A* for *R. brasiliensis* and *C. benghalensis*. The parameters *I* and *A* for *R. brasiliensis* was estimated at 50.3% and 82.1%, respectively (Table 2). In contrast, for *C. benghalensis* parameters were estimated at 210.2% (*I*) and 108.6% (*A*) (Table 2). The *P*-value showed no lack of fit for the four estimated parameters (Table 2)

According to AICc, the logistic model was the second best model to describe the data (Table 1). The maximum corn yield loss caused by the competition of *R. brasiliensis* and *C. benghalensis* (*d*) was 67.2% and 93.4%, respectively. The 50% corn yield loss (%) was 1.2 and 0.7 plants pot-1 of *R. brasiliensis* and *C. benghalensis*, respectively. However, logistic model showed parameters lack of fit (*P*-value >0.05), including slope (*b*), lower limit (*c*), and inflection point [(*e*) *R. brasiliensis*] (Table 3). Also, the standard error in *b* and *c* parameters is bigger than the estimated values (Table 3). The ME was 0.58 and 0.85 for *R. brasiliensis* and *C. benghalensis*, respectively. Moreover, RMSE for the logistic model was 13.2.

The polynomial quadratic model provided the highest AICc (Table 1). Similar trend was observed for RMSE. However, ME of *R. brasiliensis* was highest (0.71) across the three models tested (Table 1). In addition, as a linear model, R2 was include for goodness of fit. The R2 was 0.71 and 0.89 for *R. brasiliensis* and *C. benghalensis*, respectively (Table 1). There was a lack of fit (P>0.05) of the intercept (α) for both weed species (*P*-value>0.05). But not for the slope (a) and quadratic parameter (b). Slope was 35.5% and 65.5%, and quadratic parameter -5.4 and -11.1 for *R. brasiliensis* and *C. benghalensis*, respectively (Table 4)

**Model selection to evaluate weed competitiveness with the crop.** Based on AICc, the rectangular hyperbola was the top model that described the data (Table 1). The F-test of the rectangular hyperbola (Full model) indicated a reduced model (*P*-value=0.40) with different parameter *I* (corn yield at low weed densities) and similar parameter *A* (corn yield at higher densities) was the top model (Red. III) to describe corn competition to *R. brasiliensis* and *C. benghalensis* with corn (Table 5 and Figure 6). The Red. I and II models were different from the Full model (*P*-value<0.05), thus the hypothesis tested in those models were rejected (Table 5). According to the parameter estimates in the rectangular hyperbola Red. III model, at weed low densities (*I*), corn yield loss was 37.0 and 228.3% in competition to *R. brasiliensis* and *C. benghalensis*, respectively. However, at higher densities, *R. brasiliensis* and *C. benghalensis* compete similarly, and corn yield loss was 106.1% (Figure 5 and Table 6). AICc corroborates to F-test (Table 5). The model selected by the F-test (different I, but similar A) resulted in the lowest AICc of 330.4. The RMSE was similar in Red. III and Full model, but the highest ME (≥0.95) for *R. brasiliensis* and *C. benghalensis* demonstrated the goodness of fit of the top model selected.

**Discussion**

**Top model selection to describe crop-weed competition.** Rectangular hyperbola model was the top model to describe the corn yield loss (%) in response to both *R. brasiliensis* and *C. benghalensis* competition (Figure 2 and Table 1). The model with the smallest value of AICc was considered the top model or the best descriptor of the full reality given the set of candidate models and the data (Anderson, 2010). This model was also the best for describing corn leaf area, height, and stem diameter reduction in response to *R. brasiliensis* and *C. benghalensis* densities (data not shown).

In the rectangular hyperbola model, four parameters were estimated, which are *I* and *A* for *R. brasiliensis* and *C. benghalensis* (Table 2). However, parameter *I* and *A* of *C. benghalensis* were estimated over 100% (Table 2). The parameter *I* of *C. benghalensis* curve had a steep inclination, which is likely that at this pot size used, *C. benghalensis* is very competitive in corn. Therefore, bigger pots and lower *C. benghalensis* densities would have been necessary for such a study. The parameter *A* for *C. benghalensis* was also over 100%, which is likely that the pots were too small that final constant yield was reached too fast with *C. benghalensis*. Parameters *I* and *A* was also overestimated in a field study of *Amaranthus retroflexus* in competition with *Sorghum bicolor* (Knezevic and Horak 1998). Nonetheless, in the present study there is no lack of fit of parameters *I* and *A* estimated for *R. brasiliensis* and *C. benghalensis* (P<0.05).

According to AICc, the logistic was the second best model to describe the data (Table 1). Logistic model does not seem to be appropriate to describe the data from additive designs (Figure 3). The problem with using the logistic model to describe additive designs is that these models have a flexible inflection point (Figure 1C). The symmetric shape of logistic models is related to the rate of change. One of the assumptions when using the logistic model is that the inflection point (*e*) is always at 50% of the asymptotic size (Knezevic et al. 2007; Ritz et al. 2015). Therefore, the symmetric shape of yield loss (%) in function of weed density have no biological meaning for additive design studies. Though the logistic model is not recommended for additive design, it is one of the most commonly used and appropriate models in other weed research topics. Logistic (sigmoid curves) are extensively used for predicting weed emergence, herbicide dose-response, and critical time for weed removal (Knezevic et al. 2007; Knezevic and Datta 2015; Werle et al. 2014a; Werle et al. 2014b). For example, in herbicide dose-response studies, the parameter *e* is meaningful and important for comparison of herbicides doses that control 50% of a weed population (Oliveira et al. 2017).

The polynomial quadratic model was statistically the least appropriate for describing the data. The α (intercept) and a (slope) parameters estimated from a polynomial quadratic model possibly have biological meaning. However, the b (quadratic) parameter does not. Nonetheless, this model does not provide meaningful biological parameters that would improve the discussion, test hypothesis, and help researchers understand the results from crop-weed competition studies. In addition, the polynomial quadratic curve is symmetric around its maximum response value (peak), which makes such response biologically unlikely in an additive design studies (Figure 1B). For example, the maximum corn yield loss (%) is lower at four plants pot-1 than in three plants pot-1 (Figure 2). The highest ME or R2 for *R. brasiliensis* could potentially mislead model selection; however ME and R2 tests only goodness of fit of the data. Therefore, a polynomial quadratic curve should not be encouraged to fit regression in additive designs.

To understand the nature of crop-weed competition modeling, one needs to comprehend the concept of constant final yield (CFY). The CFY is described from low to high densities, whereas the relationship between total biomass per unit area and density is initially linear, but eventually reaches a constant biomass that remains constant (Weiner and Freckleton 2010). To use the rectangular hyperbola, CFY needs to be reached; otherwise, parameter estimates will not be statistically and biologically meaningful. For example, in our study, the CFY was reached too fast in *C. benghalensis*, as a result estimation of parameters I and *A* from *C. benghalensis* was estimated over 100% (Table 2). In contrast, for *R. brasiliensis*, the design was appropriate and CFY was reached without parameter overestimation. Thus, the weed density for reaching CFY can vary among species. As a result, for proper additive design studies, different weed densities based in the competitive potential from each species might be necessary. Other studies showed that CFY was reached and estimation of *I* and *A* was under 100% (Knezevic et al. 1994; Knezevic et al. 1997). In addition, a competition study that report a linear relationship trend between crop yield loss and weed density has not reached CFY yet (Figure 1A). It is likely that either the appropriated weed density for the study was not selected or plants were harvested before significant competition occured. Therefore, experimental design needs to be adjusted by increasing the weed density to achieve the CFY.

In additive design studies, because of misleading model selection (usually R2), it is common to find multiple equations fitting response variables (Ferreira et al. 2015; Silva et al. 2015). For example, more than six models were used to describe the competition of two weed species (*Urochloa decumbens* and *Ipomoea grandifolia*) with three neotropical trees (*Senegalia polyphylla, Ceiba speciosa, and Luehea divaricata*) (Monquero et al. 2015). It becomes almost impossible to evaluate and compare weed competitiveness when different equations with different parameters are used.

**Model selection to evaluate weed competitiveness with the crop.** I was statistically demonstrated the rectangular hyperbola model was the top model to describe crop weed competition in additive design. The F-test demonstrated that at high densities (A) competition of *R. brasiliensis* and *C. benghalensis* in corn yield loss is similar, but at low densities (*I*) is different. Therefore, the hypothesis that competition of *R. brasiliensis* is similar to *C. benghalensis* in corn was partially rejected. Because competition is similar at weed high densities, but different at weed low densities.

A complete review of model parameter *I* and *A* of the rectangular hyperbola is provided by (Cousens 1985). Also, this the asymptote model recommended for crop-weed studies in additive design (Ritz et al. 2015; Swanton et al. 2015). Many authors have used this model to answer their research questions and improve weed control decision-making (Cathcart and Swanton 2003; Fischer et al. 2004; Lindquist et al. 1999; Werle et al. 2014c). For example, using the rectangular hyperbola model, it was concluded the higher competitive potential of *Amaranthus palmeri* in corn and *Kochia scoparia* in sunflower (Lewis and Gulden 2014; Massinga et al. 2001). Parameters *I* and *A* are also useful for estimating weed competition across different locations and for calculating weed thresholds (Lindquist et al. 1996; Lindquist and Mortensen 1998). Additionally, using parameters *I* and *A,* it was demonstrated that organic cropping systems have the potential to tolerate great abundance of weeds compared to conventional system (Ryan et al. 2009). Thus, the rectangular hyperbola proposed by Cousens (1985) and the F-test nested model selection are important and useful tools of crop-weed competition in additive design.

Here it was demonstrated that the rectangular hyperbola was statistically and biologically the best model to describe crop-weed competition data from additive design. Potential issues, including parameter overestimation (>100%) were also addressed. Nonetheless, rectangular hyperbola model has an asymptote curve shape that fits well with the expected results from additive design studies. The parameters *I* and *A* are easily interpreted and biologically meaningful. We propose rectangular hyperbola (Cousens 1985) as a standardized model for crop-weed competition studies in additive design. Logistic models are recommended to another set of studies in weed research (e.g., herbicide dose-response), and polynomial quadratic curves are not recommended. This present study would aid statistical data analysis and interpretation of crop-weed competition from additive designs.

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